Innovation Specificity

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Abstract

We study the specificity of corporate innovation. Process patents are more specific to the inventing firm. They tend to arise at higher-cost firms, they are more likely to cite past patents of the focal firm and be undertaken by inventors with more focal-firm patenting experience. High process-patent-oriented firms are also less likely to be acquired, but this effect is reversed when there is strong textual overlap between process patent descriptions and the acquirer's product descriptions. Cost-reduction synergies are greater in such cases as well. Withdrawn attempts to acquire process-oriented targets are followed by increased bidder internal process patenting.

Keywords: Innovation, Mergers and acquisitions, Patents, Specificity, Internal knowledge.

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Asset specificity is a crucial aspect of corporate decision making. It matters for valuations as well as for investment decisions, and it influences corporate responses to uncertainty. Numerous economic theories recognize this,[1] and thus careful empirical measurement is indicated. Kim and Kung (2017) as well as Kermani and Ma (2023) provide excellent forays into this arena. However, these papers focus strictly on hard assets, and as economists have long-recognized, innovation is more difficult to value or even measure.[2] Nevertheless, the clear importance of innovative assets for both firm value and aggregate economic growth (e.g. Kogan et al. (2017)) implies the necessity of understanding their specificity. We are the first to investigate the specificity of innovation for a comprehensive sample of patents, as well as the first to explore its implications for value and investment.

Firms innovate for manifold reasons. They may be pursuing growth or efficiencies (Akcigit and Kerr (2018), Klette and Kortum (2004), Lentz and Mortensen (2008)); they may seek to be acquired (Phillips and Zhdanov (2013)); or they may seek efficiencies and synergies tied to overlapping characteristics of the two merger parties (Bena and Li (2014)). By implication, innovation can lead to product development that attracts new customers, it can create pricing power through exclusivity of characteristics, or it can reduce costs through enhanced efficiency. These value propositions logically vary with the nature and specificity of the innovation. This complicates measurement of the specific nature or goal of the innovation, unless language directly tied to that nature or goal is available and analyzable. We obtain this language and analyze it through text analysis of 90 million machine-read patent claims (e.g. Kalyani, Bloom, Carvalho, Hassan, Lerner, and Tahoun (2024), Bena, Ortiz-Molina, and Simintzi (2022)).

We use the descriptions of individual patent applications to bifurcate our sample into two general categories of innovation: process-oriented vs. non-process-oriented.[3] Compared to other types, process-oriented patents are viewed by theory as being more closely tied to the operational competencies of the innovative firm.[4] Our study confirms the specificity of process patents. We do so through several explorations, including potential firm motives to process-innovate, the internal nature of process patents, their valuation, and their redeployability by other users.

[1] A few classic examples are Pindyck (1991), Bertola and Caballero (1994), Abel and Eberly (1996), Caballero and Hammour (1998), Bloom (2009), and Pablo (2021).

[2] Bellstam, Bhagat, and Cookson (2021) highlight the difficulty in measuring innovation and present a technique based on analyzing analyst reports. However, they do not address innovation specificity, and their sample is limited to S&P500 firms.

[3] See Bena et al. (2022) who find, as we do, that about 30% of patents in the US are process patents

[4] Cohen and Levinthal (1989), Nelson (1989), Nelson (1992).

Our first result shows that firms' tendencies to process-innovate are increasing in recent cost concerns. When a firm's costs are higher relative to sales over the latest three (as well as five) years, the fraction of its (overall) patent portfolio that is process-oriented is also higher. A one standard deviation increase in COGS/Sales associates with a 7% increase in the share of process patents (to total patents), relative to the mean.

This result serves two purposes. The first is construct validity – our measure of process innovation captures innovation directed toward cost reduction as theory says it should. Moreover, the relationship between cost-inefficiencies and process innovation opens the door to perceiving process patents as more firm-specific. Cost functions are firm-specific as long as firms' production technologies are firm-specific, and there is ample support for this in the I/O literature.[5]

We provide further evidence of the specificity of process innovation by exploring the genus of each focal patent. First, process-oriented patents are more likely to cite prior patents filed by the focal firm (i.e., higher self-citations). Second, the proportion of an *inventor's* prior patents that were filed at the focal firm is higher for process patents. Third, an inventor is less likely to change firms when a larger proportion of their overall (set of) patents filed were process oriented. Finally, process patents are more likely to belong to technology classes in which the focal firm has prior innovation experience. Overall, greater process-orientation of patents associates with more focal-firm internal-development variables.

We then offer a third perspective on the specificity of process innovation by turning to the market for corporate control. We choose an M&A setting for two reasons. First, the specificity of an asset has a first-order relation with its redeployablity and M&A is an important channel through which assets, both tangible and intangible, are redeployed. Second, although a large body of finance research shows that merger decisions are affected by innovation, these studies view innovation as a homogeneous activity and do not capture how the decision to merge or the choice of merger target might vary with the composition (process vs. non-process) of the innovation portfolio.[6]

Our M&A analysis begins at the extensive margin, asking whether a firm's patent portfolio specificity influences the likelihood that the inventing firm is acquired. Using a carefully matched set of control firms that have not been involved in any M&A activity in the prior three years, we

[5] Griliches and Mairesse (1995) provide an excellent review, while Gandhi et al. (2020) in particular highlight ample cross-sectional variation in firms' production functions.

[6] See Phillips and Zhdanov (2013), Bena and Li (2014), Denes, Duchin, and Harford (2018), Frésard et al. (2020), Celik, Tian, and Wang (2022).

show that more process-orientation in a firm's innovation portfolio associates with lower likelihood of being acquired. These findings hold after controlling for firm characteristics previously shown to affect the likelihood of being acquired. Economically, firms in the top tercile of process share (of total patents) are 8% less likely to be acquired, compared to firms in the lowest tercile of process share. This result suggests more process innovation at a possible target firm offers less synergy to the average bidder.[7]

Our explanation for this finding is that process innovation has high specificity and is not easily transferable to the acquirer's business. However, a firm's emphasis on process innovation may be correlated with firm characteristics that also affect the likelihood of being acquired. We take a multi-pronged approach to identify the role of innovation specificity. To start, we turn to the defining feature of specific assets – they are designed to serve an intended purpose and have limited alternative uses (Shleifer and Vishny, 1992, Habib and Johnsen, 1999). If the reduced acquisition likelihood of process innovators is due to the specificity of process innovation, our result should weaken in situations where the target's process innovation can be effectively used by the acquirer.

We use two strategies to capture the potential for bidder deployability of the target's innovation. First, we build on the Hoberg and Phillips (2010) finding that firms with similar products are more likely to engage in mergers. We argue that if the bidder and potential target manufacture similar products, the applicability of a target's process innovation to the acquirer's product line (and therefore expected cost savings) is likely greater. Indeed, we find that the (Hoberg and Phillips, 2016) simple text-based industry classification (TNIC) overlap between the potential target and bidder mitigates the deleterious effect of high process-share of patenting on takeover likelihood.

Our second strategy, which we believe offers the sharpest identification of the redeployability of target's process innovation to the acquirer's products, relies on the language directly from patent applications. We construct a patent redeployability measure as the cosine similarity between the patent descriptions of the potential target, and the product market descriptions of potential acquirer. We document two new results. Regardless of a patent being product or process oriented, there is a strong positive influence of redeployability of patents on the likelihood that the patentor

[7] The lower acquisition likelihood is not due to cost-inefficiency of the target (see our higher-costs lead to process patenting results). It also cannot be attributed to process innovation being of lower quality. We calculate that process-oriented patents are valuable under standard value-measurement techniques (Kogan et al., 2017). In real (nominal) terms, a typical process patent has a stock-market implied economic value of $13 million ($25 million). This value may reflect either the cost-reducing nature of process patents or their ability to foster product innovation and firm growth (Baslandze, Liu, Sojli, and Tham, 2025), but in both cases, shareholders' reactions to patent grants reflect the innovation's internal value to the patenting firm.

becomes a target. More importantly, the effect is concentrated when the patentor has a more process-oriented innovation portfolio; it is more likely to become a target as the redeployability of its *process patents* rises, but not as the redeployability of its product patents does. Put differently, consistent with the specificity explanation, the negative relation between process share and acquisition likelihood weakens when the target's *process* innovation can be re-used by the acquirer.

We also employ standard techniques to address endogeneity. We use potential outcome methods such as propensity score matching and find that process innovators are significantly less likely to be acquired than non-process innovators after selecting on all observables. Further, we instrument for a firm's emphasis on process innovation with the firm's tendency to cite its own prior patents (i.e., self-citations), and find similar results.[8]

To allay any residual concerns that the relation between a firm's process share and its likelihood of being acquired is driven not by the composition of innovation, but rather by unobserved firm characteristics, we offer a different (and complementary) fourth approach. To pin down the relevance of the target's process innovation for potential merger synergies, we explore the change in the acquirer's own innovation portfolio after deals that failed to materialize. We view withdrawn deals that were met with a strong negative market reaction as deals in which the market expected synergistic gains. In this subset of failed deals, we find that bidders who tried (but failed) to buy a target with high process share subsequently step-up their own process innovation, relative to bidders who pursued firms with low process share. These results strongly indicate that bidders who attempted to buy firms with high process share were indeed seeking process innovation.

In supplemental tests, we provide further support for the specificity of process innovation. We find that combined bidder-target cumulative abnormal returns (CARs) are also decreasing in process share, but that this effect is offset when there is clear overlap (TNIC) between the two firms. Further examination of post-merger production costs helps understand why. Buying targets with a high process share is associated with a post-merger reduction in COGS/Sales when the acquirer and target have the same TNIC, but not otherwise.

We subject our tests to a variety of robustness checks. Key among them is addressing poten-

[8] Self-citations are a valid instrument for process share with a first-stage F-stat of 33, and they withstand at least one reasonable potential violation of the exclusion restriction. In particular, we consider the possibility that self-citations are a signal of innovation quality that also affect acquisition likelihood. To test whether the propensity to self-cite is correlated with lower innovation quantity or quality, we compare the KPSS value of patents, forward citations, and patenting intensity across firms with high and low self-citations, and find no significant differences.

tial endogeneity due to sample selection. It is suggested in the literature that firms may choose to not patent process innovation due to concerns about trade secrets spilling over to rival firms (Horstmann, MacDonald, and Slivinski, 1985). This could introduce a selection bias in our study if secrecy concerns also affect the likelihood of being acquired. We run a logit regression of a firm's decision to patent on the relative mention of words suggesting secrecy in firms' earnings calls (Lerner, Seru, Short, and Sun, 2024) and find the relation is insignificant. These results indicate that a firm's concerns about secrecy are unlikely to introduce a sample selection bias in our analysis. In additional robustness tests we obtain consistent results when we include in our analysis, patents that exhibit features of both process and non-process innovation ("hybrid" patents). Finally, to address the possibility that innovation specificity is simply capturing competitive threats, in untablulated tests we control for the target's market fluidity as per Hoberg et al. (2014) and find that our results still hold.

Our research is relevant to several extant literatures. Primarily, we contribute to the economic role of asset specificity by focusing on innovative assets and their varying specificity. This is a natural counterpoint to the extant work on hard assets' specificity. By providing baseline measures of innovative assets' values, internal nature and external applicability, as well as confirming their measurement efficacy, we aim to enable expansion of both the I/O and innovation literatures.

We also have deep connections to the M&A literature and its attention to risk and asset characteristics of the participant firms. First, Frésard, Hoberg, and Phillips (2020) conclude that vertical mergers are more likely once a firm patents its research, but less likely before the realization (patenting) of the innovation. We augment their view by delineating process from product innovation, and showing that process innovation discourages merger – opposite their result – but that horizontal mergers (via TNIC overlap) do not show this diminution. Second, Bena and Li (2014) show that overlapping *technologies* between potential bidder-target pairs increase merger incidence, synergy, and post-combination innovation output. Our sampling, approach, and therefore applicability are crucially broader. They focus on mergers *between innovative firms*, thereby excluding non-innovative bidders who could also benefit from a target firm's patent(s). We expressly include these and thus broaden the implications for both external valuation and, in particular, the role of innovation-driven synergies in the market for corporate control. Third, our delineation between product and process innovation, and how this distinction affects overlap's influence on mergers and outcomes, is unique but motivates subsequent work. Davydova (2024) confirms that for *executed deals*, her measure of process-orientation improves combined-firm operating performance through cost reduction. However, she does not study overlap between acquirer and target, does not utilize text analysis to construct such overlap, and does not explore the extensive margin.

Also in the M&A realm, but highlighting that innovation is difficult to value, Celik, Tian, and Wang (2022) document the influence on bidder method of payment and likelihood of transaction. We extend their inference by distinguishing between product- and process-oriented innovation in the valuation difficulty due to varying applicability to buyers' assets.[9] Beaumont, Hebert, and Lyonnet (2025) find that firms are more likely to buy (M&A) than build when they lack the human capital to operate in a new sector. We show a link between the likelihood of *being bought* and the human capital in the innovation. Process patents associate with more self-cites and lower inventor departure, and they are valuable measured via Kogan et al. (2017); but they associate with lower likelihood of being a merger target.

Another connection to the innovation and finance literature is through the marked difference between process and non-process patents' funding documented in extant work. Benfratello et al. (2008) find that firms in locales with stronger banking development are more likely to process-innovate, especially among high-tech, smaller, and external-finance dependent firms.

Finally, we are adjacent to a few recent papers. Denes, Duchin, and Harford (2018) find that patent expirations cluster by industry and trigger industry merger waves. Bellstam, Bhagat, and Cookson (2021) study innovation from another text perspective – analysts' reports. While Bellstam et al. (2021) do not distinguish between patents being process oriented or not, they do offer evidence that innovation associates with higher value and performance. They are also limited to S&P500 firms, while patent based innovation is likely to have varying valuation and effects among smaller versus larger firms.

I. Hypothesis Development

To understand the potentially different motives, the specificity, and the valuation of process patents relative to other patents, we draw on the R&D composition literature. Theories such as Cohen and Klepper (1996), Klepper (1996), Boone (2000) all provide justification for this separation between process and non-process innovation. We discuss how these papers fit into differing motives and specificity first. We then turn to discussion of differing valuation, but primarily through the lens of the market for corporate control.

[9] Our varying applicability of different types of patents also speaks to fn 14 in Phillips and Zhdanov (2013).

We begin with Boone (2000) who studies the effect of competitive pressure on a firm's incentive to invest in product and process innovation. Besides the non-innovation result when a firm exits, the tendency to choose process over product innovation rises when competition is higher. The assumption driving firm responses to competitive pressures that is of most interest to us is that the investment in process innovation necessary to achieve cost reduction is convex in the level of costs. We use this to formulate our first hypothesis:

Hypothesis 1: Process innovation is increasing in a focal firm's prior cost inefficiency w.r.t sales.

If a firm has recently experienced higher costs (relative to sales), this should encourage innovation designed to lower them.[10] Notably, given the assumption in Boone (2000) of the different natures of product vs process innovation (with process innovation being geared toward reducing costs), our test results can also be viewed as supporting construct validity.

There could be many reasons that high cost firms endogenously choose to do more process patenting, even if process patents are not more firm specific. To help pinpoint the specificity of process patents, we turn to existing R&D models that explain entry, exit and growth over the product life cycle (Klepper, 1996), as well as the allocation of R&D effort between process and product innovation (Cohen and Klepper, 1996). These models attribute two features to process innovation, both of which we view as isomorphic to them being more firm-specific than product innovation. The first is limited appropriability of process innovation - a firm is more likely to exploit process innovation (relative to product innovation) through its own output rather than selling it in disembodied form.[11] Second, process innovation is based on information the firm generates through its own production.

We then proceed to support the latter, examining characteristics of patents, inventors, and firms, and how these correlate with whether the focal patent is process-oriented or not. Several patent characteristics are helpful in identifying internal, firm-specific focus.[12] Specifically, process patents are expected to associate with more self-cites by the patent-filing-firm, greater fraction of the inventor's prior patents being filed with the patent-filing-firm, and reduced likelihood that the inventor departs for another firm. These are the examples that underpin our second hypothesis:

Hypothesis 2: The knowledge implicit in process innovation is more firm-specific than that in non-

[10] Given firm-year-level data on costs, we will need our process-innovation measure to also be at the firm-year-level. We provide measurement details in Section II.

[11] This assumption is supported by survey evidence in Levin et al. (1987) who find that licensing is rarely used to profit from process patents.

[12] Section III provides details, but we summarize them here.

process innovation.

