Innovation Specificity

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Abstract

We study the composition of corporate innovation portfolios by machine-reading 90 million patent claims. Process-oriented patents fundamentally differ from other patents in terms of both motive and specificity: they are cost-savings-oriented, and they are rooted in firm-specific knowledge. On the former, firms are more likely to file process patents when they experience increased cost pressure relative to sales. On the latter, we find that process patents are more likely to cite past patents of the innovating firm; they are undertaken by inventors who have more within-firm patenting experience; and they exploit known technologies rather than explore new ones. We find that the external value of process patents reflects their specificity. Using the market for corporate control as a setting to assess the external value of innovation, we show that firms with a higher share of process patents in their innovation portfolios are significantly less likely to be acquired. Consistent with the specificity explanation, this effect reverses when there is a strong textual overlap between process patent descriptions and the acquirer's product descriptions, indicating greater redeployability of innovation. When such overlap exists, acquisition announcement returns are also higher, and post-merger synergies—reflected in lower costs and higher operating margins—are more likely to materialize. Our study introduces a novel measure of innovation specificity and demonstrates its construct validity as well as its role in the market for corporate control.

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

JEL classification: G30, G34, O3

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1. Introduction

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] This implicitly calls for the study of innovation specificity. We are the first to do so for a comprehensive sample of patents, as well as the first to explore implications for value and investment.

Firms innovate for manifold reasons. It 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 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. Compared to other types, process-oriented patents are generally viewed as more closely tied to the operational competencies of the innovative firm.[3] They also constitute about 30% of total patents granted. Thus, our first-ever analysis of their specificity is relevant cross-sectionally. Furthermore, it allows us to address questions such as the efficacy of our bifurcation and whether different types of patents carry different values, both internally and externally.

Our analysis of process-oriented patents confirms their specificity. We explore potential firm motives to process-innovate, their internal nature and development, their valuation, and their redeployability by potential other users. Our first results highlight 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 to 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

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

share of process patents (to total patents), relative to the mean. This aligns with high specificity to process innovation since cost functions are among the unique facets that firms carefully guard for competitive reasons, and a cost reduction motive is intimated by our result.

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.

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). In both cases, shareholders' reactions to patent grants reflect the innovation's *internal* value to the patenting firm. However, this need not be the same as *external* value. As we emphasize in the second part of our paper, different types of patents have very different values to various firms, even if those firms share the same industry as the inventing firm.

The external value of patents is challenging to measure. As Kogan et al. (2017) highlight, a patent's value may stem from several factors, including restricting competition. But estimation of value for an affected (say, competing) firm, using the market-reaction-based technique of Kogan et al. (2017), requires assumptions. Key amongst them is that no other event occurs at the affected firm on the measurement date. Furthermore, the validation approach of Kogan et al. (2017) – tying economic value to forward citations – is less applicable to the affected firm for the following reason; the forward citations on the affecting patent may be driven by patent uses that are unrelated to the affected firm. Put differently, the overlap between the patent's characteristics and the affected firm's operations matters. We recognize this with our text analysis, studying the role of patents' specificities on takeover market perspectives of external value.

We begin at the extensive margin, asking whether a firm's patent portfolio specificity influences the likelihood that the inventing firm is acquired. To do so, we must form a set of potential bidders and potential targets, and ask whether the likelihood of a merger pairing is related to the potential target's portfolio of patents and the process-specificity of it. The details of the panel formation are provided in section 5.1, but we note here that it is built around a sample of actual merger pairings and carefully matched (separately, to the bidders and targets), sets of control firms. The control firms must not have been involved in any M&A activity in the prior three years.

The short answer to our extensive-margin question is yes: more process-orientation in a firm's innovation portfolio associates with lower 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. Of course, this presumes that process-oriented patents are more specific to the patentor.

We then drill down to more precisely evaluate the role of patent specificity on likelihood of patentor takeover. First, we show that (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. When the bidder and potential target share the same TNIC, they compete in the same product market. This raises the applicability of a target's process innovation to the acquirer's product line and therefore expected cost savings (given our earlier result).

Second, using the language directly from patent applications, we construct similarity measures between the patent descriptions of the potentially targeted firm, and the product market descriptions of potential acquirers. We are essentially measuring redeployability of the target's patents, and assessing its influence on the likelihood of takeover. We document three important results. First, we maintain the negative relationship between patentor process-share (tendency of their patent portfolio to be process-oriented) and likelihood that they are acquired. Second, there is a strong positive influence of redeployability of patents – regardless of their product vs process orientation – on the likelihood that the patentor becomes a target. But most importantly, when the patentor is more process-oriented in its 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. This emphasizes the view that process patents tend to be more specific in their value-proposition.

We supplement these extensive margin results with intensive margin analysis of merger economic performance. We find that the 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.[4] We also show that the post-merger operating performance of the combined firm improves with overlap, with cost reduction a key driver. Specifically, when process innovators are acquired, overlap - measured with redeployability - positively correlates with operating performance and negatively correlates with costs going forward.

[4]We lose too many observations (∼90%) if we attempt replacing TNIC with our text-based similarity between patentor and acquirer in the analysis of CARs. This is due to the necessity of public trading of stock of both bidder and target.

We subject our tests to a variety of robustness checks. Key among them is addressing potential endogeneity arising from two sources. First, a firm's emphasis on process innovation may be influenced by firm characteristics that also affect the likelihood of being acquired. We use potential outcome methods and instrumental variable regressions to address this concern and find our results continue to hold. Second, 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).

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, and confirming their 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. 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 do not show this diminution. Bena and Li (2014) show that overlapping technologies between potential bidder-target pairs increase merger incidence, synergy, and post-combination innovation output. We measure innovation differently – as product vs process – and show the importance of this delineation for overlap's influence on mergers and outcomes. More recently and building on our work,[5] Davydova (2024) confirms that for executed deals, her measure of process-orientation improves combined firm operating performance through cost reduction. She does not study overlap between acquirer and target, and does not utilize text analysis to construct such overlap.

Still in the M&A realm, Celik, Tian, and Wang (2022) recognize that innovation is difficult to value, which influences bidder method of payment and likelihood of transaction. We highlight the

[5]Our research first appeared on SSRN in April 2023.

role of process-oriented innovation in the valuation difficulty due to varying applicability to buyers' assets.[6] 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.

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 vs larger firms.

