New Technology Sectoral Disruptions

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Abstract

We construct a novel measure of technology sectoral disruptions (TSDs) using a dynamic text-based spatial model of patents based on the extent to which innovation is suddenly highly correlated across multiple industries. We identify multiple TSDs occurring over a 70-year period of time. Abnormal stock returns and insider trading indicate that TSDs are unexpected and have a permanent positive impact. Relative to large firms, small firms experience higher R&D, investments, asset growth, and long-lasting value gains. The gains among small firms are consistent with Schumpeter's 1912 theory of creative destruction and Arrow's 1962 replacement theory of innovation by smaller firms.

Keywords: Patents, sectoral disruptions, innovation, R&D, creative destruction **[JEL Codes: O31, O34, D43, F13]**

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> It is not the strongest of the species that survive, nor the most intelligent, but the one most responsive to change.
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> *Wallbank and Taylor, 1962.*

The path of technological innovation is lumpy, hard to predict, and uneven across industries and sectors over time. At certain points, innovation exhibits coordinated shifts across multiple sectors, as firms adapt to shared technological advances that affect a broad set of product markets. Well-known examples include the internet boom of the late 1990s, the diffusion of digital financial technologies following the financial crisis, and the recent expansion of artificial intelligence. Earlier episodes include telecommunications in the early twentieth century, the diffusion of plastics, and the development of computing technologies.

We define *Technology Sectoral Disruptions* (TSDs) as episodes in which innovation becomes highly correlated across multiple related sectors. We develop an ex ante measure of sectoral disruption based on comovement in patent text using large language models (LLMs) and study its implications for asset prices and firm behavior.[1]

Our new technology disruption measure captures frequent episodes of highly correlated innovation as they begin to evolve across multiple related industries, thereby permitting the first large-panel study of how TSDs affect key corporate policies. Thus, we are identifying new technology disruptions before they become larger, well-known technologies. We examine the responsiveness of large and small firms to TSDs, testing Schumpeter's and Arrow's theories of firm innovation and replacement of legacy technologies.

TSDs impact multiple related industries and hold the potential to redraw industry boundaries. Our definition of TSDs focuses on the common evolution of technologies among groups of industries (sectors), which we measure as new innovative vocabularies simultaneously permeating the patent portfolios of sectoral peer firms. This comovement concept is analogous to risk factors that simultaneously affect multiple stocks in asset pricing. Maintaining this parallel, we measure TSDs using a text-based analog to covariances. Specifically, we com-

[1] Kalyani et al. (2025) examines the labor-market impacts of how technology diffuses over geography and identifies new technologies using word bi-grams from patents.

pare simultaneous textual evolutions of industry-pair patent portfolios (comovement) to their non-simultaneous long-run averages, as implied by the standard covariance formula but applied to textual content. To assess patent similarity across firms and *across* industries, we use Google's public patent embeddings that use each individual patent's text.[2]

TSDs are pervasive during our 70-year sample period and exhibit 76% autocorrelation, indicating that they persist for roughly three years. We examine the impact of TSDs on stock returns and corporate decisions for large and small firms. Three theoretical considerations motivate our focus on heterogeneity by firm size. First, Schumpeter's early work (Schumpeter (1912)) postulates that small entrepreneurial firms are the seedbeds of innovation, predicting stronger effects for small firms. In contrast, his later work (e.g., Schumpeter (1942)) emphasizes large firms as engines of growth and innovation, given their potential monopoly power and greater resources.

Second, Arrow's (Arrow (1962)) "replacement effect" explains why innovation incentives are often stronger for smaller firms: large firms with substantial market shares have weaker incentives to innovate because the value of preserving the status quo outweighs the gains from new technologies. In Arrow's framework, for any given level of post-invention ("ex post") profits, innovation incentives decline with higher pre-invention ("ex ante") profits. Third, smaller firms may be more flexible, face less institutional rigidity, and be better positioned to adapt to TSDs.

A central result of our study is that TSDs generate substantial wealth in the form of sector-wide positive abnormal stock returns over a three-year horizon, with smaller firms earning higher abnormal returns than larger firms. These ex post abnormal returns motivate our analysis of the information environment and help establish when economic agents first become aware of TSDs. High returns signal wealth-creation opportunities, and agents adjust their behavior upon learning about sectoral disruptions. For example, investors buy

[2] See: https://deepwiki.com/google/patents-public-data/3.2-bert-for-patents. We also obtain robust results using Doc2Vec models trained solely on rolling ex ante data. The robustness of our results indicates that potential look-ahead bias from using Google's public patent embeddings is not a concern in our setting.

affected stocks, corporate insiders initiate insider purchases, and equity analysts revise earnings forecasts upward. If markets are informationally efficient, these responses should occur early, potentially even before TSDs become measurable using public data. Delayed responses, in contrast, would indicate that TSDs are initially unanticipated.

Our first major finding is that TSDs are largely unanticipated. Investors, corporate insiders, and equity analysts respond only months after TSDs become measurable using public information. When month t marks the public measurement date, stock returns become significant only two to six months later, rise in magnitude and significance through month $t + 18$, and then gradually fade. There is no evidence of pre-measurement price run-ups, indicating that price adjustment occurs almost entirely after TSDs become observable. Corporate insiders likewise show no pre-trends in trading, with insider purchases increasing only after month $t + 12$. Analysts also exhibit no advance awareness, as their forecasts remain systematically pessimistic relative to realized earnings throughout much of the three-year post-TSD period. Together, these patterns indicate that TSDs are not anticipated by key economic agents.

Corporate insiders play a central role in corporate decision-making, while stock market investors influence insiders through price signals, and analysts affect both groups through research coverage and communication. The consistent finding that all three groups respond only after TSDs become measurable suggests that TSDs plausibly represent exogenous shocks from the perspective of decision-makers, enabling identification of corporate responses.

We examine how TSDs affect a wide range of corporate finance outcomes over the three years following their onset. These outcomes include investment, acquisitions, market-to-book ratios (M/B), patent valuations, and accounting performance. Our tests employ firm-year panel regressions with firm and year fixed effects, using sectoral disruption as the primary explanatory variable. We focus on both the magnitude and timing of responses, anticipating that managers prioritize certain actions ahead of others.

We find that TSDs drive significant changes in corporate policies and performance. Consistent with Schumpeter's early theory of creative destruction, small firms increase R&D and asset growth in response to new technologies, accompanied by rising valuations that reflect a long-term strategic orientation rewarded by markets. Large firms respond differently, cutting R&D, experiencing weaker asset and sales growth, and lower valuations relative to small firms, patterns consistent with high adjustment costs and incentives to protect legacy rents. This contrast is illustrated by the responses of traditional cable and satellite providers such as Comcast and Dish Network to streaming disruption, compared with the more successful adaptation of initially smaller firms like Netflix.

To further decompose these effects, we analyze event-time dynamics over the three years following TSD measurement. In year one, small firms increase D and CAPX, and valuation multiples begin to rise. In year two, acquisition activity picks up, consistent with lagged asset reallocation, while CAPX remains elevated and sales growth improves. By year three, acquisitions and CAPX stay high, and sales growth strengthens further. These real responses are matched by innovation outcomes: small firms see higher patent values (KPSS) and greater reliance on trade secrecy, indicating higher-value innovation and stronger incentives to protect proprietary knowledge. Large firms show the opposite pattern, with reduced RD, weaker innovation, and lower valuation multiples relative to small firms. Overall, consistent with Schumpeter (1912) and Arrow (1962), small firms drive post-TSD innovation and investment, while large firms retrench. Responses are strongest among smaller firms, those with lower market shares, and those with higher organizational capital, and to a lesser extent those with greater cash holdings, while differences by firm age are weak.

We address two primary endogeneity concerns. Reverse causality is unlikely, as ex post corporate actions cannot influence ex ante TSD formation, and our evidence shows that managers become aware of TSDs only well after they are publicly measurable. This temporal separation mitigates concerns that firm behavior drives disruption measures. Omitted-variable concerns cannot be fully ruled out, but they are alleviated by the absence of anticipatory behavior by investors, insiders, and analysts. This inaction suggests that correlated unobservables are economically unimportant. More broadly, monitoring the behavior of central economic agents provides a useful diagnostic for detecting confounding omitted variables. Also helpful, our regressions include firm and year fixed effects, parallel-trends tests, and robustness checks that exclude influential patenting firms and highly cited patents.

Although TSDs are unanticipated, they are persistent, with a 76% annual autoregressive coefficient. As an additional robustness test, we identify a subset of large sectoral disruptions with clearly defined starting years and examine post-event dynamics. Despite reduced statistical power, these tests yield consistent results and reveal structural breaks only after TSDs occur, reinforcing the absence of pre-trends.

This paper contributes to the literature on innovation, creative destruction, and disruption. Kogan et al. (2017) examine stock market reactions to patent grants, while Kelly et al. (2021) develop a measure of technological waves based on patent similarity without forward-looking information. Bowen et al. (2023) study how emerging technologies affect venture capital exits, and Bena et al. (2022) examine process innovation and labor rigidity. Our contribution is distinct in its sectoral focus and its use of co-movement in patent portfolios, analogous to systematic risk, to study corporate finance and asset pricing implications.

Our work also relates to the creative destruction literature (Aghion and Howitt (1992), Akcigit and Kerr (2018), Aghion et al. (2014)), which identifies innovation-driven entry as a key driver of growth. We add to this literature by developing a novel, sectoral measure of creative destruction and showing that small firms are the primary engines of innovation.

Finally, our framework differs from Christensen's (Christensen (1997)) notion of disruption, which emphasizes within-industry entry by low-quality firms. In contrast, we define sectoral disruptions as technology-driven shocks that propagate across industries. Under this definition, ride-hailing services represent a sector-wide disruption affecting transportation, food delivery, and data analytics. We are unaware of prior work that examines disruption at this sectoral level, and we therefore introduce sectoral disruptions as a distinct and complementary concept.

1 Identifying Technology Sectoral Disruptions

In this section, we explain our methods to identify and measure TSDs, the data used to construct our measures of disruption, and the specific methodologies used to calculate the extent to which any given industry is likely exposed to systemic TSDs at any point in time. TSDs are large technological shocks that are common to multiple related industries that have an economically significant and lasting impact. To measure TSDs, we start with the 64-dimensional spatial representations of patents from the Google Cloud database, as described in the section on patent embeddings below. We use these embeddings solely to classify patents into areas based on their words. We do not use these embeddings in any prediction exercise. Thus, our use is equivalent to using a richer form of patent classification methods that would be provided by using the USPTO classification system.[3]

In the analyses, we use patent grants instead of patent applications for two reasons. First, before November 29, 2000, patent application texts were not available until the grant date (Johnson and Popp (2003)); only after November 2000, the texts became public after 18 months of the application. Since our analyses start from the 1950s, for most of our sample, the dissemination of information begins at the grant date. Second, the use of patent grant dates avoids look-ahead bias in our tests and also eliminates issues of truncation bias as described in Lerner and Seru (2021).

For a given industry j at a given time t, we compute its primary technology bundle as the average spatial location over all patents granted to firms in the given industry at time t. We denote such a patent bundle as $P_{j,t}$. As the industry's technologies evolve over time, the spatial location of the industry's average technology bundle shifts in this 64-dimensional space. $P_{j,t}$ can thus be quite different from $P_{j,t+1}$. We note that industry technology bundles continuously move in space as they evolve, even in the absence of disruption. Simple movements of these industry patent portfolios, in themselves, do not indicate disruption.

[3] One alternative would be to build a higher-dimensional embedding space than the 64 dimensions that Google provides. However, in our context, a lower number of dimensions is desirable as we want to identify broad-based sectoral shocks. In robustness, we will explore this assumption.

Even larger movements over time also might not indicate disruption, as such shifts might be unique to the given industry and thus more idiosyncratic.

We define TSDs as scenarios in which the technology bundles of multiple industries move in a common spatial direction simultaneously. For a pair of industries j and k experiencing TSDs, the evolutions ($P_{j,t+1}$ - $P_{j,t}$) and ($P_{k,t+1}$ - $P_{k,t}$) should be highly correlated. Because comovement is a second moment, and second moments can be estimated with relatively high accuracy over multiple observations, we thus estimate the comovement of patent portfolios for a pair of industries j and k using 12-month rolling windows. In particular, we compute:

$$\text{Pair Disrupted (SIC)}_{j,k,t} = \sum_{m=t,\ldots,t-11} \frac{Cosine[P_{j,m}, P_{k,m}]}{12} - Cosine[P_{j,[t,t-11]}, P_{k,[t,t-11]}] \quad (1)$$

The measure is thus the average monthly cosine similarity of the two industry i and j portfolios minus the cosine similarity of the two full-year patent portfolio locations. The functional form, more generally, is the implementation of covariance using text instead of numerical time series. The first term is the average joint variation in the spatial locations of i and j's patent portfolios (joint variation averaged over 12 months). The second term is the product of expected values of these same patent portfolios, where expectations are taken before taking the product. In fact, the cosine similarity function is a product operator and the formula for the covariance of two random variables $\tilde{X}$ and $\tilde{Y}$ is: $E[\tilde{X}\tilde{Y}] - E[\tilde{X}]E[\tilde{Y}]$. This approach is novel, as we are unaware of prior work studying textual covariance.

Our final step aggregates the pairwise disruption scores in each month to industry-month measures of the likelihood and intensity of a given industry j facing sectoral disruption in month t. For each industry, we thus compute the value-weighted sum of pairwise disruption scores over the three most related industries. For a given industry j, the three most related industries are those with the ex-ante most similar patent portfolios. Ex ante similarities are computed over the five-year rolling windows prior to the most recent year (as the most recent year is used to compute the above pair similarities).

$$\text{Sectoral Disruption(SIC)}_{j,t} = \sum_{n=1,\ldots,3} MktCap_{k[n],t} * \text{Pair Disrupted(SIC)}_{j,k[n],t} \tag{2}$$

The index $k[n]$, n=1 to 3, identifies the industry k that is industry j's most similar industry. Thus, $k[1]$, $k[2]$ and $k[3]$ are industry j's first, second and third most ex-ante similar industries. $MktCap_{k[n],t}$ is the total equity market capitalization of the firms in industry $k[n]$ in the given month, divided by the total equity market cap of all firms in the same month (this variable is bounded in $(0, 1)$). When this score is high, an impactful sectoral disruption is likely in progress as it indicates that industry j's patent portfolio is co-moving intensively with its three most spatially proximate related industries (especially the most valuable related industries).

1.1 Patent Embeddings

We use patent embeddings as the foundational database for identifying sectoral disruptions. For each patent, we gather a 64-element vector (each element containing continuous values) from the Google Cloud Public Database. These 64-dimensional patent embeddings are built using a machine learning model that predicts a patent's CPC code from its text. As previously noted, we use these embeddings only to classify patents into areas (as a more precise analog to CPC codes) using the patent words. We do not use these embeddings for any other purpose, such as predicting future content. Our use only for classification ensures that our study is not exposed to look-ahead bias, as this use is equivalent to using a richer form of existing patent classification methods (or an industry classification system) relative to the USPTO binary classification system. Overall, the embeddings simply allow us to use each patent's words to classify the patent's exposure to TSDs (using InferVec as provided by Google) to each of the 64 dimensions.

These learned embeddings are thus intended to encode information in a patent's text into a broad patent area, serving as a classification method rather than a prediction method. This database contains all patents granted by the USPTO for the 1890-2022 period. In total, this sample contains 10,844,774 patents granted during this period. Patent numbers serve as the unique identifier in this database, and we link patents to public firms using the correspondence provided by Kogan et al. (2017) (KPSS), which provides an extended link table through 2022. The KPSS database covers the 1926-2022 period, and our final patent database includes 3,156,877 patents linked to the public firms in our sample.

The distance between the two embedding vectors of two patents indicates the similarity between two patents.[4] Intuitively, highly related technologies, such as two medical devices that help with mobility, would have spatial locations that are very close. Analogously, a patent relating to chemical manufacturing and such a medical device would have spatial locations that are very far away.

As an additional robustness check, we replace Google's embeddings with document representations obtained from Doc2Vec models trained sequentially in chronological order with past patent text (i.e., no look ahead bias), and we replicate all tables using these alternative embeddings. The corresponding results, reported in the Internet Appendix, are qualitatively similar to those in the main analysis. Nevertheless, because relying on predetermined third-party embeddings helps mitigate potential researcher-induced biases (e.g., stemming from model specification or parameter choices), and because transformer models are more informative regarding context for classification tasks, we adopt Google's vectors as the primary embeddings in this study.

1.2 Disruption via SIC versus TNIC

We implement the calculation in equations (1) and (2) using three-digit SIC codes and separately using TNIC-3 industry classifications. Although SIC codes are less informative than TNIC-based metrics, SIC codes are still interesting to study because they are available

[4]https://cloud.google.com/blog/products/data-analytics/expanding-your-patent-set-with-ml-and-bigquery

alongside Compustat data going back to 1951 in our sample. The implementation using SIC-codes is straightforward, as individual firms (and their patents) are assigned to one and only one industry. Equation (1) reflects calculations based on the resulting mutually exclusive SIC-3 groupings, and equation (2) then completes the calculation by aggregating pair data to an industry-month panel structure.

Since the members of TNIC industries are not transitive, the calculation needs to be generalized to ensure that we compare the patent portfolio of each focal firm's TNIC industry to non-overlapping patent portfolios of related industries. We first compute patent portfolios for each firm's TNIC industry as above, resulting in an industry portfolio for a given firm i that we denote as $P_{tn[i],t}$. Here, $tn[i]$ denotes firm i's unique TNIC industry and $P_{tn[i],t}$ therefore denotes the total patent portfolio of both firm i (if it has any patents) and its peers. We only include TNIC industry observations in our sample in month t if the portfolio $P_{tn[i],t}$ has at least 25 patents in the last rolling 12 months.

Because TNIC industries are intransitive, it is not possible to then implement equation (1) because mutually exclusive groups are needed. We therefore identify the set of all individual firms that have at least 10 patents over the last 5 years. The patent portfolios of these firms are mutually exclusive and adequately large to serve as pseudo industries through which an analog to equation (1) is then implementable as follows (we denote a specific pseudo industry k as $psi[k]$):

$$\text{Pair Disrupted(TNIC)}_{j,psi[k],t} = \sum_{m=t,\ldots,t-11} \frac{Cosine[P_{tn[i],m}, P_{psi[k],m}]}{12} - Cosine[P_{tn[i],[t,t-11]}, P_{psi[k],[t,t-11]}] \tag{3}$$

The use of pseudo industries follows the standard logic of TNIC industries, which centers the concept of industry around individual firms as anchors. We thus compute TNIC disruption at the industry-month level using the following analog to equation 2.

$$\text{Sectoral Disruption(TNIC)}_{j,t} = \sum_{n=1,\ldots,10} MktCap_{psi[k[n]],t} * \text{Pair Disrupted(TNIC)}_{j,psi[k[n]],t} \tag{4}$$

The TNIC disruption measure is the value-weighted sum of the disruption scores of the ten pseudo-industry firms that are most proximate to firm j. We sum over the ten pseudo industries rather than three (as we did for SIC) to preserve granularity, since pseudo industries are more prevalent. Our approaches for SIC-based and TNIC-based disruption are thus analogous.

1.3 High-Disruption Firms and Industries

Table I illustrates our TNIC-based sectoral disruption measure by reporting, for each decade, the firms with the highest disruption exposure, the year of peak exposure, the disruption score (a z-score among positive realizations), and the top three co-disruptors that are jointly exposed to the same underlying technological wave. Two economic patterns stand out. First, high-exposure firms often come from industrials, energy, chemicals, healthcare, telecom, and finance, consistent with the idea that major technology waves behave like general-purpose innovations that propagate across product markets and reshape competitive boundaries. Second, the co-disruptor lists frequently connect firms that would not be grouped together under traditional SIC classifications, indicating that the TNIC network captures cross-market technological linkages. In this sense, sectoral disruption reflects periods of technological convergence—common underlying technologies influencing multiple product markets—rather than narrow, within-industry innovation.

Place Table I here

Table II reports the SIC-3 industries with the highest sectoral disruption exposures by decade, along with a z-score–style disruption intensity and the top co-disruptor industries that are jointly exposed to the same technological wave. A clear pattern is that high-disruption episodes frequently occur in traditional production sectors (e.g., textiles, metalworking, engines, motor vehicles, paper, chemicals), yet their co-disruptors repeatedly include communications equipment, semiconductors, electrical equipment, and computer-related industries. This suggests that disruptions reflect broad technological diffusion that propagates through production and supply chains, rather than being isolated within-industry innovation.

Place Table II here

2 Firm level data

We use data from multiple sources to track and measure how firms and the stock market respond to sectoral disruptions. We begin with stock market data and then study firm-level corporate finance decisions. We also examine insider trading data and analyst earnings forecasts. As these results are not the primary focus of our study, the insider trading and analyst earnings forecast results are presented in the appendix.

2.1 Stock Return Data

We use data from CRSP for monthly stock returns, and Compustat data to obtain firm financials as needed for calculating book-equity-to-market-equity (Book-to-Market) ratios. We restrict our sample to stocks that have a positive book value of equity and a share price of one dollar or more to avoid penny stocks. We compute controls for Size, Book-to-Market ratio, momentum, profitability, and investment following Davis et al. (2000) and Fama and French (2015). Size is each firm's market capitalization as of December of the most recent fiscal year, with a minimum 6-month lag. The book-to-market ratio is the natural logarithm of a firm's ratio of book equity and market equity in December of the most recent fiscal year, and a minimum 6-month lag is also applied. For momentum, we compute each stock's past return from $t-12$ to $t-2$. Profitability is revenue less COGS, SG&A and interest, scaled by book equity, and investment is the change in assets, scaled by lagged assets. We use stock market return tests in the next section to illustrate that market participants are not initially aware of sectoral disruptions, but the market learns about these disruptions roughly 12 to 24 months after the industry patents are granted. In all asset-pricing tests, we use only data available before the month of prediction to predict stock returns.

Place Table III here

Table III presents summary statistics for the asset pricing variables as well as the disruption measures. The average raw monthly return in our sample is 1.1%. The statistics for our control variables match those from prior studies. Additionally, we note that our disruption variables, given that they were constructed as an index, do not have interpretable values. Yet we do observe that the mean and median values for both disruption variables are similar, indicating a balanced distribution. Additionally, the minimum and maximum for both are not extreme relative to the overall distribution, indicating that outliers should not be a problem. The Pearson correlation coefficients in Panel B of Table III also show that the correlation between our disruption variables and the control variables is quite modest. These variables are distinct, and multicollinearity is not an issue. Finally, we note that TNIC disruption and SIC disruption are 29% correlated, indicating a strong common signal, but also that both industry classifications each capture unique information.

2.2 Corporate Finance Data

We include all public firms in the Compustat database from 1951 to 2020. We drop observations with missing asset and sales information and also those with assets or sales less than $1 million. We also exclude firms with missing sectoral disruption values (i.e., industries without meaningful patenting activity). In total, we have 17,488 unique firms and 185,697 firm-years in our sample. Table IV displays summary statistics for our key variables. We briefly describe the variables we use in this section and provide full details of the variables in Appendix A.

Place Table IV here

Panel A of Table IV presents general summary statistics, including disruption scores, firm size as measured by log assets, log sales, and log age. The key Disruption variables for SIC codes and TNIC industries cover the periods 1950-2020 and 1988-2020. The statistics show expected patterns, for example, that large firms are older, and small firms hold more cash relative to assets.

Panel B presents variables on innovation, competition, and investment policies. R&D/Assets is Compustat R&D divided by lagged assets, and this variable is set to zero if R&D is missing. CAPX/Assets is Compustat capital expenditures scaled by lagged assets. Acquisitions/Assets is the dollar value of acquisitions scaled by assets. Acquisitions data is from the Thomson Reuters Eikon database. We define a transaction as an acquisition if it was completed and more than 50% of the target was acquired. KPSS/Assets is the dollar value of patents obtained from Kogan et al. (2017), scaled by lagged assets. Summary statistics indicate that small firms invest more intensively in R&D and capital expenditures, whereas large firms rely more on acquisitions. Small firms also have relatively more organizational capital and use trade secrets more.

