Life Cycles of Firm Disclosures

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ABSTRACT

We propose that the product life cycle is important in understanding the firm's disclosure policy and test this hypothesis using a 4-dimensional text-based life cycle model. Mature-stage life cycle firms disclose more, consistent with an outward-focused investment strategy that lowers search costs for finding synergistic alliance 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, and readability. A quasi-natural experiment based on waves of rapid depreciation of protected intellectual property, and analysis of pairwise co-search of peer filings on the SEC EDGAR website, 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 explain both the incentives to be secretive and to disclose.

A key problem of traditional data and methods in the analysis of firms' life cycle stages is that of 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 prod-

[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.

uct market, and intuitively, because these market positions are not yet established, managers are particularly concerned about product substitution threats from competitors. 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 and cause the focal firm to decrease disclosures.

Our main empirical findings are that firms with more exposure to the mature 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. In contrast, firms in the early stage of the 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. When a firm's peers are in the mature life cycle stage, and are likely seeking complementary inorganic investment opportunities themselves, we find that the focal firm's disclosure strategy especially 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

[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.

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 relating to 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.

Earlier literature leads us to further predict that mature product life cycle effects should continue to matter even more for more distant product market peers, whereas the early product cycle effects should dissipate more quickly as competitive threats tend to be more local in the product space. In particular, Hoberg and Phillips (2010) find that acquisitions are especially more likely when a firm has more "moderately related peers" as acquisitions likely lack synergies when the acquirer and the target are too similar. Bena and Li (2014) find similar results as acquisitions are more likely when acquirers and targets are similar technologically or in products but not when they are similar on both dimensions. We measure product market distance for each peer using the TNIC data repository from Hoberg and Phillips (2016) and we group peers into bands around a focal firm based on how close they are in product market space. Consistent with our predictions, we find that mature product life-cycle effects remain strong even for more distant product market peers, but early-stage life cycle effects fade more quickly.

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 indicate that although

[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.

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 generally large and successful 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 from this quasi natural experiment strongly support these predictions, especially when the shock is measured at broader sectoral levels of granularity.[5]

Because many of our hypotheses have direct predictions for how and when product market peers will search a focal firm's disclosures, we also consider corporate co-search. Bernard, Blackburne, and Thornock (2019), 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.[6] This approach offers significant econometric power, as the co-search data is available

[5] 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.

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

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 comprises 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 overall conjecture that the stage of a firm's products in the life cycle is important in understanding its disclosure policies and how they relate to firms operating in related markets.

In addition to the quasi-natural experiment and the co-search mechanism tests described above, we take several steps to reduce the potential impact of endogeneity and alternative explanations. Our analysis can in part be viewed as tests of the equilibrium predictions of our hypotheses. Our approach to test several deeper implications of these hypotheses, and test for mechanisms, is a first step that reduces the likelihood that alternative explanations can fully explain our results. We also include controls and rigid firm fixed effects, and hence alternatives based on 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 including firm age (the standard proxy for life cycles used 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. We also show that our main results are not driven by any one major industry sector. Overall, our findings suggest a richer narrative and microfoundation for how firms' relationships with product market peers might influence disclosure decisions. These findings are also relevant to ongoing 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.

[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.

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 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. They establish that the likely mechanism is that product disclosure reveals information about strategies, and the progress of technological investments.

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 directly address this challenge and use textual analysis to model product life cycles as a rich 4-D vector for each firm in each year.[8]

We argue that these 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 firms 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 in modeling the efficacy of investment Q-models. We propose that these life-cycle investment strategies also predict optimal disclosure policies across several voluntary disclosure categories.

Exposure to each life-cycle stage is associated with focus on different investment and product market strategies, and, in consequence, with different incentives regarding disclosure policies. Life1 is associated with product development, where the firm retains the option of changing the products' market positioning, its technical specifications, and, possibly the required supply chain. Disclosures about these developments are valuable to competitors as they can take countermeasures. Because the focal firm does not yet have an established market presence, competitors might not otherwise observe product technology, product positioning, or supply 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

[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.

the incentive firms have to restrict disclosures in this setting will impact a wide array of disclosure policies including trade secrecy, redaction, and readability. Consistent with Kankanhalli et al. (2019) we expect that such information restrictions will increase investors' estimates of firm value. We formalize this in hypothesis H1:

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

If the focal firm's product market peer firms also have large Life1 exposures, its incentive to reduce disclosures is reinforced because in this case, peer firms are in a better position to immediately use additional disclosures in their own product positioning and development.

We expect that the effect of peers' Life1 exposures is moderated by two factors. First, increased distance between peer firms and the focal firm in the product market space can mitigate these incentives. We measure product market distance using the Hoberg-Phillips (2016) TNIC database. Second, the focal firm's disclosures about IP and innovation are likely affected differently by rivals relative to disclosures about contracts the firm has with third parties. We expect that only close peers are likely to take advantage of disclosures about contracts or performance, whereas even distant rivals might be in a position to exploit disclosures about innovations.

H2: The disclosures of the focal firm will further favor secrecy (as in H1) when its product market peers also have more exposure to Life1. The impact of peer Life1 exposures should also diminish with product market distance.

By contrast, firms high on Life3 exposure operate in markets that are stable and focus on creating value from their existing product portfolios. Since Life3 firms have products already in the market, much of the product information that is proprietary and valuable to Life1 firms is already observable by the competitors of Life3 firms. Further, as Hoberg and Maksimovic (2019) show, Life3 firms grow by investing heavily in inorganic (outward focused) investment and acquisitions.[10]. As Rhodes-Kropf

[10]This is related to the finding by Maksimovic and Phillips (2008) that conglomerate firms, which tend to be older and larger than single-segment firms, grow more heavily by acquisition rather than

and Robinson (2008), Hoberg and Phillips (2010), and Bena and Li (2014) argue, the matching of bidders and targets is a key component in the value creation from acquisitions.

H3: We predict that exposure to Life3 will be associated with decreased redactions, decreased reliance on trade secrets relative to patents and with statements having higher readability.

If peer firms also have higher exposures to Life3, and are themselves searching for matches, the focal firm's incentives to disclose increase further. Although we expect the impact of peer Life3 exposure to decay with product market distance, we expect this decay rate to be slower for Life3 effects than for Life1 effects. This prediction is based on the findings of Hoberg and Phillips (2010), that acquisitions are more likely when a firm has more "moderately related peers" as acquisitions likely lack synergies when the pair are too similar. Bena and Li (2014) find similar results as acquisitions are most likely when acquirers and targets are similar on either technology or product dimensions but not when they are too similar on both.

H4: The disclosures of the focal firm are positively associated with the Life3 exposures of its peers. Although we expect the effect of peers' Life3 exposure to diminish with product market distance, we also expect this decay rate to be slow for Life3 effects as M&A and inorganic investment opportunities remain compelling for moderately related product market peers.

Exposure to Life2 is associated with a focus on improving process efficiency and cutting costs. Since the firm's products are already in the market and may be (partially) reverse engineered, some information that was initially confidential no longer needs protection. In addition, much of the investment in improving efficiency is likely to be directed to the purchase of equipment and software from vendors specializing in machine tools and business software, rather than being created within the firm. The disclosure of this information is less likely to reveal valuable proprietary information than when the firm itself is innovating or creating new products. Thus,

by organic investment

on average, we would expect that exposure to Life2 is associated with fewer incentives to be secretive relative to Life1. At the same time, Hoberg and Maksimovic (2019) find that Life2 firms have some incentives to partake in inorganic investments, but this incentive is lower relative to Life3 firms. Thus we also expect Life2 firms to disclose less aggressively than Life3 firms. Overall, Life2 firms are thus expected to exhibit disclosure patterns that are somewhat "average" in the distribution.

Firms with exposure to Life4 are likely to be divesting some or all of their existing assets. Similar to firms with Life3 exposure, these firms are likely to be seeking parties with whom to transact, which would favor more disclosure. However, because Life4 firms' goal of transacting is to redeploy their assets to other markets (given the poor outlook of their existing Life4 product markets), it follows that increased operational disclosure is likely less useful to potential partners. Also, Hoberg and Maksimovic (2019) find that Life4 firms seek risk taking opportunties to escape decline, which can benefit from increased secrecy. Overall, Life4 firms are thus expected to exhibit disclosure patterns that are somewhat "average" in the distribution.