2. Hypothesis Development

To understand the potentially different motives, specificity, and 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. 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.

We begin with Boone (2000) who assumes different natures to product vs process innovation. However, it is done in the context of competitive pressures and where the firm's cost level is relative to the industry cost level. 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.[7] Notably, given the assumption in Boone (2000) of the different

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

[7] 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 3.

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.

But 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. We therefore explore further characteristics - this time at the patent and/or inventor level - that help pinpoint specificity of process patents to a particular firm.

Klepper (1996) assumes process innovation is different from product innovation, within the context of his model helping to explain entry and exit, along with market structure and innovation predictions for technologically progressive industries. The model argues for reduced appropriability of process patents as adjustment costs are convex in the industry's life cycle.[8] We view the lower appropriability of process patents as isomorphic to them being more firm-specific than product innovation. But this still requires empirical support that is tied to either adjustment costs or reduced appropriability.

We therefore examine characteristics of patents, inventors, and firms, and how these correlate with whether the focal patent is process-oriented or not. Several characteristics of patents are useful correlates with internal vs. external focus.[9] Specifically, process patenting is expected to associate with more self-cites by the patent-filing-firm, greater fraction of patents filed by the inventor for the focal-patent-firm, and reduced likelihood that the patent-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-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.[10] 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

[8] See also Cohen and Klepper (1996).

[9] Section 4 provides details, but we summarize them here.

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

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 M&A 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 a private-value consideration in takeover likelihood, it doesn't reflect it directly. 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.

3. Data

3.1. 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,” “system for”, “apparatus 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 7, 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.

Figure 1 plots the time series of the share of process claims for all innovative public firms in our sample between 1980 and 2020. Figure 1 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 1. When hybrid patents are included, shown in Figure A1, process innovation after 2010 continues to account for over 30% of the total patent claims.

Panel A of Table 1 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 A1 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)).

3.2. 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. Figure 2 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.[11] Our main takeaway from Figure 2 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 1 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

[11]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.

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 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 2 provides descriptive statistics for all four variables.

We source patent-level citation, inventor and technology class data from Michael Woeppel's website.[12] 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 A2 defines these variables and Appendix A provides further details on data cleaning procedures.

3.3. 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 2 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

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

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.

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. In addition to the Economic Value, we control for 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 5.

4. Firm-specificity of process innovation

This section offers tests of Hypotheses 1 and 2. We estimate the impact of a firm's recent cost structure on the relative importance of process patenting in its portfolio. We follow with analyses of process-innovation's correlation with measures of internal knowledge accumulation. Both hypotheses are supported, indicating process patents are associated with more firm-specific information.

4.1. Production costs and process innovation

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). This analysis is conducted at the firm-year level. Table 2 provides descriptive statistics of our data at the firm-year level. We estimate the following model:

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

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 years or five years. 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 A2.) The specification includes firm- and year-fixed effects. Standard errors are clustered by the SIC 3-digit industry. Panel A of Table 3 reports the estimation results.

Firms that have experienced higher COGS/Sales in the previous three or five years engage in significantly more process innovation. In Table 3 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.[13]

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 A3 by re-estimating Equation 1 after dropping all firms with SIC code 737. The coefficient β_1 continues to be positive and significant.

Next, 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:

$$\text{Economic Value}_{i,t} = \beta_0 + \beta_1 \text{COGS/Sales}_{i,t} + \gamma \mathbf{Z}_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t}, \quad (2)$$

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,

[13]Using the coefficient on 3-year COGS/Sales in column 3 of Table 3 (0.02), the standard deviation of COGS/Sales in Table 2 (0.90), and the mean of Process Share from Table 2 (0.27), the economic magnitude is 6.67% (0.02*0.9/0.27).

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. Panel B of Table 3 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 3 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.[14] Table A3 of the appendix shows that these findings are robust to the exclusion of the business services sector.

In panels A and B of Table A4 shown in the appendix, 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 3 is a cost-side or sales-side effect by re-estimating Equation 1 and Equation 2 using 3-year or 5-year average of asset turnover (Sales/Assets) as the explanatory variable. Panel C of Table A4 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 summary, the results in this sub-section strongly suggest that our measure of process patents carries information about innovation directed toward reducing production costs. In the next section, we explore whether innovation in production processes is associated with firm-specific knowledge accumulation.

[14] Using the coefficient on 3-year COGS/Sales in column 3 of Table 3 (0.121), the standard deviation of COGS/Sales in Table 2 (0.90), and the mean economic value of process patents from Table 2 (1.85), the economic magnitude is 5.9% (0.121*0.9/1.85).

4.2. Internal knowledge accumulation

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. 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. To capture this, 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.[15]

$$\text{Internal Knowledge}_{p,i,t} = \beta_0 \text{Process}_{p,i,t} + \beta_1 \text{Cumulative Patents}_{i,t} + \alpha_t + \alpha_i + \varepsilon_{p,i,t}. \qquad (3)$$

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 4 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 2).

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.

[15] Our results are qualitatively similar if we average the patent-level variables to the firm-year level. See Table A5 in the appendix.

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.

5. 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 2 about a firm's likelihood of being acquired.

5.1. 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%. Using this list of deals and firm identifiers, we merge fundamental information from COMPUSTAT database. Then, we construct three data subsets: one where fundamental information is available for targets, a second for acquirers, and a third for both parties. These are discussed in turn below.

We start with the list of 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. Then, 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 actual 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. This is the primary dataset we use to analyze the likelihood of being a target in an M&A transaction.

We repeat this procedure for the list of deals with acquirer information available. There are 13,675 deals for which acquirer data are available in COMPUSTAT database and that were innovative. These deals are constituted by 3,360 unique acquiring firms. Using the industry and size matching criteria analogous to target firms, we are able to locate five control firms for each acquirer in 7,444 deals. These firms together give us a sample of 44,664 firm-year observations of potential bidders and targets.

Table 6 compares the features of actual targets, acquirers and their respective control firms. In line with prior evidence, the descriptive statistics show that firms active in the corporate control market are larger and older.

The third subset pertains to deals where both the target and acquirers' fundamental information is available. We construct this subset by joining the previous two subsets of targets (actual and control) and acquirers (actual and control). For this sample, we retain deals where both parties are innovative. This leaves us with 611 deals, each with 1 pair of actual and 35 pairs of control acquirers and targets. In order to be consistent with the previous two subsets, we retain five randomly chosen control pairs for each deal, which gives us 3,666 observations of actual and control pairs. This dataset is needed to analyze the combined cumulative abnormal returns upon merger announcement.

