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 largely unexpected and generate positive and long-lasting value gains. Impacted small firms initially increase equity issuance, reduce equity payouts, and increase both R&D and asset growth and experience increased valuations consistent with Schumpeter's 1912 theory of creative destruction. Large firms, on average, reduce R&D and capital expenditures and experience declining valuations and decreased sales growth.

Keywords: Patents, sectoral disruptions, innovation, R&D, insider trading, analyst forecasts. **[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. In extreme periods, such as the internet boom of the late 1990s, innovation itself becomes systematic as multiple sectors attempt to internalize common technology breakthroughs in their own markets. Other recent examples of systematic evolution include the fintech revolution after the financial crisis and the recent AI revolution. Earlier episodes include telecommunications in the early 1900s, the later advent of plastics, and the invention of the computer. We define "Technology Sectoral Disruptions" (TSD) as episodes of correlated innovation that span multiple sectors. We introduce a new measure of technology sectoral disruption identified using patent text and examine TSDs and subsequent stock-market and corporate decisions. Our measure identifies rather frequent episodes of highly correlated innovation jointly evolving in multiple related industries, which permits the first large panel study of how TSDs impact key corporate policies.

TSDs impact multiple related industries and hold the potential to redraw industry boundaries. Our above definition of TSDs focuses on common evolution of technologies among groups of industries (sectors), which we measure as new innovative vocabularies permeating the patent portfolios of sectoral peer firms at the same time. This comovement concept is akin to risk factors that simultaneously impact multiple stocks in asset pricing. Maintaining the parallel to asset pricing, we measure TSDs using a text-based analog to covariances. We compare simultaneous textual evolutions of industry-pair patent portfolios (comovement) to their their non-simultaneous averages (as indicated by the standard formula for covariance but applied to textual content). TSDs are pervasive during our 70-year sample and are 76% autocorrelated, indicating they last roughly three years. They can be measured either using the SIC-based or TNIC industry classification (see Hoberg and Phillips (2016)).

A central result in our study is that TSDs create significant amounts of wealth in the form of sector-wide positive abnormal stock returns over three years. This motivates our examination of information environment dynamics and to establish when economic agents first become aware of TSDs. Due to wealth creation incentives, economic agents will change their behavior in predictable ways when they first learn of sectoral disruptions. For example, when investors first learn about TSDs, they will buy stock and prices will increase. When corporate insiders first learn, they will initiate insider buy trades. Finally, equity analysts will increase their earnings forecasts to account for the gains. If markets are informationally efficient, these actions will occur early, even prior to when TSDs become measurable using public data. If agents do not detect TSDs early, this will occur with a lag.

Our first major finding, which complements our finding that TSDs are wealth-creating, is that the arrival of TSDs is unexpected. Investors, corporate insiders, and equity analysts alike only respond months after TSDs are measurable using fully public information. Where month t is the date of public TSD measurement, stock returns only become 5%-level significant 2-6 months after month t. Predictable stock returns thereafter gradually double in both magnitude and significance through month $t + 18$, and then slowly decay. There is no evidence of run-ups prior to measurement, indicating that essentially 100% of the full price impact of TSDs is realized after its date of measurability. As they are overseeing their firm's R&D plans, one might expect that corporate insiders are informed earlier. Yet insider trading patterns also have no pre-trend and do not increase significantly until month t+12. We also do not find that analysts have any pre-knowledge of TSDs as their forecasts are consistently pessimistic relative to realized earnings during most of the entire three-year period after month t. We conclude that TSDs are unexpected by these economic agents until after the TSD has occurred. The most likely explanation is that these agents operate in local industry silos and are not aware of the broad applicability of TSD technologies in other related industries until their impact becomes more visible.

Corporate insiders are the most central agents in corporate decision-making. Stock market investors are also relevant given their influence on insiders. Analysts can also influence insiders through meetings or earnings conference calls. Our finding that all three of these central agents' behaviors indicate that TSDs are unexpected suggests that, from the perspective of decision makers, their arrival marks plausibly exogenous shifts that can identify corporate finance responses to TSDs.

There are two primary endogeneity concerns. The first, reverse causality, is unlikely a factor because ex-post corporate actions cannot causally impact ex-ante TSD evolution because our above tests indicate that corporate managers simply are not aware of the TSDs until well-after they are measurable using public data. This indicates strong temporal separation between the buildup of TSDs and the time at which corporate managers react.