Upon supporting the two hypotheses and therefore the theories, we turn to implications for the market for corporate control. Nelson (1989) views innovation as having both a private value and common value component. The common value arises from the generic component of technological knowledge that is relatively costless to communicate and can be used by others. Nelson (1989) argues that process innovation has a higher private value component than product innovation because newly developed industrial methods and procedures that work effectively in the innovating firm's establishment are either not applicable to another firm's production processes or can only be transferred at considerable cost.[13] It is this private-value component of process innovation that we consider to be relevant for M&A decisions.

Phillips and Zhdanov (2013) recognize that synergies from an acquisition depend on the extent to which the target firm's innovation can be applied to the acquirer's product line (see their footnote 14). We posit that if process innovation has higher specificity than non-process innovation, it contributes less to the profitability of the merger because it cannot be easily transferred to the acquiring firm's product line. Despite numerous references in the literature to the specificity of process innovation, to our knowledge, there is no large-sample empirical analysis of this conjecture. Therefore, we formulate our third hypothesis as follows:

Hypothesis 3: If process innovation is more firm-specific than non-process innovation, then firms emphasizing process innovation are less likely to be targeted in an acquisition.

While the third hypothesis is consistent with process innovation having higher specificity, it does not directly reflect the role of specificity. Our fourth and final hypothesis confronts this head-on.

Hypothesis 4: The negative relation between process innovation and the likelihood of being acquired (as outlined in Hypothesis 3) will be mitigated if the target's processes can be applied more easily to the acquiring firm's products or assets.

We proxy the common value or appropriability of a process innovation in two ways, both reflecting overlap between the bidder and target. The first is simple text-based industry classification (TNIC) overlap, while the second relies on language of the process patent and its overlap with the buyer's product market descriptions from the 10-K. We describe our measurement of both overlap concepts in the results section.

[13] Similar arguments about the specificity of process innovation are found in Rosenberg (1982), Pavitt (1987), and Levin et al. (1987).

II. Data

A. *Identification of process patents*

We employ a machine-read textual analytics algorithm on every claim associated with a patent to categorize it as a process or non-process patent. Classifying patents into one of the two types requires an assessment of the technological improvement they seek to achieve. Process patents are inventions that involve a unique method, process, or technique for producing a specific outcome. On the other hand, non-process patents are typically inventions that involve a new and useful device, composition of matter, or design. We exploit the fact that each patent application is accompanied by a series of "claims" that detail its specific purported contribution. Using a dictionary of words most commonly associated with process improvements, we machine-read a total of over 90 million claims linked to all the patents filed in the US between 1980 and 2020. We source patent-level claims data from the website of US Patent and Trademark Office (USPTO).

We follow Bena et al. (2022) and leverage the use of a standard vocabulary with stilted legalistic terms that are distinct for process patents. Process patent claims often contain words such as "method of," "process for," or "means for" to describe the steps or procedures involved in the invention. Non-process patent claims, on the other hand, typically use words such as "device", "composition", "apparatus" or "design" to describe the invention. We construct a dictionary of words that commonly describe process improvements and pass every claim of all the patents in our database through that dictionary to check for the presence of the process-identifier words in those claims. (Appendix A lists the specific words contained in this dictionary.) Patents where all claims contain such words are classified as process innovation, while patents whose claims contain no such words are classified as non-process innovation. We label patents that fall in-between these two types as "hybrid" patents.

For example, the first claim in patent number 7885035, filed by the Boeing Company in 2007, states, "A method for charging a pulsed-power system, providing an initial charge to a first high temperature super-conductor (HTS) ...". We classify this as a process claim. Contrarily, the first claim of patent number 4928094, filed by Boeing in 1988, reads, "Photoelectric apparatus comprising an emitter element for intermittently emitting a beam of electromagnetic radiation...". This claim is classified as non-process.

The USPTO database consists of patents filed by both public and private firms. We focus on patents filed by public firms because all our tests require controls for firm characteristics. The total number of such patents between 1980 and 2020 is 2,000,634. In 1,043,480 patents, either all claims are process claims (i.e., every claim contains the identifying terminology) or none of the claims are process claims (i..e none of the claims contain the identifying words). In our main analysis, we retain only these unambiguously classified patents. Doing so enables a sharper contrast between firms that emphasize process innovation versus firms that do not engage in process innovation. In robustness tests discussed in Section VI, we include "hybrid" patents that contain a mix of process and non-process claims, and show that our results still hold but with a smaller economic magnitude.

Panel (a) of Figure I plots the time series of the share of process claims for all innovative public firms in our sample between 1980 and 2020. Figure I shows that over the entire 40-year period, process innovation comprises a significant portion of total innovative effort ranging from 20% to 33%. The upward trend in process innovation from the mid-1980s till the late 1990s is comparable to Bena et al. (2022). We note that the steep decline in process claims after 2010 is partly due to firms switching toward hybrid patents in recent years, which is not captured in Figure I. When hybrid patents are included, shown in Figure IAI in the appendix, process innovation after 2010 continues to account for over 30% of the total patent claims.

Panel A of Table I reports considerable variation in the cross-sectional distribution of process patents by Fama-French 12 industry groups. The average process innovation across all industries (shown in the bottom row of Panel A) is 26%. The "Oil, Gas, Coal Extraction" and "Chemicals and Allied Products" industries devote the highest share of innovation portfolios to process improvements at 56% and 45% respectively, which are about four times higher than the share devoted by "Consumer Durables" industry. In our analyses, we include fixed effects to appropriately account for these variations across time and industry. Further, Table I shows the distribution of the share of process claims across the 9 Cooperative Patent Classification (CPC) "technology classes", administered by the European Patent Office and the USPTO. We continue to see a large variation in the type of innovation both within and across these technology classes, which suggests that the "nature" of innovation that we focus on is distinct from technology class-based knowledge "overlap" measures studied in the literature (e.g. Bena and Li (2014)).

B. *Innovation characteristics*

In addition to the share of (all patents that emphasize) process claims, we construct several variables that could characterize process patents differently from non-process ones. Most importantly, we assign each patent an "Economic Value", calculated by Kogan et al. (2017) as the stock market-implied dollar value of a patent when its application becomes successful and publicly known. Panel (b) of Figure I plots the time series of Economic Value per patent, averaged separately across process and non-process patents, for all innovative public firms in our sample between 1980 and 2020. Not surprisingly, this stock-market-based measure is correlated with overall stock market conditions, evident from the spike in the value of both process and non-process patents during the dotcom period and again in the pre-COVID-19 period. The real economic value of process patents (in 1980 $), which averages about $13 million across the entire sample, tends to lie slightly above that of non-process patents throughout the sample period.[14] Our main takeaway from panel (b) of Figure I is that both process and non-process innovation are value-enhancing activities from the perspective of shareholders. A secondary conclusion is that from a Kogan et al. (2017) (i.e. internal to focal firms) perspective, process patents are certainly no less valuable than product patents.

Looking cross-sectionally, Panel B of Table I shows the distribution of Economic Value per process patent by Fama-French 12 industries. The table reports that shareholders of "Finance", "'Oil, Gas, Coal Extraction", and "Consumer Nondurables" industries value process innovation more than other industries, although the effect of firm size in this comparison cannot be ruled out.

We construct four additional variables that are expected to co-move with the composition of firms' innovation portfolio. First, we define "Self-citation Share" as the proportion of (backward) citations attributed to prior patents of the inventing firm out of all the patents cited in an application. This variable helps us test whether process patents lead to internal knowledge accumulation through greater self-citations, as compared to non-process patents. Second, we define "Inventor-firm Share" as the proportion of patents filed by the *inventor* with the same inventing firm, out of all the patents filed by that inventor to date. This variable is used to test whether process innovation is more likely to be carried out by individuals whose innovation experience tends to be with the same firm, compared to individuals who bring knowledge over from other firms.

Third, we define "Technology Class Share" as the proportion of patents filed by the inventing

[14] Economic Value is in dollar terms and can be higher for firms with larger market capitalization. In the summary statistics and formal regressions that follow, we scale the Economic Value by the inventing firm's market capitalization.

firm that belongs to the same Cooperative Patent Classification (CPC) sub-section as the focal patent. We use this variable to test if process patents are more likely to belong to technology classes that the inventing firm has more experience patenting in. Finally, we create an "inventor-firm change" variable that captures inventor movement and allows us to test if inventors of process patents are less likely to switch jobs than those of non-process patents. Panel B of Table II provides descriptive statistics for all four variables.

We source patent-level citation, inventor and technology class data from Michael Woeppel's website.[15] From the same database, we also construct a running total of patents issued to each firm or inventor up to the date of filing a new patent, and term it "Cumulative Patents". We use this as a control in our patent-level tests for internal knowledge accumulation. Table II defines these variables and Appendix A provides further details on data cleaning procedures.

C. *Firm characteristics*

We collapse patent-level data into a panel of firm-year observations. We match the firm identifier ("permno") and filing year in our patent database with fundamental characteristics obtained from the CRSP/COMPUSTAT database. This creates a merged data set of over 51,000 firm-year observations for patents filed between 1980-2020. We extend the time series of this data set to include fundamental information from 1975 onwards in order to create lagged variables, which leaves us with over 53,000 firm-year observations. Panel A of Table II provides a summary of firm-year variables used in the analysis and constructed as described below.

We calculate the share of process patents ("Process Share") for each firm year as the number of process patents filed by the firm divided by all unambiguously classified patents in the firm's portfolio. In about 60% of firm-year observations, Process Share takes a binary value of 0 or 1, implying that a majority of firms either file unambiguous process or unambiguous non-process patents in a given year. Further, we calculate the Economic Value of process (non-process) patents at a firm-year level as the stock market implied economic value averaged across all process (non-process) patents filed in that year. When converting the economic value to a firm-year panel, we use the nominal dollar value and scale it by the previous year's nominal market capitalization of the inventing firm. This makes the variable free from biases arising out of inflation, differential firm size, and heterogeneity in the number of patents filed.

[15] We accessed these data in March 2023 from: mikewoeppel.com/data

The remaining patent-level innovation variables such as self-citation share, inventor-firm share, and technology-class share are converted into firm-year observations using simple annual averages. Following Bena and Li (2014), we construct a patent change index (denoted as Δ Patent Index) that controls for the firm-level annual change in its innovation output, defined as the share of patents awarded to a firm within each technology class and summed up across all technology classes. We also calculate the scientific quality of a firm's patents using the average (truncation-bias-adjusted) forward citations received by its patents.

Other fundamental variables used as controls include each firm's age (estimated from the date the firm first appeared in CRSP database), cost of goods sold (COGS), sales, total assets, book-to-market ratio, capital expenditure (capex), leverage, market capitalization, property plant and equipment (PP&E), R&D expense, return on assets, and industry classification (using both SIC and Fama-French 49 industry groups). Cost-related variables are scaled by sales and other variables by total assets to adjust for size. Finally, the distribution of all scaled variables is winsorized at 2.5% and 97.5% due to a substantial skewness in the raw data. We describe the remaining M&A-specific variables in Section V.

III. Production costs and process innovation

This section offers tests of Hypotheses 1. We take a panel-data approach and examine whether firms with a recent history of cost inefficiency invest more effort in process innovation. To capture cost-inefficiency, we use cost of goods sold over sales (COGS/Sales). The analysis is conducted at the firm-year level. Table II provides descriptive statistics of our data. We estimate the model:

$$\text{Process Share}_{i,t} = \beta_0 + \beta_1 \text{COGS/Sales}_{i,t} + \gamma \mathbf{Z}_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t}. \tag{1}$$

In Equation 1, the dependent variable is the proportion of firm i's total patents filed in year t that are classified as process patents. The regressor of interest is the variable *COGS/Sales*, which is calculated as the firm's cost-of-goods-sold scaled by sales averaged over the previous three (or five) years (separate scaling). We expect that cost-inefficient firms have a greater incentive to engage in process innovation. If our classification of process patents indeed captures innovation directed toward cost reduction, the coefficient β_1 should be positive. Vector $\mathbf{Z}$ is a set of firm-level control variables such as age (log), assets (log), book-to-market, capital expenditure/assets, leverage, market capitalization (log), property, plant & equipment/assets, R&D/assets, and return on assets. (All variables are defined in appendix Table II.) The specification includes firm- and year-fixed effects. Standard errors are clustered by the SIC 3-digit industry.

The results reported in Table III indicate that firms that have experienced higher COGS/Sales in the previous three or five years engage in significantly more process innovation. In Table III columns 1 and 2, we do not include the firm-level control variables or any fixed effects. In columns 3 and 4, we include control variables but not fixed effects. In columns 5 and 6, we include control variables as well as firm- and year-fixed effects. In all specifications, the coefficient on COGS/Sales is positive and statistically significant at the 99% confidence level. The relationship between Process Share and COGS/Sales is economically meaningful. A one-standard deviation increase in the COGS/Sales over the previous 3 years is associated with a 7% increase in Process Share relative to the mean.[16]

In the internet Appendix IAI, we provide further evidence of the link between production costs and process innovation. Using the economic value of process patents as the dependent variable, we show that the market views investment in process innovation more favorably for firms that have a recent history of high COGS/Sales. In the internet appendix we also present several other tests that emphasize the relevance of production costs for process patenting. First, we drop patents that may be revenue-generating and find our results in Table III still hold. Second, we confirm that the positive coefficient on COGS/Sales in Table III is driven by COGS, not sales. Third, we explore the link between process innovation and overhead costs and find no significant relation.

In summary, the results in this sub-section support the first hypothesis and provide validation that our measure of process innovation constructed from patent language captures innovation directed toward reducing production costs. Since production functions are firm-specific (Gandhi et al., 2020), innovation in production processes is likely associated with firm-specific knowledge accumulation. In the next section, we provide further evidence of the specificity of process innovation.

[16] Using the coefficient on 3-year COGS/Sales in column 3 of Table III (0.02), the standard deviation of COGS/Sales in Table II (0.90), and the mean of Process Share from Table II (0.27), the economic magnitude is 6.67% (0.02*0.9/0.27).

IV. Internal knowledge accumulation

In this section, we use four distinct empirical measures to test Hypothesis 2. In the first approach, we conjecture that if process innovation is more specialized to the operations of the innovating firm, then process patents are more likely to cite previous innovations by the same firm than non-process patents. We use USPTO patent citation data to calculate, for each patent, a variable called *Self-citation Share*. Self-citation Share is the proportion of prior patents cited by the focal patent that were filed by the same firm, out of all the patents cited by the focal patent. It takes a value between 0 (all citations relate to other firms' patents) and 1 (all citations relate to the focal firm's patents).

Our second approach rests on the notion that the inter-firm flow of technicians and R&D personnel increases the dissemination of scientific knowledge and technical expertise. We hypothesize that the private-value component of a firm's innovation will be higher if a greater share of its inventors' work has been done while in employment at that firm. By contrast, inventors who have innovated at multiple establishments are more likely to be in possession of knowledge that is common across firms' products or production processes. We calculate for each patent, a variable called *Inventor-firm share* which captures the share of the inventor's prior patents that have been filed with the same firm as the assignee. This variable takes a value between 0 (the inventor has never before filed a patent with the focal firm) and 1 (all of the inventor's prior patents have been with the focal firm).

Our third measure focuses on inventor mobility. Inventors whose knowledge base is tied to the firm are less likely to be poached by other firms as compared to inventors with a more general knowledge base (Ma, Wang, and Wu, 2023). To test whether inventors that are engaged in process innovation are less likely to move to another firm, we create an indicator variable called *Inventor-firm Change* for each patent which equals one if the inventor files their *next* patent at a different firm and zero otherwise.

Our fourth empirical measure is designed to test the premise that process innovation is incremental in nature and is based on information the firm generates in-house from its own production (Bright, 1958, Hollander et al., 1965). If process innovation is indeed internal and incremental, we expect process innovation to exploit technologies already known to the firm rather than exploring new technologies. We follow Balsmeier et al. (2017) and calculate for each patent a variable called *Technology-class Share* which captures the share of the firm's prior patents that have been filed in the same technology class as the focal patent. Technology class share takes a value between 0 (the patent belongs to a CPC subsection in which the focal firm has never filed a patent) and 1 (all prior patents of the focal firm belong to the same CPC subsection as the focal patent).

We run the following patent-level regression using each of the four measures as a dependent variable.[17]

$$\text{Internal Knowledge}_{p,i,t} = \beta_0 \text{Process}_{p,i,t} + \beta_1 \text{Cumulative Patents}_{i,t} + \alpha_t + \alpha_i + \varepsilon_{p,i,t}. \tag{2}$$

In this equation, the dependent variable is one of the four measures of internal knowledge accumulation for patent p filed by firm i (or inventor i for Inventor-firm Change analysis) in year t: Self-citation Share, Inventor-firm Share, Technology-class Share, and Inventor-firm Change. For the first three dependent variables, the explanatory variable of interest is an indicator variable *Process* which takes the value 1 for process patents and zero for non-process patents. We control for the cumulative number of patents (in logs) filed by the focal patent's firm up to the focal patent's filing date. In addition, the regressions include firm- and year-fixed effects.