Panel C displays statistics for performance metrics, including market-to-book (market value of equity + book value of debt) / (lagged book value of assets), sales growth ($\ln(SALE_t/SALE_{t-1})$), and assets growth ($\ln(AT_t/AT_{t-1})$). Small firms have higher sales and asset growth, and large firms have higher market-to-book ratios. We discuss insider trading and analyst data in the Internet Appendix.

3 Validation of Disruption Measure

In this section, we validate our disruption measure using two tests. First, we explore TSD growth trends following the breakthrough innovations documented by Kelly et al. (2021). Second, we test whether measured TSDs are followed by subsequent increases in product similarity across impacted industries (a direct prediction, as we define TSDs based on increased comovement in innovation across broad sectors).

3.1 Historical Breakthrough Patents

We examine whether our measure captures disruption by conducting an experiment based on historical breakthrough innovations. Specifically, we gather the list of breakthrough innovations from Appendix A of Kelly et al. (2021). This list includes 245 revolutionary patents dating back to 1840. We merge these breakthrough patents to the KPSS database, which begins in 1920, by patent number. The merged sample contains 37 patents in which the assignee is a public firm as of the grant date, and that are in our sample period. For each innovation, we then create a sample of industries within the same two-digit SIC code as the assignee company. This is consistent with our goal to explore sectoral disruptions, as firms in these industries are in the same sector and we expect them to be influenced by breakthrough innovations. The main idea, consistent with our thesis, is that industries close to the assignee company's industry are expected to be influenced by common sectoral disruptions.

Place Figure I here

Figure I presents results of estimates from a regression where the dependent variable is our three-digit SIC disruption measure, and independent variables are indicator variables for the number of years from the breakthrough patent's grant from -5 to +5 years. The reference year, 0, is the year the breakthrough patent was granted, and we exclude this base year from the regression to avoid multicollinearity and to allow all comparisons to be made relative to this benchmark year. Our regressions also include industry fixed effects to control for unobserved industry characteristics. The figure shows that sectoral disruption is roughly flat across the 5 years preceding the breakthrough innovation, supporting the parallel trends assumption. However, beginning in the year following the breakthrough innovation, we observe a structural break as sectoral disruption rises to a peak in the third year. Overall, the results are mostly in line with our expectations and support the conclusion that our measures well-capture the hypothesized notion of sectoral disruption in the intuitive setting of breakthrough innovations.

3.2 Product Similarity

As noted above, we expect total product market similarity to rise in impacted industries following TSDs. Our second validation analysis tests this prediction. As we need to develop an event-time framework for this test, we first define major TSDs.

3.2.1 Major TSDs and Trend Tests

Since disruption is a continuous firm-level variable, we first identify a set of large and long-lasting TSDs to which we can attach a specific event-year zero. Since our baseline sectoral disruption variable is persistent and 76% autocorrelated, this process is important for accurately assessing the event-time dynamics of the link between disruptions and corporate policies.

We assess timing using a 7-year window that leverages within-firm variation. We consider three years prior to the event, year zero, and three years ex post. First, for each firm in our sample, we identify the year in which the firm's average disruption from year t to $t+3$ minus its average disruption from year $t-3$ to $t-1$ experiences its largest increase among all years the firm is in our sample. We deem this year to be event year zero. Second, we require that disruption monotonically increases from year zero to year three. This final step ensures we focus on major, long-lasting sectoral disruptions. This echoes our finding that major sectoral disruptions involve significant shifts in technology that take multiple years to propagate, as was the case for the internet boom in the late 1990s.

$$y_{i,t} = \alpha_0 + \sum_{t=-3}^{3} \gamma_t Disrupted_{i,t} * D(t) + \delta_t D(t) + \theta_t Disrupted_{i,t} + \mu_i + \delta_t + \epsilon_{i,t} \qquad (5)$$

We then run equation (5) regressions with product-market similarity as the dependent variable. $D(t)$ is a dummy variable equal to one for the reference year t and is zero otherwise. We exclude t=0 from the regression so that the estimates are relative to the year-zero values.

Specifically, we plot seven yearly estimates for sectoral disruption, interacted with each event-year dummy from $t-3$ to $t+3$ (i.e., we plot the values of γ_t). In this regression, μ_i is a firm fixed effect, and δ_t is a year fixed effect. Our thesis is that product similarity will follow a flat trajectory over the three ex-ante years and then undergo a structural break after event-year zero. We plot both coefficients and error bands associated with t-tests of whether each coefficient is different from the year-zero coefficient.

3.2.2 Trend Test Results for Product Similarity

Place Figure II here

Using the model in (5) as noted, Figure II displays the evolution of log total product market similarity around major TSD events (relative to year zero). The series is flat and close to zero prior to the disruption (-3 to 0), indicating no strong pre-trend. Immediately after year 0, product similarity then rises sharply and continues to increase in years +1 to +3. These results are consistent with the predicted product-market convergence within the affected sectors following the common sectoral technology disruption. Notably, these results are compelling because the outcome variable is based on a completely different corpus (10-Ks) than that used to measure TSDs (patents), ensuring no mechanical link.

4 Economic Impact and Information Environment

In this section, we assess the extent to which technology sectoral disruptions are important and unexpected from the informational perspective of market participants and corporate managers. Our thesis predicts that TSDs generate substantial economic value, and our first objective is to use asset pricing tests to assess the magnitude of this value. Significant value creation would both motivate the use of TSDs to assess corporate finance policies (our measure would satisfy the economic relevance condition) and provide a second contribution in the form of novel evidence of predictable asset pricing returns. Our next section examines stock return predictability.

Our second, and perhaps more important, objective is to explore when market participants become aware of sectoral disruptions. If market participants only impound any newly created economic value into prices with material delay, then sectoral disruptions are unexpected and surprising from their perspective. Such a finding would have two implications. First, a delayed response would indicate return predictability that increases with lag. This would make a novel contribution to the asset pricing literature, as almost all anomalies exhibit return-prediction patterns that decay over time. Second, a finding of delayed reaction might indicate a clear ordering in time: when disruption occurs and when economic agents finally learn about it and can react by making corporate decisions. This is relevant to assessing the quality of identification when we later examine corporate finance outcomes in Section 5. We thus explore a wide array of lags to our disruption measure and assess how return predictability varies with the lag structure.

Our third objective extends this logic to firm managers themselves. We thus explore when insider trading activity becomes influenced by sectoral disruptions. If disruptions indeed create large economic value, then insiders would favor buying whenever they learn about a disruption. If insiders only react with significant delay, it would indicate that sectoral disruptions are unexpected from insider perspectives. This would also indicate a clear time-ordering of events, and corporate finance decisions would thus be a response to the event. This can further sharpen inferences in corporate finance tests. We thus explore a wide array of lags to our disruption measure and assess how insider trading activity varies with the lag structure. We also explore similar tests for analysts based on their forecasts to test for consistency between insiders and external agents, such as analysts. We present these results in the online appendix, as they represent validation tests that the TSDs are unanticipated.

We next examine whether TSDs are surprising and unanticipated. Information-gathering costs might be prohibitive, as these agents would need hyper-awareness of how firms in other industries are adopting technologies relative to those being developed by the focal firm. This requires the construction of data structures of nearly one hundred gigabytes in size and advanced language models. These factors suggest plausible frictions to price discovery and that market participants might learn about disruptions with material delay. On the other hand, market efficiency might be strong despite high information-processing costs because large, long-lasting trading profits are available to incentivize agents willing to process this data. Therefore, in this section, we examine whether TSDs are anticipated.

4.1 Sectoral Disruption and Stock Returns

We conduct calendar time portfolio analysis to examine the link between TSDs and ex-post $t+1$ monthly stock returns. Our portfolios are constructed only using information measurable as of month t, ensuring the tests are predictive. As we wish to control for other return predictors, we conduct calendar-time portfolio return analysis using the two-stage fully controlled approach from Fama (1976) and Back et al. (2015) that first runs standard monthly stock return Fama-MacBeth models as follows:

$$ret_{i,t+1} = \beta_1 Technology\ Sectoral\ Disruption_{i,t} + \beta_2 X_{i,t} + \epsilon_{i,t+1},$$

where $X_{i,t}$ is an array of control variables described in the last section, including the log book-to-market ratio, log market capitalization, profitability, investment, and past return from month $t-1$ to $t-11$. As we further predict differences for large vs small firms, we further interact our TSD variable in the above equation with small and large dummies giving us Disrupted x Small and Disrupted x Big Fama-MacBeth coefficients. As noted in Back et al. (2015), these Fama-MacBeth coefficients are zero-cost investible calendar time portfolios that load on small and large firm TSDs and that have zero exposure to all controls. We report the first stage Fama-MacBeth results in Online Appendix Tables B1 and B2. For all tests below, we report our main result calendar-time alphas estimated as the intercept from regressing the zero-cost portfolio returns on the Fama-French 5 factors from Fama and French (2015).

As a key objective is not only to understand the magnitude of return predictability but also the timing of when the market internalizes gains. We consider variations where we lag our key disruption measure by up to 36 months and lead up to 12 months. These tests illustrate the relationship between TSDs and market awareness.

Place Table V here

The results for TNIC-3 industries are presented in Table V. We report Newey-West t-statistics with two lags. The table shows that TSDs for small firms are only weakly significant around month zero at the time of measurement but then become reliably significant after 2 months. Significance levels then grow and reach a peak between 18 to 32 months and then experience some decline. Even though the requisite patents needed to compute sectoral disruption have become public by month t, the market only begins to significantly price the impact of TSDs months later. Results are long-lasting and remain significant for a protracted period. Broadly, these results suggest that the market does not immediately price TSDs, but does price their impact over a period of roughly 2-3 years. We also find that large firms also have positive but smaller returns from TSDs. The last column shows that the lower returns for bigger firms is either insignificant or borderline significant at the 10% level over time (small vs big differences are stronger for our longer sample of SIC-based TSDs reported next). These results suggest that small firms benefit most from TSDs and that larger firms also experience some gains.

Because the coefficients are standardized, we can interpret their magnitudes. The 24-month calendar-time returns of roughly 0.22 indicate an annualized return of roughly 2.6% when a small firm is in an industry with sectoral disruption 1 standard deviation above average. If we conservatively assume these returns persist for 2 years (our evidence suggests they persist longer), we can conclude that a 1-standard-deviation shift in sectoral disruption results in a 5% higher abnormal return in the future. Of course, one standard deviation shifts are commonplace, and these estimates would suggest that more interesting disruptions (of two to three standard deviations for example) would trigger abnormal returns of 10% to 15%. Because returns span multiple industries and tend to have compressed distributions due to diversification, it follows that such events are economically large and important. We thus conclude that sectoral disruptions satisfy the economic importance requirement for identification in our later corporate finance tests.

The finding that our coefficients on TSDs are significant with material lags is particularly novel from the perspective of the asset pricing literature. Most asset pricing variables, such as momentum, the value premium, and others, tend to be most significant immediately after measurement and then to decay over time. Our finding that a variable is not significant right after measurement, but becomes significant later, is a material finding that contributes to the asset pricing literature in a novel way that could support numerous future studies attempting to study the information environment in a setting where information that is measurable ex-ante is entirely (or close to entirely) unpriced. In our setting, this finding is important for a similar reason, as it supports the validity of the exclusion requirement from a corporate finance perspective. In particular, market participants initially appear unaware of sector disruptions, which are unexpected and plausibly exogenous shocks, and must then select an array of corporate finance policies to adapt to the shocks.

Place Table VI here

Table VI shows analogous results for SIC-code-based disruption. As noted earlier, although SIC codes are noisy, this measure has the advantage of being available starting in 1951, whereas the TNIC-based measure is only available in 1988 and later. For completeness, we thus show results for both TNIC and SIC. Table VI shows that disruption measures computed using SIC codes are quite similar to those computed using TNIC industries as displayed in Table V. In particular, we again observe a significantly delayed market reaction as SIC disruption grows in significance over the months after its measurement. Here we find some modest evidence of significance just prior to measurement, indicating some market awareness as patents are increasing in correlation. Yet overall the significance and coefficient magnitudes grow steadily from measurement to a maximum by 16 months. The maximum t-statistic of 5.36 is highly significant at the 1% level and the coefficient of 0.236 is more than twice the month-zero coefficient of 0.113.

Place Figure III here

We depict the overall pattern of delayed market reactions in Figure III. The figure plots the t-statistics for the small-firm calendar-time returns, using lags of up to 36 months for TNIC and SIC disruptions, from Tables V and VI. The graphs illustrate how clearly delayed and prolonged the market reaction to TSDs is, and that the extent of delay is notable for both TNIC and SIC disruptions. We note that beyond 36 months, these expected returns decay slowly, consistent with our thesis of wide-scale value creation and broader asset pricing findings that innovation-related returns are often very long-lasting (see Bena et al. (2024)).

Place Figure IV here

Figure IV plots the annualized return of our calendar time portfolios for small firms (the primary focus of our study) that invest in the SIC disruption (top figure) and TNIC disruption (lower figure) during our sample periods. As noted above, portfolio returns are computed using the optimized portfolio method as in Fama (1976) and Back et al. (2015). They are investible portfolio returns from the Fama-MacBeth slopes that have zero exposure to controls but one unit of exposure to TSDs. These are the calendar time returns indicated by the results in Tables V and VI for small firms. Because monthly returns are noisy, the displayed returns are smoothed, and the returns for each year t are the average over the five-year rolling window from $t-2$ to $t+2$. The figures illustrate that both disruption portfolios produce reliably positive returns as neither is below zero for any material period of time. Moreover, the longer horizon SIC-based figure illustrates that sectoral disruptions are quite frequent since 1951 and our results are not driven by any one time period.[5]

The figures also show that disruption returns are higher during innovative periods, such as the 1990s, when the internet boom was disrupting industries, and post-2011 for TNIC disruption, as artificial intelligence and big data, for example, became disruptive. SIC industries also show some elevation in returns during the mid-1970s and early 1980s. Overall, results differ in some cases between SIC and TNIC disruption. This is likely because TNIC industries are particularly good at modeling technology industries (see Hoberg and Phillips 2016), and SIC industries, while noisy, are best for modeling manufacturing or older sectors.

[5] Our predictable returns also remain robust if we drop the tech boom period from 1990 to 2001.

We conclude this section by examining whether the results differ under the Q-5 factor model of Hou et al. (2015) rather than the Fama-French-5 factor model. In the Online Appendix Tables B1 and B2, we rerun Tables V and VI using the Q-factor model and find similar results.

Overall, our findings of a strong positive impact for small firms and a much less significant impact for large firms are robust. We conclude that small firms benefit significantly from TSDs and that large firms generally do not; moreover, investors are surprised by TSDs and realize these gains only with significant delay after TSDs become measurable.

4.2 Sectoral Disruption and Insider Trading

We conduct Fama and MacBeth (1973) monthly regressions in which the dependent variable is the ex-post net insider trading activity of high-ranking insiders (top 5 executives for each firm) in month $t + 1$. Please see Online Appendix C regarding how we compute net high-ranking insider trading intensity. We focus on high-ranking insiders both because the literature supports their trades as more informative and because they are the very individuals who make corporate decisions (examining influences on corporate decisions is a primary objective of our paper). Our right-hand-side variables are all measurable as of month t, ensuring the absence of look-ahead bias. Our key RHS variable of interest is sectoral disruption. We thus consider the following Fama-MacBeth specification that is parallel to how we examine stock returns in the previous section ($insider_{i,t+1}$ is net high-ranking insider trading activity):

$$insider_{i,t+1} = \beta_1 Technology\ Sectoral\ Disruption_{i,t} + \beta_2 X_{i,t} + \epsilon_{i,t+1}, \tag{6}$$

where $X_{i,t}$ is an array of control variables described in the last section on return predictability.

As we did for stock returns, we both assess predictability associated with sectoral disruptions, but also the timing of when insiders trade to internalize gains. We consider variations where we lag our key disruption measure by -12 to 36 months. These tests illustrate the relationship between sectoral disruptions and the timing of insiders' awareness, which is important for identification in our later corporate finance tests. As insider trading data is quite thin for smaller firms, we do not break out the insider trading tests for large versus small firms and focus on overall results to identify the timing of information arrival with adequate power.

In the interest of space, and given that these results are examined to validate that the TSDs are not anticipated, we present and describe these results in the Online Appendix C. The results show that insider trading only occurs significantly after our dating of the initial identification of the TSDs. The results for both TNIC-3 and SIC-3 disruptions presented in Appendix Table C1. The results show the following (1) TNIC disruption predicts significant and long-lasting positive insider trading pressure consistent with large amounts of economic value created. (2) This predictability is significantly lagged and only becomes significant a full 12 months after measurement, and then increases further through month 32 before reaching a peak. (3) The results for TNIC are significantly stronger than those for SIC-based industry classifications.

In Online Appendix D, we also present results for analyst forecast errors and document similar results. In particular, analysts also initially make predictable forecast errors indicating that, like insiders, they also find TSDs to be surprising and unexpected.

5 Disruption and Firm Corporate Finance Decisions

In this section, we explore the consequences of technology sectoral disruption on important ex-post outcomes, including investment, restructuring, performance, and valuation. We thus use our Compustat-based firm-year database, and we denote our dependent variable of interest as $Y_{i,t}$ for firm i in year t. Our baseline regression model is:

$$Y_{i,t+1} = \beta_1 * Disruption_{i,t} \times Small_{i,t} + \beta_2 * Disruption_{i,t} \times Large_{i,t} + \beta_3 * Small_{i,t} + \beta_4 * X_{i,t} + \mu_i + \delta_t + \epsilon_{i,t} \tag{7}$$

The variable $Small_{i,t}$ is a dummy equal to one if the given firm has below median assets in year t. $X_{i,t}$ is a vector of controls (1/size and log age) and μ_i and δ_t are firm and time fixed effects. Our primary object of interest is the difference between β_1 and β_2, which captures the differential effect of disruption on small versus large firms. We report β_1 and β_2 separately to also characterize the effects of disruption on small and large firms, respectively.

In our regressions, we drop focal firms with breakthrough patents as listed in Kelly et al. (2021). This reduces concerns that the results are driven by a few firms that are truly innovative. In the Internet Appendix, we also report results after dropping firms that had at least one patent in the past ten years that went on to be among the top 10% most-cited in their cohort year. The results are robust. Our variables are also winsorized at the 2.5% level to reduce the impact of outliers.

As illustrated in the previous section, our sectoral disruption variable significantly predicts stock returns and insider trades, and with a delay. These results suggest that our disruption variable is economically important and also that its influences are unexpected ex-ante by corporate decision-makers. This feature enables us to examine the primary impacts of disruption across the broad set of outcomes we explore and interpret them through the lens of dynamic managerial strategies as managers become aware of the TSDs. The results can inform academics, practitioners and students alike regarding how firms manage the complex process of internalizing disruptions in contested markets.

5.1 Timing of Corporate Policy Changes and Major TSDs

In this section, we assess corporate strategies by conducting event-time analysis of corporate decisions following major TSDs. We define major TSDs as we did in section 3.2.1 where we examined validation and expected product similarity increases. This approach develops 7-year event windows (3 years ex-ante and 3 years ex post) that leverage within-firm variation with observable "start dates" for TSDs (denoted as year zero). This approach ensures we focus on major, long-lasting sectoral disruptions, as with the internet boom of the late 1990s and the current AI boom. We run regressions with firm and year fixed effects as shown in equation (8), where a given corporate finance policy variable is the dependent variable.

$$y_{i,t} = \alpha_0 + \sum_{t=-3}^{3} (\gamma_t Disrupted_{i,t} * Small_{i,t} * D(t) + \beta_t Disrupted_{i,t} * Large_{i,t} * D(t) + \mu_t Small_{i,t} * D(t)) + \delta_t D(t) + \theta_t Disrupted_{i,t} + \sigma_t Small_{i,t} + \mu_i + \psi_t + \epsilon_{i,t} \tag{8}$$

$D(t)$ is a dummy variable taking the value of one if the year of observation is t (relative to the reference year zero). We omit the t=0 event-time dummy so all coefficients can be interpreted relative to the treatment year t=0. We then plot the estimated small–large differential treatment effect, $\gamma_t - \beta_t$, for each event year $t \in \{-3, -2, -1, 1, 2, 3\}$. This approach normalizes the omitted year $t = 0$ impact to zero for clarity of comparison. We plot the series over the full event window from $t - 3$ to $t + 3$.

Our thesis is that each corporate policy variable will follow a flat trajectory over the three ex-ante years and then undergo a structural break after event-year zero. The lag from year zero to observed managerial actions can vary across policies, as agents likely internalize disruptions gradually over 1-3 years after they become visible. We plot point estimates together with confidence bands based on t-tests of the null hypothesis $H_0: \ \gamma_t - \beta_t = 0$ for each $t \neq 0$ (with $\gamma_0 - \beta_0$ normalized to zero).

This trend analysis complements the main full-sample regressions we report below. Since the sample used in the above trend analysis focuses only on major TSDs, as we need an identifiable starting year, we note that the regressions below might not have similar year-by-year interpretations relative to a treatment year. Notwithstanding that, we find that the trend analysis mostly aligns with the full-sample regressions we report next.

5.2 R&D and Acquisitions

In this section, we explore the impact of sectoral disruptions on R&D and restructuring outcomes using the baseline model in equation (7), and Table VII presents the results. Columns (1), (2), (3), and also (4), (5), (6), present regressions where dependent variables are at time *t+1*, *t+2*, and *t+3* outcomes, respectively. Disruptions are ex ante measured at time *t*. Specifications in columns (1)–(3) use the SIC-based disruption measure, and columns (4)–(6) use the TNIC-based measure.

We report results for R&D/assets in Panel A, and acquisitions/assets in Panel B. The lower part of the table reports economic magnitudes for small and large firms, computed as $\beta_{Disrupted \times Small} \times \Delta Disrupted$ and $\beta_{Disrupted \times Large} \times \Delta Disrupted$, respectively. $\Delta Disrupted$ is the interquartile range of *Disrupted* (75th minus 25th percentile).

Place Table VII here

Panel A shows that sectoral disruptions are followed by increases in R&D investment for small firms and decreases for large firms. These effects are strongest using the TNIC disruption variable in columns (4) to (6), where the small-firm coefficients are significant at the 1% level in all three years, with *t*-statistics ranging from 3.0 to 3.4. The increases in R&D for small firms are sustained over the three-year period for the TNIC measure, although they gradually decline to 55% of the initial value by the final year. The SIC small-firm coefficients are weaker, significant only at the 10% level in the first year and insignificant thereafter, consistent with the TNIC classification's strength in modeling technology sectors (Hoberg and Phillips (2016)). The large-firm coefficients are negative and significant at the 5% level in all years for both measures. In economic terms, in year $t+1$, an IQR increase in TNIC disruption implies a 5.6% increase in R&D for small firms and a 3.1% decrease for large firms relative to the respective group means (0.0763 and 0.0409). The increases in R&D for small firms and decreases for large firms are consistent with Schumpeter's 1912 theory of creative destruction and Arrow's 1962 replacement theory, which hold that innovation arises from small firms.

Panel B indicates that disruption is followed by increases in acquisition activity among small firms that emerge with a delay. For the SIC measure, the small-firm coefficient is significant only in the third year (at the 1% level), with the first two years insignificant. For the TNIC measure, the small-firm coefficient is significant in all three years, at the 5%, 1%, and 10% levels, respectively. Economically, in year $t + 3$, an IQR increase in SIC disruption implies a 10.3% increase in acquisitions relative to the sample mean for small firms (0.0279). The effect is driven largely by acquisitions of private target firms by public companies (88.1% of transactions), consistent with Phillips and Zhdanov (2013). Overall, the results align with the view that disruption reallocates assets toward new best owners as firms adjust desired asset composition.