The second endogeneity concern, omitted state variables that might be correlated with TSDs, cannot be fully ruled out. Yet this concern is also mitigated as we see no evidence of any central economic agents acting until after TSDs are measurable. This inaction implies that any correlated unobservables must be economically unimportant, and likely are not impacting corporate decisions. A novel contribution of our approach that might apply in other settings, is that central agents like corporate insiders, traders, and analysts can be viewed as early indicators of potentially correlated omitted state variables that might confound inference. Moreover, a characteristic of major innovations is that they tend to emerge as the random consequences of inventor activities, and are less likely driven by unobserved economic variables. Finally, our regressions include firm and year fixed effects, which rule out unobserved firm characteristics and macro events. We also conduct parallel trend tests and find no evidence of trends before the TSD.

We examine the impact of TSDs on a wide range of corporate finance decisions and outcomes over the 3-year period after sectoral disruptions become measurable. We consider investment, acquisitions, issuance, payout, Market to Book (M/B), patent valuations, venture financing, and accounting performance. Our tests use firm-year panel data regressions with firm and year-fixed effects and focus on sectoral disruptions as the key explanatory variable. We focus on both impact and timing, as we anticipate that the impact of TSDs is wide-ranging and that managers will prioritize some activities ahead of others.

Three theoretical considerations motivate our focus on whether the impact of TSDs is different for small vs large firms. First, Schumpeter's early writing (Schumpeter (1912)) postulates that small entrepreneurial firms are the seedbeds of innovation, thus predicting strong results for small firms. In contrast, his later writing (Schumpeter (1942)) suggests that large firms are viewed as the engines of growth given their potential monopoly power and larger resources. Which view dominates is an important empirical question our framework is well-suited to explore. Second, smaller firms may be more flexible, and with less institutional rigidity, better positioned to adapt to TSDs. Third, larger firms might have larger irreversible investments in pre-TSD productive assets with high adjustment costs.

We separately examine the corporate policies taken by large and small firms. We find that the arrival of TSDs leads to significant changes in corporate policies and performance over three years following TSD measurement. Consistent with Schumpeter's early theory of creative destruction, we find small firms increase R&D and grow assets in response to the new technologies. Profits initially decrease reflecting adjustment costs, and valuations begin to rise. These initial small firm responses indicate a longer-term view that is rewarded with higher valuations.

With respect to financing decisions, small firms significantly increase equity issuance to raise capital and reduce equity payouts to preserve liquidity in the first year. These TSD-specific findings are novel and contrary to the general results on equity issuance, which historically associate with negative market reactions and valuation losses. They are also consistent with small firms being particularly agile and dynamic in the face of market boundary-changing opportunities.

We document different reactions of large firms. They cut R&D and have decreased asset and sales growth. Interestingly, profitability initially increases for large firms, but despite these increases, their valuations decrease. Overall, our large firm results are consistent with high adjustment costs, and strong incentives to preserve rents from prior investments. This intuition is seen in the response of traditional cable and satellite television providers such as Comcast and Dish Network following the streaming technology TSD. Firms that were initially small and more entrepreneurial like Netflix were better able to adapt.

In the second year after the TSD, small firms equity issuance and R&D, which jumped in the year after the TSD, decay by half while overall asset growth continues. Acquisitions emerge in the second year after the TSD, consistent with a growing need to reallocate assets to internalize shifts in production efficiently. Internal investment thus leads to external investments such as acquisitions. Improved real performance also emerges in the form of sales growth.

Subsequently, in the third year after the TSD, we observe further increased inflows for VC-backed firms, especially in the product markets of small firms. Consistent with Phillips and Zhdanov (2013), public firm acquisitions continue to grow, particularly of private targets (as 88% of acquisitions are of private firms). CAPX remains high, and R&D declines toward historical levels. Sales growth continues to increase and profits turn positive and significant for small firms. The delayed impact on profits is expected given the need to invest and refine technologies before profits can be realized. Overall, consistent with Schumpeter (1912), we conclude that small firms conduct significant innovation and investment when TSDs arrive, whereas large firms have decreased R&D and investment.

Although TSDs are unexpected, they are persistent with a 76% yearly autoregressive coefficient. As a further robustness test, we extend our econometric analysis to identify a set of large sectoral disruptions that have a more clearly identifiable starting year. We then examine how corporate finance policies change over time after these larger TSDs. Although this smaller sample entails less power than our earlier tests based on the full panel, we find generally consistent results regarding timing and the direction of the impact of TSDs on our corporate finance policies. We observe rather clear structural breaks only after TSDs arrive, indicating the absence of pre-trends.

We note the limitation that it remains possible that an unobservable state variable might be impacting our results despite our controlled setting and evidence that TSDs are unexpected by decision-makers. To further alleviate these concerns, we drop influential patenting firms from our sample (those pioneering the TSDs) in our main tests. Moreover, in the Internet Appendix, we also provide results where we drop firms with highly-cited patents. We find that our results are robust. Yet future research identifying new sources of exogenous variation would further complement our study.