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.[16] Second, we calculate a cosine similarity measure (detailed below) between a target firm's patent descriptions and potential acquirer's 10-K product descriptions. Third, we calculate the acquirer and target stocks' combined cumulative abnormal returns (CAR) using individual stock and market returns data from CRSP database, weighted by the preceding years' market capitalization. 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.

[16]hobergphillips.tuck.dartmouth.edu

5.2. *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 it 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:

$$\text{Target}_{id,t} = \beta_0 + \beta_1 \text{Process Share (tercile)}_{id,t-1} + \gamma \text{Target Characteristics}_{id,t-1} + \alpha_d + \varepsilon_{id,t}. \quad (4)$$

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. Our matched hypothetical targets account for M&A clustering in time and industry. 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. Bena and Li (2014) show that a firm's R&D expense and growth in patents are significant determinants of the likelihood that it will be acquired. We include both as control variables. We also control for the quality of a firm's innovation by including forward citations received by the firm's patents and the economic value of the firm's patents. We know from the results in subsection 4.1 that firms with a recent history of high COGS/Sales engage in more process innovation. Since cost-inefficient firms are likely to be less attractive merger targets, we also include the firm's COGS/Sales as a control variable. The specification includes potential-deal fixed effects (one for each deal-firm and all of their controls), 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, then 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 because the remaining observations relate to only control firms for whom the dependent variable, by construction, always takes a value of 0.

Panel A of Table 7 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 7, 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 panel B of Table 7, we show that our findings are qualitatively similar if we estimate a linear probability model instead. We re-estimate Equation 4 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.[17] 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. However, the findings in Table 7 could be affected by unobserved factors that determine a firm's investment in process innovation and simultaneously affect its likelihood of being acquired. In the appendix we present two strategies to address potential endogeneity concerns. 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. In Appendix C, we use an instrumental variable estimation in which a firm's self-citation share serves as an instrument for high process share. While neither approach is perfect, both methods show that the likelihood of being acquired is lower for firms with higher share of process innovation.

We also consider the possibility of selection into patenting by firms. Prior literature suggests 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

[17]The coefficient on the process share tercile in panel B of Table 7 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.

(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 A10 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.

6. 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 5.

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 5 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 5, 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 7 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 subsection 6.1 below, we examine the likelihood of a firm being acquired conditional on product similarity between the acquirer and target. In subsection 6.2, we examine the likelihood of being acquired conditional on the text-based similarity between the target's patents and the acquirer's products. In subsection 6.3, we use cumulative abnormal return (CAR) to study how product similarity affects perceived synergistic gains from buying process innovators. Finally, in subsection 6.4 we study how the post-merger operating performance varies by redeployability when process innovators are acquired.

6.1. 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 5.2. 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.

$$\begin{aligned} \text{Target}_{id,t} = \beta_0 + \beta_1 \text{Process Share}_{id,t-1} \times \text{SameTNIC}_{ijd,t-1} + \beta_2 \text{Process Share}_{id,t-1} + \\ \beta_3 \text{SameTNIC}_{ijd,t-1} + \gamma \text{Target Characteristics}_{id,t-1} + \alpha_d + \varepsilon_{id,t}, \end{aligned} \tag{5}$$

In this equation, the dependent variable takes a value of 1 if firm i is an actual target in deal d and 0 otherwise. SameTNIC is a dummy variable that takes a value of 1 if the acquirer and target shared the same TNIC (text-based industry classification) in the year prior to the merger announcement and 0 otherwise. 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 4. Table 8 reports the estimation result.

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 subset of horizontal mergers, the negative effect of process share on the likelihood of being acquired is almost entirely reversed.

6.2. 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.[18] 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.

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

[18] 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.

p and the acquirer's product description as the normalized dot product of the two vectors

$$Cosim_p = \frac{C_p.V}{\|C_p\|\|V\|} \tag{6}$$

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 5 except that we use the Similarity measure instead of the "SameTNIC" indicator variable:

$$\begin{aligned}\text{Target}_{id,t} = \beta_0 + \beta_1\text{Process Share}_{id,t-1} \times \text{Similarity}_{ijd,t-1} + \beta_2\text{Process Share}_{id,t-1}+ \\ \beta_3\text{Similarity}_{ijd,t-1} + \gamma\text{Target Characteristics}_{id,t-1} + \alpha_d + \varepsilon_{id,t}.\end{aligned} \tag{7}$$

The results are presented in Table 9. In panel A of Table 9, 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 results in Table 9 provide further confirmation that the negative relation between process share and the likelihood of being acquired is mitigated 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. Overall, the results in this subsection provide support for Hypothesis 4.

6.3. 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. In this subsection, we provide supportive evidence that the synergies from a merger depend on the specificity of innovation.

We use the 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.[19] 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 model:

$$\text{CAR}_{d,(t-1,t+1)} = \beta_0 + \beta_1 \text{Process Share}_{id,T-1} + \gamma \mathbf{Z}_{id,T} + \alpha_T + \alpha_m + \varepsilon_{id,(t-1,t+1)}, \tag{8}$$

where the dependent variable is the combined CAR of acquirer j and target i involved in deal d with announcement date t. The regressor of interest is target i's Process Share in the year $T-1$ (note that we use notation T for year and t for date of deal announcement). Process Share is mapped to an industry-adjusted tercile measure to capture cross-sector differences in the level of process innovation. We include the following control variables: the indicator for *SameTNIC*, the acquirer's and target's leverage and book-to-market ratios in year T-1, the growth in patents of the target and acquirer, and an indicator for whether the deal had a competing bidder. The regressions include acquirer industry- and year-fixed effects. Standard errors are clustered by year.

Estimates are presented in columns 1 to 3 of Table 10, 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 takes the value of 1 if the acquirer and target have similar products (i.e., belong to the same TNIC) and zero otherwise.[20] 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

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

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

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.