When the dependent variable is Inventor-firm Change, the explanatory variable of interest is termed "Inventor Process Share", the share of process patents in the cumulative count of the inventor's prior patents. This (latter) specification tests whether inventors who have accumulated firm-specific knowledge through prior process inventions are less likely to move to another firm before their next invention. In this regression, we control for the cumulative number of patents (in logs) filed by the *inventor* up to the focal patent's filing date. In addition, the regression includes year-fixed effects (but firm-fixed effects are excluded because including them would subsume inventors that stay with the same firm throughout our sample period). Standard errors are clustered by year in all four specifications.

Table IV reports the estimation results. In column 1, we see that the coefficient on the Process indicator variable is positive and statistically significant at the 1% level, implying that process patents have a higher self-citation share. The coefficient of 0.008 implies that self-citations are about 1 percentage point higher for process patents than for non-process patents, which translates into a 6% higher self-citation share over the unconditional average of 13% (shown in Panel B of Table II).

[17] Our results are qualitatively similar if we average the patent-level variables to the firm-year level. See Table III in the appendix.

In column 2, the coefficient on Process indicator variable is positive and significant at the 1% level, which indicates that inventors who develop process patents have undertaken a higher share of their prior innovation at the same firm as compared with inventors who develop non-process patents. In column 3, where the dependent variable is Technology-class Share, the coefficient on process is positive and statistically significant at the 10% level. Thus, we find weak evidence that process patents are more likely to be developed by firms that engage in exploitative innovation (i.e. in technology classes already known to the firm) rather than exploratory innovation. Finally, in column 4 the coefficient on Process Share is negative and statistically significant at the 1% level, indicating that inventors with a higher share of prior process patents are less likely to move to a new employer before their next patent filing.

Taken together, these findings provide the first large-sample evidence that process innovation is associated with more firm-specific knowledge accumulation than non-process innovation.

V. Process Innovation and M&A

Under our conclusion that process patents are more specific to the inventing firm, it is natural to wonder about the implications of this characteristic for value. Our second part of the paper explores this with particular attention to how other (non-focal) firms may view process patents differently. Specifically, we explore the implications of innovation specificity for mergers and acquisitions. We test Hypothesis 3 outlined in Section I about a firm's likelihood of being acquired.

A. Data

We source the list of M&A deals announced between 1980 and 2020 involving US public firms from SDC Platinum database. Following Bena and Li (2014), we keep all completed deals with a value of at least $1 million and non-missing fields for the announcement date and firm identifiers. Further, we focus on deals that are coded as mergers, acquisitions of majority interest, or acquisitions of assets in excess of 50%. We limit this sample to deals for which the target appears in COMPUSTAT database in the year before the deal announcement. Our focus is on the impact of the *type* of innovation on the M&A market. Therefore, we retain only those deals where the target was "innovative" i.e. filed for at least one patent in the year of, or preceding three years of deal announcement. There are 2,830 deals for which innovative target firms' fundamental data are available.

Next, for each deal, we construct a sample of control firms that were not involved in any M&A

transaction for three years before the year of announcement [t-3, t-1 inclusive], but who are similar to the actual target along the key dimensions of size and industry. We match each target i with five firms that are in the same industry and within 50% and 150% of the market capitalization of the target firm. For industry matching, we begin by searching for firms that meet the size criterion at the 4-digit SIC level. If we cannot find five control firms, we proceed to the 3-digit SIC level, and so on. We are able to find five controls each for 1,759 actual targets, which altogether constitute a sample of 10,554 observations. The targeted firm and its five controls constitute a "deal" (for our fixed effects). Panel A of Table V presents the features of acquirers, actual targets, and the targets' matched firms. We compare targets and control firms and find several variables differ across targets and matched firms. We control for these differences in our regressions.

We source a number of additional variables for the M&A analysis. First, we define "SameTNIC" as an indicator of whether the acquirer and target firms are product market competitors or not. We use the text-based industry classification (TNIC) proposed in Hoberg and Phillips (2010, 2016) to indicate if the deal constitutes a horizontal merger. The list of firms that share a TNIC in the year before merger is sourced from the Hoberg-Phillips data library.[18] Second, we calculate a cosine similarity measure (detailed below) between a target firm's patent descriptions and potential acquirer's 10-K product descriptions. Panel B of Table V summarizes both the SameTNIC and Similarity variables for the actual and control acquirer-target pairs. Finally, we source the following deal-specific variables from SDC Platinum database: transaction value, payment method (cash or stock), and an indicator for competing deals.

B. *Likelihood of being acquired*

Hypothesis 3 states that if process innovation is more firm-specific than non-process innovation, firms that emphasize process innovation are less likely to be acquired. We test this by estimating the likelihood that a firm gets acquired based on the industry-adjusted share of process patents in its portfolio. We use a conditional logit regression, as well as a linear probability model, with each taking the general form:

$$\text{Target}_{id,t} = \beta_0 + \beta_1 \text{Process Share (tercile)}_{id,t-1} + \gamma \text{Target Characteristics}_{id,t-1} + \alpha_d + \varepsilon_{id,t}. \quad (3)$$

[18] hobergphillips.tuck.dartmouth.edu

In equation (4), the dependent variable equals 1 if firm i is an actual target in deal d, and 0 if it is a matched control firm. The regressor of interest is the firm's process-share (tercile), which takes a value of 3 (1) if the firm's process share in the previous year was in the top (bottom) tercile of its industry, and a value of 2 for firms in the middle tercile. We use within industry tercile rankings to control for cross-sector differences in the level of process innovation. Target characteristic controls include all of the firm-level controls variables described above for previous regressions, as well as the following additional control variables: R&D, patent growth (motivated by Bena and Li (2014)), firm-level forward citations (to proxy innovation quality) and their economic value. Finally, since we know from the results in Table III that firms with a recent history of high COGS/Sales engage in more process innovation, and that cost-inefficient firms are likely to be less attractive merger targets, we also include the firm's COGS/Sales as a control. The specification includes potential-deal fixed effects , and standard errors clustered by deal.

It is important to note that both the actual target and the control firms are "innovative". Therefore, if a control firm does not file for patents in the year before the deal is announced, it drops out of the analysis. Furthermore, if any of the control variables are missing for the actual target, the entire deal drops out of the conditional logit regression.

Table VI reports the estimation results using a conditional logit regression. For robustness, we present three specifications that differ on how the process share terciles are created. In column (1), a firm i's process share in year t is assigned to a tercile relative to the process share of all firms in the same Fama-French 49 industry across the entire sample period. In column (2), the process share tercile is based on all firms in the same 3-digit SIC over the sample period, and in column (3), relative to all firms in the same 2-digit SIC.

In all specifications shown in Table VI, the coefficient on process share tercile is negative and statistically significant at the 99% confidence level, indicating that firms with a higher share of process innovation are less likely to be targets of acquisition. Our findings are not due to industry effects because our matched control firms are from the same industry. These results hold even after the inclusion of the COGS/Sales variable, which indicates that relative cost inefficiencies do not explain away the lower attractiveness of process innovators in the M&A market. (The coefficient on COGS/Sales is negative but not significant). Forward citations and economic value of patents are positive and significant indicating that firms with higher quality innovation are more likely to be acquired. Consistent with Bena and Li (2014), the coefficient on change in patent index is negative and significant.

In Table IV, we show that our findings are qualitatively similar if we estimate a linear probability model instead. We re-estimate Equation 3 using ordinary least squares with deal fixed-effects and find that if a firm moves from the first to the third tercile of process share in its industry group, it has an 8% lower likelihood of getting acquired.[19] This finding is robust to the three different ways of adjusting for industry Process Share when creating the target firm's process share tercile.

Overall, the results in this sub-section are supportive of the hypothesis that process innovators are less likely to be merger targets. Next, we address concerns about endogeneity. Firms choose how much emphasis to place on process innovation and this choice may be influenced by firm characteristics that also affect the likelihood of being acquired. In Appendix B, we use potential outcome methods like propensity score matching and inverse probability weighting to estimate the effect of high process share on acquisition likelihood and find that our results hold after selecting on observables. To address concerns that *unobserved* firm characteristics that affect process innovation also influence its likelihood of being acquired, we present an instrumental variable analysis in Appendix C. Given our findings in Section III that process patents tend to build on internal knowledge, we use a firm's self-citation share as an instrument for process innovation. The IV analysis confirms that the likelihood of being acquired is lower for firms with higher process share. Appendix C discusses the validity of the instrument and reasonable violations of the exclusion restriction.

We also account for prior literature suggesting that firms are more secretive about new processes than about new products (Horstmann et al., 1985; Levin et al., 1987). If firms' preference for secrecy affects the patenting decision and also correlates with their prospects in the M&A market, we would have a selection bias. To evaluate whether a selection bias exists, we use mentions of trade secrets in the quarterly earnings calls (Lerner et al., 2024) and examine whether firms that talk about trade secrets more frequently exhibit lower tendency to patent their innovation (whether overall, or a specific type). Table V provides estimates from a probit and linear probability estimations, and shows that selection into patenting is not driven by mentions of trade secrets. Thus, the need for secrecy is unlikely to cause a selection bias in our M&A analysis.

[19] The coefficient on the process share tercile in Table IV is about -0.04 in all specifications, indicating that moving up one tercile reduces the likelihood of being acquired by 4%. This implies an 8% decline in acquisition likelihood when moving from the bottom to the top tercile.

C. The Moderating Effect of Redeployability

Our explanation for the negative relation between process share and the likelihood of being acquired is that process innovation is specialized to the operations of the innovating firm and cannot be easily exploited by another firm whose production systems and capabilities may be different. A plausible alternate explanation for why process innovators are less likely to be acquired is that process innovation is lower quality innovation than non-process innovation. Although we have controlled for the quality of innovation in our likelihood regressions, we explore this concern further in Table VI.

We compare two measures of the quality of innovation across process and non-process patents - the Kogan et al. (2017) economic value as well as the scientific value as measured by forward citations received by a patent. Panel A of Table VI presents the comparison at the patent level. We see that the economic value of process patents, both in nominal and real terms, is larger for process patents than for non-process patents. Truncation bias adjusted forward citations are comparable for process and non-process patents. In Panel B of Table VI, we conduct the comparison at the firm-level using the sample of all targets and their matched control firms. We define process (non-process) innovators as firms in the top (bottom) tercile of process share. We see that when averaged to the firm level, the value of process innovation is not significantly different from that of non-process innovation. Thus, we find no evidence that process innovation is lower-quality innovation.

In the following sub-sections we seek further support for the specificity explanation by testing Hypothesis 4. It states that the negative relation between process share and the likelihood of being acquired documented in Table VI will be dampened if the target's processes are more transferable to the acquirer. We use two strategies to capture the redeployability of the target's process innovation to the acquirer's products. The first method exploits product similarity between the acquirer and target. If process innovation is firm-specific, then the transferability of process-related knowledge is likely to be greater between firms that manufacture similar products. That is, a firm's process innovation may be of value to other firms that compete in similar product markets. The second method gets at the transferability of the target's innovation more directly through the language similarity between the text descriptions of the target's patents and the acquirer's products. Notably, the alternate explanation (discussed above with respect to differing values to product vs process innovation) does not predict a differential result based on either product similarity or patent-to-product similarity.

In subsubsection C.1 below, we examine the likelihood of a firm being acquired conditional on product similarity between the acquirer and target. In subsubsection C.2, we examine the likelihood of being acquired conditional on the text-based similarity between the target's patents and the acquirer's products. In Appendix D we study how the post-merger operating performance varies by redeployability when process innovators are acquired. Finally, in Appendix E, we use cumulative abnormal return (CAR) to study how product similarity affects perceived synergistic gains from buying process innovators.

C.1. Product similarity and acquisition likelihood

To test Hypothesis 4, we examine the likelihood of a firm being acquired conditional on whether the firm and the potential bidder have similar products. We use the Hoberg and Phillips (2010, 2016) Text-based Network Industry Classification (TNIC) to identify product similarity between the merging firms. To conduct this test, we compare the actual merger pair with hypothetical merger pairs. For each actual merger deal, we form hypothetical merger pairs by pairing five of the target's control firms with the actual acquirer. The selection of control firms is described previously in subsection B. For all pairs, actual and hypothetical, we define an indicator variable called *SameTNIC* that takes the value of 1 if the acquirer and the target (or control target) have the same TNIC classification and 0 otherwise. SameTNIC is summarized in Table V. We estimate the following regression:

$$\begin{aligned} \text{Target}_{id,t} = \beta_0 + \beta_1 \text{Process Share}_{id,t-1} \times \text{SameTNIC}_{ijd,t-1} + \beta_2 \text{Process Share}_{id,t-1} + \\ \beta_3 \text{SameTNIC}_{ijd,t-1} + \gamma \text{Target Characteristics}_{id,t-1} + \alpha_d + \varepsilon_{id,t}, \end{aligned} \tag{4}$$

In this equation, the dependent variable takes a value of 1 if firm i is an actual target in deal d and 0 if it is a control firm. The regressor of interest is the firm's Process Share (tercile) in the preceding year, interacted with SameTNIC. The hypothesis is that product similarity should mitigate the negative effect of process innovation-focus by the target, on the likelihood of being acquired. That is, we expect the coefficient β_1 on the interaction of SameTNIC and Process Share (tercile) to be positive. All control variables and details for the regression specification are the same as in Equation 3.

Table VII reports the estimation results. As before, the coefficient on the process share tercile is negative and statistically significant in all three specifications. More importantly, the coefficient on the interaction between process share and the dummy variable SameTNIC is positive and statistically significant in all three specifications. The coefficient on the interaction term is of similar magnitude as the coefficient on process share itself, which suggests that in the presence of product overlap, the negative effect of process share on the likelihood of being acquired is almost entirely reversed. In Appendix E we present evidence that these likelihood results speak to expected synergies. Using combined cumulative abnormal returns (CARs) at merger announcement, we show CARs are significantly lower when the target has high process share, which is consistent with lower expected merger synergies. However, this negative CAR is reversed when the acquirer and target share a TNIC. We also study post-merger COGS/Sales in Appendix D, and further confirm the importance of product overlap for the re-use of process innovation. Buying targets with high process share is associated with post-merger cost reductions when the merging firms share the same TNIC, but not otherwise.

C.2. Patent-to-product similarity and acquisition likelihood

The positive coefficient on the interaction of Process Share and SameTNIC is consistent with the specificity hypothesis. However, it might also be consistent with an alternative explanation in which process innovators with similar products are acquired for competitive reasons. To more directly test whether our merger likelihood results are driven by the expected synergies from transferring the target's process innovation to the acquirer's products, we create an alternative measure to capture the relevance of the potential target's innovation for the products of the potential acquirer. This measure, which we label *Similarity*, is calculated for all possible merger pairs, including the actual merger pair and the control pairs. It is the text-based cosine similarity between the target's patents and the acquirer's product descriptions calculated as follows.

From USPTO, we obtain patent descriptions (including background of the invention and summary of the invention) of all patents belonging to actual targets and control targets. For acquirer product information, we extract business descriptions provided in Section 1 or Section 1A of 10-Ks of all acquirers and control acquirers. We parse business descriptions and keep only words that are nouns or proper nouns and appear in no more than 15% of all product descriptions to avoid commonly occurring words.[20] For each patent p belonging to the target in merger pair j, we extract all the unique words that appear in the description of patent p and in the parsed acquirer's product description.

[20] If we change the cutoff to 20% or 25%, we find qualitatively comparable results but with weaker significance as we introduce more noise into the measure by including more commonly occurring words.

Next, we vectorize the patent descriptions and the acquirer's product description as follows. Designating the number of unique words as N, we create two vectors of length N where each component represents one of the N unique words. In the first vector C_p, each component represents the number of occurrences of the corresponding word in the description of patent p. In the second vector V, each component represents the number of occurrences of the corresponding word in the acquirer's product description. Next, we calculate the cosine similarity between the text of patent p and the acquirer's product description as the normalized dot product of the two vectors

$$Cosim_p = \frac{C_p.V}{\|C_p\|\|V\|} \tag{5}$$

Since the target in each merger pair often has more than one patent, we convert this patent-level measure Cosim into one value per deal pair, called *Similarity*, by taking a simple average of Cosim across all of the target's process patents or all of the target's non-process patents.