This paper contributes to the broader literature on innovation, its originality, and its quality. Kogan et al. (2017) considers the stock market reaction to patent grants to examine economic growth. Kelly et al. (2021) create a new measure of technological innovation based on the forward and backward similarity of patents and characterize technological waves. Bowen et al. (2023) examines the impact of rapidly emerging technologies on the means of VC exit. Bena et al. (2022) classify patents into process and nonprocess innovation and examines how labor rigidity affects production methods and performance. Our paper is unique as our foundation is sectoral and based on the co-movement of large industry patent portfolios akin to the traditional concept of systematic risk. Our measure of TSDs does not have a look-ahead bias, and we address an array of asset pricing and corporate finance implications not considered in the literature.

This paper is also related to the literature on creative destruction. Aghion and Howitt (1992), Akcigit and Kerr (2018), and Aghion and Howitt (2014) argue that creative destruction is the key source of economic growth. Moreover, Aghion et al. (2019) show that statistical agencies underestimate growth numbers by one-half a percentage point per year due to missing growth sourced from creative destruction. We add to this literature by creating a novel measure of creative destruction via systematic sectoral innovations and show that the engines of creative destruction are small firms consistent with Schumpeter (1912).

This paper is also related to Clayton Christensen's seminal work on disruption (Christensen et al. (2015), Bower and Christensen (1995), and Christensen (1997)). In these studies, disruption is characterized by within-industry entry by low-quality firms. For example, Uber Inc. is not a disruptor in that framework as it doesn't provide a service considered low-quality for people demanding transportation (Christensen et al. (2015)). In our framework, ride-hailing services can be considered sector-wide disruptive based on the joint sectoral evolution of the transportation, food delivery, and data analytic industries. We are unaware of prior works that examine sectoral disruptions, and are careful to define the new concept of *sectoral disruptions* as distinct from the existing literature's within-industry focus.

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 systematic TSD at any point in time. TSDs are large technological shocks that are common to multiple related industries that have economically significant and lasting impact. To measure TSDs, we start with the 64-dimensional spatial representations of patents provided by the Google Cloud database that we describe below in the section on patent embeddings.

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 Poll (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 technologies developed by an industry evolve over time, the spatial location of the industry's average technology bundle moves to a new location in this 64-dimensional space. $P_{j,t}$ can thus be quite different than $P_{j,t+1}$. 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. 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 all move in a common spatial direction at the same time. For a pair of two 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. Indeed 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).

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

The index $k[1]$ identifies the industry k that is industry j's most similar industry. $k[2]$ and $k[3]$ are industry j's 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. These learned embeddings are thus intended to encode the information in a patent's text. This database is available for 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 are the unique identifier in this database, and we link patents to public firms using the correspondence provided by Kogan et al. (2017) (KPSS), who provide an extended link table through 2022. The KPSS database has coverage for the 1926-2022 period, and our final patent database has 3,156,877 patents that are linked to the public firms in our sample.

The distance between the two embedding vectors of two patents indicates the similarity between two patents.[1] 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.

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 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

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

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 $psi[k]$):

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

The use of pseudo industries follows the standard logic of TNIC industries, which center 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.

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

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 instead of three (as we did for SIC) to preserve granularity given pseudo industries are more prevalent. Our approach for SIC-based and TNIC-based disruption are thus analogous.

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.

2.1 Stock Return Data

We use data from CRSP for monthly stock returns, and Compustat data to obtain firm financials as needed to 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, Fama, and French (2000) and Fama, and French (2014). Size is each firms' 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 six 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 after roughly 12 to 24 months after the industry patents are granted. In all asset pricing tests, we only use data that is available prior to the month of prediction to predict stock returns.

Table 3 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 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 3 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 much 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 17,506 unique firms and 186,258 firm-years in our sample. Table 4 displays summary statistics for our key variables. We briefly describe the variables we use in this section and provide full details of variables in Appendix A.

Panel A of Table 4 presents general summary statistics, including disruptions 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 periods. Panel B presents summary statistics for the investment variables and firm scope. R&D/Assets is Compustat R&D divided by lagged assets, and this variable is set to zero if R&D is missing. We define CAPX/Assets as Compustat capital expenditures scaled by lagged assets. Our measure of scope is the number of text-based operating segments associated with the given firm in the given year from Hoberg and Phillips (2022).

Panel C displays the accounting valuation and performance metrics, including the market-to-book ratio ((market value of equity + book value of debt) / lagged book value of assets), log sales growth, and profitability defined as (Operating income / Sales). Panel D presents summary statistics for innovation, acquisitions and Venture Capital . KPSS/Assets is the total dollar value of patents based on the return-based method of Kogan et al. (2017) scaled by lagged assets. We define Acquisitions/Assets as 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. *VCF/Sales* is a measure of VC entry and is the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description most closely matches the 10-K business description of the focal firm (using cosine similarities), scaled by focal firm sales.