Our hypotheses predict which firms will search which other firms' 10-Ks. Firms with Life1 exposures focus their search on other Life1 firms, and Life3 firms will principally search other Life3 firms. This last prediction can be broadened, as Life3 firms might search a broader set of potential complementary targets. We test these predictions directly using the approach of Bernard, Blackburne, and Thornock (2019). 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).

3 Data and Methods

Our life cycle variables derive purely from publicly available 10-K text. Although our textual queries can be programmed using standard languages and web-crawling techniques, for convenience, we use text processing software provided by metaHeuristica LLC. This software has pre-built modules for fast and highly flexible querying, while producing output that is easy to interpret.[11] For example, many of the variables used in this study are constructed by simply identifying which firm-year filings contain a statement indicating the maturity of its product portfolio.

3.1 Data

Our sample begins with the universe of Compustat firm-years with 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 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 informative and flexible TNIC industry classification.

3.2 The Product Life Cycle

Our approach echoes that used in Hoberg and Maksimovic (2019) and our goal is to use direct textual queries to identify the life cycle stage of a firm's product portfolio. This "anchor-phrase" method has been used in past studies including Hoberg and Maksimovic (2015), Hoberg and Moon (2017) and Fresard, Hoberg, and Phillips (2020). As noted earlier, our proposed product life cycle has four states:

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

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

(1) product innovation, (2) process innovation, (3) stability and maturity, and (4) product discontinuation. For parsimony, we will refer to these states as Life1, Life2, Life3, and Life4, respectively. Critically, our research requires that firms discuss these stages in their 10-K. Here we point readers to Regulation S-K, where Item 101 for example requires that firms provide "An explanation of material product research and development to be performed during the period covered" by the 10-K. A substantial amount of such text would indicate a firm with a high loading on the product innovation stage. Regarding process innovation, the same disclosure rules require the firm to disclose its results from operations, of which discussions of the costs of production are a significant component. A firm in the third maturity stage should be characterized by discussions of continuation and market share, but *without* reference to product or process innovation. Finally, a firm in the fourth stage will discuss obsolescence and product discontinuation.

We 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).[13]

Life1 List A: product OR products OR service OR services

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

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

expansion OR expanding OR expand

To measure the firm's loading on "Life2", we identify all paragraphs in a firm's 10-K (after above exclusions) that contain at least one word from the following lists.

Life2 List A: cost OR costs OR expense OR expenses

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

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

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.[14] 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.

[14] The approach used in the prior study requires that each life cycle stage must be compared to a baseline life stage such as Life3, as the four stages are co-linear with the intercept.

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 patent and trade secret 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

We compute our measure of intellectual property disclosure by dividing mentions of "patents" by the sum of mentions of "patents" and of "trade secrets". We exclude firms that do not report either patents or trade secrets when examining intellectual property disclosure tests. Our patent ratio measures each firm's tendency to choose between patents and trade secrets 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 and apply to many forms of disclosure, We further consider three additional measures of disclosure quality from the literature. All these measures complement each other to provide a more complete depiction of firms' disclosure strategies both in terms of proprietary information and operational activities.

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).[15]

Our second disclosure measure is the readability of financial statements. We measure readability using the Bog Index, a measure capturing plain English attributes[16] 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 major 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 sophisticated investors. Bonsall, Leone, Miller, and Rennekamp (2017) also 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

[15]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."

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

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 normalizes 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). We also measure competition in intellectual property (*Comp IP*) using the base model and additionally requiring the paragraph to contain both "intellectual" and "property" in the search. The latter measures are designed to provide insights regarding life cycle interactions with competition.

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.[17] 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

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

for other companies' filings.[18]

We limit the pairwise co-search database to only include the 1000 largest firms in each year.[19] 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[20]. 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. The Table also reports statistics for our two sets of life cycle variables based on the Text-based Network Industry Classifications (TNIC).

Table 2 displays the correlation tables for our life cycle variables and the logged age variable. We observe that Life1 and pLife1 are negatively associated with firm age, while Life4 and pLife4 are positively associated with firm age. This corroborates a primary prediction of the product life cycle theory. Firms generally begin life with a significant fraction of their product portfolio in the product innovation stage and end life with product discontinuation and eventual delisting. Life2 and Life3 measures for focal firms and peer firms do not have consistent signs. Hoberg and Maksimovic (2019) suggest that these univariate findings for life cycles are purely driven by cohort effects, and the ordering of the life cycle states relative to aging becomes closer to the theoretical predictions when we focus on within-firm variation (and control for firm fixed effects). For example, for a given firm in time series, process innovation precedes product maturity on average. Table 2 also shows that correlations are

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

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

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

generally modest and hence 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 relationship between life cycles and innovation disclosure. In particular, we consider regressions where the dependent variable is the patent ratio, which is the number of paragraphs in the 10-K mentioning patents divided by 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. Firms with zero mentions of either are excluded from this analysis. 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. Our predictions for Life2 and Life4 lie somewhere in between these two predictions and we expect little or no significant results.

To isolate the life-cycle effects on disclosures, we control for firm and year fixed effects in all cases. We also control for standard firm level variables, such as firm age, size, and Tobin's Q. Thus our results show the effect of life-cycle factors conditional on these descriptors.[21]

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 positive, indicating that firms favor patents over trade secrets as they age. However, this model cannot test our hypotheses, which predict a highly non-linear pattern over the life cycle, and moreover, firm age is only moderately correlated with our life cycle stages.

Column (2) of Table 3 thus adds the four life cycle stages of the focal firm. We

[21]Note that while conventional, this is a conservative specification, in that some of these controls may themselves predict the life-cycle variables.

find that the Life1 coefficient is negative and significant, and Life3 is positive and significant. In contrast, Life2 and Life4 are not significant. 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 negative and positive 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. Interestingly, we also find a positive and significant peer Life2 coefficient in Table 3, suggesting that a focal firm views Life2 peers as being similar to Life3 peers from a disclosure strategy perspective. These results echo the finding in Hoberg and Maksimovic (2019) that inorganic growth strategies are not fully unique to Life3 firms, but also to Life2 firms. Supporting this interpretation, the product life cycle theory would suggest that Life2 firms have stable product offerings just as Life3 firms do, but they are jointly focused on process optimization and some inorganic growth options. The negative and significant results for peer Life4 firms reinforces our non-linear predictions, as Life4 peers are focused on discontinuation and are likely less attractive as long-term strategic partners. Finally, Column (4) of Table 3 shows that our results are robust to excluding financials (SIC codes 6000-6999).

Many studies in the existing literature 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 are uniquely important in understanding firm 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 patent 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, Tian and Yu (2018) show that redacted contracts can be categorized into mainly five groups based on their objectives: employment/incentive, credit/leasing, R&D/license, manufacturing/purchase and sale of inventory or services, and investment. Other related studies include Glaeser, 2018; Boone, Floros, and Johnson, 2016; Costello, 2013; 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. In contrast to the tests in Section 4.1, we are able to use the entire sample as firms with no redaction mentions are assigned a value of zero for our dependent variable. Finally, we show the same model specifications as were 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. This is consistent with our expectation that managers have less incentive to redact and more incentive to search for outside opportunities when the firm matures. However, as noted previously, this model does not have adequate granularity to test our much richer and non-linear life cycle hypotheses.

Column (2) of Table 4 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 (pLife1-pLife4), 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 thus 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 and favors more inorganic growth for these firms, as reported in Hoberg and Maksimovic (2019).

We also find that the peer Life4 coefficient is significant and negative, further reinforcing our non-linear predictions. As noted in the previous section, this is consistent with Life4 firms having few growth options and hence little incentive to search for partnerships. Additionally, the negative coefficient also suggests that Life4 firms might be seen as having an opportunistic disposition in the product market. Given their somewhat time-sensitive need for product market resolution, they might in fact be seen as a threat to firms in earlier stages of the product life cycle who might be worried about opportunistic risk taking by Life4 firms to shift to earlier stages of the life cycle. 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 have low processing costs (Liberti and Petersen, 2019), Blankespoor, deHaan, and Marinovic (2019) suggest that low disclosure readability can be a major component of disclosure processing costs for verbal disclosures. Regarding its theoretical impact on the reader of disclosures in the context of our four hypotheses, increased verbal complexity or low readability are analogous to providing less disclosure. In particular, the reader is likely to take less away from reading an unreadable document just as they would take less away from a document having less actual disclosure. Hence we predict that Life1 firms will favor less readable disclosures and Life3 more readable disclosures. Both should be reinforced by peers having similar life cycle exposures.