6.4. Post-merger operating performance

The positive coefficient on the interaction of Process Share and product overlap in Table 10 suggests that product overlap promotes transfer of the target's cost-reducing process innovation to the bidder's product line. If process innovation is indeed specialized to the target's products, it should be more effective in reducing production costs when the acquirer has products similar to those of the target. To test this conjecture, we focus only on acquisitions in which the target firm has a high process share and examine the change in production costs and profit margins after the merger conditional on the following: (i) whether the acquirer and target belong to the same TNIC and (ii) whether the target's patent description has a high similarity with the acqurier's products. This intensive-margin analysis sidesteps endogeneity issues that might arise when comparing across targets that are process oriented versus targets that are not.

We measure production costs as the cost of goods sold divided by sales (COGS/Sales) and profit margins as operating income before depreciation and amortization divided by Sales (Operating Margin). We calculate these variables for each acquirer using data from Compustat for (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, both COGS/Sales and Operating Margin are calculated as market-value weighted averages of the acquirer and target's respective values. We estimate the following model:

$$\mathrm{Y}_{d,t} = \beta_0 + \beta_1 \mathrm{Post}_{d,t} + \beta_2 \mathrm{SameTNIC}_d + \beta_3 \mathrm{Post}_{d,t} \times \ \mathrm{SameTNIC}_d + \gamma \mathbf{Z}_{d,t} + \varepsilon_{d,t}, \tag{9}$$

This is a panel-data estimation using 205 completed mergers in which the target firm belongs to the top tercile of process share. The dependent variable Y is either COGS/Sales or Operating Margin of the acquirer calculated as described above. *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. $SameTNIC$ is an indicator variable equal to one if the acquirer and target have the same TNIC and zero otherwise. For robustness, we also use the Similarity variable described in Section 6 as an alternate measure of redeployability of the target's process patents to the acquirer's products. The coefficient of interest is β_3 which captures whether the post-merger change in COGS/Sales or Operating Margin varies depending on whether the acquirer and target have similar products. 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 9 are presented in Table 11, where panel A uses the TNIC-based measure to capture process innovation redeployability. Panel B uses the patent-to-product similarity measure described in subsection 6.2. In columns 1 to 5 of both panels, the dependent variable is COGS/sales. In column 1, we exclude all control variables and fixed effects. Column 2 includes control variables but not fixed effects. The remaining columns progressively add fixed effects and clustering. Column 3 adds industry fixed-effects, column 4 adds standard errors clustered by year, and column 5 adds year fixed effects. In both panels, across columns (1) through (5), where COGS/Sales is the dependent variable, we see that the interaction of Post with SameTNIC (or Similarity) has a negative and statistically significant coefficient. In columns (6) to (10), where the dependent variable is Operating Margin, results are largely consistent with the COGS pattern. The coefficient on the interaction term is positive and statistically significant in four of the five specifications.

These findings provide further support for the specificity explanation. Buying a firm with a high process share is associated with lower post-merger production costs and higher profits when the acquirer and target have similar products or when the target's process patents have high text-similarity with the acquirer's products. Overall, our results suggest that the specificity of process innovation is understood and priced in the market for corporate control.

7. 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). 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 A1 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 A6 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 2 using the new definition of Process Share and present the results columns columns (3) and (4) of Table A6 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 4. Results are presented in Table A7 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.

8. 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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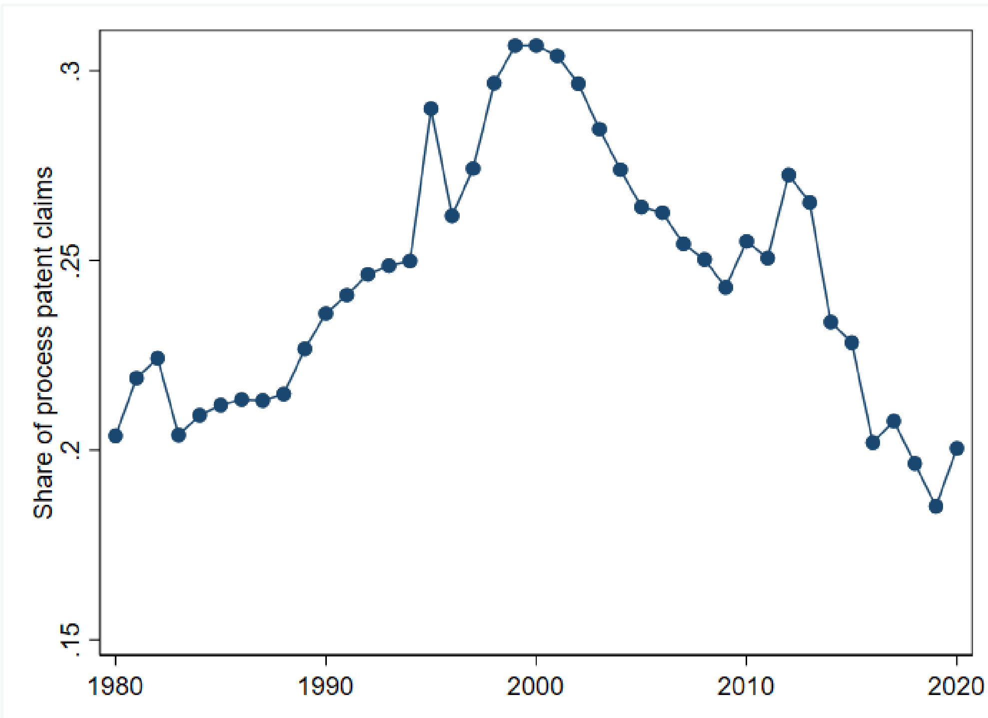
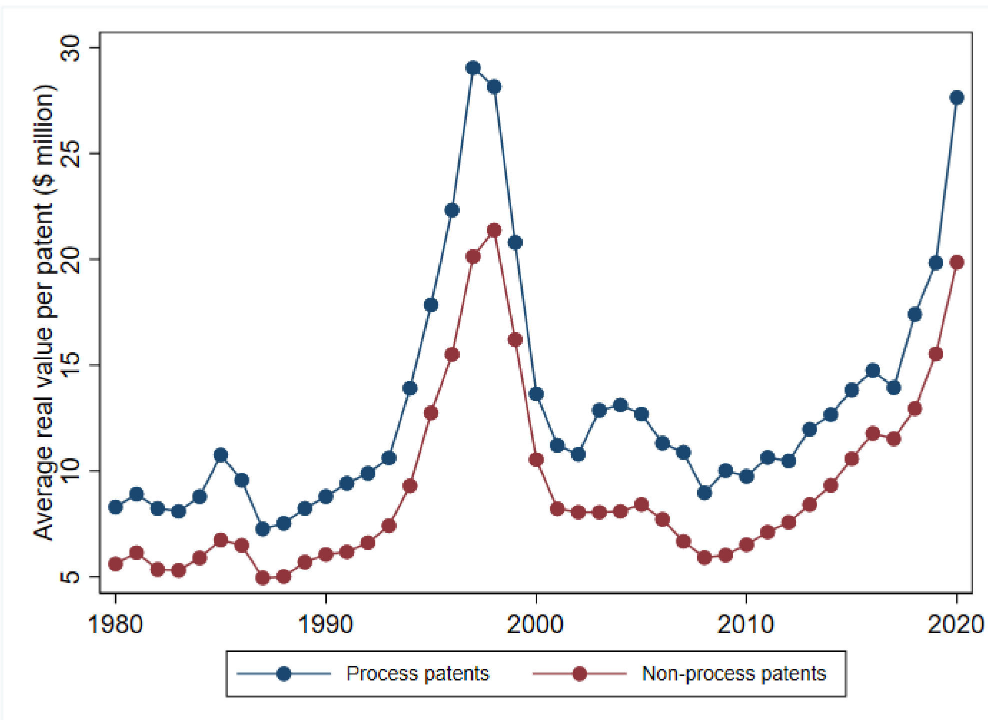
Figure 1: Share of Process Claims from 1980 to 2020