Panel E displays statistics for our measures of security issuance. Equity issuance is the net shares issued (Compustat SSTK - PRSTKC) scaled by lagged assets, and debt issuance is long-term debt issued scaled by lagged assets. The dividend yield is the dollar amount of common stock dividends paid divided by the market value of equity (share price times shares outstanding). Equity repurchases are the purchase of common and preferred stock scaled by lagged assets.

2.3 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.

$$Scaled\ Net\ Insider\ Transactions_{i,t} = \frac{Shares\ Purchased_{i,t} - Shares\ Sold_{i,t}}{Shares\ Outstanding_{i,t}} \tag{5}$$

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.

3 Validation of Disruption Measure

3.1 Historical Breakthrough Patents

We examine whether our measure captures disruption by conducting an experiment based on historical breakthrough innovations. We gather the list of breakthrough innovations from Appendix A of Kelly et al. (2021). In this list, there are 245 patents that are considered revolutionary, and they date 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 that are in the same two-digit SIC of 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 the breakthrough innovations. The main idea, consistent with our thesis, is that industries close to the industry of the assignee company are expected to be influenced by common sectoral disruptions.

Figure 1 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 comparisions 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 in each of the 5 years preceding the breakthrough innovation supporting the parallel trends assumption. However, beginning in the year following the breakthrough innovation, we see a structural break as sectoral disruption rises, and this ascent reaches its maximum 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

We investigate whether our disruption measure predicts that firms in the TSD-exposed industries will make increasingly similar products. We conjecture as basic validation that firms adopting the new TSD-technologies will experience increased product similarity. Moreover, firms in different industries that are not direct rivals ex ante might become product market peers as this similarity rises.

To test these conjectures, Table 5 provides the results of estimates from a regression where the dependent Variable is TSIMM and product market-fluidity, which are are firm-year measures of a firm's product market similarity to its competitors and product market threats from competitors, respectively. All regressions include firm and year fixed effects and control variables. In line with our conjectures, we find that disruption indeed increases product market similarity and product market fluidity. The results are statistically significant at the 1% level for both the SIC and TNIC-based measures with t-statistics ranging from 3.8 to 20.5 over specifications where dependent variable is measured from year t+1 to t+3 after a TSD is measurable. Overall, these results provide validation supporting our interpretation of the TSD measure.

4 Economic Impact and Information Environment

In this section, we assess the extent technology sectoral disruptions are important and unexpected from the informational perspective of market participants and corporate managers. Our thesis relies on the prediction that technology sectoral disruptions generate large amounts of economic value and our first objective is to use asset pricing tests to assess this economic magnitude. Significant value creation would both motivate the use of technology sectoral disruptions to assess corporate finance policies (our measure would satisfy the economic relevance condition) while also providing 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 the timing of 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, 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 have return prediction patterns that decay over time. Second, a finding of delayed reaction might indicate a clear ordering in time regarding when disruption occurs and when economic agents finally learn about the disruption and can react by making corporate decisions. This is relevant to assessing the quality 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 the timing of when insider trading activity becomes influenced by sectoral disruptions. If disruptions indeed create large amounts of economic value, then insiders would favor buying whenever they learn about the 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 next examine whether technology sectoral disruptions are surprising and not anticipated. Information gathering costs might be prohibitive as these agents would need hyper-awareness about how firms in other industries are adopting technologies relative to those being developed by a focal firm. This requires the construction of data structures near 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 production costs because large and long-lasting trading profits are available to incentivize agents who are willing to process this data. Therefore, in this section, we examine whether TSDs are anticipated or not.

4.1 Sectoral Disruption and Stock Returns

We conduct Fama-MacBeth (1973) monthly regressions in which the dependent variable is stocks' monthly returns in month $t+1$. Our right-hand-side variables are all measurable as of month t, ensuring the absence of look-ahead bias. Our key variable of interest is technology sectoral disruption. We thus consider the following specification:

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

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 a key objective of our tests is not only to understand the magnitude of return predictability associated with technology sectoral disruptions 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 leads up to 12 months. These tests illustrate the relationship between sectoral disruptions and market awareness, as is important for identification in our later corporate finance tests.

The results for TNIC-3 industries are presented in Table 6. We standardize all right-hand-side variables to make the coefficients interpretable, and we report Newey-West t-statistics with two lags. The table shows that technology sectoral disruption only becomes significant at the 5% level after a six month lag. 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 technology sectoral disruption six months later. We also note that the magnitude and significance of sectoral disruption as a return predictor grows steadily and reaches a peak around 18 months, and then remains significant for a protracted period thereafter. Broadly, these results suggest that the market does not price technology sectoral disruption immediately, but does price its impact over a period of roughly 2-3 years thereafter.