Our dependent variable in Table 5 is the Bog Index based on Bonsall, Leone, Miller, and Rennekamp (2017), which is a multifaceted index designed to capture several dimensions of plain English readability attributes. A high bog index indicates a less readable document. We adopt the same panel data structure as in Tables 3 and 4. 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 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 adds the peer firm life cycle exposures (pLife1-pLife4). The results mirror those in Column (2), especially for our Life1 and Life3 predictions, which are most crucial to our hypotheses. Not surprisingly given the ambiguous predictions for them, any Life2 or Life4 results are not robust from the peer firm perspective. These findings fully support our four key hypotheses and furthermore 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 Financial Fillings

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 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 than they are with head to head competition. 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 any one major industry sector or by firm financial constraints.[22]

5 Product Market Dynamics and Disclosures

5.1 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

[22]Please see Online Appendix Table A6 to Table A10.

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 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 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.[23] 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 (SIC2o3 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. 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.

5.1.1 Patent Expiration Waves and Disclosure Strategies

Tables 7 and 8 report our main results regarding protected IP depreciation waves and disclosures. We regress all disclosure measures (patent ratio, 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 7 report the results for the patent ratio 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 are significant at the 5% level when sectors are defined broadly using SIC-2 industries

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

or using the broad outer-peers SIC-2o3, whereas the narrowly defined SIC-3 result has a positive sign but is not significant at conventional levels with a t-statistic of 1.62. These results for the patent ratio 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 7 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 8 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 8 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.

5.2 Disclosure Policies vs Product Market Distance

A key focus throughout our study has been on the relationship between peer life cycle stages and a focal firm's disclosure policies. In this section, we explore additional predictions regarding whether this influence decays quickly or slowly as we move from the closest peers to the more distant peers. We define the closest peers as those who sell products that are very similar to those of the focal firm. More distant peers sell products that are somewhat related, but not the same as those of the focal firm. Very distant peers sell products that are only somewhat related. To formalize this concept, we use the TNIC text-based product distance measure of Hoberg and Phillips (2016), and we use various calibrations to model product distance in intuitive groups. For example, the TNIC-4 industry classification is calibrated to be as granular as are four digit SIC codes (SIC-4), and peers who are in the same industry by this metric are deemed to be close peers. TNIC-3 peers, TNIC-2 peers, and TNIC-1 peers are increasingly distant in the product space and are calibrated to be as granular as are SIC-3, SIC-2, and SIC-1 peers.

To our knowledge, this kind of analysis is entirely novel to the disclosure literature. Yet we propose that this issue is important, as some firms have large masses of peers that are very close, whereas others have many peers that are moderately close in the product space. Moreover, the life cycle stages of these peers are highly heterogeneous. Because the life cycle stages of our peers are among the most important economic determinants of the disclosure policies we model, understanding the relevance of peers as we move toward more distant peers is likely to be of large importance in understanding disclosure policies in a more comprehensive manner.

Although these predictions are not core to our hypothesis formations in Section 2, the following predictions arise form basic extensions to their logic, when considered alongside economic theories and other results in the literature. For example, Hoberg and Phillips (2010) show that mergers are especially likely to occur when a firm has large numbers of peers that are moderately similar (but not highly similar) to a focal firm. This finding suggests that asset complementarities are particularly high for moderately distant firms in the product space. This finding is important in our context as it additionally suggests that Life3 firms, whose primary investment objective is to find strategic partners, are especially likely to be influenced by peers that are more distant in the product space relative to firms in other life cycle stages. In contrast, Life1 firms are most concerned about imminent competitive threats. As direct competitors reside more closely in the product space, these firms are most likely to be influenced by the most proximate peers and less so by more distant peers.

A second prediction relates to the influence of innovation disclosure specifically. In our earlier tests, for example, we modeled the propensity of firms to disclose trade secrets versus patents. Economic theories suggest that the decision to disclose innovation specifically is likely to be different than the decision to disclose other information such as contracts or readability. In particular, innovation can be used to operationalize economies of scope, and a peer that is somewhat distant in the product space might become empowered to enter a more distant firm's market through such technology. As a consequence, it is likely that the impact of peers decays more slowly with product distance for innovation disclosures than for other disclosures.

We operationalize the tests using stepwise regression to account for the impact of each set of peers only after controlling for more proximate peer groups. our research design involves three steps. First, we divide the focal firms' peers into four groups (calibrated to match the granularity of various SIC-code groupings as indicated):

TNIC4: 1% closest, akin to SIC4 peers

TNIC3o4: Next 1%, akin to SIC3 peers that are not SIC4 peers

TNIC2o3: next 3%, akin to SIC2 peers that are not SIC3 peers

TNIC1o2: next 5%, akin to SIC1 peers that are not SIC2 peers

(Figure 2 provides a visualization of the product market distance.)

Second, we stepwise orthogonalize these groups: The first band of peer Life cycle values (TNIC-4 peer life cycle exposures) are considered in their raw form as these are the innermost peers. The life cycle stages of the second band of peers (TNIC3o4 peers) are orthogonalized relative to the first band using standard stepwise regression methods. The life cycle stages of the third band peers are then orthogonalized relative to the first and second bands and the fourth band is orthogonalized relative to the first, second and third bands.

Our last step is to include the life cycle exposures of all four bands in the same regression model for each of our dependent variables: the patent ratio, redaction, and the Bog index. We are not concerned about multicollinearity in these models as all bands are orthogonalized. We thus include all 4 Life cycle variables for each of the four bands (16 life cycle variables in total) in each specification. To ensure that our results are consistent and conservative, we also include all of our control variables as well as firm and year fixed effects.

Panels A and B of Figure 3 report the results using a convenient bar chart format where only the t-statistics for the peer Life1 exposures (Panel A) and the peer Life3 exposures (Panel B) are reported for conciseness. Although we only plot the Life1 and Life3 coefficients to save space, we note that we do include all 4 life cycle stage variables for each band of peers in the model, and also all of the controls and the firm and year fixed effects. These models therefore adopt a stringent empirical design, which places a high bar for finding results for the more distant peers.

Figure 3 illustrates general support for our predictions. In particular, innovation disclosure is unique, and peers influence a focal firm even when they are more distant in the product space. We see that the patent ratio (innovation disclosure) is generally impacted by peers in a way that exhibits the slowest decay. In both panels, the second bar (TNIC3o4 peers) is roughly as high as the first bar (TNIC-4 peers), indicating that the moderately distant peers are as important as the most similar peers. In addition, Life3 effects also tend to decay more slowly than do Life1 effects. This conclusion is particularly strong for redaction, where Panel B (Life3) shows a slow decay with distance whereas Panel A (Life1) shows a faster decay pattern. However, regarding the Bog Index, we see similar decays for Life1 and Life3. The initial faster decay (only for non-innovation disclosures) also supports the economies of scope hypothesis suggesting that potential entry threats raise the importance of more distant peers, but only for innovation disclosure. These overall findings, while speculative, suggest that economic forces relating to entry threats and economies of scope are likely important. In addition, the effects of Life3 peers are likely more important deeper into the product space than are those for Life1 peers.

6 Pairwise Search and Life Cycles

Results in the previous sections examine hypotheses regarding how firms will shape their disclosure policies given expectations regarding who will be downloading the disclosed information. In this section, we examine the actual information downloads using the EDGAR filings across specific firm-pairs to assess these expectations. 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 imply highly specialized predictions for which firms will download the filings of which other firms. Unlike our previous tests, where we have diametric opposite predictions for Life1 and Life3, we have the same prediction regarding the downloading behavior of firms in the Life1 and Life3 stages. In particular, we predict that Life1 firms will aggressively download the filings of other Life1 firms, as doing so could yield a competitive advantage about market placement of products or useful technologies. Firms in Life1 have particularly strong incentives to gather this information given they are actively searching for markets and technologies for their new products. Regarding Life3, we also expect higher than average downloads between Life3 pairs of firms, as their primary source of growth rests with attracting partners to fuel inorganic growth. By comparison, our hypotheses would generally predict less downloading between Life2 pairs or Life4 pair firms, which face both incentives with less fortitude.