Place Figure V here

Using the sample of major TSDs with a known event date identified in Section 5.1, we next plot event-time results. Figure V plots event-time differences between small and large firms (small minus large) around the disruption year zero for R&D intensity and acquisition intensity, both scaled by lagged assets. In the pre-period, both series are close to zero, indicating limited differential trends before the disruption. After year 0, the R&D/Assets gap turns sharply positive in year +1 and continues to rise through years +2 and +3. Small firms thus increase R&D spending more than large firms in the post-disruption period, consistent with Schumpeter (1912) and Arrow (1962).

The Acquisitions/Assets gap reacts with a one-year delay: it first dips insignificantly in year +1, but then increases sharply in years +2 and +3 as small firms spend significantly more on acquisitions. Overall, the figure suggests that disruptions trigger a reallocation in dynamic corporate policies toward small firms, which persistently ramp up both R&D (immediately) and acquisitions (with a one-year delay). The lag in acquisitions relative to R&D echoes the life-cycle ordering, favoring organic investment before acquisitions, as reported in Hoberg and Maksimovic (2022).

5.3 Investments and Assets Growth

We now examine capital expenditures and asset growth using the same regression framework as above. Table VIII displays the results. We find significant increases in capital expenditures for small firms using the SIC measure in all years. The TNIC small-firm coefficients are positive but not individually significant, although the small-minus-large difference is significant in all years for both measures. An IQR increase in SIC disruption yields a 10.5% increase in capital expenditures in the first year. Large firms experience decreases or an insignificant impact. The difference between small and large firms is significant in all years.

Place Table VIII here

Consistent with the CAPX results, TSDs also induce higher asset growth for small firms and lower asset growth for large firms. In the first year ex post, an IQR increase in disruption is associated with a 5.5% increase in asset growth for small firms and a 14.9% decrease for large firms. The small-minus-large difference is significant in all years for both SIC and TNIC-based measures. The small-firm coefficients are significant in all years under SIC and in the second and third years under TNIC, while the large-firm coefficients are significant in all years under TNIC and in the first year under SIC. The magnitude for large firms decreases in each year, declining to 3.8% by year 3.

Place Figure VI here

Figure VI plots the corresponding event-time dynamics for the small-minus-large firm difference. The upper panel shows that CAPX is essentially flat (and slightly declining) in the pre-period, indicating little evidence of pre-trends. The impact turns positive after year zero, especially in years +2 and +3. The lower panel reports results for asset growth, which declines slightly in the years leading up to year 0. It then jumps sharply in year +1 and continues to rise in year +2, and then levels off at the higher level in year +3. Taken together, for small firms, TSDs are followed by a sustained balance sheet expansion in which firms scale up quickly, consistent with investments to harvest new time-sensitive growth opportunities arising in the post-disruption environment.

5.4 Valuation and Sales

We now examine valuation and sales growth using the same regression framework as above. Table IX reports the results.

Place Table IX here

Panel A shows valuation gains for small firms following TSDs that are concentrated in the TNIC measure. For TNIC disruption, the small-firm coefficients are significant at the 5% level in the first year and at the 1% level in the second and third years, and the small-minus-large difference is significant at the 1% level in all three years. For SIC disruption, the small-firm coefficients are positive but not individually significant, and the small-minus-large difference is insignificant in the first year, significant at the 10% level in the second year, and at the 5% level in the third year. In economic terms, in the first year, an IQR increase in TNIC disruption implies a 2.6% increase in M/B for small firms. The large-firm coefficients are negative across both measures but are not statistically significant. Consistent with previous sections, we conclude that the valuation gains accrue to smaller firms.

Panel B shows that increases in sales growth come with some delay. For small firms, sales growth becomes positive and significant in years two and three for SIC disruptions and in year three for TNIC disruptions. These delays are intuitive as firms likely need to internalize and commercialize new technologies. By the third year, an IQR increase in disruption yields a 7.8% increase in sales growth for small firms. In contrast, large firms experience a 7.7% decrease in the first year, with an IQR increase in disruption. However, the magnitude decreases in the following years.

Place Figure VII here

Figure VII plots the corresponding event-time dynamics for the small-minus-large firm difference. Both M/B and sales-growth results are roughly flat before year 0, suggesting little evidence of pre-trends. After the disruption, M/B differences jump in year +1 and continue rising through years +2 and +3, indicating a strong shift in valuation toward small firms as investors price new growth options and/or improved expectations for performance relative to large firms. This aligns with our asset-pricing results as small firms also earn higher abnormal returns. The results for sales growth turn positive after the disruption, increase for 2 years, and then ease in year +3. The figures overall suggest that the disruption disproportionately benefits small firms in valuation and performance, consistent with the higher abnormal returns we reported earlier.

5.5 Patent Valuation and Trade Secrets

Table X uses similar panel data regressions to explore TSD impacts on KPSS patent valuations (Panel A) and trade secrets (Panel B).

Place Table X here

Panel A shows strong increases in KPSS patent valuations for small firms. All estimates are statistically significant at the 1% level for both SIC and TNIC for all years. In the first year, an IQR increase in TSDs results in an 88% increase in patent valuations for small firms. Large firms experience declines in patent valuations as a similar exposure yields a 21% decrease. These findings are consistent with small firm agility and generating higher value innovations following TSDs while large firms likely continue to focus on preserving/adapting legacy technologies.

Panel B shows that small firms increase their reliance on trade secrets relative to large firms. Under the SIC measure, the small-minus-large difference is significant at the 1% level in all three years, although neither the small-firm nor the large-firm coefficient is individually significant. Under the TNIC measure, the small-firm coefficients are significant in all three years, at the 1%, 5%, and 1% levels, and the small-minus-large difference is significant in the third year. Based on the SIC point estimates, small firms experience a 1.6% increase in trade secrets in the first year, while large firms experience a 0.9% decrease.

Place Figure VIII here

Figure VIII plots the corresponding event-time dynamics for the small-minus-large firm difference. We observe post-disruption strengthening in both the economic value of patents and the use of trade secrets for small firms. The upper panel shows that KPSS valuations are essentially flat in the pre-period, indicating little evidence of pre-trends, but valuations then rise sharply in the first year and continue to increase through years +2 and +3. The lower panel shows an analogous pattern for trade-secret intensity, with the strongest growth in later years. Overall, TSDs increase both the expected payoff to innovation (higher post-patent valuations) and the incentives to protect proprietary knowledge (greater reliance on secrecy). The increased secrecy likely reflects a more competitive, uncertain environment and a need to preserve first-mover advantage.

5.6 Mechanisms Facilitating TSD Success

Thus far, we have focused on the comparison between small and large firms. We now explore a broader array of theoretically motivated firm characteristics to further characterize firm reactions to TSDs. We consider subsamples based on firm age, industry market share, organizational capital, and corporate liquidity measured using cash/assets. Each is motivated, respectively, by hypotheses rooted in agility, industry leadership, organizational capability, and financial constraints. We now rerun our baseline regressions and report the difference in coefficients between the high and low groups for each variable.

Place Table XI here

The first column shows our baseline results for high vs. low firm Assets and repeats our main findings: disrupted small firms increase all forms of investment, perform better, innovate more, and become more secretive. Small firms are thus more successful at internalizing the benefits and growth options associated with TSDs.

The next two columns show similar, though somewhat weaker, positive results for young firms and firms with lower industry market shares. Firms with lower market shares experience material boosts in investment, performance, innovation, and secrecy. Younger firms experience analogous boosts but with significantly weaker magnitudes and significance levels. These results mainly indicate intuitive robustness with respect to measures of firm size and suggest that younger firms realize modest gains relative to older firms in the face of disruption.

In contrast, the signs of most coefficients flip to negative when we consider organizational capital, and coefficients lean negative but are much weaker for cash/assets. As our coefficients reflect the differential impact of "low minus high," the negative coefficients indicate that high-organizational-capital firms and high-cash firms tend to outperform in TSDs with higher investment, growth, valuation multiples, and innovation success. The strong results for organizational capital underscore the importance of internal capabilities in capturing new growth opportunities. The results for cash/assets suggest that financial slack is also helpful, but to a lesser degree. Overall, small firms with less prior investment in older legacy assets and with excellent organizational capabilities are best positioned to succeed in TSDs.

5.7 Robustness to the Number of Peer Industries

Our baseline SIC disruption measure aggregates pairwise disruption scores over the three most ex-ante similar SIC-3 industries for each focal industry. A natural question is whether our results are sensitive to the choice of three peer industries. Table XII examines robustness to using $N \in \{3, 5, 10\}$, and re-estimating the small versus large panel regressions in equation (7) for all outcomes. For each outcome and each neighbor count, we report $\hat{\beta}_1$ (*Disrupted* $\times$ *Small*), $\hat{\beta}_2$ (*Disrupted* $\times$ *Large*), and their difference.

We find strong robustness across all three peer count specifications for nearly every outcome. As we widen the aggregation from three to ten peer industries, the coefficient magnitudes decline in a fairly orderly way. This is intuitive, as adding less related industries to the value-weighted sum dilutes the disruption signal that is concentrated among a firm's closest sectoral peers. For example, the R&D/Assets difference in year $t+1$ falls from 3.221 under the baseline to 2.229 with five neighbors and to 1.173 with ten. The asset growth difference falls from 9.478 to 6.390 to 3.053 over the same progression.

Place Table XII here

Although the coefficients shrink as more industries enter the calculation, the statistical significance of the small-minus-large difference is preserved and, in several cases, strengthens. The capital expenditure, KPSS patent valuation, sales growth, and asset growth differences are significant at the 5% level or better under all three neighbor counts, and the KPSS difference is significant at the 1% level throughout. The valuation (Tobin's Q) results are especially telling. The year $t+1$ difference is insignificant under the three-neighbor baseline (141.107, with a t-statistic of 1.56), but becomes significant at the 10% level with five neighbors and at the 1% level with ten neighbors.

The improvement in significance as N grows is consistent with the wider aggregation reducing idiosyncratic noise in the SIC-based measure, which we have noted is less precise than the TNIC measure. The one outcome that weakens materially is trade secrets, where the year $t+1$ difference loses significance at ten neighbors, although the second- and third-year differences remain significant.

Acquisitions are insignificant in the first year across all specifications, consistent with the delayed acquisition response documented earlier. Taken together, the table indicates that our baseline three-neighbor choice is conservative with respect to statistical inferences, and that the central finding that small firms capture the gains from TSDs while large firms retrench does not depend on the number of peer industries.

6 Conclusions

This paper studies large technology sectoral disruptions (TSDs) over a 70-year period and develops a method to identify them using patent texts. We define TSDs as episodes in which innovation becomes highly correlated across multiple related industries, reflecting the emergence of broad technological waves rather than changes confined to a single industry. While recent examples include the internet, fintech, and artificial intelligence, the evidence shows that sectoral disruptions recur throughout the sample period and are persistent.

The paper introduces an ex ante measure of sectoral disruption based on comovement in the text of patent portfolios. By modeling textual similarity in innovation across industries, the measure identifies periods of coordinated technological change using publicly available data. Validation exercises based on historical breakthrough patents and subsequent increases in product market similarity indicate that the measure captures economically meaningful episodes of technological convergence.

We find that TSDs are associated with sizable economic effects that are incorporated into prices only gradually. Stock returns, insider trading, and analyst forecasts respond with a delay, indicating that these events are not immediately reflected in market expectations. Return predictability associated with TSDs increases over time and persists for several years, suggesting that information diffusion related to sectoral technological change is slow.

The delayed recognition of TSDs allows us to examine how firms adjust to technological change. Corporate responses differ sharply across firms. Small firms increase R&D and capital expenditures shortly after disruptions occur and subsequently expand through acquisitions. These actions are followed by higher growth, higher valuation multiples, increases in patent values, and greater reliance on trade secrecy. Large firms reduce R&D, experience weaker growth, and show weaker valuation and innovation outcomes relative to small firms, consistent with higher adjustment costs and incentives to maintain existing assets.

Event-time analyses indicate a systematic ordering of responses. Increases in organic investment precede acquisition activity, while improvements in sales and performance occur later. The effects are stronger among firms with higher organizational capital and, to a lesser extent, higher liquidity. Firm age and market share also matter, though firm size accounts for most of the observed heterogeneity.

Taken together, the results are consistent with a process of creative destruction in which sectoral technological change reallocates growth opportunities to smaller, more adaptable firms. Innovation following major technological shifts is concentrated among firms with fewer legacy rents at stake. The empirical framework developed here provides a way to study economy-wide technological change and its implications for firm behavior and asset prices using observable innovation data.

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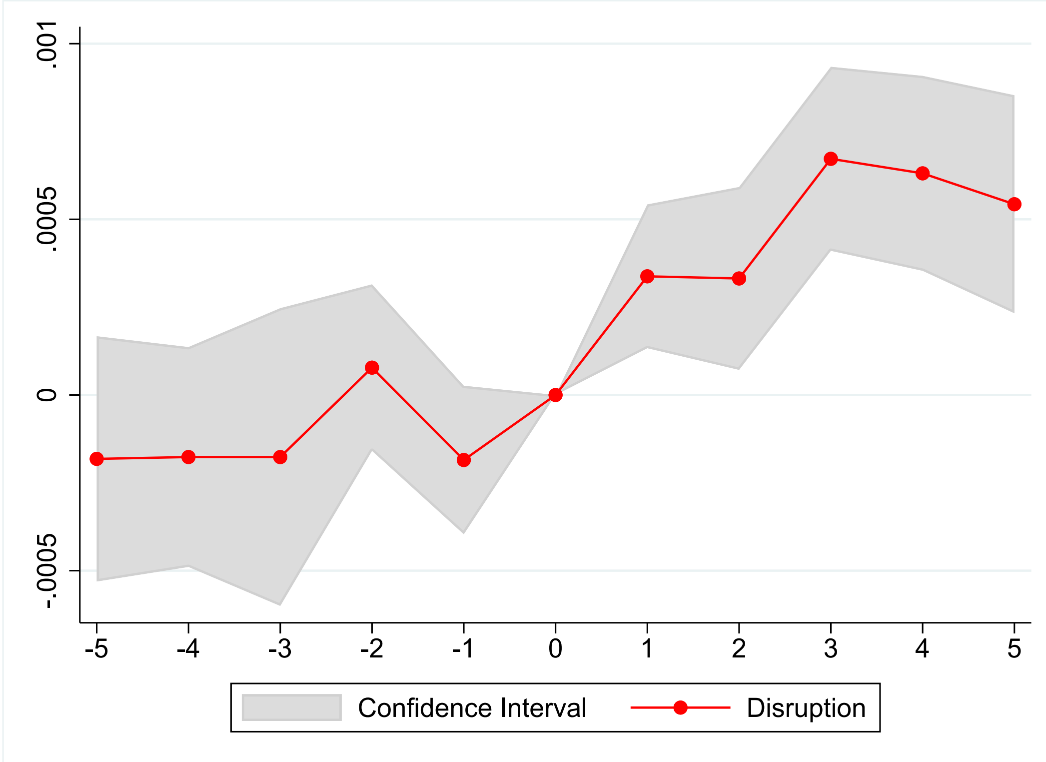


Figure I
Disruptions Around Breakthrough Innovations

This figure presents the relation of the disruption measure around breakthrough inventions, which are gathered from Appendix A of Kelly et al. (2021). In this figure, the estimates are from a regression in which the dependent variable is a three-digit SIC-based disruption measure, and the independent variables are indicator variables for the number of years from the breakthrough patent's grant, ranging from -5 to +5 years. The specification also includes two-digit industry fixed effects. The reference year, 0, is the year the breakthrough patent was granted.

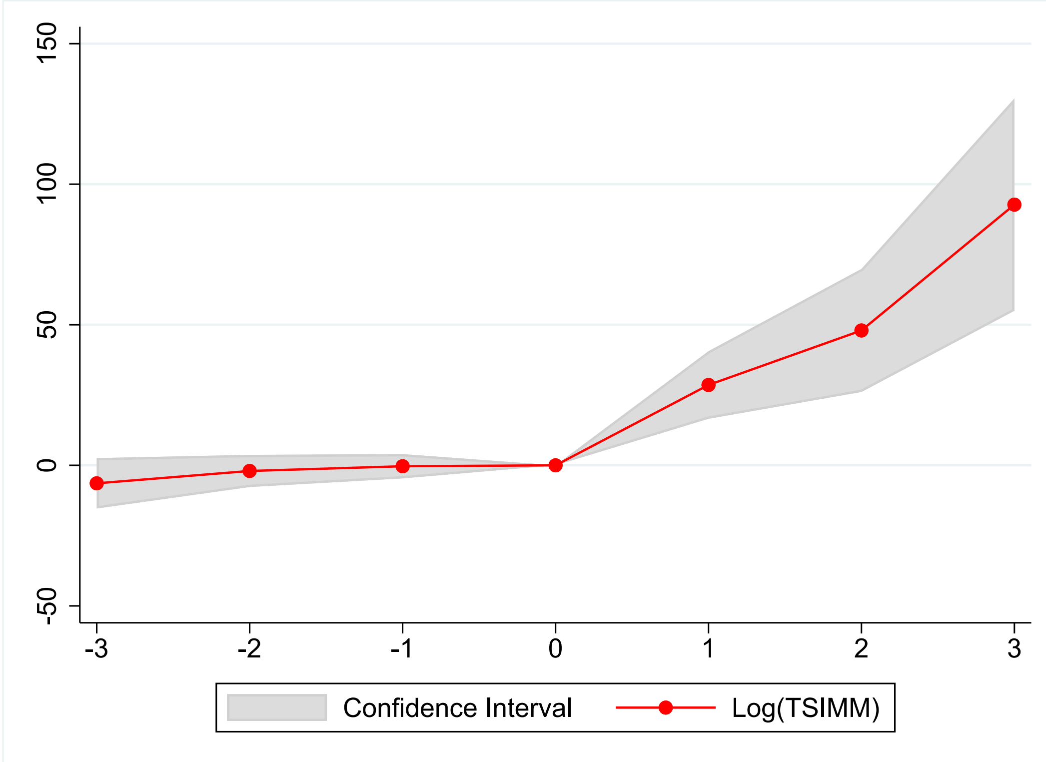


Figure II
Disruptions and Product Similarities

This figure presents the relation of product similarities around major disruptions. To define a major disruption, we assess timing using a 7-year window that leverages within-firm variation. We consider three years preceding event year zero, and three years ex-post. First, for each firm in our sample, we identify the year in which the firm's average disruption from year t to t+3 minus its average disruption from year t-3 to t-1 experiences its largest increase among all years the firm is in our sample. We deem this year to be event year zero. Second, we require that disruption monotonically increases from year zero to year three. This final step ensures we focus on major, long-lasting sectoral disruptions.

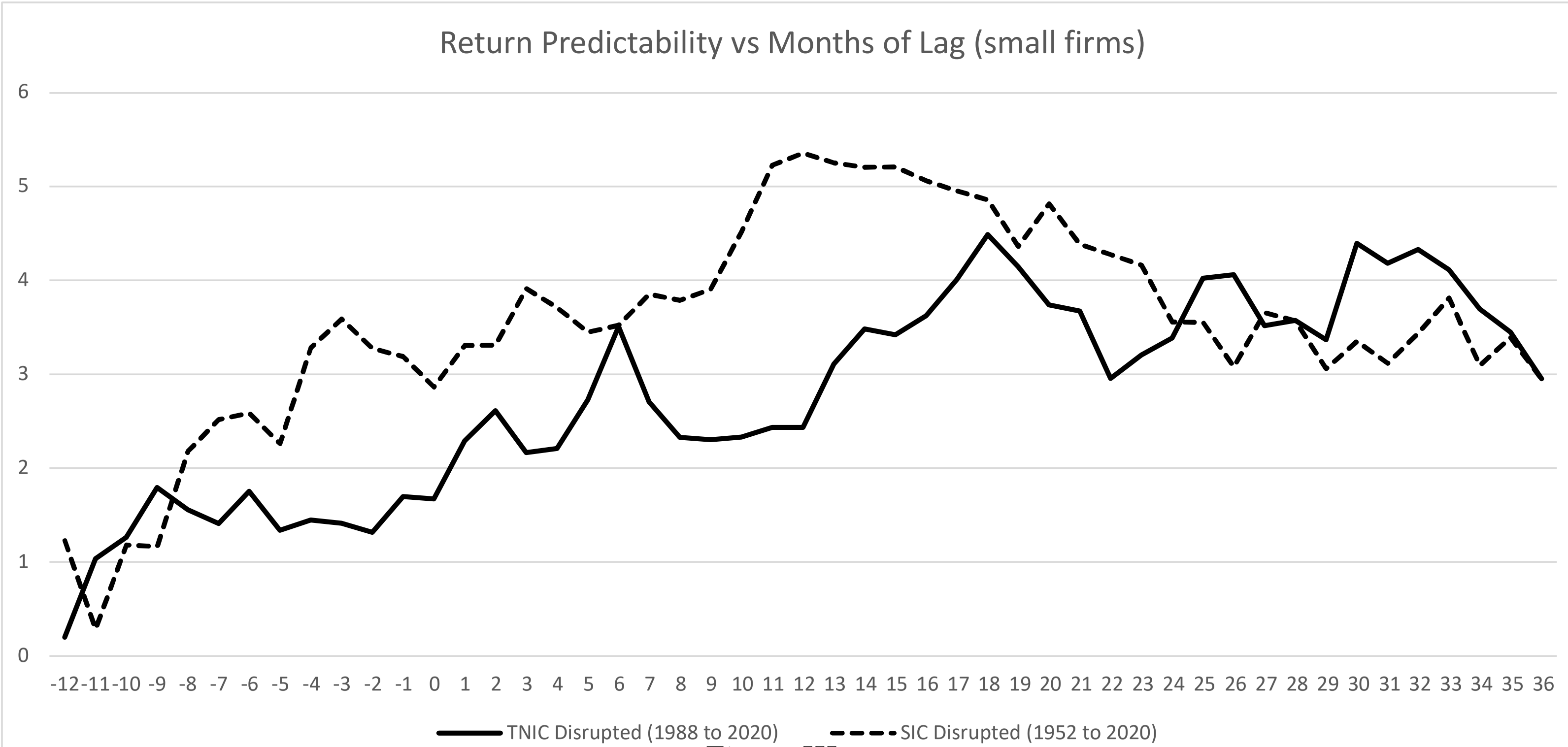


Figure III

Asset Pricing Signal versus Months of Delay

The figure plots the significance of return predictability (alphas based on the Q-factor model) for investible calendar time portfolios consisting of small firms for lags of up to 36 months for TNIC disruption and SIC disruption. Calendar time portfolio alphas reflect the rightmost columns in Tables V and VI and are computed using the optimized portfolio method as in Fama (1976) and Back, Kapadia and Ostdiek 2015 as the time series slopes (gammas) from the Fama-MacBeth regressions with calendar time controls for the Fama-French 5-factors from Fama and French 2015 included. We first run Fama-MacBeth regressions in which the dependent variable is the monthly stock return in month $t = 0$. We include TSD terms for both large and small firms and controls as indicated in Tables V and VI. We then run the same regressions but we lag our key variable "Disrupted" up to 36 months. For each lag, the figure below plots the magnitude of the small firm calendar time return alpha t-statistic versus the number of months of this lag of the disruption period (this t-statistic tests if the small firm calendar time portfolio alpha is different from zero). A t-statistic in excess of 2.0 indicates significant predictability when the TSD variable is lagged as indicated on the x-axis.