Because the coefficients are standardized, we can interpret their magnitudes. The later coefficients of roughly 0.20 indicate an annualized return of roughly 2.4% when a firm is in an industry that has a one standard deviation higher than average sectoral disruption. If we conservatively state that these returns persist for two years (our evidence suggests they persist longer), we can conclude that a one 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 such returns would span multiple industries, and industries tend to have compressed return distributions given some 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 technology sectoral disruptions are only significant with material lags is a particularly novel finding from the perspective of the asset pricing literature. In particular, most asset pricing variables such as momentum, the value premium, and others tend to be most significant immediately after measurement and decay with time. Our finding that a variable is not significant at all 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 appear to be initially unaware of sector disruptions, making them unexpected and plausibly exogenous shocks to market participants, who must then select an array of corporate finance policies to adapt to the shock.

Table 7 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 1988 and later. For completeness, we thus show results for both TNIC and SIC. Table 7 shows that disruption measures computed using SIC codes are quite similar to those computed using TNIC industries as displayed in Table

6. In particular, we again observe a significantly delayed market reaction as SIC disruption only becomes significant in predicting returns two months after its measurement. Moreover, the significance and coefficient magnitudes grow steadily from month two to a maximum by 18 months. The maximum t-statistic of 4.47 is highly significant at the 1% level and the coefficient of 0.145 is more than twice the month-2 coefficient of 0.072.

Because all right-hand side variables are standardized, magnitudes can be compared. For example, the maximum coefficient of 0.204 in Table 6 is roughly 40% larger than the maximum coefficient of 0.145 in Table 7. This suggests that TNIC-based disruption is likely more informative regarding economic impact and returns than are SIC-based disruptions. This finding is in line with Hoberg and Phillips (2018). Yet we find significant results using either classification as SIC-codes have the offsetting advantage of being available for a longer time series.

We depict the magnitude and overall pattern of delayed market reaction in Figure 2. The figure plots the t-statistics for lags of up to 36 months for TNIC disruption and SIC disruption from Table 6 and 7. The graphs illustrate just how clearly delayed the market reaction is to disruption and also that the extent of delay is similar for both TNIC and SIC disruptions. Additionally, the relatively slow rate of decay following the maximum at 18 months also illustrates how large the impact of disruption is and the fact that disruptions have lasting impact on focal industries.

Figure 3 plots the annualized return of portfolios that invest in the SIC disruption (top figure) and TNIC disruption (lower figure) during our sample period. Portfolio returns are computed using the optimized portfolio method as in Fama (1976) (and reinforced in Hoberg and Welch 2009 and Back, Kapadia and Ostdiek 2015) and are the slopes (gammas) from the Fama-MacBeth regressions displayed in Tables 6 and 7. As slopes are estimated monthly and indicate the returns of a zero cost arbitrage-portfolio with zero exposure to the controls and one unit of exposure to disruption, we can plot the gammas over time. Because monthly returns are noisy, the displayed returns are smoothed and the displayed returns in each year

t are the average return over the five year rolling window from $t-2$ to $t+2$ around a given year t. 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.[2]

The figures also shows that disruption returns are higher during intuitive periods such as the 1990s when the internet boom was disrupting industries and post-2009 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 in some cases are different for SIC and TNIC disruption. This is likely due to the fact that TNIC industries are particularly good at modeling technology industries (see Hoberg and Phillips 2016) and SIC industries, while noisy, are more effective in modeling manufacturing or old-economy sectors.

We conclude this section by examining if results are different for large vs small firms. In the Online Appendix Tables A2 and A3, we rerun Tables 6 and 7 after adding an indicator equal to one if ex-ante market capitalization is above or below median in the given month, and also the interaction term between these dummies and our Disruption variable. This allows separate assessment of asset pricing effects for large and small firms. Echoing our later corporate finance results, we find that the impact of TSDs is large and long-lasting for small firms, but this impact is significantly smaller and mostly insignificant for large firms. In these appendix tables, we report both the standard characteristic-adjusted coefficients based on the Fama-MacBeth regressions as above, and also both characteristic and risk adjusted alphas based on the 5-factor model presented in Hou et al. (2015).

We find that the small firm alphas and Fama-MacBeth slopes are positive and significant during the expected window in all cases. Regarding large firms, we observe some positive slopes when we only adjust for characteristics, and all results are insignificant when we adjust for both characteristics and risk. Our finding of strong positive impact for small firms but

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

not large firms are particularly strong when we examine SIC-based TSDs in Table A3, where we have the longest time-series data. We conclude that small firms benefit significantly from TSDs and large firms generally do not, and moreover, investors are surprised by TSDs and only realize these gains with significant delay after TSDs become measurable.