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 firms in another life stage (for example, whether Life3 firms aggressively download the filings of Life2 firms). Although our predictions regarding these different 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 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 Life2 and Life4 firms. The study also finds that the Life1 stage is unique and does not spill over. Hence we would predict generally 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.

We test these hypotheses in Table 9, 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 variables are analogously defined. We additionally include firm 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 9 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 common 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. 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 hypotheses and their microfoundation 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 Life2" is negative and mostly significant as we predict. Life1 firms are heavily focused on what other Life1 firms are doing, as firms in other life cycle stages have established product markets and hence they offer less insight for a Life1 firm. 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. As noted earlier, this is consistent with the acquisition findings in Hoberg and Maksimovic (2019) as firms in Life2 and Life4 mildly resemble Life3 firms regarding their propensity to undertake inorganic acquisitions.

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 as these firms do have stable product offerings. By doing so, they are first movers and can realize gains earlier and also before other firms might act. Downloading activity between Life3 and Life4 pairs is also sensible as Hoberg and Maksimovic show that 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 and intuitively, a higher TNIC score very strongly predicts additional downloading between the given pair of firms. We have also included both the firm-pair and year fixed effects. Firm-pair effects deal with time-invariant sources of unobservable heterogeneity unique to each firm pair.

7 Conclusion

We propose and 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 clear disclosure that is more readable.

We argue 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 an even more transparent disclosure strategy. Consistent with a hypothesis rooted in complementary assets, these mature stage effects run deep in the product space and fade slowly as we consider increasingly distant peers.

Because interactions through the life cycle are potentially endogenous, we consider a novel quasi-natural experiment based on broad sectoral waves of rapidly depreciating protected intellectual property. We propose that rapid loss of IP protection creates entry incentives that Life1 firms will primarily view as a shock in the form of unwanted competition. These firms should further curtail all forms of disclosure. In contrast, Life3 firms should view the entrants as additional opportunities for attracting inorganic alliances and they should increase all forms of disclosure, especially when the entrants are in more distant markets within the sector. Our results from this quasi natural experiment strongly support our predictions, especially when the shock is measured at broader sectoral levels of granularity.

In a final test, we adopt the framework of Bernard, Blackburne, and Thornock (2019) and analyze the intensity at which employees in one firm search the SEC EDGAR filings of peer firms. Consistent with our hypothesis, we find that both early and mature stage firms search the filings of their same-stage peer firms with a significantly higher intensity. Similar findings do not obtain for other life cycle stages. Overall, we conclude that exposures to the life cycle provide new insights explaining the disclosure policies of public firms across a range of disclosure policy choices. In turn, these results can further inform ongoing 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.

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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 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.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	sd	max	p50	min
Life1	97,311	0.281	0.306	1	0.158	0
Life2	97,311	0.347	0.259	1	0.285	0
Life3	97,311	0.294	0.296	1	0.186	0
Life4	97,311	0.0807	0.185	1	0.0164	0
pLife1	100,441	0.300	0.135	1	0.284	0
pLife2	100,441	0.350	0.106	1	0.342	0
pLife3	100,441	0.307	0.118	1	0.292	0
pLife4	100,441	0.0792	0.0427	1	0.0731	0
Log Age	113,165	2.511	0.871	4.220	2.565	0
Base Comp	113,165	0.0165	0.0123	1	0.0145	0
Comp IP	113,165	0.00371	0.00711	1	0.00152	0
Comp High	113,165	0.00613	0.00883	1	0.00494	0
Redaction	113,165	0.000906	0.00249	0.333	0	0
Log 10-K Size	113,165	6.361	0.603	9.672	6.430	0
Log Assets	112,609	5.916	2.300	14.99	5.941	-6.908
Tobin's Q	110,351	1.756	2.229	30.21	1.101	0.0826
Bog Index	108,869	83.63	7.724	211	84	47
TNIC HHI	108,062	0.262	0.271	1	0.145	0.0141
Patent Ratio	67,001	0.763	0.260	1	0.826	0

Table 2: Correlation Table (Life Cycle Variables)

Correlations for the life cycle variables are reported for our sample based on annual firm observations from 1998 to 2017. The 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 Cycle of Innovation Disclosure

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 patent ratio variable, which is calculated by dividing mentions of "patents" by the sum of mentions of "patents" and of "trade secrets" in the filings. We have scaled the patent ratio variables by 100. The 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 (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 (2) and (3) report results for a life cycle versus patent ratio model, and Column (1) is purely based on key control variables. 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	Patent ratio x 100	Patent ratio x 100	Patent ratio x 100	Patent ratio x 100
Life1		-0.964***	-0.835***	-0.846***
		(-3.229)	(-2.816)	(-2.774)
Life2		0.0928	0.0372	0.0658
		(0.388)	(0.157)	(0.268)
Life3		0.908***	0.766**	0.692**
		(2.965)	(2.529)	(2.222)
Life4		-0.219	-0.176	-0.199
		(-1.575)	(-1.275)	(-1.426)
pLife1			-1.682***	-1.576***
			(-4.537)	(-4.194)
pLife2			1.429***	1.480***
			(4.618)	(4.667)
pLife3			1.416***	1.404***
			(3.825)	(3.725)
pLife4			-0.261**	-0.302***
			(-2.370)	(-2.721)
Log Age	5.405***	5.510***	5.188***	5.341***
	(8.971)	(7.622)	(7.199)	(7.140)
Log 10-K Size	-0.527**	-0.360	-0.295	-0.199
	(-1.994)	(-1.272)	(-1.050)	(-0.684)
Log Assets	0.498	0.588	0.609	0.631
	(0.970)	(1.070)	(1.116)	(1.122)
TNIC HHI	0.690***	0.600***	0.533***	0.561***
	(4.382)	(3.589)	(3.201)	(3.331)
Tobin's Q	-0.314***	-0.274*	-0.221	-0.235
	(-2.616)	(-1.869)	(-1.511)	(-1.573)
Observations	63,714	55,761	55,656	52,427
R^2	0.815	0.820	0.821	0.808
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 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 (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 (2) and (3) report results for a life cycle versus redaction model, and Column (1) is purely based on key control variables. 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 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 (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 (2) and (3) report results for a life cycle versus readability model, and Column (1) is purely based on key control variables. 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 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 (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 (2) and (3) report results for a life cycle versus competition complaint model, and Column (1) is purely based on key control variables. 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: Patent Depreciation Waves and Disclosure Strategies