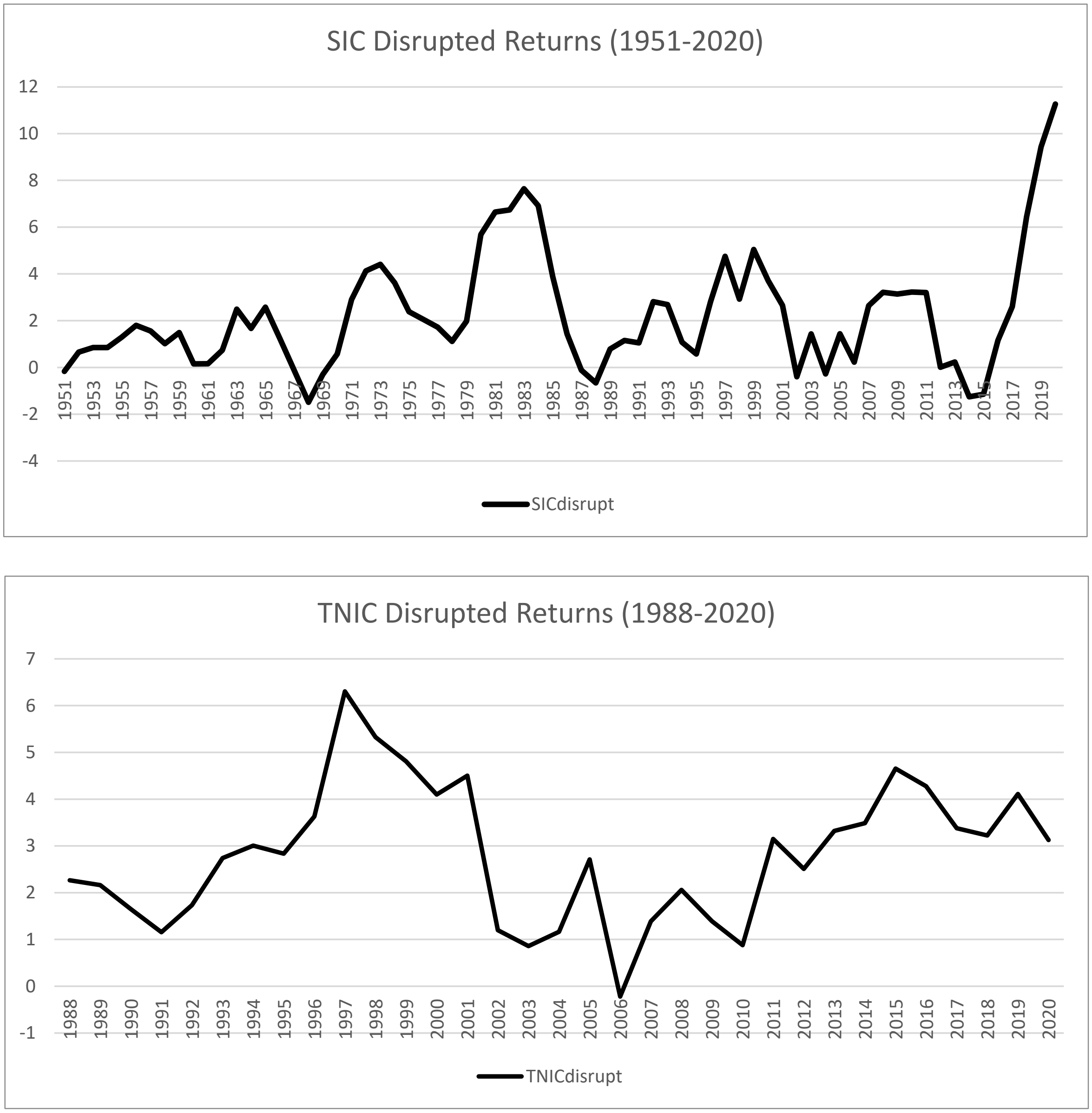
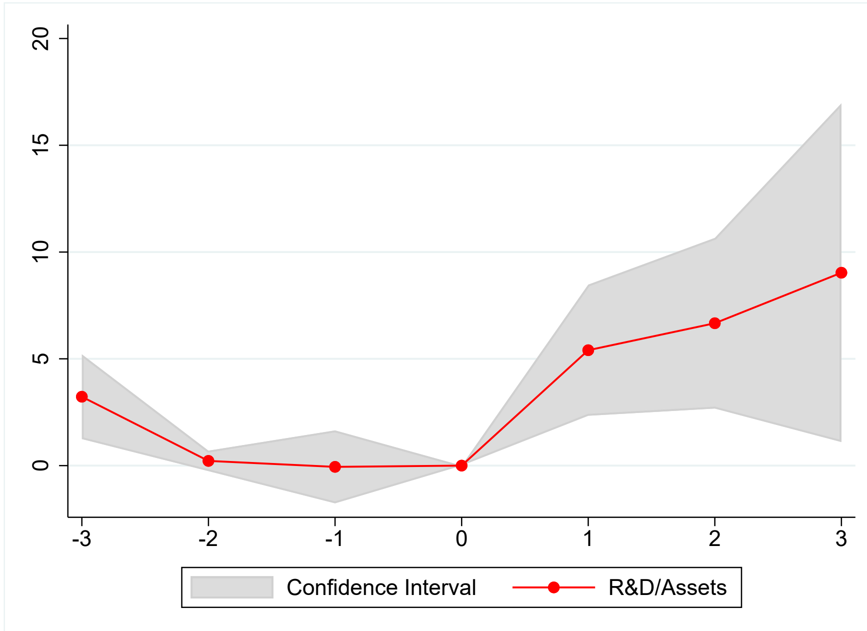


Figure IV
Asset Pricing Signal Over Time

The figure plots the annualized calendar-time return of portfolios of small firms that invest in the SIC disrupted variable (top figure) and the TNIC disrupted variable (lower figure) over our sample period. Calendar time portfolio alphas reflect the rightmost columns in Tables V and VI and are computed using the optimized portfolio method as in Fama (1976) and Back, Kapadia and Ostdiek 2015 as the time series slopes (gammas) from the Fama-MacBeth regressions with calendar time controls for the Fama-French 5-factors from Fama and French 2015 included. We use a benchmark model with 18 months of lag given the delayed market response. Displayed returns are smoothed to illustrate broad trends over time (the displayed return in each year t is the average of the five year rolling window from $t-2$ to $t+2$). We also note that both SIC and TNIC returns remain significantly different from zero if we drop the tech boom period from 1990 to 2002.



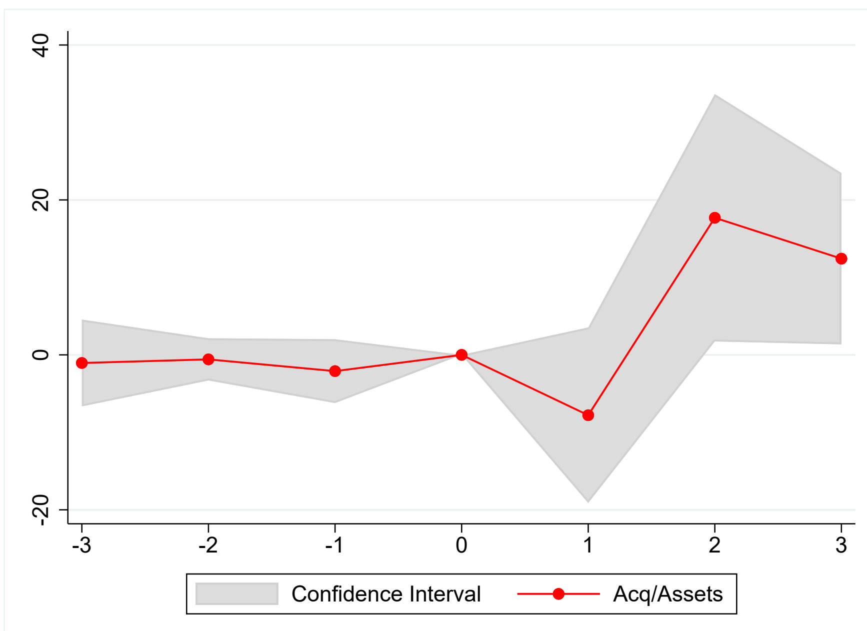
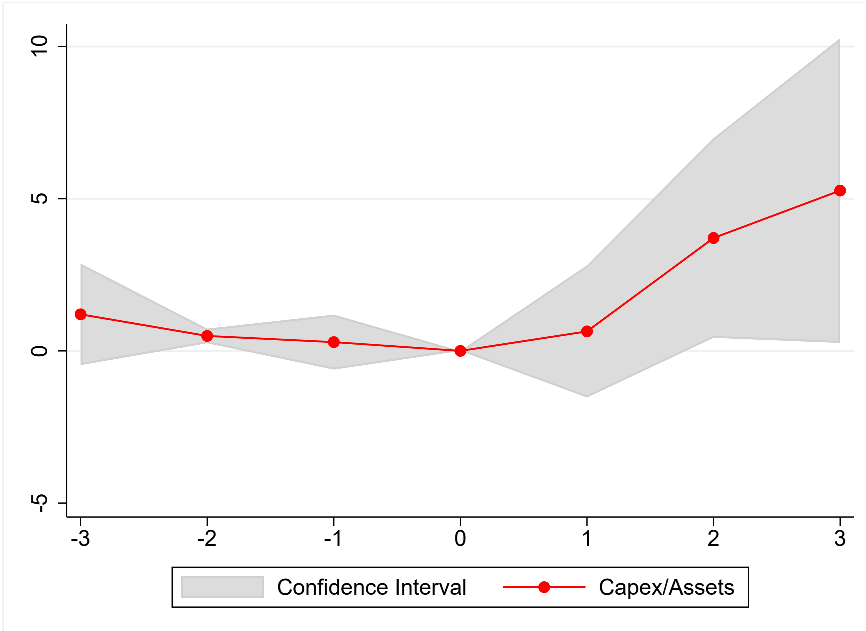


Figure V

Disruptions, R&D and Acquisitions: Difference Between Small and Large Firms

This figure displays the yearly trends for the difference between small and large firms around major disruptions for R&D in the first graph and acquisition investments in the second graph. For each firm in our sample, we identify a year as a disruption year if: the firm's average disruption from year t to $t+3$ minus its average disruption from year $t-3$ to $t-1$ experiences its largest increase among all years the firm is in our sample, and the disruption monotonically increases from year zero to year three. Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.



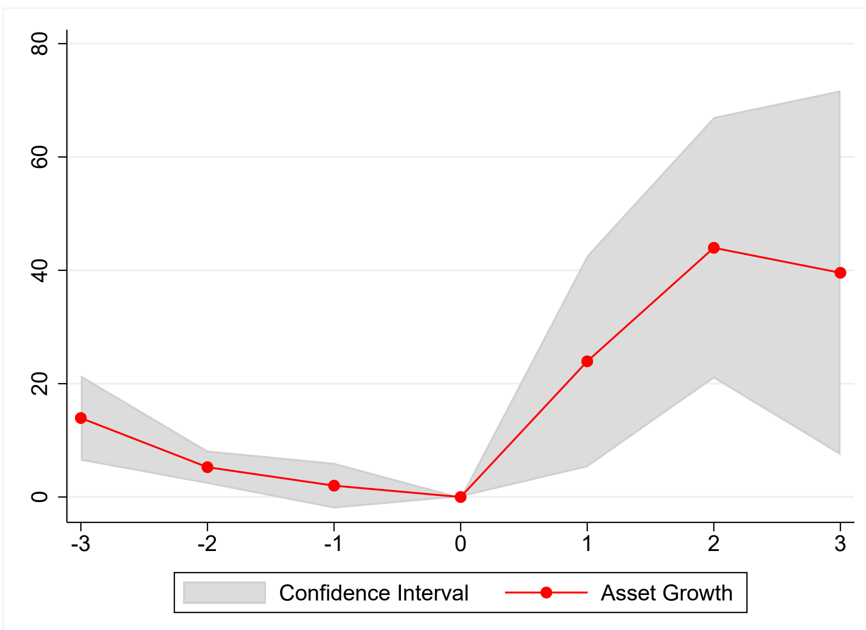


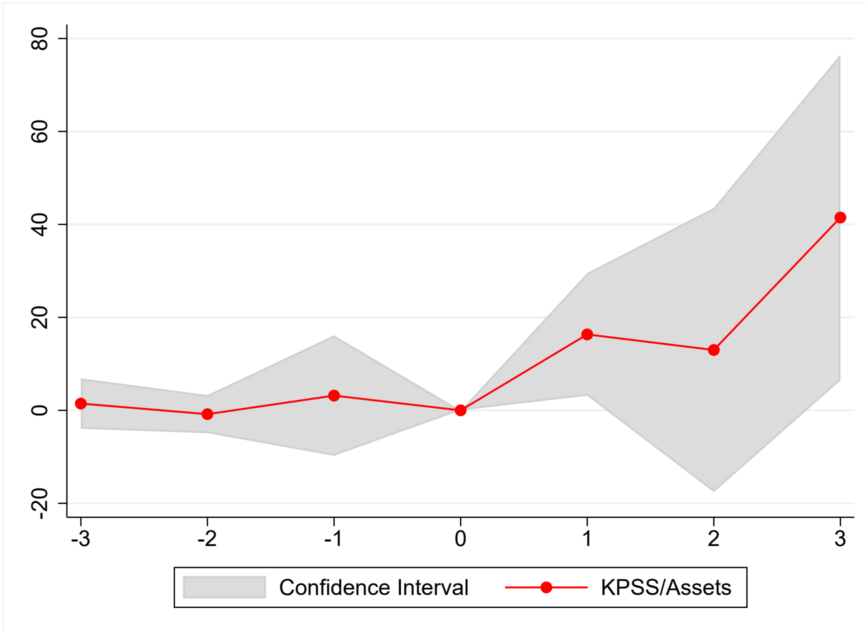
Figure VI
Disruptions, Capital Expenditures and Assets Growth: Difference Between Small and Large Firms

This figure displays the yearly trends for the difference between small and large firms around major disruptions for capital expenditures (1st graph) and asset growth (2nd graph). For each firm in our sample, we identify a year as disruption year if: the firm's average disruption from year t to $t+3$ minus its average disruption from year $t-3$ to $t-1$ experiences its largest increase among all years the firm is in our sample, and the disruption monotonically increases from year zero to year three. Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.

Figure VII

Disruptions, Valuation, and Sales Growth: Difference Between Small and Large Firms

This figure displays the yearly trends for the difference between small and large firms around major disruptions for market valuation / book equity valuation in the first graph and sales growth in the second graph. For each firm in our sample, we identify a year as disruption year if: the firm's average disruption from year t to $t + 3$ minus its average disruption from year $t - 3$ to $t - 1$ experiences its largest increase among all years the firm is in our sample, and the disruption monotonically increases from year zero to year three. Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.



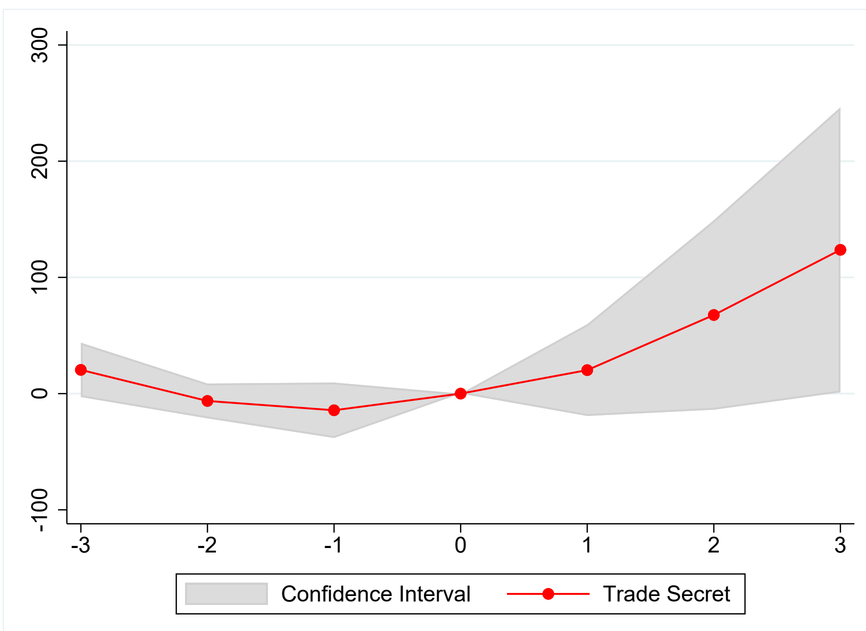


Figure VIII
Disruption, Patent Valuations and Trade Secrets: Difference Between Small and Large Firms

This figure displays the yearly trends for the difference between small and large firms around major disruptions for patent valuation from Kogan et al. (2017) in the first graph and trade secrets in the second graph. For each firm in our sample, we identify a year as disruption year if: the firm's average disruption from year t to $t+3$ minus its average disruption from year $t-3$ to $t-1$ experiences its largest increase among all years the firm is in our sample, and the disruption monotonically increases from year zero to year three. Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.

Table I:
Most Relevant TNIC Sectoral Disruption Firms by Decade

Year	Disrupt	Firm	Co-Disruptors
			1988-1989 Disruptions
1989	2.21	Sunoco	Dupont De Nemours, WR Grace, Union Carbide
1989	2.20	HalliburtonLabs	Dresser Ind, SPX Technologies, Trane Technologies
1989	2.19	Mobil	Dupont De Nemours, Union Carbide
1988	2.10	Upjohn	Pennwalt, Pharmacia, Dupont De Nemours
1988	1.93	Smithkline Beckman	American Cyanamid, Pennwalt, Pharmacia
1989	1.89	Waste Management	Chrysler, Honeywell, TRW
			1990-1999 Disruptions
1999	3.39	Computer Assoc	IBM, Sun Microsystems, Unisys
1997	3.16	Lucent Technologies	HP, Texas Instruments, IBM
1997	3.16	Ameritech	L3harris Technologies, Motorola, Scientific-Atlanta
1998	3.14	Motorola	Advanced Micro Devices, Qualcomm, Texas Instruments
1998	2.86	Caterpillar	Brunswick, Eaton, Trane Technologies Plc
1997	2.85	Deere	Chrysler, Eaton Plc, Trane Technologies Plc
1996	2.80	Chrysler	Honeywell, Raytheon Technologies, Caterpillar
1992	2.78	Atlantic Richfield	Du Pont (E I) De Nemours, Pharmacia, Texaco
1998	2.75	3m Co	Hercules, Du Pont (E I) De Nemours, Honeywell
1995	2.67	Mobil	Dupont De Nemours, WR Grace, Union Carbide
1999	2.62	Weyerhaeuser	Ppg Industries, Hercules, 3m Co
1998	2.58	Medtronic Plc	Abbott Labs, Baxter International, Becton Dickinson
			2000-2009 Disruptions
2000	3.66	Solectron	IBM, Motorola, Texas Instruments
2001	3.57	Comverse Technology	HP, IBM, Texas Instruments
2007	3.51	Applied Materials	Intel, Lsi, Texas Instruments
2003	3.48	Pfizer	Regeneron Pharma, Selective Ins Group, Xoma
2001	3.45	Pharmacia	Chiron, Regeneron Pharma, Selective Ins Group
2005	3.40	Verizon	Cisco Systems, Nortel Networks, Motorola
2008	3.39	Time Warner Cable	3com, Tellabs, Nortel Networks
2003	3.30	Wyeth	Abbott Labs, Allergan, Chiron
2008	3.29	MonsantoLabs	Archer-Daniels-Midland, Geron, Regeneron Pharma
2003	3.26	Tyco International Plc	ADC Telecom, L3harris Tech, Northrop Grumman
2003	3.23	Bristol-Myers Squibb	Becton Dickinson, Procter & Gamble, Selective
2005	3.22	Corning	Honeywell, Lockheed Martin, Northrop Grumman
			2010-2019 Disruptions
2019	4.03	Verizon	Apple, Intel, Motorola
2017	3.70	Prudential Financial	Meta Platforms, Microsoft, Walmart
2017	3.60	Apple	IBM, Meta Platforms, Microsoft
2012	3.58	Time Warner Cable	Cisco Systems, West Pharmaceutical, Motorola
2019	3.52	Nvidia	Texas Instruments, Apple, IBM
2019	3.52	Pfizer	Abbott Labs, Archer-Daniels-Midland, Zoetis
2013	3.45	Allergan	Johnson & Johnson, Regeneron Pharma, Abbott Labs
2019	3.44	Conocophillips	Exxon Mobil, Honeywell, Schlumberger Ltd
2017	3.43	Cognizant Tech	AT&T, Palo Alto Networks, Verizon
2014	3.40	Abbvie	Fmc, Immunomedics, Medtronic Plc
2017	3.38	Ford MotorLabs	Eaton Plc, General Motors, Honeywell
2015	3.34	RaytheonLabs	General Electric, Textron, Honeywell

The table reports the firms with the highest sectoral disruption exposures in each decade using the TNIC disruption score, as well as the top 3 firms jointly exposed to the common sectoral disruption as the listed firm (note that we only list the top 3 despite our calculations including ten co-disruptors due to space constraints). The Disruption Score in the second column can be interpreted as a z-score indicating the abnormality of the listed TSD among all TSDs that have a positive value.

Table II:
Most Relevant SIC-3 Sectoral Disruption Firms by Decade

Year	Disrupt	Industry	Co-Disruptor Industries
			1950-1959 Disruptions
1958	3.58	broadwoven fabric mills, cotton	carpets and rugs, misc. fabricated textile products, miscellaneous manufactures
1953	3.57	computer and data processing services	computer and office equipment, telegraph other communications, machinery, equipment, and supplies
1959	3.55	iron and steel foundries	metal forgings and stampings, metalworking machinery, refrigeration and service machinery
1958	3.55	engines and turbines	electric distribution equipment, semiconductors and related devices, radio and television broadcasting
1958	3.50	telephone communication	general industrial machinery, communications equipment, semiconductors and related devices
		1960-1969 Disruptions	
1962	3.61	motor vehicles and equipment	misc. fabricated metal products, aircraft and parts, railroad equipment
1961	3.56	millwork, plywood structural	iron and steel foundries, metal forgings and stampings, construction and related machinery
1969	3.56	telephone communication	communications equipment, semiconductors and related devices, misc. electrical equipment supplies
1965	3.53	paper mills	paperboard mills, paperboard containers and boxes, metal cans and shipping containers
1969	3.51	industrial inorganic chemicals	plastics materials and synthetics, industrial organic chemicals, agricultural chemicals
			1970-1979 Disruptions
1978	3.74	electric lighting and wiring equipment	knitting mills, electric distribution equipment,
1975	3.68	telephone communication	communications equipment, semiconductors and related devices, misc. electrical equipment supplies
1972	3.66	computer and data processing services	knitting mills, computer and office equipment, communications equipment
1977	3.65	office furniture	misc. fabricated textile products, household furniture, nonferrous foundries (castings)
1974	3.65	men's and boys' furnishings	men's and boys' suits and coats, misc. converted paper products, miscellaneous plastics products, nec
			1980-1989 Disruptions
1988	3.69	household audio and video equipment	communications equipment, semiconductors and related devices, misc. electrical equipment supplies
1981	3.64	electric lighting and wiring equipment	knitting mills, general industrial machinery, electric distribution equipment
1986	3.62	construction and related machinery	lead and zinc ores, iron and steel foundries, metal forgings and stampings
1989	3.61	motor vehicles and equipment	iron and steel foundries, metalworking machinery, general industrial machinery
1989	3.57	telephone communication	communications equipment, misc. electrical equipment supplies, search and navigation equipment

The table reports the industries with the highest sectoral disruption exposures in each decade using our SIC disruption measure as well as the top 3 related SIC-3 industries jointly exposed to the common sectoral disruption as the listed SIC-3 industry. The Disruption Score in the second column can be interpreted as a z-score indicating the abnormality of the listed TSD among all TSDs that have a positive value.