4.2 Sectoral Disruption and Insider Trading

We conduct Fama-MacBeth (1973) monthly regressions in which the dependent variable is the ex-post net insider trading activity of high ranking insiders in month $t+1$. Please see Section 2.3 regarding how we compute net high ranking insider trading intensity. We focus on high ranking insiders both because the literature supports their trades as being more informative and also because high ranking insiders are the very individuals who make corporate decisions (because 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 when insiders likely become aware of them, as is important for identification in our later corporate finance tests.

The results for both TNIC-3 and SIC-3 disruptions are presented in Table 8 and we report Newey-West t-statistics with two lags. 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 6, 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 8 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.[3] We finally note that the SIC-3 results,

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

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 4 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.

5 Disruption and Firm Corporate Finance Decisions

In this section, we explore the consequences of technology sectoral disruption on important ex-post outcomes including innovation, investment, restructuring, performance, and financial issuance. 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 consisting of 1/size and logged age. μ_i is a firm fixed effect and δ_t is a time fixed effect. Our main focus is on β_1, which is the direct impact of small firm disruption on the given policy. We also examine β_2, which displays the impact of disruption on large firms.

In all of our regressions, we drop all firms with breakthrough patents listed in Kelly et al. (2021). This screening would reduce the concerns that the results are driven by a few firms that are truly innovative. In the Internet Appendix, we also provide regression outputs where we drop all firms that 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. However, the results are mostly qualitatively unchanged. All of our variables are winsorized at 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, but only with delay. These results suggest that our disruption variable is economically important and also that this variable's influences are unexpected ex-ante from the perspective of corporate decision-makers, and this allows us to document the primary impacts of disruption on the wide array of outcomes we explore.

5.1 R&D and Acquisitions

In this section, we explore the impact of sectoral disruptions on R&D and restructuring estimating equation (7). Table 9 present results for regressions with indicator variables for small and large firms interacted with the TSD disruption variable. We consider R&D/assets (Panel A), acquisitions/assets (Panel B), and target of acquisition dummy (Panel C) as dependent variables.

Panel A shows that sectoral disruptions are followed by highly significant increases in innovation investment for small firms and decreases for large firms. These results are particularly strong using the TNIC disruption variable in columns (4) to (6) where t-statistics range from 6.2 to 12.6. The table also shows that increased R&D is long-lasting as it remains high for the full three-year period, although it gradually declines to 55% its initial value by the final year. It is noteworthy that TNIC disruptions are stronger both in terms of significance levels and coefficients (and SIC disruptions decay to insignificance by the third year ex-post). This is likely because modeling technology sectors, in particular, is a strength of the TNIC industry classification (see Hoberg and Phillips 2016). The high increases in R&D for small firms and decreases for large firms are strongly consistent with the early Schumpeter 1912 theory of creative destruction where innovation arises from small firms.

Panel B shows evidence that disruption leads to significant increases in acquisition activity (8.2%), and these results are also long-lasting. We also note that these results are primarily driven by acquisitions of private firms by public firms (these transactions are 88.1% of our sample), consistent with Phillips and Zhdanov (2013) These results are significant at the 1% level for all but the first row (first-year SIC results). These findings are consistent with acquisitions re-distributing assets to new best-owners as the changes induced by disruption likely induce a change in the asset composition sought by affected firms.

Panel C shows weaker positive results for being the target of an acquisition as the results are significant at the 1% level for SIC disruption but insignificant for TNIC disruption. As before, larger firms are less impacted. These results broadly indicate that disruption induces acquisition activity by smaller publicly traded firms as they reposition themselves to internalize the disruptive technology.

5.2 Valuation and Sales

To examine the impact of disruption on valuation and sales, we estimate equation (7) using the M/B ratio, KPSS/assets and sales growth as outcomes. Table 10 reports the regression coefficients and their significance levels. In the footer of this table, we also report economic magnitudes as $\beta_{Disrupted \times Small} \times \Delta Disrupted$, which is the product of coefficient estimate of $Disrupted \times Small$ and the quantity $\Delta Disrupted$, which is the interquartile range (IQR) (i.e., calculated by subtracting the value at the 25th percentile from the value at the 75th percentile) of the *Disrupted* distribution.

Panel A reports the results for M/B, Panel B reports the average KPSS valuation of ex-post patents, and Panel C reports results for sales growth. In this table, columns (1), (2), (3) and (4), (5), (6) present regressions where dependent variables are at time *t+1*, *t+2*, and *t+3*, respectively; and the independent variable of interest, Disrupted, is measured at time *t*.