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 only those patents where all claims are unambiguously identified as "process" or otherwise. Figure A1 shows the corresponding plot for all patents in our sample.

Figure 2: Economic Value of Patents from 1980 to 2020



Notes: This figure plots the average real economic value per patent (in millions of dollars) over the years 1980 through 2020 using 1980 prices. Economic value per patent is 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 1: Descriptive Statistics of Process Patents by Fama-French 12 Industry Groups

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

Notes: 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.

Table 2: Descriptive Statistics

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

Notes: 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 A2 defines the variables.

Table 3: Determinants of Process Innovation

	Process Share					
Panel A	(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

Continued on next page

Table 3: Determinants of Process Innovation – continued from previous page

	Economic Value					
Panel B	(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

Notes: This table reports estimates from a fixed effects panel regression of the form in Equation 1 at a firm-year level. In panel A, the dependent variable is Process Share, the proportion of patents filed by a firm in a given year that we classify as process innovation. In panel B, 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. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

Table 4: Internal Knowledge Accumulation

	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

Notes: This table reports estimates from a fixed effects regression of the form in Equation 3. 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 A2 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5: Comparative Statistics for Process and Non-process Innovation

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***

Notes: 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. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

Table 6: **Descriptive Statistics of Acquirer and Target Firms**

	Mean	SD	Median	Mean	SD	Median
	Acquirers			Industry-Size Matched Acquirers		
Process Share	0.30	0.32	0.22	0.32*	0.33	0.22
Economic Value (per process patent)	0.89	3.36	0.30	0.78	2.67	0.298***
Patents (count)	29.99	65.24	7.00	41.11***	141.80	6.00
Process Patents (count)	9.33	25.07	1.00	10.88*	36.45	2.00
Non-process Patents (count)	20.67	43.52	5.00	30.24***	113.90	4.00
Age (in years)	21.78	19.12	16.00	19.54***	19.15	13.00***
Assets ($, million)	7,350	18,000	1,636	6,943	19,000	1206***
Book-to-market	0.71	0.59	0.57	0.69	0.62	0.51***
Capital Expenditure/Assets	0.05	0.04	0.04	0.06***	0.05	0.05***
Leverage	0.19	0.16	0.18	0.17***	0.18	0.15***
Market Capitalization ($, million)	10,000	23,000	2,094	9004**	21,000	1925*
Property, Plant & Equipment/Assets	0.21	0.16	0.16	0.23***	0.17	0.18***
R&D/Assets	0.09	0.12	0.06	0.10***	0.12	0.07***
Return on Assets	0.11	0.19	0.14	0.10***	0.22	0.14
	Targets			Industry-Size Matched Targets		
Process Share	0.29	0.40	0.00	0.30	0.37	0.12***
Economic Value (per process patent)	1.19	2.91	0.65	3.51*	60.36	0.57
Patents (count)	3.36	9.17	1.00	9.81***	35.59	3.00***
Process Patents (count)	1.02	3.75	0.00	2.76***	9.15	1.00***
Non-process Patents (count)	2.34	6.55	1.00	7.04***	28.82	2.00***
Age (in years)	15.28	16.03	10.00	13.83***	14.53	10.00**
Assets ($, million)	1,755	6,003	198	1,844	8,435	177***
Book-to-market	0.79	0.66	0.62	0.74***	0.65	0.56***
Capital Expenditure/Assets	0.05	0.05	0.04	0.05	0.05	0.04
Leverage	0.17	0.17	0.13	0.16**	0.20	0.10**
Market Capitalization ($, million)	2,114	6,597	292	2,016	6,486	286
Property, Plant & Equipment/Assets	0.20	0.16	0.16	0.20	0.16	0.15
R&D/Assets	0.13	0.13	0.09	0.14***	0.13	0.10***
Return on Assets	0.04	0.22	0.10	0.01***	0.24	0.10**

Notes: This table compares innovation and fundamental features of actual and control acquirers and 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.

Table 7: Likelihood of Being a Target

	Target (1/0)		
Panel A (conditional logit)	(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

Continued on next page

Table 7: Likelihood of Being a Target – (continued)

Panel B (linear probability)	(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

Notes: This table reports estimates for a model of the form in Equation 4 at a deal level. Panel A uses conditional logit while panel B uses a linear probability model. 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), which takes a value of 3 when the firm falls under the top one-third of process innovators in its industry, 1 when it falls in the bottom one-third, and 2 when it falls in the middle. 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. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table 8: **Likelihood of Being a Target (Interaction with Product Market Overlap)**

	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

Notes: This table reports estimates from a conditional logit regression of the form in Equation 5 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 7 but are eclipsed for brevity. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table 9: Likelihood of Being a Target (Interaction with Cosine Similarity)

Panel A: Similarity 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: Similarity 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

Notes: This table reports estimates from a conditional logit regression of the form in Equation 7 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 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 7 but are eclipsed for brevity. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