Table II:
Most Relevant SIC-3 Sectoral Disruption Firms by Decade (continued)

Year	Disrupt	Industry	Co-Disruptor Industries
			1990-1999 Disruptions
1999	3.83	photographic equipment and supplies	household audio and video equipment, misc. electrical equipment supplies, holding offices
1999	3.79	metalworking machinery	general industrial machinery, electric distribution equipment, electrical industrial apparatus
1998	3.76	broadwoven fabric mills, manmade	forest products, yarn and thread mills, miscellaneous textile goods
1999	3.72	computer and data processing services	computer and office equipment, household audio and video equipment, semiconductors and related devices
1992	3.69	drugs	plastics materials and synthetics, industrial organic chemicals, agricultural chemicals
			2000-2009 Disruptions
2003	4.01	semiconductors and related devices	computer and office equipment, household audio and video equipment, misc. electrical equipment supplies
2005	3.95	drugs	crop services, industrial inorganic chemicals, professional commercial equipment
2001	3.94	miscellaneous nonmetallic minerals	broadwoven fabric mills, manmade, miscellaneous textile goods, concrete, gypsum, and plaster products
2001	3.92	photographic equipment and supplies	commercial printing, household audio and video equipment, misc. electrical equipment supplies
2006	3.89	computer and office equipment	household audio and video equipment, misc. electrical equipment supplies, computer and data processing services
			2010-2019 Disruptions
2014	4.05	semiconductors and related devices	household audio and video equipment, communications equipment,
2012	3.98	electrical goods	electric distribution equipment, electrical industrial apparatus, household audio and video equipment
2011	3.98	photographic equipment and supplies	household audio and video equipment, misc. electrical equipment supplies, holding offices
2012	3.94	household audio and video equipment	semiconductors and related devices, misc. electrical equipment supplies,
2017	3.92	communications equipment	semiconductors and related devices, telephone communication, communication services, nec

The table reports the industries with the highest sectoral disruption exposures in each decade using our SIC disruption measure as well as the top 3 related SIC-3 industries jointly exposed to the common sectoral disruption as the listed SIC-3 industry. The Disruption Score in the second column can be interpreted as a z-score indicating the abnormality of the listed TSD among all TSDs that have a positive value.

Table III:
Summary Statistics of Stock Return Variables

Panel A: Summary Statistics

Variable	Mean	Std.Dev.	Minimum	Median	Maximum	Obs.
Monthly Return	1.135	16.210	-98.129	0.000	1988.36	1,628,066
TNIC Disruption	-0.002	0.002	-0.017	-0.002	0.001	854,623
SIC Disruption	-0.002	0.003	-0.024	-0.001	-0.000	1,628,066
Log B/M Ratio	-7.383	1.173	-18.216	-7.375	4.006	1,628,066
Log Mkt Cap	12.138	2.215	3.503	11.981	21.170	1,628,066
Past Return	0.161	0.820	-1.000	0.061	436.684	1,628,066
Profitability	0.147	0.515	-7.289	0.207	6.468	1,628,066
Investment	0.147	0.384	-0.697	0.062	5.307	1,628,066

Panel B: Pearson Correlation Coefficients

Variable	TNIC Disrupted	SIC Disrupted	Log B/M	Log Mkt Cap	Past Return	Prof-itability	Invest-ment
TNIC Disruption	1.000	0.290	-0.085	0.018	-0.015	-0.057	0.005
SIC Disruption	0.290	1.000	-0.040	-0.029	-0.001	-0.021	0.006
Log B/M Ratio	-0.085	-0.040	1.000	-0.268	0.000	-0.044	-0.175
Log Mkt Cap	0.018	-0.029	-0.268	1.000	0.035	0.214	0.092
Past Return	-0.015	-0.001	0.000	0.035	1.000	0.016	-0.017
Profitability	-0.057	-0.021	-0.044	0.214	0.016	1.000	0.121
Investment	0.005	0.006	-0.175	0.092	-0.017	0.121	1.000

Panel A reports the summary statistics, and Panel B reports Pearson correlation coefficients, for variables used in our return prediction tests. Monthly stock returns from a given month t are from the CRSP database. Size, book-to-market, profitability and investment are computed following Fama and French (2014). The Past Return is the firm-specific return from month $t-12$ to $t-2$.

Table IV:
Firm Summary Statistics

Variable	N	Median	Mean	Mean (Small)	Mean (Large)	Std. Error (Mean)
Panel A: Disruption & Firm Characteristics						
Age	185697	11.0000	14.9118	11.6247	18.1707	0.0289
Assets	185697	132.4620	7346.1940	219.7806	14411.0900	182.5723
Cash/Assets	162265	0.0524	0.1534	0.2010	0.1050	0.0008
Disrupted (SIC)	185697	-0.0013	-0.0022	-0.0023	-0.0022	0.0000
Disrupted (TNIC)	104123	-.0018	-.0025	-.0025	-.0024	0.0000
Sales	185697	93.8130	2100.4140	132.9231	4050.9200	27.0385
Panel B: Innovation, competition & investment policies						
Acquisition Amount/Assets	115030	0.0000	0.0312	0.0279	0.0344	0.0004
Capital Expenditures/Assets	185672	0.0430	0.0745	0.0787	0.0703	0.0002
KPSS/ Assets	185672	0.0000	0.0351	0.0170	0.0530	0.0003
Log (Tsimm)	87224	0.6933	1.1975	1.1602	1.2291	0.0043
Market Share	185697	.0013	.0235	.0038	.04301	.0001
Organization Capital	182562	.2434	.8032	1.3649	.2462	.1375
R&D/Assets	185672	0.0024	0.0585	0.0763	0.0409	0.0003
Trade Secrets	72184	0.0000	1.7822	1.9257	1.6413	0.0087
Panel C: Firm Performance						
Assets Growth	185672	0.0693	0.1208	0.1508	0.0911	0.0008
Market to Book	159774	1.1593	2.2740	2.8162	1.7709	0.0121
Sales Growth	184418	0.0894	0.1274	0.1542	0.1011	0.0008

This table provides summary statistics for our sample of public firms based on annual firm observations. All variables are described in detail in the variable list in Appendix A.

Table V:
Stock Market Return Regressions (TNIC Disruption) (Small vs Big)

			Calendar Time Results		
		months	Disrupted x Small	Disrupted x Big	Big-Small Difference
Row	Lag	/Obs	Alpha	Alpha	Test
(1)	-12 Months	396	0.010	0.202	0.192
		1,167,965	(0.20)	(4.23)	(3.64)
(2)	-10 Months	396	0.067	0.202	0.135
		1,185,584	(1.26)	(4.62)	(2.69)
(3)	-8 Months	396	0.081	0.175	0.094
		1,203,763	(1.56)	(4.22)	(1.87)
(4)	-6 Months	396	0.085	0.134	0.048
		1,222,335	(1.75)	(3.61)	(0.94)
(5)	-4 Months	396	0.069	0.087	0.018
		1,243,086	(1.45)	(2.40)	(0.34)
(6)	-2 Months	396	0.066	0.045	-0.021
		1,265,522	(1.31)	(1.15)	(-0.39)
(7)	0 Months	395	0.089	0.063	-0.025
		1,290,905	(1.67)	(1.56)	(-0.47)
(8)	2 Months	393	0.132	0.145	0.013
		1,268,355	(2.61)	(3.26)	(0.25)
(9)	4 Months	391	0.112	0.140	0.028
		1,250,466	(2.21)	(3.02)	(0.53)
(10)	6 Months	389	0.170	0.160	-0.010
		1,232,586	(3.51)	(3.59)	(-0.19)
(11)	8 Months	387	0.113	0.173	0.060
		1,213,771	(2.33)	(3.77)	(1.08)
(12)	10 Months	385	0.123	0.165	0.042
		1,193,781	(2.33)	(3.60)	(0.77)
(13)	12 Months	383	0.129	0.169	0.040
		1,172,513	(2.43)	(3.70)	(0.79)
(14)	14 Months	381	0.225	0.203	-0.021
		1,150,641	(3.48)	(4.49)	(-0.35)
(15)	16 Months	379	0.217	0.203	-0.015
		1,128,868	(3.62)	(4.57)	(-0.24)
(16)	18 Months	377	0.247	0.170	-0.077
		1,107,888	(4.49)	(3.55)	(-1.35)
(17)	20 Months	375	0.221	0.149	-0.072
		1,087,114	(3.74)	(3.12)	(-1.23)
(18)	22 Months	373	0.189	0.118	-0.070
		1,066,630	(2.96)	(2.38)	(-1.16)
(19)	24 Months	371	0.207	0.130	-0.077
		1,046,711	(3.39)	(2.65)	(-1.33)
(20)	26 Months	369	0.266	0.155	-0.111
		1,027,134	(4.06)	(3.02)	(-1.85)
(21)	28 Months	367	0.228	0.156	-0.072
		1,007,982	(3.57)	(3.05)	(-1.22)
(22)	30 Months	365	0.259	0.167	-0.092
		989,494	(4.39)	(3.21)	(-1.60)
(23)	32 Months	363	0.237	0.150	-0.087
		971,656	(4.33)	(2.98)	(-1.58)
(24)	34 Months	361	0.209	0.120	-0.090
		954,064	(3.70)	(2.25)	(-1.67)
(25)	36 Months	359	0.175	0.134	-0.041
		936,785	(2.95)	(2.49)	(-0.78)

The table reports the results of calendar-time portfolio results where the monthly firm stock return is the dependent variable. Our period is from January 1988 to December 2020. Our central variable of interest, Disrupted, indicates the level of TNIC disruption the given firm faces based on correlated patenting activity over the past months (we also interact this variable with above and below median firm assets indicators). Monthly stock returns from a given month t are from the CRSP database. The columns report the calendar-time alphas of the investment strategies implied by Disrupted x Small and the Disrupted x Big Fama MacBeth coefficients (which are zero-cost calendar time investible portfolios, see Back et al. (2015) for example, with controls for the Fama-French 5 factors of Fama and French 2015 included). Our first stage Fama MacBeth models (shown in appendix Table B2) include controls for Size, book-to-market, profitability and investment, and momentum. The third of these three reports the t-statistic regarding the difference in calendar time returns for the small minus the large firms. All calendar time alphas are estimated as the intercept of the portfolio return on the 5 factor model from Fama and French (2015).

Table VI:
Stock Market Return Regressions (SIC Disruption) (Small vs Big)

Row	Lag	months /Obs	Calendar Time Results Disrupted x Small Alpha	Disrupted x Big Alpha	Big-Small Difference Test
(1)	-12 Months	822	0.053	0.005	-0.048
		1,469,274	(1.23)	(0.12)	(-1.14)
(2)	-10 Months	824	0.049	0.019	-0.030
		1,493,166	(1.18)	(0.48)	(-0.78)
(3)	-8 Months	826	0.091	0.025	-0.067
		1,517,881	(2.18)	(0.65)	(-1.66)
(4)	-6 Months	828	0.108	0.023	-0.085
		1,543,791	(2.59)	(0.61)	(-2.03)
(5)	-4 Months	830	0.128	0.036	-0.092
		1,571,896	(3.28)	(0.96)	(-2.23)
(6)	-2 Months	832	0.124	0.034	-0.090
		1,602,217	(3.28)	(0.89)	(-2.27)
(7)	0 Months	833	0.113	0.046	-0.067
		1,637,396	(2.86)	(1.14)	(-1.59)
(8)	2 Months	833	0.123	0.087	-0.036
		1,618,519	(3.31)	(2.08)	(-0.84)
(9)	4 Months	833	0.135	0.058	-0.077
		1,604,873	(3.71)	(1.44)	(-1.78)
(10)	6 Months	833	0.147	0.095	-0.052
		1,589,410	(3.52)	(2.28)	(-1.23)
(11)	8 Months	833	0.171	0.115	-0.057
		1,571,902	(3.79)	(2.53)	(-1.30)
(12)	10 Months	833	0.193	0.099	-0.093
		1,552,417	(4.52)	(2.30)	(-2.24)
(13)	12 Months	833	0.227	0.109	-0.118
		1,531,205	(5.36)	(2.54)	(-2.80)
(14)	14 Months	833	0.236	0.101	-0.135
		1,509,368	(5.21)	(2.32)	(-3.03)
(15)	16 Months	833	0.226	0.117	-0.108
		1,487,594	(5.06)	(2.72)	(-2.65)
(16)	18 Months	833	0.213	0.124	-0.090
		1,465,874	(4.86)	(3.06)	(-2.06)
(17)	20 Months	833	0.202	0.132	-0.070
		1,444,474	(4.82)	(3.06)	(-1.69)
(18)	22 Months	833	0.177	0.108	-0.069
		1,423,493	(4.28)	(2.76)	(-1.64)
(19)	24 Months	833	0.163	0.083	-0.080
		1,402,856	(3.56)	(1.91)	(-1.73)
(20)	26 Months	833	0.144	0.090	-0.054
		1,382,367	(3.08)	(2.09)	(-1.19)
(21)	28 Months	833	0.164	0.103	-0.061
		1,362,276	(3.57)	(2.43)	(-1.32)
(22)	30 Months	833	0.158	0.101	-0.057
		1,342,676	(3.35)	(2.36)	(-1.29)
(23)	32 Months	833	0.168	0.093	-0.075
		1,323,387	(3.44)	(2.10)	(-1.62)
(24)	34 Months	833	0.148	0.090	-0.059
		1,304,459	(3.10)	(2.04)	(-1.25)
(25)	36 Months	833	0.154	0.086	-0.068
		1,285,872	(2.95)	(1.90)	(-1.40)

The table reports the results of calendar-time portfolio results where the monthly firm stock return is the dependent variable. Our period is from January 1988 to December 2020. Our central variable of interest, Disrupted, indicates the level of SIC disruption the given firm faces based on correlated patenting activity over the past months (we also interact this variable with above and below median firm assets indicators). Monthly stock returns from a given month t are from the CRSP database. The three columns report the calendar-time alphas of the investment strategies implied by the Disrupted x Small and the Disrupted x Big Fama MacBeth coefficients (which are zero-cost investible portfolios, see Back et al. (2015) for example, with controls for the Fama-French 5 factors of Fama and French 2015 included). Our first stage Fama MacBeth models (shown in appendix Table B2) include controls for Size, book-to-market, profitability and investment, and momentum. The third of these three reports the t-statistic regarding the difference in calendar time returns for the small minus the large firms. All calendar time alphas are estimated as the intercept of the portfolio return on the 5 factor model from Fama and French (2015).

Table VII:
Disruption, R&D, and Acquisitions

The table displays panel data regressions in which R&D and acquisition variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the industry level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: R&D/Assets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	1.405*	0.588	0.080	1.672***	1.147***	0.928***
	(1.837)	(1.248)	(0.236)	(3.370)	(3.197)	(3.050)
Disrupted × Large	-1.816**	-1.039**	-0.740**	-0.515**	-0.501**	-0.355**
	(-2.348)	(-2.139)	(-2.257)	(-2.031)	(-2.407)	(-2.350)
Difference	3.221**	1.627**	0.820**	2.187***	1.648***	1.283***
Observations	185,672	163,765	146,250	104,123	87,929	75,368
R-squared	0.095	0.043	0.019	0.060	0.040	0.028
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0033	.0014	.0002	.0043	.0029	.0023
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0042	-.0024	-.0017	-.0013	-.0013	-.0009
Panel B: Acquisition/Assets						
Disrupted × Small	0.194	0.962	1.304***	1.271**	1.989***	1.030*
	(0.405)	(1.134)	(2.729)	(1.978)	(3.873)	(1.839)
Disrupted × Large	-0.151	0.046	0.179	0.553	0.648*	-0.065
	(-0.503)	(0.169)	(0.745)	(1.232)	(1.756)	(-0.179)
Difference	0.346	0.916	1.125**	0.718	1.341***	1.095*
Observations	115,030	102,285	91,780	94,138	80,471	68,478
R-squared	0.028	0.039	0.030	0.030	0.027	0.024
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0004	.0021	.0029	.0033	.0052	.0027
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0003	.0001	.0004	.0014	.0017	-.0002

Table VIII: **Disruption, Capex, and Assets Growth**

The table displays panel data regressions in which capital expenditures and asset growth are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the industry level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: Capital Exp./Assets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	1.156**	1.202***	1.182***	0.361	0.312	0.313
	(2.153)	(3.173)	(3.540)	(1.349)	(1.202)	(1.383)
Disrupted × Large	-0.686	-0.190	0.107	-0.197	-0.240	-0.213
	(-0.938)	(-0.351)	(0.227)	(-0.674)	(-1.107)	(-1.053)
Difference	1.842**	1.392***	1.075***	0.558***	0.551**	0.526**
Observations	185,672	163,765	146,250	104,123	87,929	75,368
R-squared	0.121	0.098	0.082	0.084	0.084	0.085
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0027	.0028	.0027	.0009	.0008	.0008
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0016	-.0004	.0002	-.0005	-.0006	-.0005
Panel B: Asset Growth						
Disrupted × Small	3.582*	4.754***	2.104*	1.357	1.809*	2.636***
	(1.839)	(3.080)	(1.715)	(1.437)	(1.935)	(2.664)
Disrupted × Large	-5.896**	-2.623	-1.507	-4.354***	-2.946***	-1.679**
	(-2.224)	(-1.645)	(-1.555)	(-4.206)	(-3.466)	(-2.477)
Difference	9.478**	7.377***	3.611***	5.711***	4.755***	4.315***
Observations	185,672	163,765	146,250	104,123	87,929	75,368
R-squared	0.163	0.111	0.070	0.079	0.074	0.062
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0083	.011	.0049	.0035	.0045	.0066
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0136	-.0061	-.0035	-.0111	-.0074	-.0042

Table IX:
Disruption, Valuation and Sales Growth

The table displays panel data regressions in which market valuation and sales growth variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the industry level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: Valuation (M/B ratio)	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	84.856	54.711	17.519	28.484**	38.053***	34.032***
	(1.488)	(1.627)	(0.842)	(2.484)	(3.653)	(3.858)
Disrupted × Large	-56.252	-22.707	-21.331	-4.924	-4.773	-2.027
	(-1.437)	(-1.120)	(-1.563)	(-0.587)	(-0.761)	(-0.465)
Difference	141.107	77.418*	38.850**	33.408***	42.826***	36.059***
Observations	159,774	144,920	130,792	103,587	87,496	75,007
R-squared	0.142	0.100	0.066	0.107	0.103	0.090
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.1879	.1193	.0387	.0726	.0952	.0848
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.1246	-.0495	-.0471	-.0125	-.0119	-.0051
Panel B: Sales Growth						
Disrupted × Small	0.203	4.341***	5.250***	0.313	0.501	2.231***
	(0.188)	(2.987)	(3.630)	(0.329)	(0.560)	(3.020)
Disrupted × Large	-3.366***	-0.730	1.658	-3.521***	-1.316	-0.077
	(-3.211)	(-0.485)	(0.925)	(-4.143)	(-1.582)	(-0.090)
Difference	3.568**	5.071**	3.592***	3.834***	1.817	2.308**
Observations	184,417	163,765	146,070	103,678	87,929	75,309
R-squared	0.112	0.111	0.084	0.091	0.086	0.079
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0005	.01	.0121	.0008	.0013	.0056
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0078	-.0017	.0038	-.009	-.0033	-.0002

Table X: **Disruption, Patent Valuation, and Trade Secrets**

The table displays panel data regressions in which patent valuation and trade secrecy variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the industry level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: KPSS/Assets						
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	5.977***	7.079***	8.340***	2.705***	2.294***	2.248***
	(3.467)	(3.919)	(4.931)	(3.472)	(2.772)	(2.689)
Disrupted × Large	-4.527**	-4.011**	-2.850	0.567	-0.039	-0.766
	(-2.256)	(-2.034)	(-1.642)	(0.519)	(-0.039)	(-0.648)
Difference	10.504***	11.090***	11.190***	2.138*	2.333*	3.014**
Observations	80,074	74,444	69,786	40,017	35,934	32,564
R-squared	0.136	0.154	0.169	0.111	0.119	0.126
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0151	.0179	.0211	.0079	.0065	.0063
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0115	-.0101	-.0072	.0016	-.0001	-.0021
Panel B: Trade Secrets						
Disrupted × Small	14.415	10.531	8.152	20.332***	16.070**	19.176***
	(1.432)	(1.017)	(0.759)	(2.731)	(2.058)	(2.619)
Disrupted × Large	-6.821	-12.069	-11.830	12.588**	6.658	1.381
	(-0.677)	(-1.184)	(-1.241)	(2.516)	(1.474)	(0.322)
Difference	21.236***	22.601***	19.981***	7.744	9.412	17.796***
Observations	72,166	66,761	60,767	77,271	68,333	60,958
R-squared	0.032	0.035	0.032	0.040	0.041	0.042
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0312	.0229	.0186	.0469	.0377	.0454
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0148	-.0263	-.027	.029	.0156	.0033

Table XI:
Alternative Categorizations to Assets

This table reports differences between *SmallX Disrupted* and *LargeX Disrupted* using alternative firm-based classification variables instead of Assets (as used in the main text). The first column ("Assets") reproduces the main-table specifications and is included only for comparison. *Small (Large)* is a dummy equal to one if a firm's classification variable is below (above) the industry median for that variable, and zero otherwise. All regressions include firm and year fixed effects and control variables. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Assets**	**Age**	**Market Share**	**Organizational Capital**	**Cash/Assets**
R&D/Assets (t+1)	3.221**	0.875	1.773**	-4.110***	-1.821**
	(2.33)	(1.46)	(2.15)	(-2.77)	(-2.21)
R&D/Assets (t+2)	1.627**	0.190	1.326**	-2.711***	0.010
	(2.24)	(1.16)	(2.01)	(-3.10)	(0.05)
R&D/Assets (t+3)	0.820**	0.086	0.794*	-1.880***	0.098
	(2.28)	(0.84)	(1.81)	(-2.67)	(0.66)
Acquisition/Assets (t+1)	0.346	0.503	-0.143	-1.159	-1.053
	(0.89)	(0.86)	(-0.29)	(-1.12)	(-1.22)
Acquisition/Assets (t+2)	0.916	0.826	0.637	-0.910	-1.061
	(1.03)	(0.93)	(0.80)	(-1.00)	(-1.58)
Acquisition/Assets (t+3)	1.125**	1.188*	0.885*	0.484	-0.391
	(2.33)	(1.84)	(1.70)	(1.06)	(-1.07)
Capital Expenditures/Assets (t+1)	1.842**	1.282***	1.598***	-1.218	-0.376
	(2.46)	(2.84)	(2.74)	(-1.62)	(-0.58)
Capital Expenditures/Assets (t+2)	1.392***	0.883***	1.506***	-0.637	0.368
	(3.44)	(3.10)	(3.24)	(-1.25)	(0.69)
Capital Expenditures/Assets (t+3)	1.075***	0.589**	1.200***	-0.537	0.279
	(3.44)	(2.19)	(3.41)	(-1.24)	(1.00)
Asset Growth (t+1)	9.478**	1.574	3.640**	-6.885	-9.513*
	(2.23)	(0.56)	(2.10)	(-1.46)	(-1.76)
Asset Growth (t+2)	7.377***	0.289	6.116***	-4.758**	-0.751
	(2.75)	(0.18)	(2.60)	(-2.02)	(-0.62)
Asset Growth (t+3)	3.611***	-0.202	3.899**	-1.525	-0.132
	(3.52)	(-0.17)	(2.54)	(-1.20)	(-0.19)
M/B (t+1)	141.107	55.124	60.730	-128.090	-115.555
	(1.56)	(1.25)	(1.49)	(-1.44)	(-1.54)
M/B (t+2)	77.418*	38.693	59.497	-65.955**	-4.899
	(1.79)	(1.35)	(1.50)	(-2.41)	(-0.43)
M/B (t+3)	38.850**	32.944**	33.581	-37.014	2.682
	(2.21)	(2.00)	(1.32)	(-1.64)	(0.35)
Sales Growth (t+1)	3.568**	1.014	1.141	-3.205	-2.093
	(2.47)	(0.37)	(1.05)	(-1.39)	(-0.98)
Sales Growth (t+2)	5.071**	0.074	6.155***	-0.344	-1.131
	(2.23)	(0.04)	(2.75)	(-0.14)	(-0.60)
Sales Growth (t+3)	3.592***	0.670	5.579***	-3.052	-0.945
	(2.85)	(0.51)	(3.26)	(-1.59)	(-1.48)
KPSS/Assets (t+1)	10.504***	0.392	9.502***	-3.185*	1.284
	(4.74)	(0.19)	(3.98)	(-1.65)	(1.02)
KPSS/Assets (t+2)	11.090***	-0.014	9.750***	-3.051	0.450
	(5.06)	(-0.01)	(4.56)	(-1.45)	(0.63)
KPSS/Assets (t+3)	11.190***	0.492	8.528***	-2.709*	0.848
	(5.09)	(0.26)	(3.71)	(-1.89)	(0.46)
Trade Secrets (t+1)	21.236***	27.446***	16.705**	-47.675*	-5.526
	(5.38)	(4.01)	(2.49)	(-1.66)	(-0.89)
Trade Secrets (t+2)	22.601***	25.943***	16.196*	-51.424*	-4.182
	(4.98)	(3.26)	(1.68)	(-1.65)	(-0.58)
Trade Secrets (t+3)	19.981***	25.415***	14.805	-49.693*	-4.454
	(4.77)	(3.02)	(1.42)	(-1.69)	(-0.65)