Panel A shows strong and long-lasting valuation gains for small firms following sectoral disruptions. The results are significant at the 1% level except for the year-three SIC disruption coefficient, which is significant at the 5% level. In economic terms, an IQR increase in disruption yields an increase of 8.25% in the Market to Book ratio at the sample mean. Consistent with the implications for investment in the previous sections, the gains in valuation are only reaped by smaller firms as Disrupted X Large is negative or insignificant.

Panel B shows some evidence that TSDs are followed by improved patent quality based on KPSS valuations. For small firms, the measures are highly significant with *t*-statistics ranging from 4.0 to 9.0. The results show that an IQR increase in disruption is associated with an increase of 17.89% for KPSS values at the mean value. In contrast to the results for small firms, the results for large firms show that large firms experience a decrease in the quality of patents. This result is consistent with small firms being more agile and having less ex-ante investment in the status quo. Thus, small firms are able to produce innovation with higher value as is facilitated by the disruption.

Panels C show that an increase in sales comes 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 must internalize and commercialize the new technologies before sales increase.

5.3 Performance and Growth

Table 11 uses similar panel data regressions to explore the impact of sectoral disruptions on performance and growth. The dependent variable is profitability (Panel A), asset growth (Panel B), and firm's scope (Panel C).

Improved profitability in Panel C comes with a delay as both SIC and TNIC disruptions show a pattern of improving profitability over the three-year horizon. Yet only the three-year

SIC disruption coefficient is positive. These results overall illustrate that improvements near the top of the income statement (sales) accrue more quickly than gains near the bottom (profitability). The delays are intuitive as firms must internalize and commercialize the new technologies before gains in sales are possible. After products are developed and put on the market, firms must then further internalize process and cost improvements in order for the gains to show up as gains in profits. These results are supportive of the Abernanthy and Utterback (1978) life cycle.

Panel B shows that asset growth is significant in all six rows, and it increases 6.79% with an IQR increase in disruption, illustrating that the impacts of TSDs are economically large and thus also visible in asset growth.

Panel C shows evidence that both small and large firms experience some increases in product scope over time. These results are consistent with disruptive technologies being quite general, allowing firms to redefine industry boundaries, increase their product offerings and serve more markets.

5.4 Financing

Our earlier sections examine how treated firms manage their corporate decisions. As we document increased investment across a wide-array of investments in earlier sections, financing activity is important as the large investments require capital. We thus examine equity issuance (Panel A), equity outflows (repurchase+dividends) (Panel B) and venture investments scaled by assets (Panel C). We report results for debt issuance in the appendix. Our central prediction is that the primary impact of disruption is a shift in high-risk growth options requiring risky investments in innovation. Because firms investing in more opaque and risky investments are more susceptible to financial constraints and need flexibility to further increase investments as the results of innovative spending become realized, we anticipate that TSD-treated firms will focus on equity financing. This form of capital, unlike debt, crucially preserves the needed flexibility noted above.

Table 12 displays the results. Panel A shows that small firms dramatically increase their equity issuance, especially in the first one to two years after the disruption shock (20.7% with an IQR increase in disruption). Issuance then decays and is insignificant for SIC disruption by year three although still significant for TNIC disruption by this time. These results are consistent with expectations on timing, as capital needs to be raised before investments can be undertaken. Hence we expect high levels of issuance in the earliest years after the shock. We also observe that larger firms do not increase equity issuance (and even decrease), consistent with our earlier findings that they also do not increase investment.

Panels B shows that small treated firms also curtail equity outflows (payouts to shareholders both in the form of dividends and share repurchases). In economic terms, an IQR increase in disruption yields 3.5% decrease in equity outflows. These results reinforce our findings regarding equity issuance as reducing payouts has the same impact on liquidity and flexibility as does equity issuance itself. The policies in Table 12 thus point to small firms increasing the equity share in their capital structure.

Panel C shows that venture capital investment also increases for firms in markets facing TSDs. The increases affecting smaller firms come in the second and third years after the TSD. As we indicated in the previous section, market participants might not initially be aware of the scale of sectoral disruptions, especially as implemented by smaller more secretive firms. Startups are thus only likely to materialize and need financing after external market participants come to fully learn about the sophisticated growth opportunities available in these markets. The TNIC disruption variable only predicts increases in VC activity in year three, whereas the SIC disruption variable predicts increases in both years two and three. Neither disruption variable is significant in year 1 except for larger firms, which realize venture capital earlier.

5.5 Timing of Corporate Policy Changes

Our earlier findings on asset pricing, insider trading, and analyst forecasts indicated that corporate insiders and other agents, on average, are initially unaware of sectoral disruptions for roughly one year. A consequence is that sectoral disruptions are unexpected and their sectoral nature is plausibly exogenous from the perspective of corporate decision makers.