Next, we estimate the following equation, which closely follows Equation 4 except that we use the Similarity measure instead of the "SameTNIC" indicator variable:

$$\begin{aligned}\text{Target}_{id,t} = \beta_0 + \beta_1 \text{Process Share}_{id,t-1} \times \text{Similarity}_{ijd,t-1} + \beta_2 \text{Process Share}_{id,t-1} + \\ \beta_3 \text{Similarity}_{ijd,t-1} + \gamma \text{Target Characteristics}_{id,t-1} + \alpha_d + \varepsilon_{id,t}.\end{aligned} \tag{6}$$

The results are presented in Table VIII. In panel A of Table VIII, the variable Similarity measures the text-based similarity between the acquirer's product descriptions and the target firm's *process* patents only. In panel B, Similarity measures the text-based similarity between the acquirer's product descriptions and the target firm's *non-process* patents only. As before, the three columns in the table vary based on the industry classification used to create the process share terciles. In Panel A we see that while the coefficient on process share tercile is negative and significant, the interaction between process share and Similarity is positive and statistically significant. The size of the coefficient on the interaction term indicates that the negative effect of process share on acquisition likelihood is reversed when the target's process innovation is more transferable to the acquirer's products

In contrast, we see that in Panel B, the interaction of Process Share and Similarity is statistically insignificant. That is, for a target whose innovation is heavily process oriented, the similarity (or redeployability) of its non-process innovation does not significantly affect its likelihood of being acquired. This non-result further supports the notion that impediment to takeover likelihood is the specificity of the firm's *process* patents. Overall, the results in this subsection provide support for Hypothesis 4.

D. Withdrawn deals

In this section, we use withdrawn deals to highlight the role of process innovation in merger synergies. Our conjecture is as follows. If the bidder pursues a merger because it hopes to generate synergies by redeploying the target's process innovation to its own product lines, then failure of the deal would likely require the bidder to conduct the process innovation in-house. We therefore examine the change in the composition of bidder's innovation portfolio after a deal is withdrawn, conditional on the composition of the target's innovation portfolio.

From the SDC Platinum database we identify deals in which the bidder announced a majority-stake acquisition that was subsequently withdrawn. The sample period is the same as our main M&A sample. Since we want to examine the bidders innovation portfolio conditional on the innovation characteristics of the target, we require both the bidder and the target to be innovative firms, i.e., both must have filed for at least one patent in the three years preceding the merger announcement. We also wish to focus on withdrawn deals in which synergies were expected. We identify these based on the stock market's reaction to the withdrawal announcement. Specifically, we limit our analysis to withdrawn deals for which the 3-day cumulative abnormal return around the merger withdrawal date is in the bottom quartile.

We calculate the acquirer's process share (or process-share tercile) from (at most) five years before merger withdrawal date till (at most) five years after. We run the following panel regression using ordinary least squares

$$\begin{aligned}\text{Bidder\_proc}_{d,t} = \beta_0 + \beta_1 \text{Post}_{d,t} + \beta_2 \text{Process share (tercile)}_d + \beta_3 \text{Post}_{d,t} \times \text{ Process share (tercile)}_d \\ + \alpha_i + \delta_{d,t} + \xi_T + \gamma \mathbf{Z}_{d,t} + \varepsilon_{d,t}\end{aligned} \tag{7}$$

In this regression, *Bidder_proc* is the bidder firm's process-share tercile (or continuous version in follow-up tests) in withdrawn deal d in year t relative to the year of withdrawal, where t ranges from - 5 to +5. *Post* is an indicator variable that takes the value zero for the years preceding withdrawal year and one for the years following withdrawal year. *Process share (tercile)* is the target firm's process share tercile (using FF 49 industries) measured in the year prior to merger announcement. Our hypothesis predicts a positive and significant coefficient on the interaction of Post with Process share (tercile). That is, when a bidder pursues but fails to acquire a target with a high process share, the bidder's in-house process innovation will rise in the years following withdrawal date. For controls, we have α_i as firm-fixed effects, $\delta_{d,t}$ as event-time fixed effects, and ξ_T as deal-withdrawal year fixed effects.[21] Z represents the following bidder control variables - market capitalization, leverage, and market-to-book. Standard errors are clustered by calendar year. The sample contains about 500 deal-year observations pertaining to 72 withdrawn deals announced by 66 unique bidders.

Results are presented in Table IX. In columns 1 and 2 of Table IX, the dependent variable is the bidder's process share tercile (based on FF49 industries). In column 1, event-time fixed effects are excluded, so that the coefficient on the variable Post can be estimated. In column 2, event-time fixed effects are included and these subsume the indicator variable Post. In both columns, we see that the interaction of Post and target's Process share has a positive and statistically significant coefficient. In columns 3 and 4, we use the acquirer's process share (continuous raw variable) as the dependent variable.[22] In column 3 (column 4) event-year fixed effects are excluded (included). Again, we see that the coefficient on the interaction term is positive and statistically significant. These results indicate that bidders step-up their in-house process innovation, after failing to execute a merger with high expected synergies-via-process-improvement. This aligns with our conclusion that process innovation is firm-specific.

VI. Robustness to Inclusion of Hybrid Patents

In this section, we describe the robustness of our main results to the inclusion of hybrid patents – i.e., patents that contain claims that are classified as process claims and those classified as non-process claims. In our main analysis, we ignore hybrid patents and construct all variables using only patents that are unambiguously classified as process patents (patents in which all claims are process claims) or non-process patents (patents in which none of the claims are process claims).

[21] In case there are multiple withdrawn deals in any particular year of our sample.

[22] This reflects the recognition that withdrawn deal analysis is effectively intensive margin.

The reason for this choice is to obtain a sharper contrast between patents that are likely to generate firm-specific knowledge (due to heavy emphasis on process innovation) and patents that are less likely to generate firm-specific knowledge (due to the absence of any reference to methods and procedures). Since almost half of the initial sample of patents awarded to publicly traded firms are hybrid patents, our choice might lead to concerns about the generalizability and robustness of our findings. To address such concerns, we rerun our key tests using all patents, including hybrid patents. Figure IAI shows the share of process claims over time from 1980 through 2020 based on the approximately 2 million patents including hybrid patents. We see that the share of process claims is higher than in our main sample, ranging from just under 25% to just over 35%.

Next, we create a firm-level measure of process innovation using all claims across all patents of the firm, including hybrid patents. That is, Process Share is now defined as the number of process claims across all the firm's patents divided by the total number of claims. Then, we estimate Equation 1 again using this new definition of Process Share. The results are presented in columns (1) and (2) of Table IAIV of the appendix. We see that the coefficient on COGS/Sales continues to be positive and statistically significant, indicating that firms with a recent history of high costs engage in more process innovation. We note, however, that the magnitude of the coefficients is smaller than in our main results. Next, we estimate Equation 13 using the new definition of Process Share and present the results columns columns (3) and (4) of Table IAIV of the appendix. We find that the coefficient on COGS/Sales is positive and statistically significant, indicating that the economic value of process innovation is significantly higher for firms that experience cost inefficiencies in the preceding three or five years.

We also check the robustness of our merger likelihood analysis by estimating the conditional logit model shown in Equation 3. Results are presented in Table IAV in the appendix. We see that the coefficient on Process Share Tercile is negative and statistically significant in all specifications, but again the magnitude of the coefficient is smaller than in our main specification. Overall, we find that our main results are robust to the inclusion of hybrid patents. However, the smaller economic magnitude is likely because hybrid patents create noise in identifying the firm-specific component of process innovation.

VII. Conclusion

We offer a first-ever broad exploration of the specificity of innovative assets. Given the documented importance of hard-asset specificity for corporate decision making, and the known challenges to measuring and valuing innovation, our research provides important measurement and valuation prescripts. It also opens the door to further research on specific corporate questions surrounding compensation, payout, and financing, and other decisions, using our data. We provide a straightforward characterization of high innovation specificity in a firm, tied to a preponderance of their patents being process-oriented.

We confirm that process patents have high specificity. They are pursued when costs are relatively high, and they associate with more firm-internal-knowledge than product patents do. This carries important implications for their valuation, particularly by other firms. We therefore explore how specificity of innovation affects a firm's attractiveness in the market for corporate control.

We argue that the internal specialization of process innovation makes firms less attractive merger targets. Our tests confirm that process innovators are significantly less likely to be targets of a merger as compared to firms that emphasize non-process innovation. However, consistent with the specificity argument, we further show that the likelihood of a firm being acquired depends on the cross-firm fungibility of innovation. We provide support for the hypothesis that the knowledge generated by process innovation is more adaptable to the production process of competing firms that produce similar products. We do so in two ways: by showing that the negative impact of process innovation on merger likelihood is significantly dampened if the acquirer's products are similar to the target's products; and the same mitigation is evident when there is stronger text-overlap between the process patents of the inventor-firm and the product-language of the buying firm. Our results provide novel evidence that the composition of a firm's innovation portfolio affects its prospects in the M&A market.

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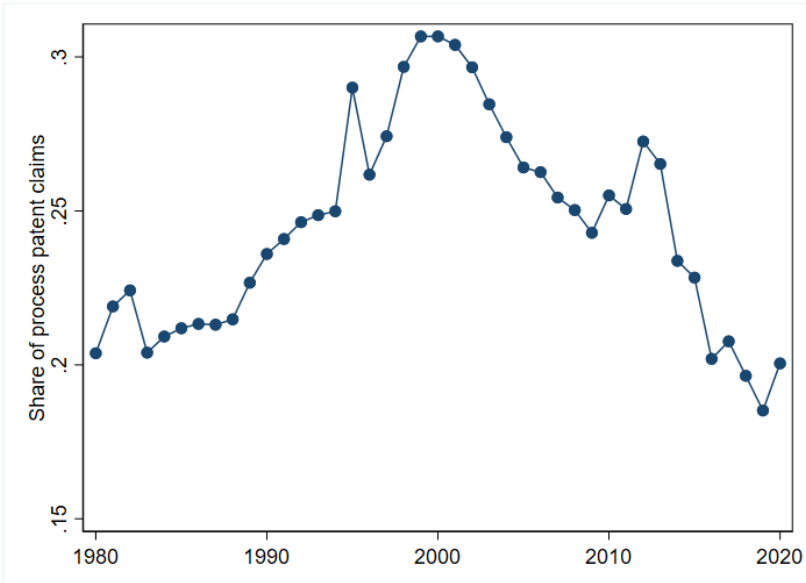
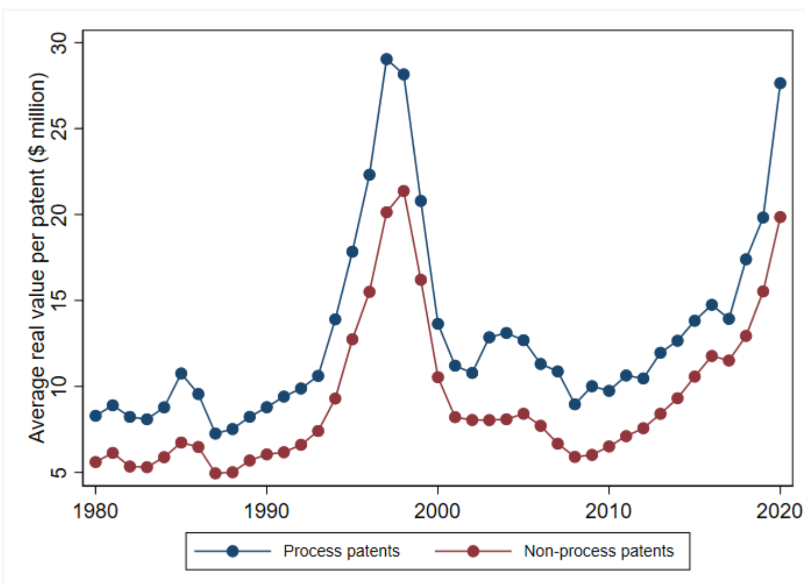
Figure I: Time Series of Process Innovation



(a) Share of Process Claims



(b) Economic Value of Patents

Notes: Panel (a) of this figure plots the average share of process claims in our data over the years 1980 through 2020. We identify process claims using a machine-read textual classification algorithm applied to all the claims in support of a patent application. This figure includes only those patents where all claims are unambiguously identified as "process" or otherwise. Figure IAI shows the corresponding plot for all patents in our sample. Panel (b) plots the average real economic value per patent (in millions of dollars), measured as the stock-market implied dollar valuation assigned to each patent, averaged over all the patents granted in a year for that type.

Table I: Descriptive Statistics of Process Patents by Fama-French 12 Industry Groups

This table presents descriptive statistics by Fama-French 12 industry groups for process patents filed between 1980-2020. Panel A shows the share of process patents and panel B shows the real economic value (in 1980 $ million) per process patent.

Panel A: Share of process patents	Mean	SD	p10	p25	p50	p75	p90	N
Consumer Nondurables	0.24	0.43	0	0	0	0	1	11,354
Consumer Durables	0.12	0.33	0	0	0	0	1	100,182
Machinery/Truck Manufacturing	0.17	0.38	0	0	0	0	1	204,601
Oil, Gas, Coal Extraction	0.56	0.50	0	0	1	1	1	34,419
Chemicals and Allied Products	0.45	0.50	0	0	0	1	1	58,209
Business Equipment	0.27	0.44	0	0	0	1	1	378,606
Telephone, Television Transmission	0.28	0.45	0	0	0	1	1	19,581
Utilities	0.23	0.42	0	0	0	0	1	1,568
Wholesale, Retail, Some Services	0.29	0.45	0	0	0	1	1	6,223
Healthcare, Medical Equipment, Drugs	0.34	0.47	0	0	0	1	1	90,111
Finance	0.26	0.44	0	0	0	1	1	5,812
Other (Mines, Construction, Hotels)	0.22	0.42	0	0	0	0	1	132,814
Full sample	0.26	0.44	0	0	0	1	1	1,043,480

Panel B: Real economic value per process patent ($ million)								
Consumer Nondurables	37.75	75.17	1.08	4.10	14.97	36.59	86.46	2,776
Consumer Durables	6.49	12.98	0.14	0.36	2.38	7.24	16.63	12,150
Machinery/Truck Manufacturing	7.69	13.71	0.05	0.23	3.69	9.68	18.60	35,170
Oil, Gas, Coal Extraction	40.99	65.75	4.30	8.51	18.46	45.31	99.46	19,303
Chemicals and Allied Products	10.92	17.53	0.67	2.42	5.52	11.77	27.04	25,917
Business Equipment	7.37	23.56	0.06	0.99	2.71	7.05	15.53	102,289
Telephone, Television Transmission	23.23	48.84	1.60	4.35	10.62	23.64	49.64	5,494
Utilities	8.41	11.81	0.10	1.57	4.96	10.17	17.93	363
Wholesale, Retail, Some Services	8.60	35.06	0.01	0.02	0.06	2.13	24.32	1,794
Healthcare, Medical Equipment, Drugs	26.86	52.33	0.81	2.53	8.99	28.32	67.77	30,679
Finance	48.64	120.06	0.25	0.74	2.87	43.38	142.62	1,540
Other (Mines, Construction, Hotels)	8.92	23.33	0.06	0.17	1.56	7.93	22.00	29,860
Full sample	13.44	35.71	0.10	1.03	4.09	11.62	30.27	267,335

Table II: Summary Statistics at Firm, Patent, and Inventor Levels

This table presents descriptive statistics for firm-year innovation and fundamental variables in panel A, and patent and inventor-level innovation variables in panel B. In panel A, "Economic Value" is the stock-market implied value of patents, averaged over all patents of that type (process or non-process) filed by a firm in a year and scaled by the previous year's market capitalization. It is expressed as a percentage. Table II defines the variables.