The table displays the baseline results of the patent expiration shock. The dependent variable is a patent ratio variable, which is calculated by dividing mentions of "patents" by the sum of 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 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) Patent ratio x 100	(2) Patent ratio x 100	(3) Patent ratio x 100	(4) Redaction x 1000	(5) Redaction x 1000	(6) Redaction x 1000
Life1	-0.744**	-0.817**	-0.752**	0.0597	0.0664	0.0617
	(-2.222)	(-2.519)	(-2.307)	(1.330)	(1.474)	(1.368)
Life2	0.0652	0.111	0.124	0.0330	0.0342	0.0333
	(0.247)	(0.436)	(0.477)	(1.452)	(1.509)	(1.458)
Life3	0.663*	0.755**	0.678**	-0.0690***	-0.0738***	-0.0724***
	(1.895)	(2.236)	(1.991)	(-2.856)	(-2.997)	(-2.943)
Life4	-0.180	-0.202	-0.209	0.00643	0.00462	0.00619
	(-1.212)	(-1.395)	(-1.427)	(0.564)	(0.407)	(0.538)
SIC2 PatDepWave	0.394**			0.0791***		
	(2.024)			(4.652)		
Life1 x SIC2 PatDepWave	-0.429**			0.158***		
	(-2.156)			(4.098)		
Life2 x SIC2 PatDepWave	0.109			-0.0325*		
	(0.740)			(-1.672)		
Life3 x SIC2 PatDepWave	0.433**			-0.0703**		
	(2.250)			(-2.304)		
Life4 x SIC2 PatDepWave	-0.0683			-0.0167		
	(-0.680)			(-1.500)		
SIC3 PatDepWave		0.359*			0.0846***	
		(1.948)			(3.735)	
Life1 x SIC3 PatDepWave		-0.330*			0.104***	
		(-1.797)			(2.756)	
Life2 x SIC3 PatDepWave		-0.0106			-0.0214	
		(-0.0688)			(-0.936)	
Life3 x SIC3 PatDepWave		0.301			-0.0414	
		(1.630)			(-1.230)	
Life4 x SIC3 PatDepWave		-0.0480			-0.0173	
		(-0.562)			(-1.416)	
SIC2o3 PatDepWave			0.356*			0.0697***
			(1.835)			(3.879)
Life1 x SIC2o3 PatDepWave			-0.467**			0.158***
			(-2.436)			(4.037)
Life2 x SIC2o3 PatDepWave			-0.00714			-0.0354*
			(-0.0489)			(-1.881)
Life3 x SIC2o3 PatDepWave			0.455**			-0.0721**
			(2.417)			(-2.330)
Life4 x SIC2o3 PatDepWave			-0.0175			-0.0111
			(-0.179)			(-1.094)
Observations	55,750	55,744	55,750	93,167	93,161	93,167
R^2	0.820	0.820	0.820	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 8: 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 10K filings. The 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	0.141***			0.176***		
	(2.802)			(4.332)		
Life1 x SIC2 PatDepWave	0.335***			0.262***		
	(5.414)			(4.395)		
Life2 x SIC2 PatDepWave	0.0122			-0.0712*		
	(0.266)			(-1.682)		
Life3 x SIC2 PatDepWave	-0.203***			-0.150***		
	(-3.487)			(-2.796)		
Life4 x SIC2 PatDepWave	-0.0416			-0.00244		
	(-1.334)			(-0.0774)		
SIC3 PatDepWave		0.169***			0.181***	
		(3.046)			(4.058)	
Life1 x SIC3 PatDepWave		0.187***			0.118	
		(2.768)			(1.496)	
Life2 x SIC3 PatDepWave		0.0102			-0.00372	
		(0.212)			(-0.0692)	
Life3 x SIC3 PatDepWave		-0.0911			-0.0576	
		(-1.592)			(-1.055)	
Life4 x SIC3 PatDepWave		-0.0442			-0.0169	
		(-1.160)			(-0.409)	
SIC2o3 PatDepWave			0.0802			0.156***
			(1.505)			(3.857)
Life1 x SIC2o3 PatDepWave			0.369***			0.267***
			(6.139)			(4.960)
Life2 x SIC2o3 PatDepWave			-0.0213			-0.0702*
			(-0.477)			(-1.798)
Life3 x SIC2o3 PatDepWave			-0.235***			-0.155***
			(-4.171)			(-3.025)
Life4 x SIC2o3 PatDepWave			-0.0316			-0.0173
			(-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 9: 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 based on Bernard, Blackburne, and Thornock (2018). 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 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 life cycle stage of the searcher firm, *LifeX Search Target* variable captures the 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

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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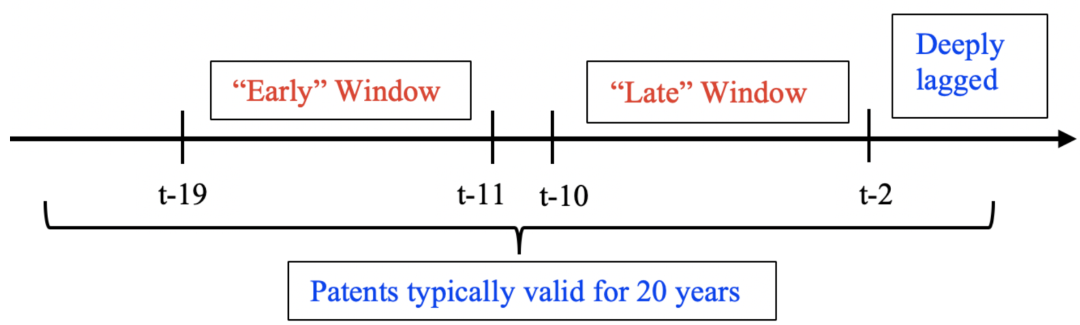

Figure 2: Visualization of the four TNIC granularities calibrated to SIC granularities. Specifically, we divide focal firms' peers into four groups: TNIC4 (1% closest, akin to SIC4 peers), TNIC3o4 (Next 1%, akin to SIC3 peers that are not SIC4 peers), TNIC2o3 (next 3%, akin to SIC2 peers that are not SIC3 peers), and TNIC1o2 (next 5%, akin to SIC1 peers that are not SIC2 peers).

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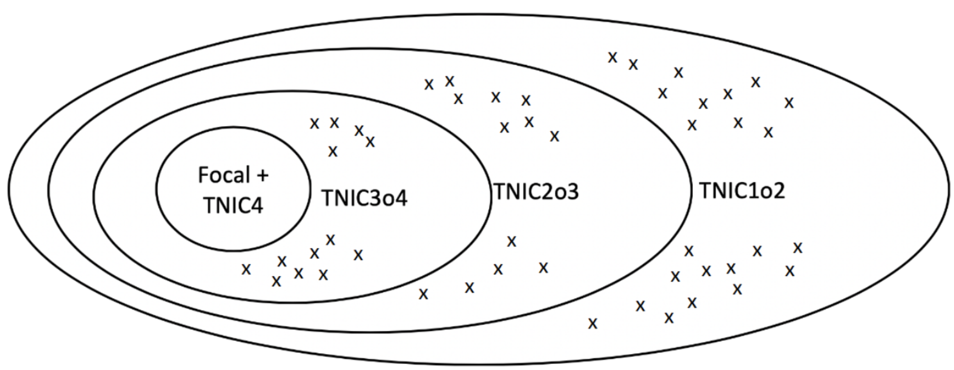

Figure 3: Plot of the t-statistics of stepwise regressions using four TNIC granularities calibrated to SIC granularities. The bar charts are the t-statistics of the various peer life1 variables (Panel A) or peer life3 variables (Panel B) for the near vs. more-distant peers as indicated in the legend. Specifically, we divide focal firms' peers into four groups: TNIC4 (1% closest, akin to SIC4 peers), TNIC3o4 (Next 1%, akin to SIC3 peers that are not SIC4 peers), TNIC2o3 (next 3%, akin to SIC2 peers that are not SIC3 peers), and TNIC1o2 (next 5%, akin to SIC1 peers that are not SIC2 peers). Then, we stepwise orthogonalize these groups: The first band of peer LifeX values are not orthogonalized; The second band is orthogonalized relative to the first band; The third band is orthogonalized relative to the first and second bands; The fourth band is orthogonalized relative to the first and second and third bands. We include all four bands in the same model where we separately consider dependent variables of the patent ratio, redaction, and bog index. Note we do not have problem with multicollinearity as all bands are orthogonal. Also, we include all 4 LifeX variables in the specification, and all of the peer groups and all of the controls and the firm and year fixed effects.