Table XII: Comparison of Results Across Neighbour Specifications

This table examines the robustness of the main corporate finance results to the number of peer SIC-3 industries (N) used in computing the Technology Sectoral Disruption (TSD) score. For a given industry j, the SIC-based TSD measure aggregates market-capitalization-weighted pairwise disruption scores over the $N \in \{3, 5, 10\}$ most ex-ante similar SIC-3 industries (equation (2) in the paper), where $N = 3$ is the baseline specification. Reported coefficients are OLS estimates of $\hat{\beta}_1$ (*Disrupted* × *Small*) and $\hat{\beta}_2$ (*Disrupted* × *Large*) from the panel regression

$$Y_{i,t+\tau} = \beta_1\, Disruption_{i,t} \times Small_{i,t} + \beta_2\, Disruption_{i,t} \times Large_{i,t} + \beta_3\, Small_{i,t} + \beta_4\, X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t},$$

where $Small_{i,t}$ is an indicator equal to one for firms with below-median total assets in year t, $X_{i,t}$ includes inverse size and log firm age as controls, and μ_i and δ_t are firm and year fixed effects (equation (7) in the paper). The row labelled *Difference* reports $\hat{\beta}_1 - \hat{\beta}_2$, capturing the differential effect of disruption on small versus large firms; significance is assessed via a Wald test. Within each neighbour-count group, columns (1), (2), and (3) correspond to $\tau = 1, 2, 3$, respectively (contemporaneous, one-period, and two-period forward outcomes). Standard errors are clustered at the SIC-3 industry level. The sample covers all public Compustat firms from 1951 to 2020. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

		3-Neighbour			5-Neighbour			10-Neighbour		
Outcome	Statistic	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
RD Assets Disrupted	*Disrupted* × *Small*	1.405*	0.588	0.080	1.417***	0.650**	0.174	0.802***	0.368***	0.181***
		(1.837)	(1.248)	(0.236)	(2.624)	(2.364)	(1.178)	(3.575)	(3.937)	(3.203)
	Disrupted × *Large*	−1.816**	−1.039**	−0.740**	−0.813*	−0.550**	−0.419**	−0.371*	−0.251*	−0.171*
		(−2.348)	(−2.139)	(−2.257)	(−1.876)	(−2.247)	(−2.404)	(−1.857)	(−1.972)	(−1.741)
	Difference	3.221**	1.627**	0.820**	2.229**	1.199***	0.593***	1.173***	0.619***	0.352***
Asset Growth Disrupted	*Disrupted* × *Small*	3.582*	4.754***	2.104*	3.267**	2.478***	0.648	1.352***	0.981**	0.547
		(1.839)	(3.080)	(1.715)	(2.444)	(2.717)	(0.901)	(2.802)	(2.550)	(1.380)
	Disrupted × *Large*	−5.896**	−2.623	−1.507	−3.123*	−2.187**	−1.547***	−1.702***	−1.270***	−0.630*
		(−2.224)	(−1.645)	(−1.555)	(−1.780)	(−2.020)	(−2.796)	(−3.030)	(−3.230)	(−1.877)
	Difference	9.478**	7.377***	3.611***	6.390**	4.666***	2.195***	3.053***	2.251***	1.177***
Capital Expenditures	*Disrupted* × *Small*	1.156**	1.202***	1.182***	1.037***	0.859***	0.631***	0.625***	0.598***	0.513***
		(2.153)	(3.173)	(3.540)	(2.636)	(3.077)	(3.127)	(2.675)	(3.719)	(4.012)
	Disrupted × *Large*	−0.686	−0.190	0.107	−0.326	−0.158	−0.125	−0.107	0.007	0.090
		(−0.938)	(−0.351)	(0.227)	(−0.677)	(−0.445)	(−0.464)	(−0.454)	(0.035)	(0.574)
	Difference	1.842**	1.392***	1.075***	1.364***	1.017***	0.756***	0.733***	0.591***	0.424***
KPSS Assets	*Disrupted* × *Small*	5.977***	7.079***	8.340***	4.721***	5.635***	6.617***	2.567***	3.015***	3.292***
		(3.467)	(3.919)	(4.931)	(5.403)	(6.290)	(6.659)	(4.900)	(4.885)	(4.533)
	Disrupted × *Large*	−4.527**	−4.011**	−2.850	−2.781**	−2.681**	−2.039	−0.887	−0.885	−0.828
		(−2.256)	(−2.034)	(−1.642)	(−2.172)	(−2.001)	(−1.584)	(−1.377)	(−1.398)	(−1.329)
	Difference	10.504***	11.090***	11.190***	7.502***	8.316***	8.656***	3.454***	3.900***	4.120***
Sales Growth Disrupted	*Disrupted* × *Small*	0.203	4.341***	5.250***	0.184	1.625*	2.334***	0.653	1.336**	1.086**
		(0.188)	(2.987)	(3.630)	(0.270)	(1.715)	(3.885)	(1.095)	(2.548)	(2.297)
	Disrupted × *Large*	−3.366***	−0.730	1.658	−2.371***	−1.486	0.250	−0.464	−0.213	0.125
		(−3.211)	(−0.485)	(0.925)	(−3.644)	(−1.497)	(0.271)	(−0.605)	(−0.454)	(0.284)
	Difference	3.568**	5.071**	3.592***	2.555***	3.111**	2.084***	1.117***	1.549***	0.961***
Tobin's Q Disrupted	*Disrupted* × *Small*	84.856	54.711	17.519	61.422**	34.853*	8.526	38.977***	22.938***	11.100**
		(1.488)	(1.627)	(0.842)	(2.015)	(1.955)	(0.906)	(2.700)	(3.007)	(2.235)
	Disrupted × *Large*	−56.252	−22.707	−21.331	−22.646	−15.416	−14.795*	2.003	−0.458	0.560
		(−1.437)	(−1.120)	(−1.563)	(−1.141)	(−1.541)	(−1.890)	(0.317)	(−0.079)	(0.106)
	Difference	141.107	77.418*	38.850**	84.068*	50.269**	23.321***	36.974***	23.397***	10.540***
Trade Secrets	*Disrupted* × *Small*	14.415	10.531	8.152	13.254**	11.040**	9.161**	9.071**	8.086**	7.369**
		(1.432)	(1.017)	(0.759)	(2.435)	(2.205)	(2.118)	(2.100)	(2.243)	(2.265)
	Disrupted × *Large*	−6.821	−12.069	−11.830	0.511	−4.247	−6.055	4.501*	0.917	0.569
		(−0.677)	(−1.184)	(−1.241)	(0.099)	(−0.844)	(−1.365)	(1.663)	(0.324)	(0.179)
	Difference	21.236***	22.601***	19.981***	12.743***	15.287***	15.215***	4.570	7.169**	6.800**
Acq Assets Disrupted	*Disrupted* × *Small*	0.194	0.962	1.304***	0.665	0.720	0.914***	0.378*	0.664***	0.448***
		(0.405)	(1.134)	(2.729)	(1.555)	(1.656)	(3.404)	(1.971)	(3.040)	(4.016)
	Disrupted × *Large*	−0.151	0.046	0.179	0.604*	0.062	0.179	0.456	0.204	0.194
		(−0.503)	(0.169)	(0.745)	(1.854)	(0.437)	(1.213)	(1.529)	(1.112)	(1.167)
	Difference	0.346	0.916	1.125**	0.061	0.658	0.735***	−0.079	0.460***	0.255

Appendix A. Variable definitions

Table XIII: Variable definitions

Variable	Definition
Panel A: Financial Characteristics	
Assets	Compustat item AT.
Assets Growth	Natural logarithm of total assets in the current year t divided by total assets in the previous year $t-1$.
Capital Exp./Assets	Compustat CAPX scaled by lagged assets.
Cash/Assets	Cash and short-term investments (Compustat CHE) divided by lagged total assets (AT).
Log(Age)	Natural logarithm of one plus the current year of observation minus the first year the firm appears in the Compustat database.
M/B Ratio	Compustat sum of market equity (CSHO $\times$ PRCC_F), DLC, DLTT, PSTKL, all scaled by lagged book assets.
Profitability	Compustat OIBDP divided by lagged total assets.
Sales	Compustat item SALE.
Sales Growth	Natural logarithm of total sales in the current year t divided by total sales in the previous year $t-1$.
TSIMM	Hoberg-Phillips's firm-level measure of product-market competition formed by summing cosine-similarity scores from firms' 10-K business descriptions. Higher TSIMM means the firm resembles more rivals more closely, indicating less differentiation and stronger competitive pressure.
Panel B: Innovation, Acquisition & Competition Characteristics	
Acquisitions/Assets	The total amount of acquisitions divided by lagged firm assets.
Disruption (SIC-3)	SIC-based technology sectoral disruption measure as defined in Section 1 (Eq.2); based on correlated patenting activity across related SIC-3 industries.
Disruption (TNIC-3)	TNIC-based technology sectoral disruption measure as defined in Section 1 (Eq.4); based on correlated patenting activity across related TNIC industries.
KPSS/Assets	Total dollar value of granted patents calculated by the values in the KPSS database scaled by lagged assets.
Market Share	Firm sales divided by total sales of all firms in the same industry-year (industry defined consistently with the industry scheme used in the corresponding tests).
Organizational Capital	It is constructed by capitalizing SG&A using a perpetual-inventory method following Eisfeldt and Papanikolaou (2013), and it is scaled by total assets.
R&D/Assets	Compustat XRD divided by lagged total assets. This variable is set to zero if XRD is missing.
Trade Secrets	#10K paragraphs mentioning trade secrets, proprietary information, or confidential information along with a protection word as computed in Hoberg and Maksimovic (2015), all scaled by the total paragraphs in the 10-K.
Panel C: Additional Internet Appendix Variables	
Analyst Forecast Error	Mean analyst forecast (most recent before the earnings announcement) minus actual earnings, scaled by stock price 10 trading days before the announcement.
Scaled Net Insider Transactions	$(\text{Shares Purchased}_{i,t} - \text{Shares Sold}_{i,t})/\text{Shares Outstanding}_{i,t}$ (high-ranking insiders; monthly).

Online Appendix For "Technology Sectoral Disruptions" (Not For Publication)

Appendix B. Additional Asset Pricing Results

Table B1: **Fama MacBeth Regressions and Q-Factor Model Alphas (TNIC Disruption)**

This table reports robustness to Table V where the only change made is we use the Fama-French-5 factor model instead of the Q-factor to compute calendar time alphas in the last three columns. We also display the first stage Fama-MacBeth models for convenience. The table's first three columns report the results of Fama-MacBeth regressions where the monthly firm stock return is the dependent variable. The Fama-MacBeth regressions include controls for Size, book-to-market, profitability and investment, and momentum (but we do not display these coefficients to conserve space). Our period is from January 1988 to December 2020. Our central variable of interest, Disrupted, indicates the level of TNIC disruption the given firm faces based on correlated patenting activity over the past months. The final three columns report the time-series alpha of the investment strategies implied by the Disrupted x Small and the Disrupted x Big Fama MacBeth coefficients (which are zero-cost investible portfolios, see Back et al. (2015) for example). We also report the t-statistic of the difference in returns. The alpha is estimated as the intercept of the portfolio return regressed on the 5 Q-factors of Hou et al. (2015).

		Fama MacBeth Results				Calendar Time Results		
Row	Lag	Disrupted x Small	Disrupted x Big	Big	months /Obs	Disrupted x Small Alpha	Disrupted x Big Alpha	Big-Small Difference Test
(1)	-12 Months	-0.045	0.182	0.231	396	-0.021	0.135	0.155
		(-0.67)	(2.79)	(2.46)	1,167,965	(-0.36)	(2.58)	(2.75)
(2)	-10 Months	0.016	0.169	0.209	396	0.047	0.144	0.097
		(0.23)	(2.73)	(2.30)	1,185,584	(0.86)	(2.98)	(1.88)
(3)	-8 Months	0.012	0.137	0.173	396	0.055	0.115	0.060
		(0.18)	(2.33)	(1.85)	1,203,763	(0.95)	(2.41)	(1.12)
(4)	-6 Months	0.033	0.110	0.205	396	0.057	0.086	0.030
		(0.51)	(2.01)	(2.27)	1,222,335	(0.99)	(1.91)	(0.51)
(5)	-4 Months	-0.000	0.067	0.140	396	0.025	0.048	0.023
		(-0.01)	(1.26)	(1.49)	1,243,086	(0.41)	(1.04)	(0.40)
(6)	-2 Months	0.025	0.042	0.198	396	0.044	0.006	-0.038
		(0.37)	(0.76)	(2.34)	1,265,522	(0.71)	(0.13)	(-0.67)
(7)	0 Months	0.058	0.059	0.044	395	0.070	0.012	-0.058
		(0.81)	(1.05)	(0.53)	1,290,905	(1.15)	(0.25)	(-1.04)
(8)	2 Months	0.096	0.128	0.061	393	0.125	0.084	-0.041
		(1.39)	(2.28)	(0.77)	1,268,355	(1.97)	(1.61)	(-0.75)
(9)	4 Months	0.081	0.120	0.008	391	0.081	0.059	-0.023
		(1.19)	(2.21)	(0.09)	1,250,466	(1.34)	(1.19)	(-0.42)
(10)	6 Months	0.146	0.148	0.092	389	0.119	0.070	-0.050
		(2.20)	(2.74)	(1.11)	1,232,586	(2.15)	(1.43)	(-0.89)
(11)	8 Months	0.086	0.158	0.034	387	0.034	0.080	0.046
		(1.23)	(2.92)	(0.43)	1,213,771	(0.57)	(1.55)	(0.74)
(12)	10 Months	0.119	0.178	0.030	385	0.050	0.070	0.020
		(1.63)	(3.22)	(0.38)	1,193,781	(0.75)	(1.40)	(0.31)
(13)	12 Months	0.125	0.189	0.041	383	0.075	0.075	-0.000
		(1.70)	(3.25)	(0.55)	1,172,513	(1.17)	(1.49)	(-0.00)
(14)	14 Months	0.196	0.205	0.052	381	0.131	0.109	-0.022
		(2.47)	(3.58)	(0.69)	1,150,641	(1.62)	(2.20)	(-0.28)
(15)	16 Months	0.201	0.198	0.090	379	0.151	0.099	-0.052
		(2.66)	(3.50)	(1.22)	1,128,868	(2.18)	(1.98)	(-0.77)
(16)	18 Months	0.241	0.174	0.070	377	0.189	0.061	-0.128
		(3.22)	(2.93)	(0.94)	1,107,888	(2.92)	(1.09)	(-1.87)
(17)	20 Months	0.223	0.152	0.058	375	0.176	0.051	-0.125
		(2.94)	(2.54)	(0.76)	1,087,114	(2.77)	(0.91)	(-1.99)
(18)	22 Months	0.199	0.125	0.059	373	0.155	0.016	-0.138
		(2.54)	(2.11)	(0.74)	1,066,630	(2.24)	(0.28)	(-2.07)
(19)	24 Months	0.232	0.136	0.073	371	0.221	0.052	-0.169
		(2.83)	(2.19)	(0.93)	1,046,711	(3.17)	(0.92)	(-2.48)
(20)	26 Months	0.260	0.161	0.070	369	0.268	0.094	-0.174
		(3.19)	(2.58)	(0.90)	1,027,134	(3.80)	(1.59)	(-2.67)
(21)	28 Months	0.239	0.148	0.017	367	0.217	0.093	-0.124
		(2.91)	(2.38)	(0.22)	1,007,982	(3.07)	(1.56)	(-2.05)
(22)	30 Months	0.266	0.169	0.033	365	0.221	0.101	-0.120
		(3.28)	(2.66)	(0.41)	989,494	(3.34)	(1.58)	(-2.06)
(23)	32 Months	0.243	0.157	0.064	363	0.194	0.068	-0.126
		(3.17)	(2.56)	(0.84)	971,656	(3.11)	(1.15)	(-2.19)
(24)	34 Months	0.244	0.142	0.053	361	0.167	0.040	-0.127
		(3.26)	(2.29)	(0.72)	954,064	(2.58)	(0.66)	(-2.06)
(25)	36 Months	0.213	0.152	-0.005	359	0.154	0.044	-0.110
		(2.64)	(2.24)	(-0.06)	936,785	(2.29)	(0.73)	(-1.89)

Table B2: **Fama MacBeth Regressions and Q-Factor Model Alphas (SIC Disruption)**

This table reports robustness to Table VI where the only change made is we use the Fama-French-5 factor model instead of the Q-factor to compute calendar time alphas in the last three columns. We also display the first stage Fama-MacBeth models for convenience. The table's first three columns report the results of Fama-MacBeth regressions where the monthly firm stock return is the dependent variable. The Fama-MacBeth regressions include controls for Size, book-to-market, profitability and investment, and momentum (but we do not display these coefficients to conserve space). Our period is from January 1988 to December 2020. Our central variable of interest, Disrupted, indicates the level of TNIC disruption the given firm faces based on correlated patenting activity over the past months. The final three columns report the time-series alpha of the investment strategies implied by the Disrupted x Small and the Disrupted x Big Fama MacBeth coefficients (which are zero-cost investible portfolios, see Back et al. (2015) for example). We also report the *t*-statistic of the difference in returns. The alpha is estimated as the intercept of the portfolio return regressed on the 5 Q-factors of Hou et al. (2015).

		Fama MacBeth Results				Calendar Time Results		
Row	Lag	Disrupted x Small	Disrupted x Big	Big	months /Obs	Disrupted x Small Alpha	Disrupted x Big Alpha	Big-Small Difference Test
(1)	-12 Months	0.038	-0.024	-0.028	822	-0.017	-0.038	-0.021
		(0.96)	(-0.65)	(-0.51)	1,469,274	(-0.37)	(-0.78)	(-0.43)
(2)	-10 Months	0.027	-0.013	0.002	824	0.016	-0.022	-0.038
		(0.72)	(-0.38)	(0.04)	1,493,166	(0.32)	(-0.47)	(-0.80)
(3)	-8 Months	0.058	-0.009	0.008	826	0.073	-0.015	-0.088
		(1.51)	(-0.26)	(0.15)	1,517,881	(1.60)	(-0.34)	(-1.85)
(4)	-6 Months	0.081	-0.006	0.010	828	0.095	-0.005	-0.100
		(2.11)	(-0.16)	(0.19)	1,543,791	(1.96)	(-0.12)	(-2.01)
(5)	-4 Months	0.092	0.011	0.050	830	0.095	0.001	-0.095
		(2.43)	(0.33)	(0.91)	1,571,896	(2.04)	(0.01)	(-1.87)
(6)	-2 Months	0.075	0.002	0.075	832	0.096	-0.012	-0.108
		(2.08)	(0.07)	(1.41)	1,602,217	(2.04)	(-0.27)	(-2.14)
(7)	0 Months	0.070	0.014	0.016	833	0.089	0.001	-0.089
		(1.94)	(0.38)	(0.30)	1,637,396	(1.76)	(0.01)	(-1.61)
(8)	2 Months	0.096	0.050	0.006	833	0.108	0.030	-0.078
		(2.69)	(1.32)	(0.11)	1,618,519	(2.13)	(0.61)	(-1.43)
(9)	4 Months	0.118	0.034	-0.006	833	0.080	0.005	-0.074
		(3.38)	(0.98)	(-0.12)	1,604,873	(1.77)	(0.12)	(-1.35)
(10)	6 Months	0.117	0.048	0.001	833	0.106	0.055	-0.051
		(3.05)	(1.34)	(0.02)	1,589,410	(2.26)	(1.23)	(-0.96)
(11)	8 Months	0.131	0.057	-0.005	833	0.119	0.060	-0.059
		(3.28)	(1.55)	(-0.09)	1,571,902	(2.45)	(1.30)	(-1.09)
(12)	10 Months	0.161	0.049	0.008	833	0.127	0.035	-0.092
		(4.21)	(1.39)	(0.14)	1,552,417	(2.86)	(0.79)	(-1.78)
(13)	12 Months	0.197	0.065	0.016	833	0.162	0.057	-0.104
		(4.89)	(1.81)	(0.30)	1,531,205	(3.77)	(1.30)	(-2.13)
(14)	14 Months	0.201	0.054	0.014	833	0.185	0.051	-0.134
		(5.08)	(1.52)	(0.26)	1,509,368	(3.93)	(1.13)	(-2.50)
(15)	16 Months	0.186	0.073	0.013	833	0.153	0.038	-0.114
		(4.62)	(2.02)	(0.24)	1,487,594	(3.13)	(0.84)	(-2.09)
(16)	18 Months	0.193	0.093	0.021	833	0.136	0.054	-0.082
		(4.81)	(2.59)	(0.38)	1,465,874	(2.91)	(1.19)	(-1.51)
(17)	20 Months	0.181	0.096	0.041	833	0.142	0.054	-0.088
		(4.59)	(2.56)	(0.75)	1,444,474	(2.84)	(1.09)	(-1.45)
(18)	22 Months	0.172	0.078	0.045	833	0.144	0.048	-0.096
		(4.55)	(2.22)	(0.85)	1,423,493	(2.78)	(1.03)	(-1.63)
(19)	24 Months	0.163	0.063	0.061	833	0.132	0.027	-0.105
		(4.06)	(1.69)	(1.13)	1,402,856	(2.36)	(0.54)	(-1.57)
(20)	26 Months	0.149	0.066	0.043	833	0.126	0.047	-0.079
		(3.72)	(1.79)	(0.78)	1,382,367	(2.24)	(0.96)	(-1.24)
(21)	28 Months	0.156	0.078	0.053	833	0.118	0.061	-0.056
		(3.96)	(2.12)	(0.98)	1,362,276	(2.18)	(1.30)	(-0.92)
(22)	30 Months	0.147	0.077	0.055	833	0.137	0.065	-0.072
		(3.64)	(2.05)	(1.04)	1,342,676	(2.28)	(1.33)	(-1.17)
(23)	32 Months	0.160	0.066	0.048	833	0.119	0.041	-0.078
		(3.92)	(1.72)	(0.91)	1,323,387	(2.19)	(0.82)	(-1.36)
(24)	34 Months	0.139	0.064	0.048	833	0.087	0.038	-0.049
		(3.53)	(1.66)	(0.86)	1,304,459	(1.59)	(0.80)	(-0.89)
(25)	36 Months	0.147	0.061	0.049	833	0.114	0.049	-0.065
		(3.55)	(1.58)	(0.92)	1,285,872	(2.05)	(0.99)	(-1.12)

Appendix C. Insider Trading Data & Results

0.1 Insider Trading Data

Corporate insiders are required to file SEC forms 3, 4, and 5 when they trade their company's stock. We use Thomson Financial Insider Filing database (hereafter, TFN), which collects data from SEC filings, to gather information for these insider transactions. Our goal is to test whether high-ranked insiders, who are in the best position to make corporate decisions regarding disruptive technologies, internalize the economic impact of disruption in a timely way. We focus on all open-market transactions of high-ranked insiders: Chairman of the Board, President, Chief Executive Officer, Chief Financial Officer, Chief Operating Officer, and Directors. As in Anginer et al. (2020), we exclude shares acquired through the exercise of options, stock awards, and trades with corporations.