Panel A: Firm-year level variables	Mean	SD	p25	p50	p75	N
Process Share	0.27	0.35	0.00	0.07	0.50	51,387
Process Patents (count)	5.53	26.44	0.00	1.00	2.00	51,819
Non-process Patents (count)	16.41	73.99	1.00	2.00	7.00	51,819
Economic Value (per process patent)	1.85	38.01	0.26	0.59	1.26	22,259
Economic Value (per non-process patent)	1.80	24.66	0.38	0.73	1.41	34,750
Δ Patent Index	0.02	23.63	-1.50	0.00	1.52	48,868
Self-citation Share	0.08	0.12	0.00	0.03	0.11	51,387
Inventor-firm Share	0.26	0.24	0.00	0.25	0.43	51,387
Technology Class Share	0.32	0.26	0.11	0.25	0.49	51,387
COGS/Sales (3-year average)	0.80	0.90	0.48	0.64	0.76	45,481
COGS/Sales (5-year average)	0.81	0.89	0.49	0.65	0.76	46,473
Age (in years)	19.15	18.49	6.00	13.00	26.00	53,203
Assets ($, million)	10,525.78	77,403.62	74.14	362.17	2,382.37	54,015
Book-to-market	1.04	0.92	0.40	0.75	1.34	53,460
Capital Expenditure/Assets	0.06	0.04	0.02	0.04	0.07	53,331
Leverage	0.20	0.17	0.04	0.18	0.30	53,829
Market Capitalization ($, million)	7,143.30	31,442.44	83.78	426.45	2,432.79	53,673
Property, Plant & Equipment/Assets	0.24	0.18	0.10	0.21	0.34	53,916
R&D/Assets	0.10	0.12	0.02	0.05	0.12	44,897
Return on Assets	0.06	0.21	0.04	0.12	0.18	53,856

Panel B: Patent and inventor-level variables						
Self-citation Share	0.13	0.22	0.00	0.00	0.19	1,043,480
Inventor-firm Share	0.37	0.36	0.00	0.38	0.70	1,043,480
Technology Class Share	0.24	0.25	0.04	0.15	0.37	1,043,480
Inventor-firm Change	0.16	0.37	0.00	0.00	0.00	1,316,919

Table III: Determinants of the Share of Process Innovation

This table reports estimates from a fixed effects panel regression of the form in Equation 1 at firm-year level. The dependent variable is Process Share, the proportion of patents filed by a firm in a given year that we classify as process innovation. The regressor of interest is COGS/Sales averaged over prior 3 years (in columns (1), (3) and (5)) or prior 5 years (in columns (2), (4) and (6)). Columns (1) and (2) do not include controls and fixed effects, columns (3) and (4) include controls, and columns (5) and (6) additionally include firm and year fixed effects. Standard errors clustered by industry (SIC 3 digit) and year are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Process Share					
	(1)	(2)	(3)	(4)	(5)	(6)
COGS/Sales (3-year average)	0.060***		0.020**		0.010***	
	(0.010)		(0.009)		(0.003)	
COGS/Sales (5-year average)		0.064***		0.024**		0.012***
		(0.010)		(0.009)		(0.003)
Age (log)			-0.022***	-0.022***	0.003	0.003
			(0.005)	(0.005)	(0.009)	(0.009)
Assets (log, t-1)			-0.038**	-0.038**	-0.023*	-0.023*
			(0.015)	(0.015)	(0.013)	(0.013)
Book-to-market (t-1)			0.010	0.010	0.015**	0.015**
			(0.008)	(0.008)	(0.006)	(0.006)
Capital Expenditure/Assets (t-1)			-0.675***	-0.675***	-0.035	-0.033
			(0.121)	(0.120)	(0.059)	(0.060)
Leverage (t-1)			-0.035	-0.036	0.023	0.023
			(0.039)	(0.038)	(0.025)	(0.025)
Market Capitalization (log, t-1)			0.064***	0.064***	0.017**	0.017**
			(0.014)	(0.014)	(0.008)	(0.008)
Property, Plant & Equipment/Assets (t-1)			0.379***	0.378***	0.040	0.041
			(0.088)	(0.087)	(0.042)	(0.042)
R&D/Assets (t-1)			0.308***	0.301***	-0.042	-0.039
			(0.064)	(0.066)	(0.039)	(0.039)
Return on Assets (t-1)			-0.210***	-0.200***	-0.001	-0.000
			(0.028)	(0.027)	(0.016)	(0.017)
Observations	38,924	39,613	30,000	30,024	29,370	29,395
Adj. R^2	0.02	0.03	0.10	0.10	0.45	0.45
Firm, Year FE	N	N	N	N	Y	Y

Table IV: Internal Knowledge Accumulation

This table reports estimates from a fixed effects regression of the form in Equation 2. The dependent variables are one of the four measures of internal knowledge accumulation: self-citation share in column (1), inventor-firm share in column (2), technology class share in column (3), and inventor-firm change in column (4). Table II defines these variables. The regressor of interest is "Process" in columns (1) through (3), which takes a value of 1 when the patent is classified as "process" and 0 otherwise. In column (4), the regressor of interest is "Inventor Process Share", which is the proportion of cumulative patents filed by an inventor that are classified as "process". All columns control for the (log) cumulative number of patents filed by the firm or the inventor until the focal patent's filing date. Standard errors clustered by year are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Self-citation Share	Inventor-firm Share	Technology Class Share	Inventor-firm Change
	(1)	(2)	(3)	(4)
Process (0/1)	0.008***	0.006***	0.003*	
	(0.001)	(0.001)	(0.002)	
Inventor Process Share				-0.018***
				(0.003)
Cumulative Patents (log)	0.021***	0.048***	-0.014***	-0.017***
	(0.001)	(0.001)	(0.000)	(0.003)
Observations	1,043,480	1,043,480	1,043,480	1,316,919
Adj. R^2	0.15	0.15	0.44	0.01
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	N

Table V: Descriptive Statistics of Acquirer and Target Firms

Panel A compares the innovation and fundamental features of actual acquirers, and actual and control target firms. For each deal, we obtain five control firms using an industry and size matched sample of actual firms engaged in M&A transactions between 1980 and 2020. Statistical significance for the difference between actual and control targets' characteristics is shown in the last and third-to-last columns. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$. Panel B describes the SameTNIC and Similarity variables for acquirer-target pairs (both actual and control pairs). SameTNIC is a binary variable that indicates product market similarity using text-based industry classification, while Similarity is a continuous variable that captures cosine similarity between the target firm's patent description and acquirer's 10-K product description.

Panel A: Firm level	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
	Acquirers			Targets			Industry-Size Matched Targets		
Process Share	0.3	0.32	0.22	0.29	0.40	0.00	0.30	0.37	0.12***
Economic Value (per process patent)	0.89	3.36	0.3	1.19	2.91	0.65	3.51*	60.36	0.57
Patents (count)	29.99	65.24	7	3.36	9.17	1.00	9.81***	35.59	3.00***
Process Patents (count)	9.33	25.07	1	1.02	3.75	0.00	2.76***	9.15	1.00***
Non-process Patents (count)	20.67	43.52	5	2.34	6.55	1.00	7.04***	28.82	2.00***
Age (in years)	21.78	19.12	16	15.28	16.03	10.00	13.83***	14.53	10.00**
Assets ($, million)	7,350	18,000	1,636	1,755	6,003	198	1,844	8,435	177***
Book-to-market	0.71	0.59	0.57	0.79	0.66	0.62	0.74***	0.65	0.56***
Capital Expenditure/Assets	0.05	0.04	0.04	0.05	0.05	0.04	0.05	0.05	0.04
Leverage	0.19	0.16	0.18	0.17	0.17	0.13	0.16**	0.20	0.10**
Market Capitalization ($, million)	10,000	23,000	2,094	2,114	6,597	292	2,016	6,486	286
Property, Plant & Equipment/Assets	0.21	0.16	0.16	0.20	0.16	0.16	0.20	0.16	0.15
R&D/Assets	0.09	0.12	0.06	0.13	0.13	0.09	0.14***	0.13	0.10***
Return on Assets	0.11	0.19	0.14	0.04	0.22	0.10	0.01***	0.24	0.10**

Panel B: Acquirer-target pair level	Mean	SD	Median
SameTNIC (binary)	0.12	0.33	0
Similarity (continuous)	0.018	0.029	0.008

Table VI: Likelihood of Being a Target

This table reports estimates from a conditional logit regression of the form in Equation 3 at a deal level. The dependent variable equals 1 when the firm is a target and 0 if it is a control. The regressor of interest is Process Share (tercile). Terciles are constructed using: Fama-French 49-industry in column (1), SIC 3 digit-industry in column (2), and SIC 2 digit-industry in column (3). Each actual target is industry and size matched with five controls. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

	Target (1/0)		
	(1)	(2)	(3)
Process Share (tercile)	-0.290***	-0.300***	-0.327***
	(0.053)	(0.053)	(0.053)
Δ Patent Index	-0.023***	-0.023***	-0.023***
	(0.005)	(0.005)	(0.005)
Forward citations	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Economic value (1980 $)	0.014***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)
COGS/Sales (3-year average)	-0.058	-0.056	-0.058
	(0.068)	(0.068)	(0.068)
Age (log)	0.121**	0.123**	0.116**
	(0.052)	(0.052)	(0.052)
Assets (log, t-1)	0.160	0.161	0.165
	(0.126)	(0.126)	(0.126)
Book-to-market (t-1)	0.173	0.175	0.176
	(0.133)	(0.133)	(0.133)
Leverage (t-1)	0.808**	0.796**	0.786**
	(0.338)	(0.338)	(0.338)
Market Capitalization (log, t-1)	0.437***	0.436***	0.441***
	(0.147)	(0.146)	(0.147)
R&D/Assets (t-1)	-0.154	-0.140	-0.119
	(0.635)	(0.635)	(0.637)
Return on Assets (t-1)	-0.100	-0.087	-0.109
	(0.382)	(0.383)	(0.384)
Observations	3,429	3,429	3,429
Pseudo R^2	0.08	0.08	0.08
Deal FE	Y	Y	Y

Table VII: Likelihood of Being a Target (Interaction with Product Market Overlap)

This table reports estimates from a conditional logit regression of the form in Equation 4 at a deal level. The dependent variable takes a value of 1 when the firm is a target and 0 if it is a control. The regressors of interest are Process Share (tercile) and its interaction with SameTNIC that captures product market similarity between firms. Terciles are constructed using: Fama-French 49-industry in column (1), SIC 3 digit-industry in column (2), and SIC 2 digit-industry in column (3). Each actual target is industry and size matched with five controls. All columns include firm-level controls analogous to Table VI but are eclipsed for brevity. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Target (1/0)		
	(1)	(2)	(3)
Process Share (tercile)	-0.404***	-0.398***	-0.430***
	(0.128)	(0.130)	(0.129)
SameTNIC (1/0)	1.769***	1.804***	1.693***
	(0.455)	(0.462)	(0.455)
Process Share (tercile) × SameTNIC	0.383**	0.362*	0.414**
	(0.193)	(0.196)	(0.192)
Δ Patent Index	-0.040***	-0.041***	-0.040***
	(0.010)	(0.010)	(0.010)
Forward citations	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
Economic value (1980 $)	0.005	0.005	0.005
	(0.006)	(0.006)	(0.006)
Observations	1,309	1,309	1,309
Pseudo R^2	0.25	0.25	0.25
Firm controls	Y	Y	Y
Deal FE	Y	Y	Y

Table VIII: Likelihood of Being a Target (Interaction with Cosine Similarity)

This table reports estimates from a conditional logit regression of the form in Equation 6 at a deal level. The dependent variable equals 1 when the firm is a target and 0 if it is a control. The regressors of interest are Process Share (tercile) and its interaction with Similarity that captures the cosine similarity between the target firm's patent descriptions and the acquirer 10-K business descriptions. Panel A uses Similarity constructed using only process patents, and panel B uses Similarity constructed using only non-process patents. Terciles are constructed using: Fama-French 49-industry in column (1), SIC 3 digit-industry in column (2), and SIC 2 digit-industry in column (3). Each actual target is industry and size matched with five controls. All columns include firm-level controls analogous to Table VI but are eclipsed for brevity. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Panel A: Using process patents	Target (1/0)		
	(1)	(2)	(3)
Process Share (tercile)	-0.388**	-0.395**	-0.441***
	(0.156)	(0.156)	(0.156)
Similarity	18.575*	18.862*	17.742*
	(10.284)	(10.221)	(10.367)
Process Share (tercile) × Similarity	9.568**	9.373**	10.031**
	(4.495)	(4.490)	(4.518)
Observations	657	657	657
Controls	Y	Y	Y
Deal FE	Y	Y	Y

Panel B: Using non-process patents	Target (1/0)		
	(1)	(2)	(3)
Process Share (tercile)	-0.377***	-0.376***	-0.406***
	(0.145)	(0.145)	(0.145)
Similarity	48.441***	48.758***	47.891***
	(10.939)	(10.918)	(10.896)
Process Share (tercile) × Similarity	-2.459	-2.734	-2.237
	(3.919)	(3.918)	(3.900)
Observations	872	872	872
Controls	Y	Y	Y
Deal FE	Y	Y	Y

Table IX: Withdrawn Deals and Acquirer's Process Innovation

This table reports estimates from a model of the form in Equation 7. The dependent variable is the bidder firm's process innovation in year t relative to the year of deal withdrawal, where t ranges from - 5 to +5. Columns (1) and (2) use the tercile measure of process share using Fama-French 49-industry, while columns (3) and (4) use the continuous variable. Standard errors clustered by year are reported in parentheses. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

	Acquirer Process Share (tercile)		Acquirer Process Share	
	(1)	(2)	(3)	(4)
Post	-0.141		-0.047	
	(0.138)		(0.041)	
Process Share (target, tercile)	-0.019	-0.058	-0.010	-0.019*
	(0.048)	(0.037)	(0.010)	(0.011)
Post x Process Share (target, tercile)	0.129**	0.122**	0.043**	0.040**
	(0.061)	(0.059)	(0.020)	(0.019)
Observations	533	533	533	533
Adj. R^2	0.43	0.45	0.59	0.61
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Event Time FE	N	Y	N	Y
Withdrawal Year FE	N	Y	N	Y

Appendix

Innovation Specificity

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A. Data Appendix

A. Classification of patents

We construct a dictionary of words commonly found in the legalistic language that describes operational efficiency, and pass every claim text through an algorithm that checks for the presence of the following words.

"a process of, a process for, a method of, a method for, the method of, the method for, a method such that, the method such that, a method according to which,the method according to which, a process such that, the process such that, a process according to which, the process according to which, method of, method for, method that, method to, method by, method as, method according, method such, method using, process of, process for, process that, process to, process by, process as, process according, process such, process using."

Our text analytics algorithm returns a true (false) value for each claim that contains (does not contain) any of these words. We aggregate this classification at a patent level and retain those patents where all claims are either true or false. The former are tagged as process patents and the latter as non-process patents. In robustness analysis, we also include patents with both kinds of claims, and represent "Process Share" as the fraction of claims classified as process innovation.

B. Data sources and merging procedure

Our raw data come from the following sources.

1. Patent-claims text data: USPTO website. We download all the claims for patents filed between 1980 and 2020. We retain two columns, patent number and claims text, and collapse

the data into a patent-level classified file after tagging them as process or non-process.

2. Economic Value of patents data: Noah Stoffman's website. We download the stock-market implied dollar value of all patents filed by public firms and retain patent number, firm identifier, and the real and nominal values of these patents. These are merged into the patent-level classified file.
3. Patent-level citations, inventors, and technology class data: Michael Woeppel's website. We download the full set of patent-level citations, inventors, and technology class files and construct the three internal knowledge variables (self-citation share, inventor-firm share, and technology-class share). Then, we use the patent numbers to merge the file into the patent-level classified file.
4. Firm fundamentals and stock returns: annual COMPUSTAT/CRSP files. We download fundamental characteristics for public firms and merge them into the patent-level classified file using firm identifier ("permno") and filing year as matching variables. We collapse the data into firm-year averages.
5. M&A data: SDC platinum database. We filter all deals tagged as mergers, acquisition of majority interest or assets in excess of 50%, that were announced between 1980 and 2020 (and subsequently completed), with a value of over $1 million between US public firms. We retain columns on announcement date, firm identifiers, premium paid, and a flag for competing deal.
6. Horizontal acquisitions: Text-based Industry Classification (TNIC) from Hoberg-Phillips library. We match the firms in our data with GVKEYs in this library to ascertain whether the acquiring and target (actual or control) firms operated in similar product market in the year before deal announcement.

B. Potential outcome methods

In observational studies treatment effects are difficult to estimate because the treatment is not randomized and, therefore, the outcome and treatment are not necessarily independent. In this section, we use three different potential outcome methods – (i) Inverse probability weighting estimator (IPW), (ii) Regression adjustment estimator (RA), (iii) Propensity score matching estimator (PSM). These methods use different strategies to specify the potential outcomes each firm would obtain under each treatment level. The common theme across potential outcome methods is that they utilize covariates to make treatment and outcome independent once we condition on those covariates.