Table 10: Combined Cumulative Abnormal Returns for Acquirer and Target

	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)
Competing Deal (1/0)	-0.030*	-0.029*	-0.029*	-0.032*	-0.032*	-0.031*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Δ Patent Index (acquirer)	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Patent Index (target)	-0.001*	-0.001*	-0.001	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage (t-1, acquirer)	0.017	0.017	0.016	0.017	0.017	0.017
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Leverage (t-1, target)	0.023	0.024	0.024	0.025	0.026	0.026
	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)
Book-to-market (t-1, acquirer)	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Book-to-market (t-1, target)	0.025***	0.025***	0.025***	0.025***	0.026***	0.025***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	461	461	461	461	461	461
Adj. R^2	0.10	0.10	0.10	0.11	0.11	0.11
Industry (SIC-3, acquirer), Year FE	Y	Y	Y	Y	Y	Y

Notes: This table reports estimates for a model of the form in Equation 8 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11: Post Acquisition Performance

Panel A	COGS/Sales					Operating Margin				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SameTNIC	-0.022	0.031	0.012	0.012	-0.028	-0.115***	-0.132***	-0.126***	-0.126**	-0.034
	(0.026)	(0.027)	(0.026)	(0.041)	(0.033)	(0.036)	(0.037)	(0.036)	(0.063)	(0.054)
Post	-0.041*	-0.014	-0.017	-0.017	-0.060***	0.062*	0.000	-0.005	-0.005	0.088***
	(0.024)	(0.025)	(0.024)	(0.021)	(0.018)	(0.032)	(0.034)	(0.033)	(0.029)	(0.026)
SameTNIC x Post	-0.084**	-0.105***	-0.105***	-0.105**	-0.087**	0.108**	0.120**	0.118**	0.118**	0.077
	(0.038)	(0.038)	(0.036)	(0.041)	(0.039)	(0.051)	(0.052)	(0.050)	(0.057)	(0.051)
Leverage		0.358***	0.352***	0.352***	0.374***		0.033	0.041	0.041	-0.021
		(0.091)	(0.090)	(0.068)	(0.074)		(0.123)	(0.125)	(0.101)	(0.115)
Book-to-market		0.023	0.011	0.011	0.055**		0.117**	0.111**	0.111***	0.061*
		(0.034)	(0.033)	(0.024)	(0.025)		(0.046)	(0.045)	(0.030)	(0.033)
Assets (log)		-0.038***	-0.041***	-0.041***	-0.049***		0.067***	0.078***	0.078***	0.095***
		(0.006)	(0.006)	(0.010)	(0.011)		(0.008)	(0.008)	(0.012)	(0.014)
Relative size		0.007	-0.014	-0.014	-0.030		-0.012	-0.003	-0.003	0.026
		(0.021)	(0.020)	(0.024)	(0.024)		(0.029)	(0.028)	(0.031)	(0.030)
Percentage cash		0.004	0.024	0.024	0.020		0.014	-0.017	-0.017	0.018
		(0.021)	(0.021)	(0.019)	(0.018)		(0.029)	(0.029)	(0.024)	(0.023)
Observations	1,742	1,669	1,669	1,669	1,668	1,740	1,668	1,668	1,668	1,667
Adj. R^2	0.018	0.069	0.182	0.182	0.208	0.016	0.069	0.152	0.152	0.187
Industry FE	N	N	Y	Y	Y	N	N	Y	Y	Y
Year FE	N	N	N	N	Y	N	N	N	N	Y
Clustered SE	N	N	N	Year	Year	N	N	N	Year	Year

Notes: This table reports estimates for a model of the form in Equation 9. The sample is restricted to deals in which the target is in the top process-share tercile. In columns (1) through (5), the dependent variable is COGS/Sales for acquirers in year t, where t ranges from (at most) five years before merger completion year to (at most) five years after completion. In columns (6) through (10), the dependent variable is the operating income before depreciation scaled by sales. For the pre-merger years, the dependent variable is a market-value weighted average of the acquirer and target's respective values. SameTNIC is an indicator variable equal to 1 if the process innovator being targeted has the same TNIC as the acquirer and zero otherwise. Standard errors are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11: Post Acquisition Performance (continued)

Panel B	COGS/Sales					Operating Margin				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Similar	0.234***	0.218***	0.164**	0.164**	0.166**	-0.417***	-0.298***	-0.241**	-0.241**	-0.213*
	(0.078)	(0.079)	(0.072)	(0.070)	(0.076)	(0.108)	(0.109)	(0.103)	(0.112)	(0.124)
Post	-0.108	-0.102	-0.138*	-0.138***	-0.132**	0.109	0.081	0.134	0.134***	0.189***
	(0.088)	(0.087)	(0.075)	(0.042)	(0.054)	(0.121)	(0.119)	(0.107)	(0.042)	(0.059)
Similar x Post	-0.213*	-0.260**	-0.191**	-0.191***	-0.210***	0.334**	0.300*	0.227	0.227**	0.214*
	(0.113)	(0.112)	(0.097)	(0.069)	(0.069)	(0.155)	(0.154)	(0.139)	(0.104)	(0.116)
Leverage		1.109***	1.086***	1.086**	1.174**		-0.688	-1.056**	-1.056*	-1.101*
		(0.335)	(0.308)	(0.404)	(0.460)		(0.462)	(0.442)	(0.523)	(0.583)
Book-to-market		0.079	0.063	0.063	0.037		0.242	0.078	0.078	0.141
		(0.120)	(0.112)	(0.119)	(0.126)		(0.164)	(0.161)	(0.180)	(0.191)
Assets (log)		-0.109***	-0.100***	-0.100***	-0.100***		0.153***	0.154***	0.154***	0.154***
		(0.016)	(0.016)	(0.022)	(0.022)		(0.021)	(0.022)	(0.026)	(0.026)
Relative size		-0.185**	-0.139**	-0.139	-0.142		0.074	0.022	0.022	0.018
		(0.076)	(0.069)	(0.103)	(0.110)		(0.105)	(0.099)	(0.147)	(0.154)
Percentage cash		-0.162**	-0.004	-0.004	-0.001		0.159*	0.063	0.063	0.091
		(0.063)	(0.065)	(0.057)	(0.054)		(0.087)	(0.093)	(0.085)	(0.080)
Observations	519	509	509	509	509	518	508	508	508	508
Adj. R^2	0.050	0.159	0.386	0.386	0.411	0.059	0.166	0.343	0.343	0.367
Industry FE	N	N	Y	Y	Y	N	N	Y	Y	Y
Year FE	N	N	N	N	Y	N	N	N	N	Y
Clustered SE	N	N	N	Year	Year	N	N	N	Year	Year

Notes: This table reports estimates for a model of the form in Equation 9. The sample is restricted to deals in which the target is in the top process-share tercile. In columns (1) through (5), the dependent variable is COGS/Sales for acquirers in year t, where t ranges from (at most) five years before merger completion year to (at most) five years after completion. In columns (6) through (10), the dependent variable is the operating income before depreciation scaled by sales. For the pre-merger years, the dependent variable is a market-value weighted average of the acquirer and target's respective values. Similar is an indicator variable equal to 1 if the process innovator being targeted has above median similarity of patents with the acquirer firm's 10-K business description and zero otherwise. Standard errors are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix

Innovation Specificity

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A. Data Appendix

A.1. 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.