For each firm i in month t, we calculate the net insider number of shares as the number of shares purchased minus the number of shares sold. Following Seyhun (1990), we then scale the net number of shares traded by the number of shares outstanding at the end of month t. If a firm has no insider trades in a given month, we assign a value of zero for the insider trading variable.

$$Scaled\ Net\ Insider\ Transactions_{i,t} = \frac{Shares\ Purchased_{i,t} - Shares\ Sold_{i,t}}{Shares\ Outstanding_{i,t}} \tag{9}$$

TFN insider transaction data covers the 1986-2022 period. After matching this dataset to the CRSP database, we have 17,000 unique firms, and 410,382 firm-month observations that have different than zero insider transaction data. Of these 410,382 firm-month observations, 165,568 (%40.34) are positive net purchases and 244,814 (%59.66) are negative net sales. Therefore, our sample is quite balanced sample over purchases and sales but favors sales being more prevalent consistent with the literature.

0.2 Insider Trading Results

This appendix describes our insider trading results. We display both for t-tests regarding if our disruption coefficients are different from zero (second column), and t-tests regarding if our disruption coefficients are different in months after the measurement of our disruption variable relative to the average coefficient prior to measurement (third column). This latter t-test is the one that is theoretically motivated in our setting as insider trading is typically not centered around zero as is the case for stock returns, and more innovative firm insiders sell more shares on average than they buy (as reflected by the steady negative coefficients in the second column). The intuition is the third column t-tests are testing for "abnormal insider trading intensities" relative to a pre-measurement benchmark. The results for TNIC disruption are presented in the first three columns and SIC disruption in the final three columns.

The first three columns show that sectoral disruption only becomes significantly different from pre-measurement levels after a significant lag. Significance levels first become positive 12 months after measurement and then gradually rise to a peak t-statistic value of 5.4 by month 32. These results indicate a significant lagged response by insiders. In fact, insiders appear to react to disruption even later than external stock market participants (stock return predictability reaches a peak after just 18 months in Table V, which is less than the 32 months for insider trades). We also note that the magnitude and significance of insider trading predictability grows with longer lags and remains highly significant for a protracted period of time. Broadly, these results suggest that insiders are not aware of major sectoral disruptions during their measurement periods and appear to be surprised in the months that follow.

The final three columns of Table C1 show that results for SIC codes (focusing on the most important last column) are consistent with the results for TNIC industries but are not significant. In particular, the t-statistics increase over time and have the same sign as do the TNIC results, although the SIC results are not statistically significant. This reinforces results in Hoberg and Phillips (2016) that SIC-codes are significantly less informative than are TNIC industries, especially for technology firms.[6] We finally note that the SIC-3 results, while weaker, are nevertheless consistent with our conclusion that insiders likely were not aware of the value gains associated with sectoral disruptions in the pre-measurement period. This follows because insider awareness in the pre-period would predict more insider buying pressure in the pre-period than in the post-measurement period (indeed we do not find negative and significant t-tests in the post-measurement period).

Figure C1 displays these results graphically. The figure displays the post-measurement t-test regarding differences from the pre-measurement coefficients. The figure displays results for both TNIC and SIC disruption and it illustrates three conclusions. (1) TNIC disruption predicts significant and long-lasting positive insider trading pressure consistent with large amounts of economic value created. (2) This predictability is significantly lagged and only becomes significant a full 12 months after measurement and then increases further through month 32 before reaching a peak. (3) The results for TNIC are significantly stronger than those for SIC as noted above.

[6] Hoberg and Phillips (2016) show that gains to using TNIC over SIC industries are particularly large for technology firms.

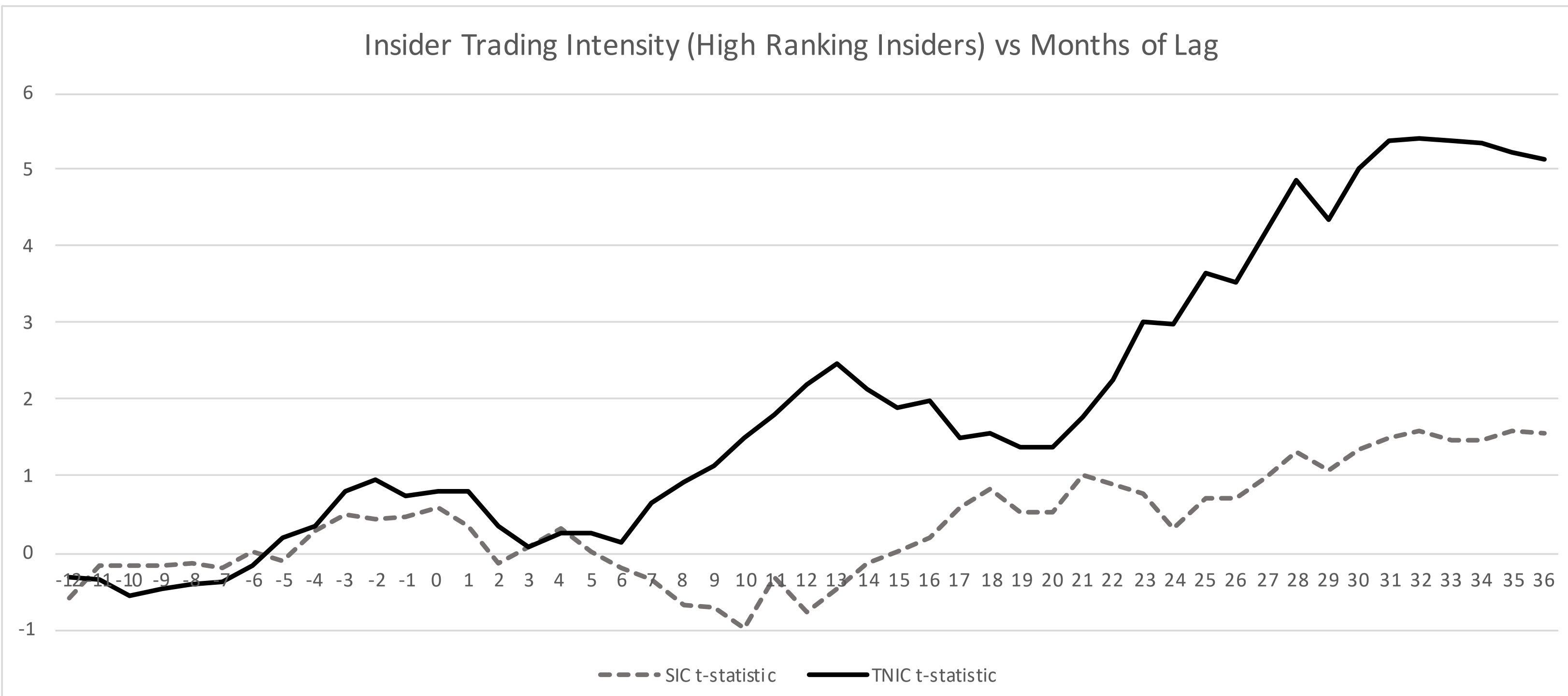
Table C1: **Fama MacBeth Regressions and Insider Trading Activity**

The table reports the results of Fama-MacBeth regressions where directional insider trading by high ranking insiders is the dependent variable. Directional insider trading is the total shares bought minus the total shares sold, all divided by total shares outstanding. Our sample period is from January 1987 to December 2020. Our central variable of interest, Disrupted, indicates the level of TNIC disruption the given firm faces based on correlated patenting activity over the past months. We consider regressions where we change the lag imposed on our key disruption variable from -12 months to +36 months (for example, when the lag is zero, then disruption is measured simultaneously with the insider trading variable on the LHS). We only display even numbered lags for most months to conserve space and because coefficients are very similar for these neighboring lags. The table shows the coefficient for the disruption variable and two t-statistics. The first is a t-test for whether the coefficient is different from zero and the second is a t test for whether the coefficient in the given month of lag is different from the average coefficient obtained in the first 12 month period prior to month $t = 0$. This second t-test thus examines if insider trading in periods with lag zero to 36 are significantly higher or lower than the coefficient observed in the 12 month pre-period prior to the patent grant dates needed to measure Disruption. We display results for both TNIC and SIC disruption as indicated. Although we do not show them for parsimony, all regressions include the following controls. Size, book-to-market, profitability and investment are computed following Fama and French (2014). The Past Return is the firm-specific return from month $t - 12$ to $t - 2$ from the CRSP database.

		TNIC Disruption			**SIC Disruption**	
Lag	Coefficient	t H0: zero	t H0: pre-period	Coefficient	t H0: zero	t H0: pre-period
-12	-0.045	-11.40	-0.34	-0.039	-11.20	-0.62
-10	-0.046	-11.35	-0.56	-0.037	-11.52	-0.17
-8	-0.045	-12.17	-0.42	-0.037	-11.52	-0.14
-6	-0.044	-12.25	-0.18	-0.037	-11.52	-0.01
-4	-0.042	-11.68	0.34	-0.036	-10.73	0.27
-2	-0.040	-11.44	0.93	-0.035	-10.57	0.42
0	-0.041	-11.27	0.79	-0.035	-10.91	0.59
2	-0.042	-12.38	0.33	-0.037	-11.04	-0.14
4	-0.043	-13.17	0.26	-0.036	-10.63	0.30
6	-0.043	-13.63	0.13	-0.037	-11.39	-0.20
8	-0.041	-12.85	0.93	-0.039	-11.36	-0.70
10	-0.039	-11.82	1.50	-0.040	-11.51	-1.00
12	-0.037	-11.55	2.18	-0.039	-11.32	-0.78
14	-0.037	-11.83	2.11	-0.037	-11.31	-0.14
16	-0.037	-11.48	1.98	-0.036	-11.29	0.19
18	-0.038	-10.79	1.55	-0.034	-10.85	0.81
20	-0.039	-10.91	1.37	-0.035	-10.31	0.51
22	-0.036	-11.42	2.23	-0.034	-10.48	0.88
24	-0.035	-11.51	2.96	-0.036	-10.36	0.30
26	-0.033	-10.92	3.52	-0.034	-9.53	0.70
28	-0.029	-10.17	4.86	-0.032	-8.22	1.31
30	-0.029	-10.11	5.01	-0.031	-8.32	1.34
32	-0.028	-9.61	5.38	-0.031	-8.54	1.60
34	-0.028	-9.84	5.34	-0.031	-8.71	1.46
36	-0.029	-10.04	5.13	-0.031	-8.58	1.56

Figure C1: Insider Trading Signal versus Months of Delay

The figure plots the coefficient of Fama-MacBeth regressions of insider trading intensity regressed on either TNIC Disruption or SIC Disruption as in Table C1 . We display results for lags from -12 months to +36 months. We first run Fama-MacBeth regressions in which the dependent variable is insider trading intensity in month $t = 0$. We then run the same regressions but we lag our key variable TNIC or SIC"Disruption" for -12 to 36 months. For each lag, the figure below plots the magnitude of the t-statistic testing if the coefficient for the given month of lag is statistically different from the average coefficient associated with the ex-ante period coefficients (lags -12 to -1). A t-statistic in excess of 2.0 indicates significant predictability when the disrupted variable is lagged as indicated on the x-axis.



Appendix D. Analyst Forecast Errors

0.3 Analyst Forecast Data

We consider quarterly analyst forecast data from the I/B/E/S database from 1985 to 2020. Our focus is on the mean consensus forecast just prior to an earnings announcement and its degree of variance. In particular, we later test if analysts internalize the economic impact of sectoral disruptions in a timely way or if their forecasts are abnormally low indicating a potential lack of awareness.

We compute analyst forecast errors following convention in the literature. We compute it as the average analyst forecast (using the most recent forecasts before the earnings announcement) minus the actual earnings that are announced. As in Kumar et al. (2022), we scale the errors by the firm's stock price ten trading days before the earnings announcement. For stock prices, we use CRSP adjusted prices to take into account the stock splits. We winsorize this variable at the 1/99% level within each quarter.

0.4 Sectoral Disruption and Analyst Forecast Errors

We also examine whether analysts internalize the economic impact of sectoral disruptions in their earnings forecasts. Our key dependent variable is the quarterly analyst forecast error (see Section 0.3 for details). Our right-hand-side variables include controls for size and age, and are all measurable as of month t, ensuring no look-ahead bias. In the interest of space, we present these results in the appendix in Table A4 and a graphical presentation of the t-statistics for each quarter in Appendix Figure A1.

The results show that analysts do not anticipate or forecast the impact of TSDs. Their projected earnings are too low in the months after sectoral disruption becomes measurable, and thus, they make significant negative forecast errors for the TNIC-based disruption measure beginning in the 3rd quarter and in the 2nd year for the SIC-based disruption measure. The results show significantly delayed reactions and no ex-ante anticipation of the TSDs, as was the case for stock returns and insider trading. These findings reinforce the conclusion that the sectoral disruptions are not anticipated by the stock market, the firms' managers themselves, and the analysts processing information - and that the TSDs can be viewed as exogenous shocks.

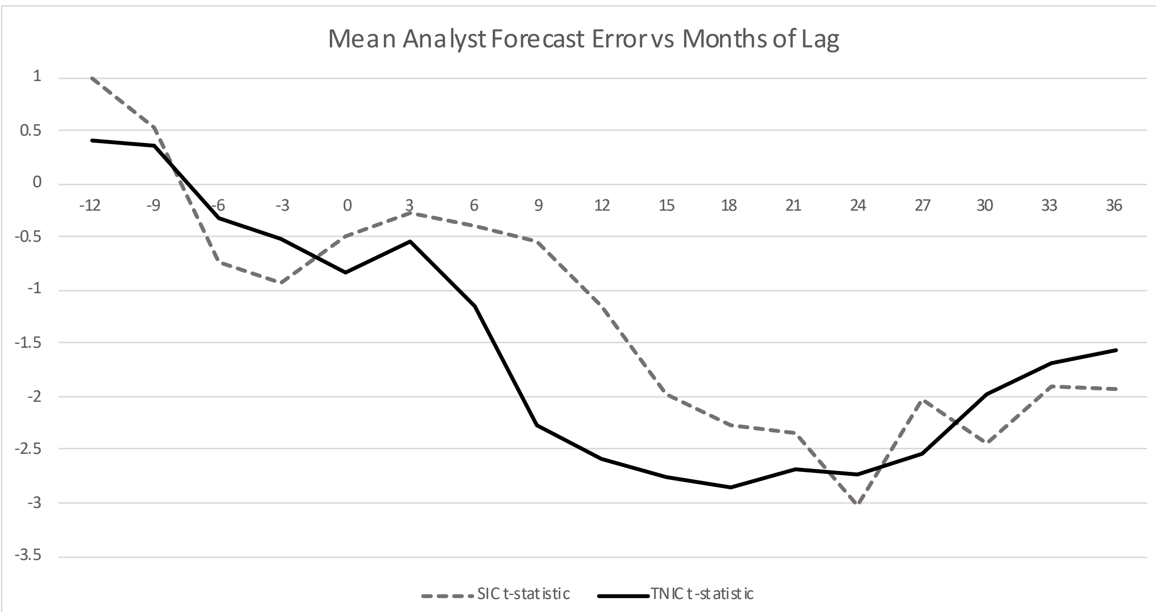
Table D1: **Fama MacBeth Regressions and Analyst Forecast Errors**

The table reports the results of Fama-MacBeth regressions where the analyst forecast error is the dependent variable. Analyst forecast error is the mean consensus forecast minus the actual earnings, divided by the firm's stock price ten trading days prior to the announcement date. Our sample period is from January 1985 to December 2020. We consider regressions where we change the lag imposed on our key disruption variable from -12 months to +36 months. We report in increments of three because our panel is quarterly given that earnings are quarterly. The table shows the coefficient for the disruption variable and two t-statistics. The first is a t-test for whether the coefficient is different from zero and the second is a t test for whether the coefficient in the given month of lag is different from the average coefficient obtained in the first 12 month period prior to month $t = 0$. This second t-test thus examines if the analyst variables in periods with lag zero to 36 are significantly higher than the coefficient observed in the 12 month pre-period prior to the patent grant dates needed to measure Disruption. We display results for both TNIC and SIC disruption. Although we do not show them for parsimony, all regressions include controls for log assets and log age (Compustat listing vintage).

	TNIC Disruption			SIC Disruption		
Lag	Coefficient	t H0: zero	t H0: pre-period	Coefficient	t H0: zero	t H0: pre-period
			Signed Analyst Forecast Error			
-12	-0.195	-1.21	0.41	0.254	1.44	1.01
-9	-0.208	-1.38	0.35	0.169	0.98	0.54
-6	-0.312	-1.98	-0.32	-0.038	-0.25	-0.73
-3	-0.330	-2.43	-0.50	-0.081	-0.48	-0.93
0	-0.381	-2.68	-0.84	-0.024	-0.12	-0.49
3	-0.344	-2.20	-0.53	0.015	0.07	-0.27
6	-0.451	-2.72	-1.14	-0.020	-0.08	-0.38
9	-0.666	-3.75	-2.28	-0.062	-0.25	-0.55
12	-0.735	-4.00	-2.58	-0.220	-0.86	-1.15
15	-0.718	-4.32	-2.74	-0.400	-1.66	-1.97
18	-0.750	-4.37	-2.85	-0.447	-1.94	-2.27
21	-0.733	-4.18	-2.69	-0.463	-2.01	-2.34
24	-0.912	-3.83	-2.73	-0.492	-2.62	-3.02
27	-1.009	-3.42	-2.54	-0.359	-1.67	-2.02
30	-0.847	-2.86	-1.98	-0.465	-2.10	-2.44
33	-0.775	-2.55	-1.69	-0.441	-1.62	-1.89
36	-0.840	-2.26	-1.56	-0.476	-1.67	-1.94

Figure D1: Analyst Forecast Error versus Months of Delay

The figure plots the coefficient of Fama-MacBeth regressions of analyst forecast error regressed on either TNIC Disruption or SIC Disruption as in Table D1 . We display results for lags from -12 months to +36 months at quarterly frequency. We first run Fama-MacBeth regressions in which the dependent variable is a measure of analyst quality in month $t = 0$. We then run the same regressions but we lag our key variable TNIC or SIC"Disruption" for -12 to 36 months. For each lag, the figure below plots the magnitude of the t-statistic testing if the coefficient for the given quarter of lag is statistically different from the average coefficient associated with the ex-ante period coefficients (lags -12 to -1). A t-statistic in excess of 2.0 indicates significant predictability when the disrupted variable is lagged as indicated on the x-axis.



Appendix E. Additional Corporate Finance Responses

Table E1: Comparison of Results Across Neighbour Specifications (TNIC)

This table examines the robustness of the main corporate finance results to the number of pseudo-industry firms (N) used in computing the Technology Sectoral Disruption (TSD) score based on TNIC-3 industry classifications. For a given firm j, the TNIC-based TSD measure aggregates market-capitalization-weighted pairwise disruption scores over the $N \in \{3, 5, 10\}$ most ex-ante spatially proximate pseudo-industry firms (equation (4) in the paper), where $N = 3$ is the baseline specification. Reported coefficients are OLS estimates of $\hat{\beta}_1$ (*Disrupted* × *Small*) and $\hat{\beta}_2$ (*Disrupted* × *Large*) from the panel regression

$$Y_{i,t+\tau} = \beta_1\, Disruption_{i,t} \times Small_{i,t} + \beta_2\, Disruption_{i,t} \times Large_{i,t} + \beta_3\, Small_{i,t} + \beta_4\, X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t},$$

where $Small_{i,t}$ is an indicator equal to one for firms with below-median total assets in year t, $X_{i,t}$ includes inverse size and log firm age as controls, and μ_i and δ_t are firm and year fixed effects (equation (7) in the paper). The row labelled *Difference* reports $\hat{\beta}_1 - \hat{\beta}_2$, capturing the differential effect of disruption on small versus large firms; significance is assessed via a Wald test. Within each neighbour-count group, columns (1), (2), and (3) correspond to $\tau = 1, 2, 3$, respectively (contemporaneous, one-period, and two-period forward outcomes). Because TNIC-3 industries are firm-specific and intransitive, pseudo-industry patent portfolios are constructed at the individual-firm level following equation (3) in the paper, and the sample is restricted to firms with at least 25 patents in the preceding 12-month rolling window. Standard errors are clustered at the industry level. The sample covers all public Compustat firms from 1988 to 2020. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

		3-Neighbour			5-Neighbour			10-Neighbour		
Outcome	Statistic	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
RD Assets Disrupted	*Disrupted* × *Small*	1.672***	1.147***	0.928***	1.443***	0.981***	0.709***	0.953***	0.650***	0.438***
		(3.370)	(3.197)	(3.050)	(3.332)	(3.214)	(3.000)	(3.021)	(3.131)	(2.759)
	Disrupted × *Large*	−0.515**	−0.501**	−0.355**	−0.412**	−0.412**	−0.300**	−0.295**	−0.263**	−0.203***
		(−2.031)	(−2.407)	(−2.350)	(−2.084)	(−2.394)	(−2.388)	(−2.319)	(−2.586)	(−2.626)
	Difference	2.187***	1.648***	1.283***	1.856***	1.393***	1.009***	1.248***	0.913***	0.641***
Asset Growth Disrupted	*Disrupted* × *Small*	1.357	1.809*	2.636***	1.042	2.033**	1.917**	0.674	1.588***	1.455***
		(1.437)	(1.935)	(2.664)	(1.451)	(2.589)	(2.274)	(1.319)	(2.993)	(3.267)
	Disrupted × *Large*	−4.354***	−2.946***	−1.679**	−3.575***	−2.550***	−1.291**	−2.585***	−1.733***	−1.016**
		(−4.206)	(−3.466)	(−2.477)	(−4.536)	(−3.807)	(−2.371)	(−5.371)	(−4.169)	(−2.545)
	Difference	5.711***	4.755***	4.315***	4.616***	4.583***	3.207***	3.259***	3.321***	2.471***
Capital Expenditures	*Disrupted* × *Small*	0.361	0.312	0.313	0.360*	0.300	0.245	0.220*	0.172	0.147
		(1.349)	(1.202)	(1.383)	(1.755)	(1.378)	(1.307)	(1.797)	(1.364)	(1.348)
	Disrupted × *Large*	−0.197	−0.240	−0.213	−0.125	−0.211	−0.133	−0.101	−0.159	−0.104
		(−0.674)	(−1.107)	(−1.053)	(−0.550)	(−1.143)	(−0.846)	(−0.638)	(−1.299)	(−0.983)
	Difference	0.558***	0.551**	0.526**	0.485***	0.511**	0.377*	0.321***	0.330**	0.251*
KPSS Assets	*Disrupted* × *Small*	2.705***	2.294***	2.248***	2.869***	2.135***	1.479**	1.880***	1.646***	1.248**
		(3.472)	(2.772)	(2.689)	(3.827)	(2.952)	(2.443)	(3.310)	(3.133)	(2.402)
	Disrupted × *Large*	0.567	−0.039	−0.766	0.742	−0.045	−0.977	0.089	−0.375	−0.756*
		(0.519)	(−0.039)	(−0.648)	(1.087)	(−0.079)	(−1.237)	(0.263)	(−1.221)	(−1.938)
	Difference	2.138*	2.333*	3.014**	2.127**	2.180**	2.456**	1.791**	2.021***	2.004**
Sales Growth Disrupted	*Disrupted* × *Small*	0.313	0.501	2.231***	−0.118	0.453	1.683***	0.165	0.524	1.592***
		(0.329)	(0.560)	(3.020)	(−0.158)	(0.663)	(2.868)	(0.363)	(1.275)	(4.412)
	Disrupted × *Large*	−3.521***	−1.316	−0.077	−2.857***	−1.414**	0.147	−1.916***	−1.037***	0.053
		(−4.143)	(−1.582)	(−0.090)	(−4.163)	(−2.246)	(0.218)	(−4.156)	(−2.912)	(0.114)
	Difference	3.834***	1.817	2.308**	2.739***	1.867**	1.537*	2.081***	1.562***	1.539***
Tobin's Q Disrupted	*Disrupted* × *Small*	28.484**	38.053***	34.032***	25.711***	35.059***	25.156***	14.918**	20.865***	16.714***
		(2.484)	(3.653)	(3.858)	(2.984)	(3.936)	(3.383)	(2.594)	(3.665)	(3.516)
	Disrupted × *Large*	−4.924	−4.773	−2.027	−4.400	−3.200	−1.069	−5.124	−4.565*	−2.965
		(−0.587)	(−0.761)	(−0.465)	(−0.710)	(−0.717)	(−0.338)	(−1.302)	(−1.686)	(−1.355)
	Difference	33.408***	42.826***	36.059***	30.111***	38.259***	26.225***	20.042***	25.430***	19.679***
Trade Secrets	*Disrupted* × *Small*	20.332***	16.070**	19.176***	18.814***	13.666**	16.530***	12.716***	8.927**	12.549***
		(2.731)	(2.058)	(2.619)	(3.145)	(2.148)	(2.715)	(3.031)	(2.069)	(3.025)
	Disrupted × *Large*	12.588**	6.658	1.381	10.211***	4.942	3.151	7.269***	3.577*	3.074
		(2.516)	(1.474)	(0.322)	(2.680)	(1.444)	(0.961)	(3.039)	(1.705)	(1.370)
	Difference	7.744	9.412	17.796***	8.603*	8.724	13.379**	5.448	5.350	9.476***
Acq Assets Disrupted	*Disrupted* × *Small*	1.271**	1.989***	1.030*	1.246**	1.593***	1.036**	0.773***	1.176***	0.769***
		(1.978)	(3.873)	(1.839)	(2.561)	(4.036)	(2.359)	(3.054)	(4.376)	(2.708)
	Disrupted × *Large*	0.553	0.648*	−0.065	0.236	0.536*	0.065	−0.057	0.315*	0.025
		(1.232)	(1.756)	(−0.179)	(0.697)	(1.961)	(0.215)	(−0.215)	(1.755)	(0.121)
	Difference	0.718	1.341***	1.095*	1.010*	1.057**	0.971**	0.831**	0.861***	0.744**