The first strategy we use is inverse probability of treatment weighting proposed by Rosenbaum (1987). This method uses weights based on the propensity score to correct the treated and untreated group means for the missing potential outcomes, i.e., for the couterfactuals. The weight for each firm is equal to the inverse of the probability of receiving the treatment that the firm actually received. Outcomes of firms that receive a likely treatment get a weight close to one. Outcomes of firms that receive unlikely treatment get a weight larger than one. The weighting creates a synthetic sample in which the distribution of baseline covariates is independent of treatment assignment. The average treatment effect using the IPW estimator is provided in Panel B of Table VII. The average treatment effect of -0.455 is statistically significant at the 1% level and indicates that process innovators are significantly less likely to be acquired than non-process innovators after selecting on all observables. Notably, Panel C, shows that after inverse probability weighting, the covariates are balanced across the sample of process innovators (the treated group) and non-process innovators (the untreated group)

In Panel D of Table VII, we present estimates of the average treatment effect using other potential outcome estimators. We present propensity score matching estimators that compare outcomes of firms that are as similar as possible (along covariates) with the sole exception of their treatment status. We match each treated firm, i.e. each process innovator, to non-process innovators with the nearest propensity score $\hat{\pi}_i$, the two nearest scores, or three nearest scores. Regardless of the number of nearest neighbors used, we find that process-innovators have significantly lower likelihood of being acquired as compared to the propensity score matched non-process innovators with the average treatment effect varying from -0.0515 to -0.0601.

In Panel D, we also present a regression adjustment estimator which uses a regression model to predict potential outcomes adjusted for covariates. This method involves regressing the outcome variable Target on all covariates in the subsample of process innovators and separately in the subsample of non-process innovators. The former subsample regression is used to predict each firm's outcome assuming the firm was a process innovator. The latter subsample regression is used to predict each firm's outcome assuming the firm was not a process innovator. This process results in two values for each firm – respectively, the prediction η_1 that the firm is acquired if it is a process innovator, and the prediction η_0 that it is acquired if it is a non-process innovator. The average treatment effect is the sample mean of the difference $\eta_1 - \eta_0$. Panel D shows that the average treatment effect using the regression adjustment estimator is -0.0454 and statistically significant at the 1% level. Note that the regression adjustment estimator is similar to running a regression of the outcome variable on the treated indicator variable, but including interaction terms of the treated indicator with demeaned values of all covariates.

C. Instrumental variables estimation

We also use an instrumental variable (IV) approach to address unobserved sources of variability that might affect both process innovation and merger likelihood. To this end, we seek a variable that is positively correlated with the share of a firm's process innovation but does not affect the likelihood of the firm being acquired through any avenue other than the composition of the firm's innovative effort. We use a firm's propensity to cite its own prior patents as an instrument. We know from the results in Table IV and Table III that firms with higher self-citation ratio engage in more process innovation.

In the first stage of our IV approach, we estimate the following model using ordinary least squares,

$$\text{Process Share (tercile)}_{i,t} = \beta_0 + \beta_1 \text{Self-citation Share (tercile)}_{i,t} + \gamma \mathbf{Z}_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t}. \qquad (8)$$

In this equation, the dependent variable is the process share of firm i in year t, mapped to an industry-adjusted tercile. The instrument is self-citation share of firm i in year t, also industry-adjusted by mapping to a tercile. Other control variables and fixed effects are the same as previously described in Equation 3. Specifically, we control for the quality of patents by including the patent's forward citations and economic value as control variables. We control for industry effects in the process share measure and self-citation share measure by mapping both variables to terciles within the industry. Standard errors are clustered by year. Panel B of Table VIII reports the estimation result and the instrument F-statistics. As in subsection B, we present three different specifications, which differ on how the process share terciles are created. All three specification indicate that this variable serves as a relevant instrument. The first-stage F-statistic is in the range of 26 to 41 depending on the industry group used for creating terciles.

We use the predicted value of Process Share (tercile) from Equation 8 to explore the likelihood that a firm is acquired. In this second-stage regression, we estimate the following model using ordinary least squares,

$$\text{Target}_{id,t} = \beta_0 + \beta_1 \text{Process } \widehat{\text{Share}} \text{ (tercile)}_{id,t-1} + \gamma \mathbf{Z}_{id,t-1} + \alpha_d + \varepsilon_{id,t}, \qquad (9)$$

where the dependent variable takes a value of 1 if firm i is an actual target in deal d and 0 otherwise. The regressor of interest is the predicted process share (tercile). The control variables are the same as described for Equation 3. Panel A of Table VIII reports estimates of Equation 9. As before, we present three different specifications that differ on how the process share terciles are created. In all specifications, the coefficient on predicted process share is negative and statistically significant at the 99% confidence level. The IV analysis indicates that a greater emphasis on process innovation reduces a firm's likelihood of being acquired. We check for possible violations of the exclusion restriction. A higher self-citation share could indicate lower innovation or firm quality and, thus, directly reduce acquisition likelihood. However, we find no evidence to support this concern. In Table IAVI provided in the internet appendix, we examine the relation between a firm's self-citation share and the following variables (i) economic value of the firm's patents, (ii) growth in patents as measured by the change in the patent index, (iii) forward citations received by the firm's patents and (iv) production efficiency as measured by COGS/Sales. The only significant result in Table IAVI is that self-citation share is significantly negatively related with the change in patent index. However, this would predict a *positive* relation between self-citations and acquisition likelihood (the opposite of our finding) because we know from Table VI and from the findings in Bena and Li (2014) that the change in patent index is associated with lower acquisition likelihood.

D. Post-merger operating performance

If process innovation is indeed specialized to the target's products, it should be more effective in reducing production costs when the acquirer and target have similar products. To test this conjecture, we examine the change in acquirer's production costs after the acquisition conditional on the target firm's process share and the similarity between the acquirer and target's products. Specifically, we calculate COGS/Sales from (at most) five years before the merger completion year till (at most) five years after the merger completion year. In the years prior to merger completion, COGS/Sales is calculated as the market-value weighted average of the acquirer and target's respective values. In the years after merger completion, we use the acquirer's COGS/Sales. We estimate the following panel regression:

$$\begin{aligned}\text{COGS/Sales}_{d,t} = \beta_0 + \beta_1 \text{Post}_{d,t} + \beta_2 \text{Process Share (tercile)}_d + \beta_3 \text{Post}_{d,t} \times \text{ Process Share (tercile)}_d \\ + \alpha_i + \delta_{d,t} + \xi_T + \gamma \mathbf{Z}_{d,t} + \varepsilon_{d,t}\end{aligned} \tag{10}$$

In this regression, COGS/Sales (calculated as described above) relates to completed deal d in year t relative to merger completion date T, where t ranges from -5 to +5. *Post* is an indicator variable that takes the value zero for the years prior to merger completion and the value one for the years after merger completion. Process Share (tercile) is the target firm's process share tercile (based in Fama French 49 industries) in the year prior to merger completion. The coefficient of interest is β_3 which captures whether the post-merger change in COGS/Sales depends on the target's process share. α_i are firm-fixed effects, $\delta_{d,t}$ are event-time fixed effects, and ξ_T are merger completion year fixed effects. Z represents firm-level and deal-level control variables. These control variables are the acquirer's size as measured by its market value of assets (in logs), the acquirer's leverage calculated as the acquirer's total long-term and short-term debt divided by market value of assets, book-to-market ratio calculated as book value of common equity divided by market value of assets, relative size of the target calculated as deal transaction value divided by acquirer's market value of equity, and percentage of deal consideration paid in cash. All variables except deal consideration are winsorized at the 2.5/97.5 level.

Estimates of Equation 10 are presented in Table IX. In column 1, we present estimates without event-time or deal year-fixed effects. In the absence of event-time fixed effects, the coefficient on the indicator variable Post can be estimated. In column 2, event-time fixed effects and deal-year fixed effects are included and the former absorb the indicator variable Post. In both columns, we see that the coefficient β_3 on the interaction term is negative and statistically significant, indicating that COGS/Sales is lower after the merger when the target's process share is higher. These results indicate that buying process innovators is associated with a post-merger decline in production costs of the acquirer. To test if this result depends on product similarity, we re-estimate Equation 10 in two subsamples - (i) deals in which the acquirer and target belong to the same TNIC (column 3) and (ii) deals where acquirer and target have different TNICs (column 4). [23] In column 3, the coefficient on the interaction, β_3 is negative and statistically significant while in column 4, β_3 is insignificant.

To test if the estimates of β_3 in column 3 and 4 are statistically different from each other, we employ a triple interaction term in column 5 (using the full sample). The triple interaction of Process share, Post, and Same TNIC is negative and statistically significant. This allows us to conclude that the target's process innovation is associated with a decline in production costs only when the merging firms have similar products. Overall, the results in Table IX provide support for the specificity of process innovation.

We recognize that this test does not establish a causal effect of process innovation on post-merger cost reductions because selection concerns exist - acquirers expecting a decline in product costs may prefer to buy process innovators. A commonly-used solution in the literature is to compare the post-merger performance of completed deals to that of withdrawn deals with similar target-firm characteristics. This strategy is not a viable solution in our setting because we know from the results in Table IX that bidders that try but fail to buy process innovators step up their own in-house process innovation.

[23] In this test, we do not use the measure of patent-to-product similarity due to a significant loss in sample size.

E. Product similarity and cumulative abnormal returns

Hypotheses 3 and 4 rest on the premise that process innovation is customized to the innovating firm's products and, therefore, contributes less to merger synergies than non-process innovation. The results in Appendix D provide support for this premise by showing that, in the presence of product similarity, production costs are lower after the merger if the target has high process share. In this subsection, we look at merger announcement returns to provide further supportive evidence that the synergies from a merger depend on the specificity of innovation.

We use the 3-day combined cumulative abnormal returns (CAR) of the acquirer and target as a proxy for merger synergies. The combined CAR is the weighted average of the acquirer and target firm's CAR with the pre-announcement market capitalization serving as the weight.[24] To calculate a firm's CAR, we first calculate daily abnormal returns over the three-day window surrounding merger announcement by deducting the return on the CRSP value-weighted index from the firm's return as $AR_{it} = R_{it} - R_{mt}$, where R_{it} is firm i's daily stock return on date t and R_{mt} is the return for the value-weighted CRSP index on date t. The CAR for each firm is calculated by cumulating the abnormal return, AR, over the three-day window.

We estimate the following cross-sectional regression:

$$\text{CAR}_d = \beta_0 + \beta_1 \text{Process Share (tercile)}_d + \gamma \mathbf{Z}_d + \alpha_T + \alpha_j + \varepsilon_d \tag{11}$$

where the dependent variable is the combined 3-day CAR of acquirer and target involved in deal d. The regressor of interest is the target's Process Share tercile in the year prior to merger announcement year. The target's process share is mapped to an industry-adjusted tercile measure to capture cross-sector differences in the level of process innovation. Z includes the following control variables: the indicator for *SameTNIC*, the acquirer's and target's leverage and book-to-market ratios in the year preceding merger announcement year, the growth in patents of the target and the acquirer, and an indicator for whether the deal had a competing bidder. α_j are industry-fixed effects, and α_T are deal-year fixed effects. Standard errors are clustered by year.

Estimates are presented in columns 1 to 3 of Table X, with the columns differing only on how the process share terciles are created. The coefficient on Process Share (tercile) is negative and weakly significant in two of the three specifications shown, which suggests that expected synergies from the merger are lower when the target firm has a high share of process innovation in its patent portfolio. The statistical significance strengthens once we tease out the role of product similarity. In columns 4 to 6, we include an interaction of Process Share and SameTNIC where SameTNIC

[24] We use the average market capitalization over three years preceding the merger announcement to smooth the impact of outliers.

takes the value of 1 if the acquirer and target have similar products (i.e., belong to the same TNIC) and zero otherwise.[25] In columns 4 to 6, the coefficient on Process Share is negative and significant at the 5% level in all three specifications. The magnitude of the coefficients on Process Share tercile indicate that, if the acquirer and target *do not* sell similar products, moving up one tercile of the target's process innovation lowers the combined CAR between 1.5 to 2 percentage points. These findings support our premise that expected synergy gains from buying innovative targets are lower when the target's innovation is less transferable to the acquirer's assets.

The coefficient on the interaction of Process Share and SameTNIC in columns 4 to 6 further highlights the importance of product similarity. The interaction term has a positive and statistically significant coefficient in two of the three specifications. Moreover, the magnitude of the positive coefficient on the interaction term is similar to the magnitude of the negative coefficient on Process Share itself, which implies that the negative relation between combined CARs and process innovation dissipates when the acquirer and target sell similar products.

Overall, the analysis of combined CARs supports our central premise that process innovation contributes less to merger synergies unless it is easily transferable to the acquiring firm's assets.

[25] In this test, we do not use the measure of patent-to-product similarity due to substantially reduced (by about 90%) sample size.

Table I: Descriptive Statistics at Technology Class Level

This table reports the distribution of the share of process patents within each of the nine Cooperative Patent Classification (CPC) sections. A process patent takes a value of 1 while a non-process patent takes a value of 0. We include all patents (process, non-process, and hybrid) filed between 1980 and 2020 to construct this table.

CPC Section	Definition	Mean	SD	p25	p50	p75	N
A	Human Necessities	0.29	0.38	0.00	0.03	0.52	149,030
B	Performing Operations; Transporting	0.26	0.38	0.00	0.00	0.45	233,328
C	Chemistry; Metallurgy	0.45	0.43	0.00	0.31	1.00	238,327
D	Textiles; Paper	0.36	0.43	0.00	0.06	0.94	16,269
E	Fixed Constructions	0.28	0.36	0.00	0.08	0.48	32,793
F	Mechanical Engineering	0.16	0.30	0.00	0.00	0.20	128,449
G	Physics	0.34	0.33	0.00	0.30	0.52	664,054
H	Electricity	0.34	0.35	0.00	0.25	0.55	674,708
Y	General	0.27	0.40	0.00	0.00	0.50	52

Table II: Variable Definitions

Innovation measures	
Cumulative Patents (log)	Logarithm of the total number of patents granted as on date.
Economic Value	The stock market implied nominal value of a patent, estimated using the data provided in Kogan et al. (2017). It is calculated at a patent level and scaled by the firm's market-capitalization (in the year before filing) to adjust for firm-size.
Forward citations	Average number of citations received by all patents of a firm in the year before acquisition.
Inventor-firm Change	An indicator variable that takes a value of 1 when an inventor changes the firm that they file their next patent with, and 0 if they remain with the same firm.
Inventor-firm Share	Proportion of patents that a patent's inventor has filed with the inventing firm out of all the patents filed by that inventor up to the filing date. It takes a value between 0 (innovator has never before patented for the focal firm) and 1 (innovator has patented only for the focal firm).
Inventor Process Share	Cumulative share of process patents filed by an inventor.
Process Share	Proportion of patents classified as "process" out of all patents filed by a firm in a given year. It takes a value between 0 (no patent is process) and 1 (all patents are process). This continuous variable is also mapped to an industry-adjusted tercile measure.
Self-citation share	Proportion of patents cited by the focal patent that were filed by the same firm, out of all the patents cited by the focal patent. It takes a value between 0 (all citations relate to other firms' patents) and 1 (all citations relate to the same firm's patents).
Technology Class Share	Proportion of patents filed by the firm that belong to the same CPC sub-section as the focal patent. It takes a value between 0 (the patent belongs to a new CPC sub-section) and 1 (all prior patents belong to the same CPC-subsection).

Continued on next page

Δ Patent Index	Annual growth rate of Patent Index, which is the ratio of number of patents granted to a firm in a technology class, scaled by the median number of patents granted to any firm in that class and year. This is summed across all technology classes that a firm files patents in.
	M&A variables
Combined CAR	Market-capitalization weighted cumulative abnormal returns of the acquiring and target firm, measured from one day before to one day after the announcement of an M&A deal. Abnormal returns are calculated by subtracting the value-weighted CRSP returns from each firm's stock returns, and market-capitalizations are the averages of the three years prior to the deal announcement year.
Competing Deal (1/0)	An indicator for competing deal in the SDC Platinum database.
SameTNIC	A binary variable that takes a value of 1 when the acquirer and target firm share the Text-based Industry Classification as defined in Hoberg and Phillips (2016), and 0 otherwise. SameTNIC = 1 indicates that the acquirer and target firms may have been product market competitors in the year before merger announcement.
Similarity	A continuous variable between 0 and 1 that indicates the degree of cosine similarity between the target firm's patent description and the acquirer firm's product market. We obtain the language on patent descriptions from USPTO, and on the acquirer's product descriptions from Section 1 or Section 1A of 10-Ks. We parse business descriptions and keep only words that are nouns or proper nouns and appear in no more than 15% of all product descriptions to avoid commonly occurring words. We construct the Similarity measure for each patent, and then average it at the target firm level.
Premium (over 1-day price)	The percentage premium paid by acquirer compared to the 1-day ago stock price of the target.