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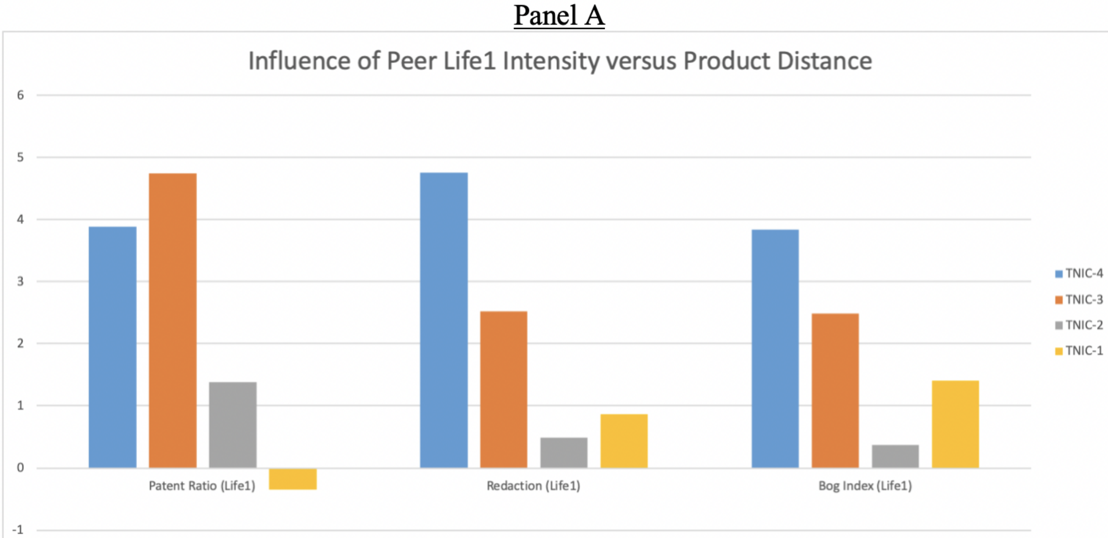
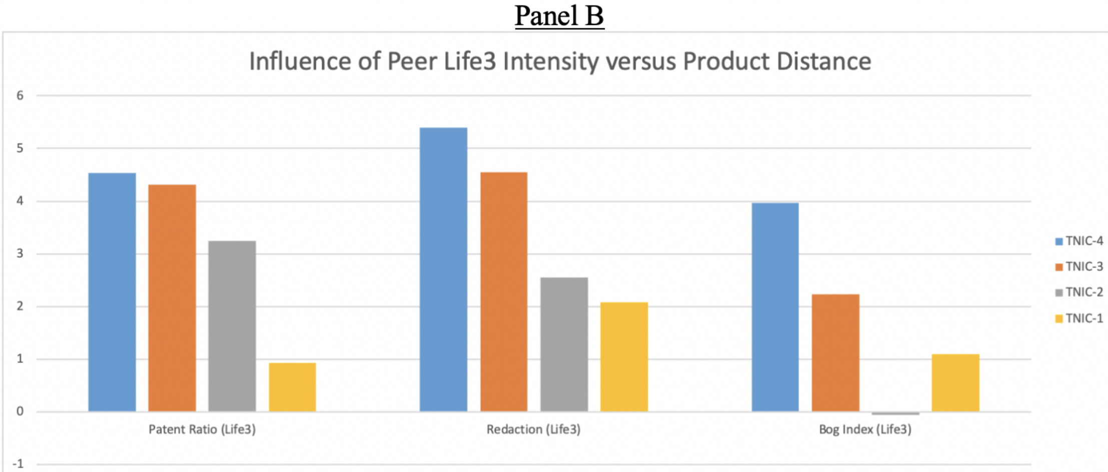
Panel A



Panel B



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 10K filings. We search for two types of complaints in the 10K 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 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 (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 (3)-(6) report results for a life cycle versus competition complaint model, and Column (1) and (2) are purely based on key control variables. Column (7) and (8) show the test results 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)	(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 a patent ratio variable, which is calculated by dividing mentions of "patents" by the sum of 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 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) measure 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) Patent ratio x 100	(2) Patent ratio x 100	(3) Patent ratio x 100	(4) Redaction x 1000	(5) Redaction x 1000	(6) Redaction x 1000
Life1	-0.815**	-0.895***	-0.763**	0.0591	0.0685	0.0589
	(-2.369)	(-2.715)	(-2.298)	(1.306)	(1.506)	(1.282)
Life2	0.0321	0.123	0.00528	0.0319	0.0318	0.0336
	(0.121)	(0.479)	(0.0201)	(1.402)	(1.399)	(1.463)
Life3	0.676*	0.763**	0.702**	-0.0663***	-0.0718***	-0.0700***
	(1.921)	(2.240)	(2.079)	(-2.734)	(-2.873)	(-2.813)
Life4	-0.175	-0.203	-0.191	0.00605	0.00416	0.00581
	(-1.139)	(-1.335)	(-1.292)	(0.532)	(0.366)	(0.505)
SIC2 PatDepWaveHV	0.359*			0.0804***		
	(1.753)			(4.391)		
Life1 x SIC2 PatDepWaveHV	-0.279			0.181***		
	(-1.227)			(4.233)		
Life2 x SIC2 PatDepWaveHV	0.164			-0.0340*		
	(1.016)			(-1.758)		
Life3 x SIC2 PatDepWaveHV	0.440*			-0.0769**		
	(1.959)			(-2.259)		
Life4 x SIC2 PatDepWaveHV	-0.0973			-0.0270*		
	(-0.955)			(-1.942)		
SIC3 PatDepWaveHV		0.277			0.0723***	
		(1.632)			(3.036)	
Life1 x SIC3 PatDepWaveHV		-0.145			0.143***	
		(-0.667)			(3.153)	
Life2 x SIC3 PatDepWaveHV		-0.0508			-0.0395	
		(-0.288)			(-1.605)	
Life3 x SIC3 PatDepWaveHV		0.356			-0.0587	
		(1.565)			(-1.337)	
Life4 x SIC3 PatDepWaveHV		-0.0545			-0.0175	
		(-0.503)			(-1.222)	
SIC2o3 PatDepWaveHV			0.285			0.0857***
			(1.301)			(4.936)
Life1 x SIC2o3 PatDepWaveHV			-0.419**			0.161***
			(-1.980)			(3.883)
Life2 x SIC2o3 PatDepWaveHV			0.226			-0.0268
			(1.412)			(-1.587)
Life3 x SIC2o3 PatDepWaveHV			0.401*			-0.0674**
			(1.894)			(-2.107)
Life4 x SIC2o3 PatDepWaveHV			-0.0644			-0.0201*
			(-0.642)			(-1.690)
Observations	55,750	55,744	55,750	93,167	93,161	93,167
R^2	0.820	0.820	0.820	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 10K filings. The 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) measure 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	0.140***			0.167***		
	(2.977)			(4.091)		
Life1 x SIC2 PatDepWaveHV	0.298***			0.299***		
	(4.769)			(5.070)		
Life2 x SIC2 PatDepWaveHV	0.0322			-0.0790*		
	(0.691)			(-1.893)		
Life3 x SIC2 PatDepWaveHV	-0.127**			-0.178***		
	(-2.130)			(-3.336)		
Life4 x SIC2 PatDepWaveHV	-0.0671**			-0.00162		
	(-2.428)			(-0.0572)		
SIC3 PatDepWaveHV		0.118***			0.163***	
		(2.600)			(4.209)	
Life1 x SIC3 PatDepWaveHV		0.226***			0.197***	
		(3.596)			(3.151)	
Life2 x SIC3 PatDepWaveHV		0.0351			-0.0318	
		(0.804)			(-0.624)	
Life3 x SIC3 PatDepWaveHV		-0.0897			-0.101**	
		(-1.515)			(-1.973)	
Life4 x SIC3 PatDepWaveHV		-0.0636**			0.00441	
		(-2.275)			(0.143)	
SIC2o3 PatDepWaveHV			0.0914*			0.161***
			(1.952)			(4.103)
Life1 x SIC2o3 PatDepWaveHV			0.306***			0.286***
			(5.118)			(5.306)
Life2 x SIC2o3 PatDepWaveHV			-0.0329			-0.0756**
			(-0.760)			(-2.063)
Life3 x SIC2o3 PatDepWaveHV			-0.116**			-0.178***
			(-2.023)			(-3.522)
Life4 x SIC2o3 PatDepWaveHV			-0.0448*			-0.0142
			(-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	Patent ratio x 100	Redaction x 1000	Bog Index	BaseComp x 1000
D_Life1	-0.0889	0.0380	0.158**	0.395***
	(-0.318)	(0.975)	(2.229)	(2.656)
D_Life2	-0.0731	-0.0674*	-0.187***	0.0543
	(-0.288)	(-1.779)	(-3.493)	(0.319)
D_Life3	0.0483	-0.0270	-0.321***	-0.0819
	(0.193)	(-0.831)	(-6.074)	(-0.417)
D_Life5	0.396	-0.0206	0.381***	0.123
	(1.264)	(-0.524)	(4.635)	(0.619)
Log Age	5.727***	-0.323***	-1.041***	-2.628***
	(9.138)	(-5.739)	(-7.844)	(-8.096)
Log 10-K Size	-0.512*	-0.232***	0.911***	-6.969***
	(-1.935)	(-2.664)	(12.83)	(-6.965)
Log Assets	0.742	0.0850	1.270***	3.121***
	(1.418)	(1.507)	(9.986)	(9.447)
TNIC HHI	0.685***	-0.0587**	-0.244***	-0.747***
	(4.324)	(-2.313)	(-6.185)	(-7.958)
Tobin's Q	-0.314***	0.0606***	-0.165***	0.336***
	(-2.582)	(2.895)	(-5.179)	(5.567)
Observations	63,020	100,838	97,455	100,838
R^2	0.814	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 life cycle measures in the current paper and the Dickinson (2011) life cycle stages.The 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 Constraint