Table E2: **Disruption, Valuation and Sales (Firms With Highly-Cited Patents Removed)**

The table is analogous to Table VII except that we remove firm-years where the firm had at least one patent in the preceding ten years that went on to be among the top 10% most-cited patents in that specific year. In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small}$ is the coefficient estimate of $Disrupted \times Small$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: R&D/Assets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	1.360***	0.560***	0.045	1.342***	0.900***	0.770***
	(9.225)	(4.136)	(0.338)	(10.428)	(6.411)	(5.373)
Disrupted × Large	-1.817***	-1.024***	-0.695***	-0.414***	-0.431***	-0.257***
	(-16.450)	(-10.379)	(-7.340)	(-4.688)	(-4.877)	(-2.842)
Difference	3.177***	1.584***	0.741***	1.756***	1.332***	1.027***
Observations	171,311	149,695	132,605	93,627	77,980	65,988
R-squared	0.091	0.039	0.015	0.055	0.035	0.024
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0032	.0014	.0001	.0036	.0024	.002
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0043	-.0025	-.0017	-.0011	-.0011	-.0007
Panel B: Acquisition/Assets						
Disrupted × Small	0.216	0.882***	1.213***	0.901*	1.691***	0.766
	(0.852)	(3.034)	(4.311)	(1.879)	(3.876)	(1.604)
Disrupted × Large	-0.326	-0.053	0.070	0.521	0.494	-0.025
	(-1.462)	(-0.247)	(0.343)	(1.374)	(1.468)	(-0.070)
Difference	0.543*	0.935***	1.143***	0.380	1.196**	0.791
Observations	109,978	97,019	86,454	89,268	75,548	63,730
R-squared	0.027	0.036	0.027	0.028	0.025	0.022
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0005	.002	.0027	.0024	.0045	.002
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0007	-.0001	.0002	.0014	.0013	-.0001

Table E3: **Disruption, R&D, and Acquisitions (Firms With Highly-Cited Patents Removed)**

The table is analogous to Table VIII except that we remove firm-years where the firm had at least one patent in the preceding ten years that went on to be among the top 10% most-cited patents in that specific year. In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small}$ is the coefficient estimate of $Disrupted \times Small$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: Capital Expenditures/Assets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	1.025***	1.057***	1.052***	0.265*	0.204	0.226
	(5.804)	(6.692)	(6.809)	(1.849)	(1.315)	(1.428)
Disrupted × Large	-0.803***	-0.289**	0.093	-0.271**	-0.284**	-0.294**
	(-5.798)	(-2.297)	(0.772)	(-2.396)	(-2.486)	(-2.517)
Difference	1.828***	1.345***	0.959***	0.537***	0.489***	0.519***
Observations	171,311	149,695	132,605	93,627	77,980	65,988
R-squared	0.115	0.091	0.074	0.074	0.074	0.073
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0024	.0026	.0025	.0007	.0005	.0006
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0019	-.0007	.0002	-.0007	-.0007	-.0008
Panel B: Asset Growth						
Disrupted × Small	3.468***	4.425***	1.699***	0.922	1.601**	2.800***
	(5.742)	(7.888)	(3.046)	(1.233)	(2.010)	(3.368)
Disrupted × Large	-6.287***	-3.052***	-1.797***	-4.209***	-2.725***	-1.732***
	(-12.783)	(-6.590)	(-4.089)	(-6.844)	(-4.312)	(-2.623)
Difference	9.755***	7.477***	3.496***	5.130***	4.326***	4.531***
Observations	171,311	149,695	132,605	93,627	77,980	65,988
R-squared	0.166	0.112	0.071	0.082	0.076	0.063
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0082	.0107	.0041	.0025	.0042	.0074
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0149	-.0074	-.0043	-.0112	-.0072	-.0045

Table E4: **Disruption, Performance, and Growth (Firms With Highly-Cited Patents Removed)**

The table is analogous to Table IX except that we remove firm-years where the firm had at least one patent in the preceding ten years that went on to be among the top 10% most-cited patents in that specific year. In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small}$ is the coefficient estimate of $Disrupted \times Small$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: Valuation (M/B ratio)	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	83.293***	54.362***	14.585**	24.510***	29.672***	30.984***
	(9.747)	(7.173)	(2.147)	(4.472)	(5.345)	(5.301)
Disrupted × Large	-57.567***	-22.788***	-19.940***	-8.947**	-9.205***	-6.604*
	(-10.076)	(-5.160)	(-4.817)	(-2.398)	(-2.597)	(-1.826)
Difference	140.860***	77.150***	34.525***	33.458***	38.877***	37.588***
Observations	145,829	131,151	117,421	93,140	77,596	65,677
R-squared	0.143	0.100	0.064	0.113	0.107	0.092
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.1904	.1253	.0335	.0651	.0781	.0814
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.1316	-.0525	-.0458	-.0238	-.0242	-.0173
Panel B: Sales Growth						
Disrupted × Small	-0.153	3.785***	4.707***	-0.166	0.564	2.343***
	(-0.271)	(6.888)	(8.338)	(-0.207)	(0.681)	(2.796)
Disrupted × Large	-3.518***	-1.055**	1.541***	-3.580***	-1.297*	-0.087
	(-7.796)	(-2.337)	(3.322)	(-5.719)	(-1.956)	(-0.130)
Difference	3.365***	4.840***	3.166***	3.414***	1.861*	2.430**
Observations	170,129	149,695	132,431	93,237	77,980	65,933
R-squared	0.108	0.108	0.080	0.085	0.083	0.075
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	-.0004	.0092	.0114	-.0004	.0015	.0062
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0083	-.0026	.0037	-.0095	-.0034	-.0002

Table E5: **Disruption and Financing Variables (Firms With Highly-Cited Patents Removed)**

The table is analogous to Table X except that we remove firm-years where the firm had at least one patent in the preceding ten years that went on to be among the top 10% most-cited patents in that specific year. In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small}$ is the coefficient estimate of $Disrupted \times Small$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: KPSS/Assets						
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	4.725***	5.409***	6.295***	1.273***	0.852*	1.061**
	(4.986)	(5.206)	(6.044)	(3.153)	(1.911)	(2.179)
Disrupted × Large	-3.694***	-3.382***	-2.466**	0.357	-0.025	-0.308
	(-3.740)	(-3.163)	(-2.404)	(1.163)	(-0.085)	(-0.969)
Difference	8.419***	8.791***	8.761***	0.916*	0.878	1.370**
Observations	73,939	67,793	62,900	36,271	32,067	28,705
R-squared	0.122	0.132	0.142	0.092	0.094	0.094
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0121	.014	.0162	.0038	.0025	.003
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0095	-.0087	-.0063	.0011	-.0001	-.0009
Panel B: Trade Secrets						
Disrupted × Small	11.718***	8.620**	5.260	17.108***	11.458***	14.109***
	(3.343)	(2.388)	(1.359)	(4.380)	(2.875)	(3.307)
Disrupted × Large	-7.292**	-12.458***	-11.333***	12.645***	6.499*	1.992
	(-2.124)	(-3.526)	(-3.028)	(3.460)	(1.761)	(0.529)
Difference	19.010***	21.079***	16.593***	4.462	4.959	12.117**
Observations	66,258	60,934	55,062	70,664	61,926	54,759
R-squared	0.027	0.030	0.027	0.034	0.034	0.035
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0262	.0199	.0123	.0414	.0283	.0351
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0163	-.0288	-.0264	.0306	.016	.005

1 Further Years

Table E6: **Disruption, R&D, and Acquisitions (T+4 to T+6)**

The table displays three panel data regressions in which organic investment variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small}$ is the coefficient estimate of $Disrupted \times Small$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: R&D/Assets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+4$	$t+5$	$t+6$	$t+4$	$t+5$	$t+6$
Disrupted × Small	0.111	0.234*	0.170	0.203	0.170	0.108
	(0.874)	(1.812)	(1.358)	(1.226)	(1.018)	(0.654)
Disrupted × Large	-0.350***	-0.311***	-0.179**	-0.414***	-0.418***	-0.292***
	(-3.921)	(-3.518)	(-2.116)	(-4.258)	(-4.346)	(-2.949)
Difference	0.461***	0.545***	0.349**	0.617***	0.588***	0.400**
Observations	120,416	109,812	100,745	59,234	52,924	47,401
R-squared	0.013	0.012	0.011	0.017	0.015	0.012
Panel B: Acquisition/Assets						
Disrupted × Small	0.874***	1.056***	0.768**	0.639	-0.721	0.550
	(2.974)	(3.655)	(2.551)	(1.232)	(-1.438)	(1.013)
Disrupted × Large	0.146	-0.223	0.076	-1.107***	-1.441***	-1.182***
	(0.693)	(-0.949)	(0.319)	(-2.793)	(-3.601)	(-3.098)
Difference	0.728**	1.279***	0.692**	1.746***	0.720	1.732***
Observations	75,410	68,821	63,262	53,120	47,190	42,003
R-squared	0.025	0.024	0.022	0.021	0.020	0.018

Table E7: **Disruption, Performance, and Growth (T+4 to T+6)**

This table runs the same model as the earlier tables for financing variables. All dependent variables are described in detail in Appendix A.

	SIC (Full Sample)			**TNIC**		
Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
	$t+4$	$t+5$	$t+6$	$t+4$	$t+5$	$t+6$
Panel C: Capital Expenditures/Assets						
Disrupted × Small	0.892***	0.994***	0.934***	0.025	-0.156	-0.185
	(5.691)	(6.232)	(5.958)	(0.146)	(-0.868)	(-0.989)
Disrupted × Large	0.080	0.333***	0.476***	-0.330***	-0.398***	-0.305**
	(0.683)	(2.709)	(4.006)	(-2.948)	(-3.276)	(-2.504)
Difference	0.812***	0.661***	0.458**	0.355*	0.242	0.121
Observations	120,416	109,812	100,745	59,234	52,924	47,401
R-squared	0.080	0.081	0.079	0.081	0.081	0.079
Panel B: Asset Growth						
Disrupted × Small	3.186***	3.876***	3.570***	0.365	0.731	2.473***
	(5.898)	(6.925)	(6.353)	(0.416)	(0.826)	(2.690)
Disrupted × Large	0.201	1.270***	1.307***	-2.301***	-0.753	-0.061
	(0.468)	(2.829)	(2.882)	(-3.570)	(-1.153)	(-0.093)
Difference	2.985***	2.606***	2.263***	2.667***	1.484	2.534**
Observations	120,416	109,812	100,745	59,234	52,924	47,401
R-squared	0.056	0.051	0.047	0.052	0.049	0.044

Table E8: **Disruption, Valuation and Sales (T+4 to T+6)**

The table displays three panel data regressions in which patenting variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small}$ is the coefficient estimate of $Disrupted \times Small$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: Valuation (M/B ratio)	(1)	(2)	(3)	(4)	(5)	(6)
	$t+4$	$t+5$	$t+6$	$t+4$	$t+5$	$t+6$
Disrupted × Small	5.578	2.048	2.153	-9.647	-10.321*	-1.845
	(0.885)	(0.349)	(0.401)	(-1.523)	(-1.724)	(-0.303)
Disrupted × Large	-18.027***	-12.633***	-14.837***	-22.746***	-22.437***	-17.797***
	(-4.666)	(-3.322)	(-4.245)	(-5.672)	(-5.840)	(-4.567)
Difference	23.605***	14.681**	16.990***	13.099*	12.115*	15.952**
Observations	109,410	100,310	92,297	58,958	52,686	47,193
R-squared	0.051	0.046	0.045	0.075	0.070	0.065
Panel B: Sales Growth						
Disrupted × Small	2.802***	4.322***	6.688***	2.600***	3.137***	3.206***
	(4.934)	(7.402)	(11.346)	(2.828)	(3.390)	(3.170)
Disrupted × Large	1.393***	2.241***	4.669***	0.778	1.578**	1.691**
	(3.099)	(4.743)	(9.703)	(1.115)	(2.259)	(2.375)
Difference	1.409**	2.081***	2.019***	1.822*	1.559	1.516
Observations	120,242	109,650	100,593	59,187	52,880	47,359
R-squared	0.075	0.070	0.070	0.079	0.081	0.080

Table E9: **Disruption, Valuation and Sales (T+4 to T+6)**

The table displays three panel data regressions in which patenting variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small}$ is the coefficient estimate of $Disrupted \times Small$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: KPSS/Assets)	(1)	(2)	(3)	(4)	(5)	(6)
	$t+4$	$t+5$	$t+6$	$t+4$	$t+5$	$t+6$
Disrupted × Small	8.980***	9.725***	10.124***	0.551	0.191	0.520
	(6.655)	(7.336)	(7.569)	(0.812)	(0.273)	(0.663)
Disrupted × Large	-0.756	0.018	0.768	-2.657***	-2.955***	-4.122***
	(-0.628)	(0.015)	(0.641)	(-5.300)	(-5.534)	(-6.806)
Difference	9.737***	9.707***	9.355***	3.208***	3.146***	4.642***
Observations	63,116	60,133	57,290	28,167	26,430	24,829
R-squared	0.203	0.220	0.233	0.129	0.135	0.143

Panel B: Trade Secrets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+4$	$t+5$	$t+6$	$t+4$	$t+5$	$t+6$
Disrupted × Small	3.474	4.410	11.902***	3.121	0.181	0.392
	(0.859)	(1.085)	(2.740)	(0.652)	(0.037)	(0.079)
Disrupted × Large	-10.475***	-12.785***	-11.000***	-1.481	-1.814	-4.334
	(-2.735)	(-3.379)	(-2.866)	(-0.374)	(-0.454)	(-1.111)
Difference	13.949***	17.195***	22.903***	4.601	1.995	4.726
Observations	51,129	47,111	43,547	50,696	46,501	42,893
R-squared	0.032	0.033	0.035	0.043	0.044	0.045

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Table E10: **Disruption, R&D, and Acquisitions**

The table is similar to Table VII expect that it uses Doc2VEC embeddings rather than Google patent vectors. It displays three panel data regressions in which R&D and acquisition variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: R&D/Assets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	1.520***	0.816***	0.315***	1.553***	1.113***	0.867***
	(18.485)	(11.267)	(4.400)	(13.074)	(8.866)	(6.660)
Disrupted × Large	-1.022***	-0.552***	-0.359***	-0.470***	-0.446***	-0.342***
	(-17.291)	(-10.440)	(-6.972)	(-5.644)	(-5.523)	(-4.114)
Difference	2.542***	1.368***	0.674***	2.023***	1.558***	1.210***
Observations	184,828	162,606	144,960	104,123	87,929	75,368
R-squared	0.097	0.043	0.020	0.060	0.040	0.029
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0058	.0031	.0012	.0045	.0032	.0025
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0039	-.0021	-.0014	-.0014	-.0013	-.001
Panel B: Acquisition/Assets						
Disrupted × Small	0.335**	0.803***	0.530***	0.462	1.795***	1.024**
	(2.357)	(5.498)	(3.363)	(1.043)	(4.635)	(2.439)
Disrupted × Large	0.155	0.082	0.124	-0.130	0.349	-0.312
	(1.292)	(0.714)	(1.096)	(-0.357)	(1.150)	(-0.966)
Difference	0.180	0.722***	0.407**	0.592	1.446***	1.336***
Observations	114,087	100,775	90,111	94,138	80,471	68,478
R-squared	0.028	0.038	0.029	0.030	0.027	0.024
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0009	.002	.0013	.0014	.0053	.003
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	.0004	.0002	.0003	-.0004	.001	-.0009

Table E11: **Disruption, Capex, and Assets Growth**

The table is similar to Table VIII except that it uses Doc2VEC embeddings rather than Google patent vectors. It displays three panel data regressions in which capital expenditures and asset growth are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: Capital Expenditures/Assets	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	0.810***	0.685***	0.499***	0.251**	0.121	0.140
	(7.517)	(6.837)	(5.123)	(2.010)	(0.904)	(1.027)
Disrupted × Large	-0.778***	-0.544***	-0.365***	-0.106	-0.313***	-0.230**
	(-9.346)	(-6.785)	(-4.819)	(-1.067)	(-3.135)	(-2.280)
Difference	1.588***	1.228***	0.864***	0.357**	0.435***	0.370**
Observations	184,828	162,606	144,960	104,123	87,929	75,368
R-squared	0.120	0.098	0.082	0.084	0.084	0.085
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0031	.0026	.002	.0007	.0003	.0004
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0029	-.0021	-.0014	-.0003	-.0009	-.0007
Panel B: Asset Growth						
Disrupted × Small	4.332***	3.159***	1.079***	0.543	1.766**	2.014***
	(13.279)	(10.273)	(3.666)	(0.801)	(2.544)	(2.769)
Disrupted × Large	-3.823***	-2.728***	-1.852***	-4.375***	-2.927***	-1.796***
	(-14.129)	(-10.719)	(-7.737)	(-7.910)	(-5.528)	(-3.362)
Difference	8.155***	5.887***	2.931***	4.917***	4.692***	3.810***
Observations	184,828	162,606	144,960	104,123	87,929	75,368
R-squared	0.163	0.112	0.070	0.079	0.074	0.062
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0164	.0121	.0042	.0016	.0051	.0057
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0145	-.0105	-.0073	-.0128	-.0084	-.0051

Table E12: **Disruption, Valuation and Sales Growth**

The table is similar to Table IX except that it uses Doc2VEC embeddings rather than Google patent vectors. It displays displays three panel data regressions in which market valuation and sales growth variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: Valuation (M/B ratio)	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	67.604***	43.318***	8.166**	22.347***	35.750***	33.029***
	(13.775)	(10.296)	(2.486)	(4.255)	(7.092)	(6.043)
Disrupted × Large	-34.378***	-16.993***	-15.547***	-8.016**	-6.743**	-1.240
	(-10.564)	(-7.092)	(-7.189)	(-2.252)	(-2.067)	(-0.372)
Difference	101.982***	60.311***	23.714***	30.363***	42.493***	34.269***
Observations	158,963	143,735	129,444	103,587	87,496	75,007
R-squared	0.141	0.099	0.066	0.107	0.103	0.090
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.2294	.1485	.03	.0654	.1029	.0943
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.1167	-.0582	-.0571	-.0235	-.0194	-.0035
Panel B: Sales Growth						
Disrupted × Small	0.751**	1.702***	1.867***	-0.957	0.671	2.026***
	(2.421)	(5.620)	(5.997)	(-1.354)	(0.949)	(2.754)
Disrupted × Large	-2.748***	-2.832***	-0.946***	-3.867***	-1.733***	0.350
	(-10.963)	(-11.536)	(-3.918)	(-7.113)	(-3.124)	(0.628)
Difference	3.499***	4.534***	2.812***	2.910***	2.404***	1.675*
Observations	183,583	162,606	144,786	103,678	87,929	75,309
R-squared	0.112	0.112	0.085	0.091	0.086	0.079
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0028	.0065	.0073	-.0028	.0019	.0058
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.0104	-.0109	-.0037	-.0113	-.005	.001

Table E13: **Disruption, Patent Valuation, and Trade Secrets**

The table is similar to Table X except that it uses Doc2VEC embeddings rather than Google patent vectors. It displays three panel data regressions in which patent valuation and trade secrecy variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021). In columns (1)-(3), *Disrupted* is the SIC-based sectoral disruption represented in Equation (2); and in columns (4)-(6), it is the TNIC sectoral disruption represented in Equation (4). From columns (1) to (3) and (4) to (6), the independent variables are lagged one year. *Small* is a dummy variable that equals one if the firm's assets is smaller than the median assets in that industry and zero otherwise. All dependent variables are described in detail in Appendix A. All regressions include firm and year fixed effects and control variables. $\beta_{Disrupted \times Small(Large)}$ is the coefficient estimate of $Disrupted \times Small(Large)$. $\Delta Disrupted$ is calculated by subtracting the value at the 25th percentile from the value at the 75th percentile of the *Disrupted* distribution. Difference is the difference between $Disrupted \times Small$ and $Disrupted \times Large$. All variables are defined in Appendix A. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

	SIC (Full Sample)			**TNIC**		
Panel A: KPSS/Assets						
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	3.577***	3.890***	3.666***	3.777***	3.062***	2.899***
	(5.910)	(5.934)	(5.615)	(7.752)	(5.638)	(4.821)
Disrupted × Large	-3.886***	-3.596***	-3.243***	0.886**	0.317	-0.471
	(-5.683)	(-5.105)	(-4.807)	(2.234)	(0.766)	(-1.083)
Difference	7.463***	7.486***	6.910***	2.891***	2.745***	3.370***
Observations	80,222	74,510	69,803	40,017	35,934	32,564
R-squared	0.142	0.160	0.174	0.112	0.120	0.126
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0147	.0163	.0155	.0124	.0098	.0091
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	-.016	-.0151	-.0137	.0029	.001	-.0015
Panel B: Trade Secrets						
Disrupted × Small	9.938***	6.339***	2.024	18.642***	13.422***	18.540***
	(5.766)	(3.471)	(1.093)	(5.240)	(3.721)	(4.818)
Disrupted × Large	0.460	-3.157*	-4.953**	11.609***	6.829**	5.281
	(0.256)	(-1.660)	(-2.469)	(3.623)	(2.057)	(1.561)
Difference	9.478***	9.496***	6.977***	7.033	6.593	13.259***
Observations	71,555	65,840	59,645	77,271	68,333	60,958
R-squared	0.033	0.036	0.034	0.040	0.041	0.042
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0231	.0148	.0048	.0482	.0358	.0494
$\beta_{Disrupted \times Large} \times \Delta Disrupted$	.0011	-.0074	-.0117	.03	.0182	.0141