A.2. 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

Table 7 shows that firms with high process share are less likely to be acquired. It is difficult to make a causal statement based on Table 7 because firms are not randomly assigned a high process share. Firms endogenously choose how much emphasis to place on process innovation and the decision to emphasize process innovation may be influenced by firm characteristics that also affect the likelihood of being acquired. Panel A of Table A8 shows that characteristics of firms that emphasize process innovation (top tercile of process share using FF48 industries) are systematically different from those that emphasize non-process innovation (bottom tercile of process share). If we think of high process share in a firm's innovation portfolio as the treatment (which we will call D) and the firm being acquired or not as the outcome (which we call Target), it is clear from Panel A of Table A8 that covariates that affect the potential outcomes are related to treatment.

Treatment effects are difficult to estimate in observational studies like ours because the treatment is not randomized and, therefore, the outcome and treatment are not necessarily independent. When covariates that affect the potential outcomes are related to treatment, we cannot use a difference in sample means, because the missing data are informative. Thus, observational studies suffer from a missing data problem - we only observe a firm getting one treatment or the other. For example, if a firm that emphasizes process innovation is acquired, we do not get to observe whether it would also have been acquired had it not emphasized process innovation. 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.

To obtain the propensity score, we estimate the following logit model using all target firms and their matched control firms:

$$\mathrm{D}_i = \alpha + \beta \mathrm{X}_i + \varepsilon_i. \tag{10}$$

Here D_i is a treatment variable that takes the value 1 if firm i has process share in the top tercile (referred to as process innovators) and 0 if the firm has process share in the bottom tercile (non-process innovators). X_i is a vector of covariates that affect the likelihood of a firm being acquired. We include all covariates used in Table 6. The propensity score, $\hat{\pi}_i$, is the predicted probability that a firm i will be classified as a process innovator given the set of baseline covariates.

Next, the inverse of the propensity score is used to weight the outcome variable $Target_i$ which takes the value 1 if firm i is acquired and value 0 if firm i is not acquired. Recall that the weight for each firm is equal to the inverse of the probability of receiving the treatment that the subject actually received. That is, a treated firm (i.e. firms with D_i=1 or process innovators) receives the weight $1/\hat{\pi}_i$ where as an untreated firm (i.e. firms with D_i=0 or non-process innovators) receives the weight $1/(1-\hat{\pi}_i)$.

The weighted mean of the treated group (i.e., process innovators) is:

$$\hat{\mu_1} = \frac{\sum_{i=1}^{N} \mathrm{Target}_i D_i \hat{\pi}(X_i)}{\sum_{i=1}^{N} D_i \hat{\pi}(X_i)} \tag{11}$$

The weighted mean of the untreated group (i.e., non-process innovators) is:

$$\hat{\mu_0} = \frac{\sum_{i=1}^{N} \mathrm{Target}_i (1-D_i)(1-\hat{\pi}(X_i))}{\sum_{i=1}^{N} (1-D_i)(1-\hat{\pi}(X_i))} \tag{12}$$

The average treatment effect on the likelihood of being acquired is:

$$\mathrm{ATE}^{\mathrm{IPW}} = \hat{\mu_1} - \hat{\mu_0} \tag{13}$$

This average treatment effect using the IPW estimator is provided in Panel B of Table A8. 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 A8, 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 X 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. Our choice of instrument is based on the argument presented in subsection 4.2 that process innovation builds on prior knowledge generated within the firm.

We use a firm's propensity to cite its own prior patents as an instrument. We know from the results in Table A5 that firms with higher self-citation ratio engage in more process innovation. We believe the self-citation ratio satisfies the exclusion restriction because a firm's proclivity to cite its own patents is unlikely to affect acquisition likelihood through channels other than the information it carries about the nature of innovation. Having said this, a lingering concern with our choice of instrument is that a higher self-citation share could indicate lower quality of innovation and thus predict lower acquisition likelihood independent of the specificity of innovation. Nevertheless, the average internal value of patents argues against this possibility. We find that both measures of innovation quality - forward citations and economic value of patents, are comparable for firms with high (above-median) and low (below-median) self-citation shares. Finally, we also explicitly control for these two measures of innovation quality, and other firm characteristics to account for firm fundamentals that might simultaneously impact self-citation share and likelihood of being acquired.

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

$$\text{Process Share (tercile)}_{i,t} = \beta_0 + \beta_1 \text{Self-citation Share (tercile)}_{i,t} + \gamma \mathbf{Z}_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t}. \quad (14)$$

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 4.