Continued on next page

Table II: Variable definitions – continued from previous page

Firm characteristics	
Age (log)	Logarithm of age, calculated using the earliest year when a firm appears in the CRSP/Compustat database.
Assets (log)	Logarithm of total assets.
Book-to-market	Book value of common equity scaled by its market value; winsorized at top/bottom 2.5% of the distribution.
Capital Expenditure/Assets	Capital expenditure scaled by total assets; winsorized at top/bottom 2.5% of the distribution.
COGS/Sales	Cost-of-goods-sold scaled by total sales; winsorized at top/bottom 2.5% of the distribution and industry-adjusted by subtracting the SIC 3-digit industry median.
Leverage	Total debt scaled by total assets; winsorized at top/bottom 2.5% of the distribution.
Market Capitalization (log)	Logarithm of market capitalization.
Property, Plant & Equipment/Assets	Expenditure on property, plant and equipment scaled by total assets; winsorized at top/bottom 2.5% of the distribution.
R&D/Assets	Research and development expenses scaled by total assets; winsorized at top/bottom 2.5% of the distribution.
Return on Assets	Operating income before depreciation scaled by total assets; winsorized at top/bottom 2.5% of the distribution.

Table III: Internal Knowledge Accumulation (Firm-year level)

This table reports estimates from a fixed effects panel regression of the form in Equation 2 at firm-year level. The dependent variable is one of the three measures of internal knowledge accumulation: self-citation share in columns (1) and (2), inventor-firm share in columns (3) and (4), and technology class share in columns (5) and (6). The regressor of interest is "Process Share", the proportion of patents filed by a firm in a given year that we classify as process innovation. Columns (2), (4) and (6) include firm and year fixed effects. Standard errors clustered by year are reported in parentheses. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

	Self-citation Share		Inventor-firm Share		Technology Class Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Process Share	0.043***	0.016***	0.030***	0.016**	0.010*	0.009*
	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.005)
Cumulative Patents (log)	0.024***	0.029***	0.057***	0.072***	-0.011***	0.007**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Age (log,t-1)	0.015***	0.004	0.014***	0.007*	0.010**	-0.009**
	(0.002)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)
Assets (log,t-1)	-0.026***	-0.010***	-0.043***	-0.018***	-0.065***	-0.007***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Capital Expenditure/Assets (t-1)	-0.129***	-0.02	-0.086**	0.03	-0.346***	0.036
	(0.024)	(0.020)	(0.036)	(0.040)	(0.041)	(0.030)
Leverage (t-1)	0.024***	0.024***	-0.003	0.012	0.019**	0.016**
	(0.005)	(0.006)	(0.008)	(0.011)	(0.009)	(0.006)
Market Capitalization (log, t-1)	0.016***	0.002	0.014***	0.001	0.060***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
R&D/Assets (t-1)	0.083***	0.065***	-0.026**	-0.023	-0.018	0.008
	(0.012)	(0.011)	(0.014)	(0.015)	(0.014)	(0.011)
Observations	31,076	30,397	31,076	30,397	31,076	30,397
Adj. R^2	0.16	0.39	0.16	0.34	0.10	0.65
Firm, Year FE	N	Y	N	Y	N	Y

Table IV: Likelihood of Being a Target (Linear Probability Model)

This table reports estimates from a linear probability regression of the form in Equation 3 at a deal level. The dependent variable takes a value of 1 when the firm is a target and 0 if it is a control. The regressor of interest is Process Share (tercile). Terciles are constructed using: Fama-French 49-industry in column (1), SIC 3 digit-industry in column (2), and SIC 2 digit-industry in column (3). Each actual target is industry and size matched with five controls. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Target (1/0)		
	(1)	(2)	(3)
Process Share (tercile)	-0.040***	-0.041***	-0.044***
	(0.007)	(0.007)	(0.007)
Δ Patent Index	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Forward citations	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Economic value (1980 $)	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
COGS/Sales (3-year average)	-0.004	-0.004	-0.004
	(0.008)	(0.008)	(0.008)
Age (log)	0.016**	0.016**	0.015**
	(0.007)	(0.007)	(0.007)
Assets (log, t-1)	0.016	0.016	0.017
	(0.015)	(0.015)	(0.015)
Book-to-market (t-1)	0.031*	0.030*	0.031*
	(0.018)	(0.018)	(0.018)
Leverage (t-1)	0.129***	0.127***	0.126***
	(0.043)	(0.043)	(0.043)
Market Capitalization (log, t-1)	0.059***	0.059***	0.060***
	(0.018)	(0.018)	(0.018)
R&D/Assets (t-1)	-0.023	-0.023	-0.018
	(0.073)	(0.073)	(0.073)
Return on Assets (t-1)	-0.023	-0.023	-0.025
	(0.046)	(0.046)	(0.046)
Observations	5,587	5,587	5,587
Adj. R^2	0.17	0.17	0.17
Deal FE	Y	Y	Y

Table V: Likelihood of Filing a Patent (Selection using Secret Words)

This table reports estimates of a model of the form:

$$\text{Patent } (0/1)_{i,t} = \beta \text{Secret}_{i,t} + \varepsilon_{i,t}. \tag{12}$$

The dependent variable in column (1) equals 1 if the firm files any patent in a year, and 0 otherwise. In column (2), it equals 1 if the firm files any process patent in a year, and 0 otherwise. In column (3), it equals 1 if the firm files any non-process patent in a year, and 0 otherwise. The regressor of interest is "Secret", which refers to the fraction of words referencing trade secrets in firm i's earnings calls. Panels A and C use earning calls in the same year as the patent filing year, while panels B and D lag the regressor by one year. Panels A and B use a probit estimation, while panels C and D use a linear probability model with firm and year fixed effects. We construct the sample for this exercise using the earnings calls reports of all firms (innovative and non-innovative) that are available starting in the year 2003. We scale the number of words indicating "trade secrets" by the total number of words in the report to measure the firm's reliance on trade secrets, which might affect its propensity to file patents. Standard errors are reported in parentheses. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

	Any patent	Process patent	Non-process patent
Panel A: contemporaneous (probit)	(1)	(2)	(3)
Secret	4.504	3.028	2.419
	(3.496)	(4.002)	(3.805)
Observations	56,485	56,485	56,485
Panel B: lagged (probit)	(1)	(2)	(3)
Secret (t-1)	1.462	3.145	0.966
	(4.103)	(4.215)	(4.308)
Observations	49,392	49,392	49,392
Panel C: contemporaneous (linear probability)	(1)	(2)	(3)
Secret	-0.526	-0.527	-1.077
	(0.751)	(0.682)	(0.731)
Observations	56,103	56,103	56,103
Firm, Year FE	Y	Y	Y
Panel D: lagged (linear probability)	(1)	(2)	(3)
Secret (t-1)	-0.747	-0.227	-0.706
	(0.820)	(0.747)	(0.799)
Observations	48,870	48,870	48,870
Firm, Year FE	Y	Y	Y

Table VI: Comparative Statistics for Process and Non-process Innovation

This table compares process and non-process patents, and process and non-process innovators. A firm is called process innovator in year t if its process share lies in the highest tercile of the process shares in the Fama-French 49 industry group to which it belongs. Likewise, it is called non-process innovator if it lies in the lowest tercile. The rightmost column reports the difference in means with statistical significance conducted using a t-test with unequal sample variances. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

Patent-level	Process patent			Non-process patent			
	Mean	SD	Median	Mean	SD	Median	Diff. in means
Economic value (real $ mln)	13.444	35.711	4.090	9.176	26.347	2.466	4.267***
Economic value (nominal $ mln)	25.409	69.384	7.232	17.418	50.938	4.263	7.991***
Forward citations (trunc. adj.)	0.49	3.10	0.01	0.50	3.00	0.01	-0.01
Firm-level (actual and control targets)	**Process innovator**			**Non-process innovator**			
Economic value (real, scaled)	1.887	22.430	0.602	1.533	5.321	0.775	0.354
Economic value (nominal, scaled)	3.293	39.069	1.004	2.347	9.628	1.122	0.946
Patent (count)	9.814	31.353	3.000	3.241	6.175	2.000	6.573***
COGS/Sales	0.854	1.126	0.586	0.734	0.775	0.626	0.120***
Book-to-market	0.833	0.744	0.624	0.985	0.794	0.766	-0.152***

Table VII: Potential Outcome Methods and Balance Test

This table reports the difference in the likelihood of getting acquired after matching firms using propensity scores. Panel A shows that process innovators (top process share tercile) can have fundamentally different characteristics than non-process innovators (bottom process share tercile). Panel B confirms that process innovators are less likely to be acquired, and Panel C validates the matching by reporting no significant difference in the fundamental attributes. Panel D reports the likelihood test results using four other matching methods.

Panel A: All targets	Process Innovator	Non-process Innovator	Difference
Target (1 for targets, 0 for control)	0.1358	0.1782	-0.0425***
COGS/Sales (3-year average)	0.8483	0.7959	0.0524*
Age (log)	2.2605	2.2619	-0.0014
Assets (log, t-1)	5.6962	5.1697	0.5265***
Book-to-market (t-1)	0.8368	0.9315	-0.0947***
Leverage (t-1)	0.1637	0.1691	-0.0054
Market Capitalization (log, t-1)	6.0167	5.3471	0.6696***
R&D/Assets (t-1)	0.1247	0.1043	0.0204***
Return on Assets (t-1)	0.0343	0.0600	-0.0257***
Δ Patent Index	-0.2361	-0.5106	0.2745
Forward citations	27.8107	28.8406	-1.0299
Economic value (1980 $)	5.5242	4.1953	1.3289**

Panel B: ATE using IPW	Process Innovator	Non-process Innovator	ATE
Target (1 for targets, 0 for control)	0.1252	0.1707	-0.0455***

Panel C: Balance test after IPW	Process Innovator	Non-process Innovator	Difference
COGS/Sales (3-year average)	0.8211	0.8171	0.0039
Age (log)	2.3267	2.3347	-0.008
Assets (log, t-1)	5.3201	5.3253	-0.0052
Book-to-market (t-1)	0.8487	0.8631	-0.0144
Leverage (t-1)	0.1567	0.1589	-0.0022
Market Capitalization (log, t-1)	5.6117	5.5921	0.0196
R&D/Assets (t-1)	0.1115	0.1104	0.0011
Return on Assets (t-1)	0.0455	0.0466	-0.001
Δ Patent Index	-0.5799	-0.6167	0.0368
Forward citations	27.8348	27.4598	0.375
Economic value (1980 $)	5.465	4.7911	0.6739

Panel D: Other methods	ATE
Regression adjustment (RA)	-0.0454***
Propensity score matching (nearest)	-0.0601***
Propensity score matching (2 nearest)	-0.0525***
Propensity score matching (3 nearest)	-0.0515***

Table VIII: Likelihood of Being a Target (Instrumental Variables Estimation)

This table reports estimates from a linear probability instruments variables regression of the form in Equation 8 (Panel B) and Equation 9 (Panel A) at firm-year level. Panel A reports the second-stage where the dependent variable takes a value of 1 when the firm is a target and 0 if it is a control, with the instrumented process share tercile as the regressor of interest. Panel B reports the corresponding first stage with self-citation share (tercile) as the instrument. Both the stages use a common set of controls and deal fixed effects. Terciles are constructed using: Fama-French 49-industry in column (1), SIC 3 digit-industry in column (2), and SIC 2 digit-industry in column (3). Each actual target is industry and size matched with five controls. All columns include firm-level controls analogous to Table VI but are eclipsed for brevity. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Panel A: Second-stage	Target (1/0)		
	(1)	(2)	(3)
Process $\widehat{\text{share}}$ (tercile)	-0.283***	-0.309***	-0.341***
	(0.092)	(0.103)	(0.107)
Δ Patent Index	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Forward citations	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Economic value (1980 $)	0.001**	0.001**	0.001***
	(0.000)	(0.000)	(0.000)
Panel B: First-stage	**Process share (tercile)**		
	(1)	(2)	(3)
Self-citation Share (tercile)	0.097***	0.087***	0.087***
	(0.016)	(0.017)	(0.017)
Δ Patent Index	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Forward citations	-0.001**	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)
Economic value (1980 $)	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Observations	5,547	5,547	5,547
Instrument F-statistic	33.27	41.06	26.75
Firm controls	Y	Y	Y
Deal FE	Y	Y	Y

Table IX: Post-Acquisition Performance

This table reports estimates for a model of the form in Equation 10. The dependent variable in all specifications is COGS/Sales in year t, where t ranges from (at most) five years before merger completion year to (at most) five years after completion. For the pre-merger years, we use a market-value weighted average of the acquirer and target's COGS/Sales and for the post-merger years, we use the acquirer's COGS/Sales. The regressors of interest are the target firm's "Process Share (tercile)" and its interaction with "SameTNIC" that captures product market similarity between the acquirer and target. Target's process share terciles are constructed using Fama-French 49 industries. Standard errors clustered by year are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	COGS/Sales				
	All deals		Same TNIC	Different TNIC	All deals
	(1)	(2)	(3)	(4)	(5)
Process Share (tercile)	0.001	-0.001	0.023	-0.048	-0.046*
	(0.015)	(0.015)	(0.018)	(0.058)	(0.026)
Post	-0.018				
	(0.025)				
Post x Process Share (tercile)	-0.041***	-0.046***	-0.073***	0.014	0.015
	(0.012)	(0.012)	(0.023)	(0.012)	(0.012)
Post x SameTNIC x Process Share (tercile)					-0.088***
					(0.027)
SameTNIC					-0.052
					(0.073)
SameTNIC x Process Share (tercile)					0.068**
					(0.034)
Post x Same TNIC					0.013
					(0.057)
Observations	2,730	2,730	1,391	1,339	2,730
Adj. R^2	0.685	0.692	0.721	0.569	0.697
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Event Time FE	N	Y	Y	Y	Y
Deal Year FE	N	Y	Y	Y	Y

Table X: Combined Cumulative Abnormal Returns for Acquirer and Target

This table reports estimates for a model of the form in Equation 11 at a deal level. The dependent variable is the combined three-day cumulative abnormal returns (CAR) of the acquirer and target firms' stocks, centered on the deal announcement date. CARs are obtained by subtracting the value-weighted CRSP index return from the firm's stock returns and cumulating the abnormal return over the 3-day window. The regressors of interest are the target firm's "Process Share (tercile)" and its interaction with "SameTNIC" that captures product market similarity between the two firms. Terciles are constructed using: Fama-French 49-industry in columns (1) and (4), SIC 3 digit-industry in columns (2) and (5), and SIC 2 digit-industry in columns (3) and (6). Standard errors clustered by year are reported in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

	Combined 3-day CAR					
	(1)	(2)	(3)	(4)	(5)	(6)
Process Share (tercile)	-0.008	-0.010*	-0.009*	-0.016**	-0.019**	-0.017**
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
SameTNIC (1/0)	0.005	0.005	0.005	-0.022	-0.029	-0.025
	(0.007)	(0.007)	(0.007)	(0.019)	(0.019)	(0.019)
Process Share (tercile) × SameTNIC				0.015	0.019**	0.017*
				(0.009)	(0.009)	(0.009)
Observations	461	461	461	461	461	461
Adj. R^2	0.10	0.10	0.10	0.11	0.11	0.11
Controls	Y	Y	Y	Y	Y	Y
Industry (SIC-3, acquirer), Year FE	Y	Y	Y	Y	Y	Y

Internet Appendix

Innovation Specificity

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IAI. Further analysis of link between costs and process patents

In this section, we supplement the results from Section III of the paper. First, we use our Economic Value measure to examine how the stock market views greater investment in process innovation by cost-inefficient firms. To test this, we estimate the model:

$$\text{Economic Value}_{i,t} = \beta_0 + \beta_1 \text{COGS/Sales}_{i,t} + \gamma \mathbf{Z}_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t}, \tag{13}$$

where the dependent variable is the stock market implied value per patent, averaged across all process patents at a firm-year level and scaled by the market capitalization as of the preceding year. Note that this measure is not mechanically higher for firms that do more process innovation, and it is orthogonal to Process Share, (the dependent variable used in Equation 1), because it captures the average value *per process patent* in a firm-year. The regressor of interest is the firm's cost of goods sold (COGS) scaled by sales and averaged over the preceding three and five years for separate estimations. Vector **Z** includes the same controls as in Equation 1 except for market capitalization because it forms the denominator of the dependent variable. The specification also includes firm and year-fixed effects. Standard errors are clustered by the SIC 3-digit industry. Table IAI reports the estimation results.