The table presents the subsampling tests based on financial constraints measures. Our financial constraint measures come from Hoberg and Maksimovic (2015). *delaycon* shows that firms with higher 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 data. 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)
	High FC	Low FC	High FC	Low FC	High FC	Low FC	High FC	Low FC
VARIABLES	Patent ratio x 100	Patent ratio x 100	Redaction x 1000	Redaction x 1000	Bog Index	Bog Index	BaseComp x 1000	BaseComp x 1000
Life1	-0.874**	-0.585	0.0349	0.0147	0.505***	0.379***	1.082***	0.749***
	(-2.124)	(-1.130)	(0.347)	(0.191)	(3.784)	(3.197)	(4.275)	(3.175)
Life2	0.0124	0.0754	0.0310	0.0285	0.0808	0.108	-0.00922	0.241
	(0.0357)	(0.209)	(0.469)	(1.073)	(0.778)	(1.268)	(-0.0439)	(1.469)
Life3	0.691	-0.0727	-0.0699	-0.0476	-0.378***	-0.276**	-0.246	-0.239
	(1.555)	(-0.148)	(-0.987)	(-1.000)	(-2.867)	(-2.360)	(-0.915)	(-0.944)
Life4	-0.0734	0.160	0.0282	-0.0201	-0.00388	0.0490	-0.156	-0.227**
	(-0.320)	(0.772)	(1.150)	(-1.052)	(-0.0656)	(1.057)	(-1.194)	(-2.451)
pLife1	-1.476**	-2.192***	0.144*	0.120**	0.395*	0.978***	1.046***	1.048***
	(-2.318)	(-3.626)	(1.802)	(2.457)	(1.904)	(5.561)	(2.881)	(3.208)
pLife2	1.233*	1.333***	-0.0699	-0.0447	-0.0808	0.0329	-0.116	0.167
	(1.786)	(3.067)	(-0.979)	(-1.319)	(-0.593)	(0.310)	(-0.388)	(0.780)
pLife3	1.561**	1.849***	-0.333***	-0.115***	-0.335*	-0.852***	-0.356	-1.185***
	(2.340)	(3.563)	(-3.645)	(-2.609)	(-1.673)	(-5.099)	(-0.914)	(-4.131)
pLife4	-0.288	-0.142	0.0858***	0.0406***	0.0580	-0.0355	0.0909	0.139*
	(-1.028)	(-0.986)	(3.184)	(2.710)	(0.909)	(-0.889)	(0.706)	(1.685)
Log Age	4.558***	4.191***	-0.312**	-0.136	-0.470	-1.055***	-1.120**	-2.847***
	(3.916)	(3.266)	(-2.393)	(-1.261)	(-1.601)	(-3.743)	(-2.074)	(-5.584)
Log 10-K Size	0.506	-0.596	-0.283***	-0.171	0.767***	0.867***	-5.790***	-5.343***
	(1.023)	(-1.419)	(-3.682)	(-1.369)	(5.141)	(7.573)	(-7.888)	(-7.618)
Log Assets	0.227	0.588	0.160	-0.000553	1.068***	1.127***	2.659***	2.862***
	(0.309)	(0.637)	(1.614)	(-0.00639)	(4.973)	(4.948)	(6.859)	(6.581)
TNIC HHI	0.318	0.562**	-0.0491	-0.0677*	-0.124*	-0.172***	-0.731***	-0.600***
	(1.141)	(2.462)	(-0.777)	(-1.932)	(-1.683)	(-2.954)	(-5.189)	(-5.451)
Tobin's Q	-0.200	-0.174	0.103**	-0.00307	-0.0587	-0.283***	0.315***	0.0208
	(-1.215)	(-0.808)	(2.262)	(-0.118)	(-1.123)	(-4.384)	(3.339)	(0.178)
Observations	18,051	22,321	24,017	31,063	23,092	30,129	24,017	31,063
R-squared	0.876	0.843	0.718	0.649	0.879	0.843	0.788	0.732
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 A7: Innovation Disclosures and FF5 Industries

The table presents the subsampling tests based on FF5 industries. We drop one FF5 industry for each of the test. Fama-French 5 industries are: FF1 Consumer is for "Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops)". FF2 Manuf is for "Manufacturing, Energy, and Utilities". FF3 Tech is for "Business Equipment, Telephone and Television Transmission". FF4 Healthcare is for "Healthcare, Medical Equipment, and Drugs". FF5 Other is for "Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance". 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)
VARIABLES	Drop Consumer	Drop Manuf	Drop Tech	Drop Healthcare	Drop Other
Life1	-0.894***	-0.863***	-0.887***	-0.637*	-0.807***
	(-2.796)	(-2.629)	(-2.715)	(-1.662)	(-2.641)
Life2	0.0489	0.113	-0.119	0.142	-0.0301
	(0.189)	(0.421)	(-0.426)	(0.529)	(-0.120)
Life3	0.894***	0.717**	1.069***	0.417	0.674**
	(2.630)	(2.113)	(3.087)	(1.150)	(2.168)
Life4	-0.117	-0.196	-0.223	-0.153	-0.183
	(-0.749)	(-1.282)	(-1.422)	(-0.965)	(-1.263)
pLife1	-1.671***	-1.884***	-0.824**	-2.136***	-1.767***
	(-4.047)	(-4.231)	(-2.150)	(-4.426)	(-4.656)
pLife2	1.595***	1.501***	0.734**	1.576***	1.622***
	(4.511)	(3.633)	(2.243)	(4.829)	(4.892)
pLife3	1.274***	1.703***	0.839**	1.502***	1.618***
	(3.013)	(3.678)	(2.219)	(3.372)	(4.213)
pLife4	-0.234*	-0.338**	-0.165	-0.201*	-0.326***
	(-1.917)	(-2.081)	(-1.457)	(-1.755)	(-2.817)
Log Age	5.501***	5.333***	3.912***	5.390***	5.255***
	(7.022)	(6.494)	(4.774)	(6.280)	(6.914)
Log 10-K Size	0.0434	-0.271	-0.432	-0.491	-0.285
	(0.137)	(-0.846)	(-1.316)	(-1.545)	(-0.985)
Log Assets	0.572	0.829	0.0114	0.735	0.776
	(1.017)	(1.428)	(0.0186)	(1.026)	(1.335)
TNIC HHI	0.603***	0.475**	0.531***	0.559***	0.475***
	(3.243)	(2.386)	(2.827)	(3.082)	(2.678)
Tobin's Q	-0.182	-0.118	-0.286*	-0.289	-0.244
	(-1.201)	(-0.788)	(-1.883)	(-1.351)	(-1.626)
Observations	46,432	45,313	37,934	45,463	47,482
R-squared	0.820	0.826	0.831	0.821	0.801
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses