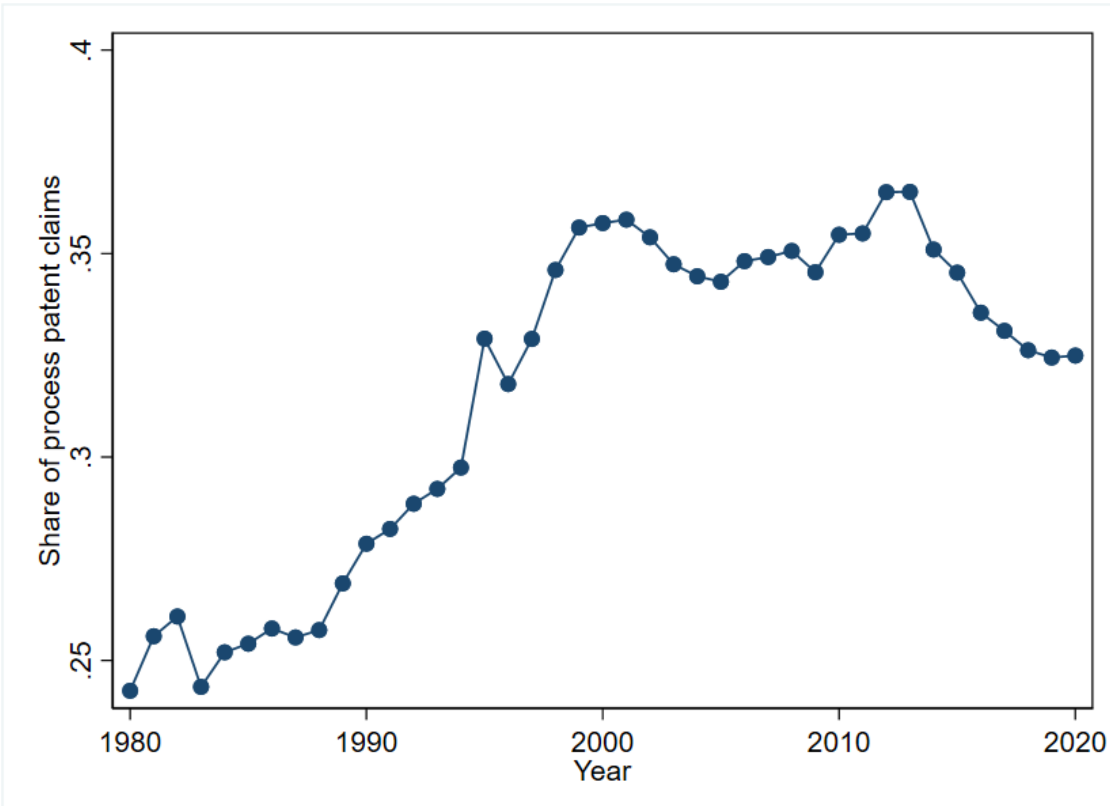
Specifically, we control for the quality of patents by including the patent's forward citations and economic value as control variables. We control for industry effects in the process share measure and self-citation share measure by mapping both variables to terciles within the industry. Standard errors are clustered by year. Panel B of Table A9 reports the estimation result and the instrument F-statistics. As in subsection 5.2, we present three different specifications, which differ on how the process share terciles are created.

Consistent with Table A5, the self-citation share strongly correlates with process share. The first-stage F-statistic is in the range of 26 to 41 depending on the industry group used for creating terciles, indicating that this variable serves as a relevant instrument. We use the predicted value of Process Share (tercile) from Equation 14 to explore the likelihood that a firm is acquired. In this second-stage regression, we estimate the following model using ordinary least squares,

$$\text{Target}_{id,t} = \beta_0 + \beta_1 \text{Process } \widehat{\text{Share}} \text{ (tercile)}_{id,t-1} + \gamma \mathbf{Z}_{id,t-1} + \alpha_d + \varepsilon_{id,t}, \tag{15}$$

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 4. Panel A of Table A9 reports estimates of Equation 15. As before, we present three different specifications, which 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.

Figure A1: 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 1 shows the corresponding plot for patents unambiguously classified as process or otherwise.

Table A1: Descriptive Statistics at Technology Class Level

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

Notes: 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.

Table A2: 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

Table A2: Variable definitions – continued from previous 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.
Common Knowledge	The number of patents in the common knowledge base of the acquirer and target. To obtain the common knowledge base, we first determine the set of patents that received at least one citation from any of the acquirer's patents awarded in the three years preceding merger announcement year ("the acquirer's knowledge base"). Next, we determine the set of patents that received at least one citation from any of the target's patents awarded in the three years preceding merger announcement year ("the target firm's knowledge base"). Common Knowledge is the intersection of these two sets and captures the set of patents cited by both the acquirer and the target firm.
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.
Premium (over 1-day price)	The percentage premium paid by acquirer compared to the 1-day ago stock price of the target.
Process Share Tercile Distance	Signed difference between the acquirer and target firm's Process Share (tercile). A positive value suggests that the acquirer conducts more industry-adjusted process innovation than the target.

Continued on next page

Table A2: 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 A3: Determinants of Process Innovation (Excluding SIC 737)

	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

Notes: This table reports estimates from a fixed effects panel regression of the form in Equation 1 in columns (1) and (2), and Equation 2 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. $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$.

Table A4: Other Determinants of Share and Economic Value of Process Innovation

	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

Notes: This table reports coefficient estimates from a fixed effects panel regression of the form in Equation 1 in columns (1) and (2), and Equation 2 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 3. Standard errors are clustered by industry (SIC 3 digit) and year, and reported in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Table A5: Internal Knowledge Accumulation (Firm-year level)

	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

Notes: This table reports estimates from a fixed effects panel regression of the form in Equation 3 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. ${}^{*}p < 0.1$; ${}^{**}p < 0.05$; ${}^{***}p < 0.01$.

Table A6: Determinants of Process Innovation (Including Hybrid Patents)

	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

Notes: 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 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) 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. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table A7: Likelihood of Being a Target (Including Hybrid Patents)

	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

Notes: 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 regressor of interest is Process Share (tercile), which takes a value of 3 when the firm falls under the top one-third of process innovators in its industry, 1 when it falls in the bottom one-third, and 2 when it falls in the middle. 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 controls and deal fixed effects. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1$;$^{**} p < 0.05$;$^{***} p < 0.01$.

Table A8: Potential Outcome Methods and Balance Test

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***

Notes: This table reports the difference in the likelihood of getting acquired after matching firms using the propensity score method. Panel A shows that process innovators (firms in the top tercile of process share) can have fundamentally different characteristics than non-process innovators (firms in the bottom tercile of process share). Panel B confirms that process innovators are less likely to be acquired even after firms are matched on fundamental characteristics, 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.

Table A9: Likelihood of Being a Target (Instrumental Variables Estimation)

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

Notes: This table reports estimates from a linear probability instruments variables regression of the form in Equation 14 (Panel B) and Equation 15 (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 7 but are eclipsed for brevity. Standard errors clustered by deal are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table A10: Likelihood of Filing a Patent (Selection using Secret Words)

	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

Notes: This table reports estimates of a model of the form:

$$\text{Patent } (0/1)_{i,t} = \beta \text{Secret}_{i,t} + \varepsilon_{i,t}. \tag{16}$$

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. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.