We find that the economic value of process patents is significantly higher for firms that experience relative cost inefficiencies in the preceding three or five years. In Table IAI, columns 1 and 2, we do not include the firm-level control variables or any fixed effects. In columns 3 and 4, we include control variables but not fixed effects. In columns 5 and 6, control variables as well as firm- and year-fixed effects are included. In all specifications the coefficient on COGS/Sales is positive and statistically significant for the 3-year and for the 5-year horizon. This suggests that the market views investment in process innovation more favorably for firms that have a recent history of high costs. A one-standard deviation increase in the industry-adjusted COGS/Sales associates with a 6% higher Economic Value per process patent relative to the mean.[26]

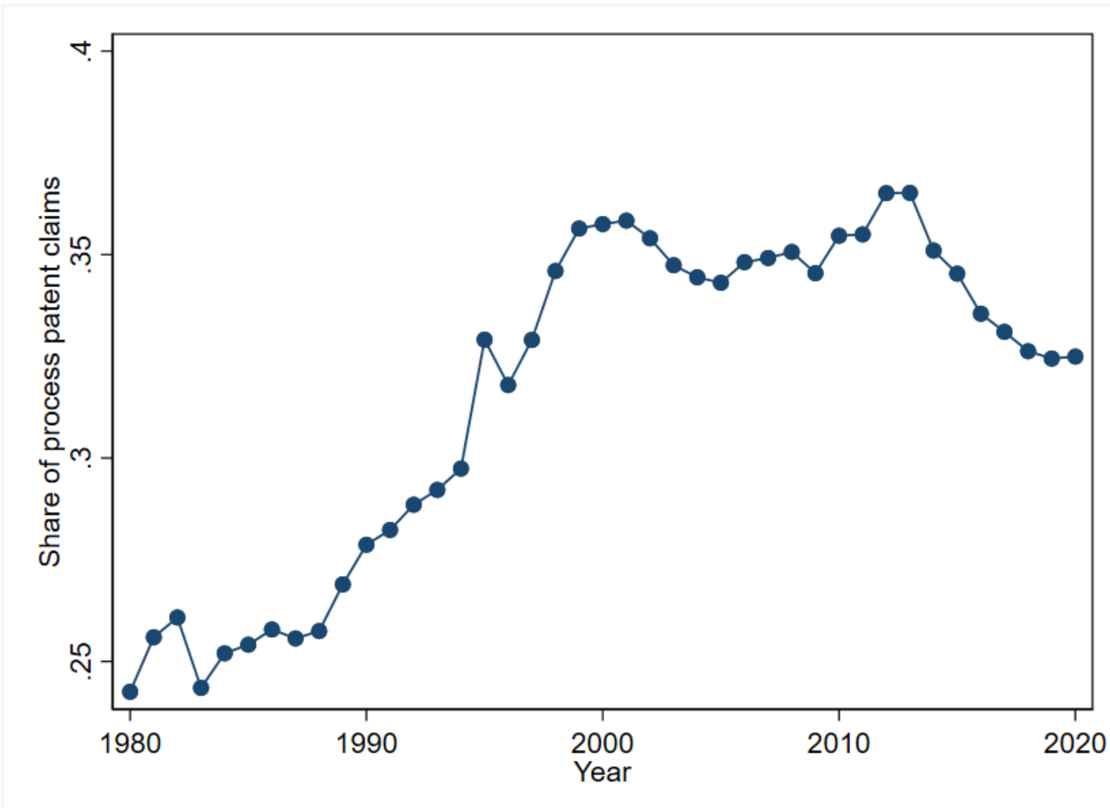
[26]Using the coefficient on 3-year COGS/Sales in column 3 of Table IAI (0.121), the standard deviation of COGS/Sales

Next, we recognize that some firms in the business services sector may conduct process innovation on behalf of customer firms. That is, process patents may be revenue-generating business for firms in the business services sector. We address this concern in Table IAII by re-estimating Equation 1 and Equation 13 after dropping all firms with SIC code 737. The coefficient β_1 continues to be positive and significant.

In panels A and B of Table IAIII, we explore the link between process innovation and overhead costs such as SG&A or the number of employees. We do not find evidence of a positive link between the share or value of process innovation and overhead costs. We also explore whether the positive coefficient on COGS/Sales in Table III is a cost-side or sales-side effect by re-estimating Equation 1 and Equation 13 using 3-year or 5-year average of asset turnover (Sales/Assets) as the explanatory variable. Panel C of Table IAIII shows that the coefficient on asset turnover is insignificant, which indicates that the positive relation between Process Share or Economic Value and COGS/Sales is driven by costs and not sales.

in Table II (0.90), and the mean economic value of process patents from Table II (1.85), the economic magnitude is 5.9% (0.121*0.9/1.85).

Figure IAI: Share of Process Claims from 1980 to 2020 (Including Hybrid Patents)



Notes: This figure plots the average share of process claims in our data over the years 1980 through 2020. We identify process claims using a machine-read textual classification algorithm applied to all the claims in support of a patent application. This figure includes all patents filed by public firms. Each patent takes a value between 0 and 1 depending on the fraction of claims classified as process innovation. Figure I shows the corresponding plot for patents unambiguously classified as process or otherwise.

Table IAI: Determinants of the Economic Value of Process Innovation

This table reports estimates from a fixed effects panel regression of the form in Equation 13 at firm-year level. The dependent variable is Economic Value of process innovation, measured as the firm-year average of stock-market implied patent value and scaled by the firm's preceding year market capitalization. The regressor of interest is COGS/Sales averaged over prior 3 years (in columns (1), (3) and (5)) or prior 5 years (in columns (2), (4) and (6)). Columns (1) and (2) do not include controls and fixed effects, columns (3) and (4) include controls, and columns (5) and (6) additionally include firm and year fixed effects. Standard errors clustered by industry (SIC 3 digit) and year are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Economic Value					
	(1)	(2)	(3)	(4)	(5)	(6)
COGS/Sales (3-year average)	0.605***		0.121*		0.253**	
	(0.219)		(0.065)		(0.108)	
COGS/Sales (5-year average)		0.650***		0.132**		0.315***
		(0.200)		(0.065)		(0.107)
Age (log)			-0.094*	-0.096*	-0.153	-0.152
			(0.053)	(0.053)	(0.096)	(0.097)
Assets (log, t-1)			-0.400***	-0.400***	-1.566***	-1.556***
			(0.052)	(0.051)	(0.247)	(0.243)
Book-to-market (t-1)			0.462***	0.464***	1.118***	1.121***
			(0.137)	(0.137)	(0.279)	(0.280)
Capital Expenditure/Assets (t-1)			0.196	0.190	-2.138	-2.228
			(1.360)	(1.364)	(1.635)	(1.695)
Leverage (t-1)			0.876***	0.874***	1.345***	1.343***
			(0.254)	(0.256)	(0.385)	(0.384)
Property, Plant & Equipment/Assets (t-1)			-0.066	-0.071	0.913*	0.946*
			(0.350)	(0.354)	(0.528)	(0.536)
R&D/Assets (t-1)			4.883***	4.817***	3.761***	3.769***
			(0.770)	(0.777)	(1.312)	(1.310)
Return on Assets (t-1)			-0.350	-0.295	-0.229	-0.188
			(0.593)	(0.582)	(0.643)	(0.623)
Observations	22,056	22,081	18,558	18,577	17,920	17,938
Adj. R^2	0.00	0.00	0.11	0.11	0.31	0.31
Firm, Year FE	N	N	N	N	Y	Y

Table IAII: Determinants of Process Innovation (Excluding SIC 737)

This table reports estimates from a fixed effects panel regression of the form in Equation 1 in columns (1) and (2), and Equation 13 in columns (3) and (4), at firm-year level for firms not belonging to the business services industry (SIC 737). The dependent variable is Process Share in columns (1) and (2), and Economic Value of process patents in columns (3) and (4). The regressor of interest is COGS/Sales averaged over prior 3 years (in columns (1) and (3)) or prior 5 years (in columns (2) and (4)). All columns include firm-level controls, and firm and year fixed effects. Standard errors clustered by industry (SIC 3 digit) and year are reported in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

	Process Share		Economic Value	
	(1)	(2)	(3)	(4)
COGS/Sales (3-year average)	0.009***		0.158***	
	(0.003)		(0.050)	
COGS/Sales (5-year average)		0.011***		0.198***
		(0.003)		(0.045)
Age (log)	0.007	0.007	-0.202***	-0.201***
	(0.008)	(0.008)	(0.070)	(0.070)
Assets (log, t-1)	-0.013	-0.013	-0.893***	-0.886***
	(0.010)	(0.010)	(0.141)	(0.137)
Book-to-market (t-1)	0.011*	0.011*	0.636***	0.638***
	(0.006)	(0.006)	(0.143)	(0.144)
Capital Expenditure/Assets (t-1)	-0.039	-0.037	-1.209	-1.257
	(0.061)	(0.061)	(0.918)	(0.943)
Leverage (t-1)	0.014	0.015	0.811***	0.809***
	(0.025)	(0.025)	(0.283)	(0.285)
Market Capitalization (log, t-1)	0.012	0.012	0.460	0.478
	(0.008)	(0.008)	(0.326)	(0.332)
Property, Plant & Equipment/Assets (t-1)	0.050	0.050	1.798**	1.799**
	(0.044)	(0.044)	(0.734)	(0.731)
R&D/Assets (t-1)	-0.033	-0.030	0.123	0.147
	(0.036)	(0.037)	(0.352)	(0.337)
Observations	28,061	28,086	17,035	17,053
Adj. R^2	0.45	0.45	0.31	0.31
Firm, Year FE	Y	Y	Y	Y

Table IAIII: Other Determinants of Share and Economic Value of Process Innovation

This table reports coefficient estimates from a fixed effects panel regression of the form in Equation 1 in columns (1) and (2), and Equation 13 in columns (3) and (4), at firm-year level using three alternative cost regressors: SG&A/Sales in Panel A, Employees/Sales in Panel B and Turnover in Panel C. All three predictor variables are averaged over prior 3 years (in columns (1) and (3)) or prior 5 years (in columns (2) and (4)). All columns include controls, and firm and year fixed effects. Control variables are analogous to Table III. Standard errors are clustered by industry (SIC 3 digit) and year, and reported in parentheses. $^{*}p < 0.1$;** $p < 0.05$;*** $p < 0.01$.

	Process Share		Economic Value	
Panel A	(1)	(2)	(3)	(4)
SG&A/Sales (3-year average)	-0.004		-1.141**	
	(0.024)		(0.496)	
SG&A/Sales (5-year average)		0.003		-0.794*
		(0.028)		(0.459)
Observations	23,751	23,865	14,477	14,560
Adj. R^2	0.44	0.44	0.33	0.33
Panel B	(1)	(2)	(3)	(4)
Employees/Sales (3-year average)	-0.516		-11.804	
	(0.647)		(11.651)	
Employees/Sales (5-year average)		-0.842		-8.501
		(0.570)		(10.683)
Observations	29,174	29,232	18,016	18,016
Adj. R^2	0.45	0.45	0.30	0.30
Panel C	(1)	(2)	(3)	(4)
Turnover (Sales/Assets, 3-year average)	0.012		0.037	
	(0.014)		(0.501)	
Turnover (Sales/Assets, 5-year average)		0.013		-0.101
		(0.017)		(0.343)
Observations	29,560	29,560	18,056	18,056
Adj. R^2	0.45	0.45	0.31	0.31
Controls	Y	Y	Y	Y
Firm, Year FE	Y	Y	Y	Y

Table IAIV: Determinants of Process Innovation (Including Hybrid Patents)

This table reports estimates from a fixed effects panel regression of the form in Equation 1 at firm-year level. The sample includes all patents in our database. The dependent variable is Process Share, the proportion of process patents filed by a firm in a given year. The regressor of interest is COGS/Sales averaged over prior 3 years (in columns (1) and (3)) or prior 5 years (in columns (2) and (4)). All columns include firm-level controls, and firm and year fixed effects. Standard errors clustered by industry (SIC 3 digit) and year are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Process Share		Economic Value	
	(1)	(2)	(3)	(4)
COGS/Sales (3-year average)	0.009***		0.165***	
	(0.003)		(0.061)	
COGS/Sales (5-year average)		0.010***		0.194***
		(0.002)		(0.064)
Age (log)	0.008	0.008	-0.103**	-0.105**
	(0.005)	(0.006)	(0.044)	(0.045)
Assets (log, t-1)	-0.012	-0.012	-1.026***	-1.021***
	(0.011)	(0.011)	(0.179)	(0.177)
Book-to-market (t-1)	0.008	0.008	0.784***	0.785***
	(0.005)	(0.005)	(0.169)	(0.169)
Capital Expenditure/Assets (t-1)	0.002	0.001	-0.966	-1.026
	(0.043)	(0.043)	(1.118)	(1.148)
Leverage (t-1)	0.004	0.005	1.038***	1.035***
	(0.019)	(0.019)	(0.202)	(0.202)
Market Capitalization (log, t-1)	0.007	0.007		
	(0.007)	(0.007)		
Property, Plant & Equipment/Assets (t-1)	0.005	0.006	0.755**	0.788**
	(0.032)	(0.032)	(0.368)	(0.380)
R&D/Assets (t-1)	-0.028	-0.026	2.242**	2.260**
	(0.033)	(0.033)	(1.001)	(0.993)
Return on Assets (t-1)	-0.001	-0.002	-0.036	-0.029
	(0.016)	(0.016)	(0.330)	(0.330)
Observations	32,891	32,920	27,776	27,804
Adj. R^2	0.46	0.46	0.30	0.30
Firm, Year FE	Y	Y	Y	Y

Table IAV: Likelihood of Being a Target (Including Hybrid Patents)

This table reports estimates from a conditional logit regression of the form in Equation 3 at a deal level. The dependent variable equals 1 when the firm is a target and 0 if it is a control. The regressor of interest is Process Share (tercile). Terciles are constructed using: Fama-French 49-industry in column (1), SIC 3 digit-industry in column (2), and SIC 2 digit-industry in column (3). Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Target (1/0)		
	(1)	(2)	(3)
Process Share (tercile)	-0.193***	-0.206***	-0.254***
	(0.048)	(0.047)	(0.048)
Δ Patent Index	-0.023***	-0.023***	-0.023***
	(0.004)	(0.004)	(0.004)
Forward citations	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)
Economic value (1980 $)	0.014***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)
COGS/Sales (3-year average)	-0.068	-0.068	-0.071
	(0.057)	(0.057)	(0.057)
Age (log)	0.084*	0.086*	0.081*
	(0.045)	(0.045)	(0.045)
Assets (log, t-1)	0.235**	0.239**	0.237**
	(0.105)	(0.105)	(0.106)
Book-to-market (t-1)	0.033	0.027	0.030
	(0.115)	(0.115)	(0.115)
Leverage (t-1)	0.553**	0.537*	0.527*
	(0.282)	(0.282)	(0.282)
Market Capitalization (log, t-1)	0.296**	0.290**	0.300**
	(0.121)	(0.121)	(0.121)
R&D/Assets (t-1)	-0.324	-0.334	-0.238
	(0.518)	(0.519)	(0.520)
Return on Assets (t-1)	-0.059	-0.063	-0.058
	(0.314)	(0.314)	(0.315)
Observations	4,819	4,819	4,819
Pseudo R^2	0.06	0.06	0.06
Deal FE	Y	Y	Y

Table IAVI: Self-citation Share and Firm-level Characteristics

This table reports the relationship between firm-level self-citation share and its other fundamental characteristics: economic value of patents in column (1), change in patent index in column (2), truncation-adjusted forward citations in column (3), and cost of good sold (COGS) scaled by sales in column (4). In panel A, the regressor is the firm-level self citation share in year t, a continuous variable that takes a value between 0 and 1. In panel B, we map the raw variable to an industry-adjusted tercile measure (using the Fama-French 49-industry classification). The sample comprises of all actual and control target firms. Standard errors clustered by firm are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

	Economic Value	Δ Patent Index	Forward citations	COGS/Sales
Panel A: Continuous variable	(1)	(2)	(3)	(4)
Self-citation Share	-1.28	-4.39*** -0.084	-0.198	
	(1.61)	(1.51)	(0.136)	(0.139)
Observations	7,622	7,156	8,730	6,737
Firm FE	Y	Y	Y	Y
Adj. R^2	0.94	0.36	0.54	0.83
Panel B: Tercile	(1)	(2)	(3)	(4)
Self-citation Share (tercile)	-0.857	-0.083	-0.051	-0.024
	(0.778)	(0.137)	(0.046)	(0.017)
Observations	7,622	7,156	8,730	6,737
Firm FE	Y	Y	Y	Y
Adj. R^2	0.94	0.36	0.54	0.83