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

Table A8: Redaction and FF5 Industries

The table presents the subsampling tests based on FF5 industries. We drop one FF5 industry for each of the test. Fama-French 5 industries are: FF1 Consumer is for "Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops)". FF2 Manuf is for "Manufacturing, Energy, and Utilities". FF3 Tech is for "Business Equipment, Telephone and Television Transmission". FF4 Healthcare is for "Healthcare, Medical Equipment, and Drugs". FF5 Other is for "Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance". 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)
VARIABLES	Drop Consumer	Drop Manuf	Drop Tech	Drop Healthcare	Drop Other
Life1	0.0728	0.0740	0.0915***	0.0190	0.0848
	(1.410)	(1.462)	(3.249)	(0.401)	(1.202)
Life2	0.0278	0.0413	0.0204	0.0265	0.0365
	(1.036)	(1.611)	(0.967)	(1.144)	(1.055)
Life3	-0.0720**	-0.0898***	-0.0733***	-0.0204	-0.0817**
	(-2.559)	(-3.305)	(-2.680)	(-0.946)	(-2.165)
Life4	-0.00128	0.00599	0.000967	-0.00450	-0.00238
	(-0.103)	(0.452)	(0.0844)	(-0.406)	(-0.153)
pLife1	0.183***	0.170***	0.129***	0.185***	0.160***
	(4.539)	(4.247)	(3.196)	(5.226)	(4.002)
pLife2	-0.00896	-0.0295	-0.00206	-0.0455**	-0.0336
	(-0.362)	(-0.990)	(-0.103)	(-2.180)	(-1.279)
pLife3	-0.276***	-0.269***	-0.232***	-0.209***	-0.242***
	(-6.220)	(-5.802)	(-5.357)	(-6.031)	(-5.120)
pLife4	0.0543***	0.0754***	0.0540***	0.0405***	0.0650***
	(4.522)	(5.397)	(5.193)	(3.901)	(4.930)
Log Age	-0.139***	-0.194***	-0.152***	-0.102**	-0.243***
	(-2.709)	(-3.480)	(-3.636)	(-2.176)	(-3.297)
Log 10-K Size	-0.170***	-0.122***	-0.146***	-0.105***	-0.185***
	(-3.646)	(-3.822)	(-3.250)	(-2.714)	(-2.994)
Log Assets	0.0486	0.0315	0.0738	0.0533	0.0573
	(1.016)	(0.655)	(1.435)	(1.243)	(1.047)
TNIC HHI	-0.0599*	-0.0467	-0.0241*	-0.0480	-0.0668*
	(-1.647)	(-1.271)	(-1.738)	(-1.552)	(-1.714)
Tobin's Q	0.0692***	0.0646**	0.0520	0.0634**	0.0656**
	(2.584)	(2.423)	(1.643)	(2.499)	(2.218)
Observations	78,632	76,940	73,528	81,879	61,177
R-squared	0.597	0.604	0.582	0.589	0.595
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

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

Table A9: Financial Reporting Readability and FF5 Industries

The table presents the subsampling tests based on FF5 industries. We drop one FF5 industry for each of the test. Fama-French 5 industries are: FF1 Consumer is for "Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops)". FF2 Manuf is for "Manufacturing, Energy, and Utilities". FF3 Tech is for "Business Equipment, Telephone and Television Transmission". FF4 Healthcare is for "Healthcare, Medical Equipment, and Drugs". FF5 Other is for "Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance". 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)
VARIABLES	Drop Consumer	Drop Manuf	Drop Tech	Drop Healthcare	Drop Other
Life1	0.322***	0.284***	0.263***	0.135*	0.465***
	(4.279)	(3.783)	(3.563)	(1.876)	(5.326)
Life2	0.0970*	0.125**	0.153***	0.170***	0.152**
	(1.792)	(2.207)	(2.788)	(3.264)	(2.317)
Life3	-0.190***	-0.260***	-0.224***	-0.140**	-0.351***
	(-2.636)	(-3.525)	(-3.043)	(-1.961)	(-4.080)
Life4	0.0675**	0.100***	0.116***	0.106***	0.0355
	(2.078)	(3.034)	(3.542)	(3.496)	(1.009)
pLife1	0.828***	0.845***	0.755***	0.776***	0.787***
	(6.615)	(6.983)	(6.040)	(7.159)	(6.064)
pLife2	0.140*	0.146	0.148*	0.0691	0.0652
	(1.674)	(1.637)	(1.900)	(0.953)	(0.806)
pLife3	-0.994***	-1.055***	-0.801***	-0.838***	-0.732***
	(-8.474)	(-9.179)	(-6.994)	(-7.973)	(-5.956)
pLife4	0.108***	0.0690*	0.0422	0.0778***	-0.0208
	(2.953)	(1.800)	(1.309)	(2.588)	(-0.632)
Log Age	-0.521***	-0.494***	-0.597***	-0.574***	-0.818***
	(-3.591)	(-3.284)	(-4.058)	(-4.125)	(-4.518)
Log 10-K Size	0.943***	0.977***	1.000***	0.968***	0.941***
	(12.17)	(12.63)	(12.40)	(13.23)	(10.72)
Log Assets	1.349***	1.241***	1.303***	1.396***	1.454***
	(9.786)	(9.333)	(8.247)	(10.13)	(9.183)
TNIC HHI	-0.252***	-0.221***	-0.216***	-0.167***	-0.193***
	(-5.645)	(-4.952)	(-4.605)	(-4.296)	(-4.356)
Tobin's Q	-0.0980***	-0.118***	-0.121**	-0.201***	-0.131***
	(-2.645)	(-3.193)	(-2.362)	(-4.993)	(-3.414)
Observations	75,940	74,573	71,076	79,371	58,988
R-squared	0.817	0.825	0.829	0.797	0.835
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

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

Table A10: Competition Complaints and FF5 Industries

The table presents the subsampling tests based on FF5 industries. We drop one FF5 industry for each of the test. Fama-French 5 industries are: FF1 Consumer is for "Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops)". FF2 Manuf is for "Manufacturing, Energy, and Utilities". FF3 Tech is for "Business Equipment, Telephone and Television Transmission". FF4 Healthcare is for "Healthcare, Medical Equipment, and Drugs". FF5 Other is for "Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance". 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)
VARIABLES	Drop Consumer	Drop Manuf	Drop Tech	Drop Healthcare	Drop Other
Life1	0.954***	0.992***	0.779***	0.880***	1.098***
	(5.482)	(5.975)	(4.493)	(5.076)	(6.262)
Life2	0.179	0.0368	0.250*	0.198	0.300**
	(1.177)	(0.252)	(1.761)	(1.419)	(2.090)
Life3	-0.334*	-0.361*	-0.370*	-0.424**	-0.572**
	(-1.689)	(-1.838)	(-1.686)	(-2.049)	(-2.522)
Life4	-0.106	-0.0334	-0.0748	-0.0823	-0.127*
	(-1.474)	(-0.447)	(-1.043)	(-1.176)	(-1.692)
pLife1	1.145***	1.235***	0.746***	1.620***	1.095***
	(4.961)	(5.792)	(3.654)	(6.801)	(4.815)
pLife2	0.113	-0.0286	0.117	0.0645	0.219
	(0.544)	(-0.135)	(0.750)	(0.363)	(1.021)
pLife3	-1.255***	-1.365***	-0.932***	-1.788***	-1.389***
	(-6.270)	(-6.874)	(-5.026)	(-8.997)	(-6.621)
pLife4	0.184**	0.110	0.201***	0.186***	0.138*
	(2.311)	(1.435)	(3.135)	(2.811)	(1.947)
Log Age	-1.897***	-2.873***	-1.898***	-2.195***	-2.164***
	(-5.704)	(-8.452)	(-5.589)	(-6.674)	(-6.368)
Log 10-K Size	-6.288***	-6.037***	-6.272***	-6.276***	-5.772***
	(-6.580)	(-6.486)	(-6.524)	(-7.101)	(-8.057)
Log Assets	2.952***	2.774***	2.689***	2.737***	2.829***
	(8.743)	(8.657)	(7.667)	(8.407)	(9.130)
TNIC HHI	-0.738***	-0.830***	-0.635***	-0.674***	-0.736***
	(-7.361)	(-8.202)	(-6.303)	(-7.569)	(-8.444)
Tobin's Q	0.245***	0.266***	0.109	0.298***	0.212***
	(3.634)	(3.925)	(1.448)	(3.725)	(2.999)
Observations	78,632	76,940	73,528	81,879	61,177
R-squared	0.613	0.621	0.573	0.606	0.657
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

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