In this section, we assess timing further by conducting event-time analysis of corporate decisions around major sectoral disruptions. We first identify a set of large and long-lasting TSDs to which we can attach a specific event-year zero. Because our baseline sectoral disruption variable is persistent and 76% autocorrelated, this process is important to accurately assess the timing 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 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 the year three. This final step ensures we limit attention to major sectoral disruptions that are long-lasting. 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.

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

We then run regression specifications in equation (8) in which a given corporate finance policy variable is the dependent variable. In this specification, $D(t)$ is a dummy variable that takes the value of one if the year of distance to the reference year is t and zero otherwise. We exclude t=0 from the regression to avoid multicolliniearity. Therefore, estimates are relative to the year zero values. Specifically, we plot seven yearly estimates for sectoral disruption of small firms 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 time fixed effect. Our thesis is that each corporate policy variable's plot will experience a flat trajectory in the three ex-ante years and then experience a structural break at some point after event-year zero. The lag from year zero to observed managerial-actions can vary across policies as we showed earlier that agents do not internalize disruptions for 1-2 years after disruptions become measurable. We plot both coefficients and error bands associated with t-tests regarding whether each coefficient is different from the baseline year-zero coefficient.

Figure 5 documents that small firms increase their R&D/Assets in the first year following a TSD, strongly consistent with Schumpeter (1912). The figure also shows that acquisitions experience a positive structural break but with an even-longer two-year lag. These results indicate that corporate managers first increase organic innovation investments following disruptions and then later increase acquisition activity. The delayed response for acquisitions likely reflects managerial priorities and the harvesting of the most valuable organic growth options first.

In Figure 6, we start by plotting market-to-book ratio, KPSS values and sales growth using the above event-year methodology for small firms. We find that the market-to-book ratio is roughly flat in the three ex-ante years and this is followed by a distinctive period of strong and consistent increase starting in event-year one. In Appendix Figure A2, we show that the opposite pattern exists for large firms. These changes are persistent and long-lasting, and begin following a one-year delay.[4] This finding suggests that sectoral disruptions are followed by significant increases in growth options especially for small firms.

[4]For consistency, the year-zero coefficient is calibrated to be based on the standard one-year lagged disruption variable used in our baseline regressions in the last section.

6 Conclusions

We examine large-scale technology sectoral disruptions (TSDs) over a 70-year period. We introduce a new measure of TSDs identified using patent text, which identifies periods of highly correlated innovation jointly evolving in multiple related industries. Well-known recent episodes include the technology boom, the fin-tech revolution, and the AI revolution. We show that multiple TSDs occur throughout our 70-year period and that TSDs are persistent. Their impact is positive as they generate stock price gains lasting three years.

Informational efficiency surrounding these events takes time to develop. Stock market investors, corporate insiders, and equity analysts alike do not react to TSDs until months have passed. Sectoral disruptions are thus unexpected and plausibly exogenous from the perspective of corporate insiders, investors and analysts. We further analyze how corporate managers react to TSDs given their large consequences for firms and market structure.

We find that corporate decisions react over the three years following the TSDS. In the first year, small firms issue equity and reduce both repurchases and dividends. Small firms then invests in R&D and CAPX. In the second year, small firms begin to reduce equity issuance and R&D while maintaining CAPX, and begin acquisitions. Large firms cut R&D and capital expenditures and have decreased asset and sales growth. Valuations and equity issuance decrease for large firms.

At the same time, VC-funded entrants begin to appear. Sales growth also begins to increase. In the third year, abnormal issuance and R&D decrease further while CAPX is maintained, and acquisitions further increase. VC-funded entry also increases while public firms experience increased sales growth and corporate profits. As they are likely more agile and less invested in the status quo, these results are strong for smaller firms and generally negative for large firms. Our results are consistent with Schumpeter's 1912 theory of creative destruction in which small firms are the engines of innovation and growth

These results illustrate that public firms maintain a first-mover advantage and realize significant and long-lasting gains. Yet adequate rents remain for later VC-funded private firms to enter. Our results also illustrate that managers in small firms first turn to organic investments such as R&D and CAPX, and only later turn to acquisitions in order to grow further and consolidate their positions. Although stock-market gains come early, real gains in the form of profits come later, likely due to time-to-build constraints. This first comprehensive look at technology sectoral disruptions motivates future research on other forms of disruption and subsequent changes to market structure.

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Figure 1: Disruptions Around Breakthrough Innovations

This figure presents the relation of 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 where the dependent variable is three digit SIC-based 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 specification also includes two-digit industry fixed effects. The reference year, 0, is the year the breakthrough patent was granted.

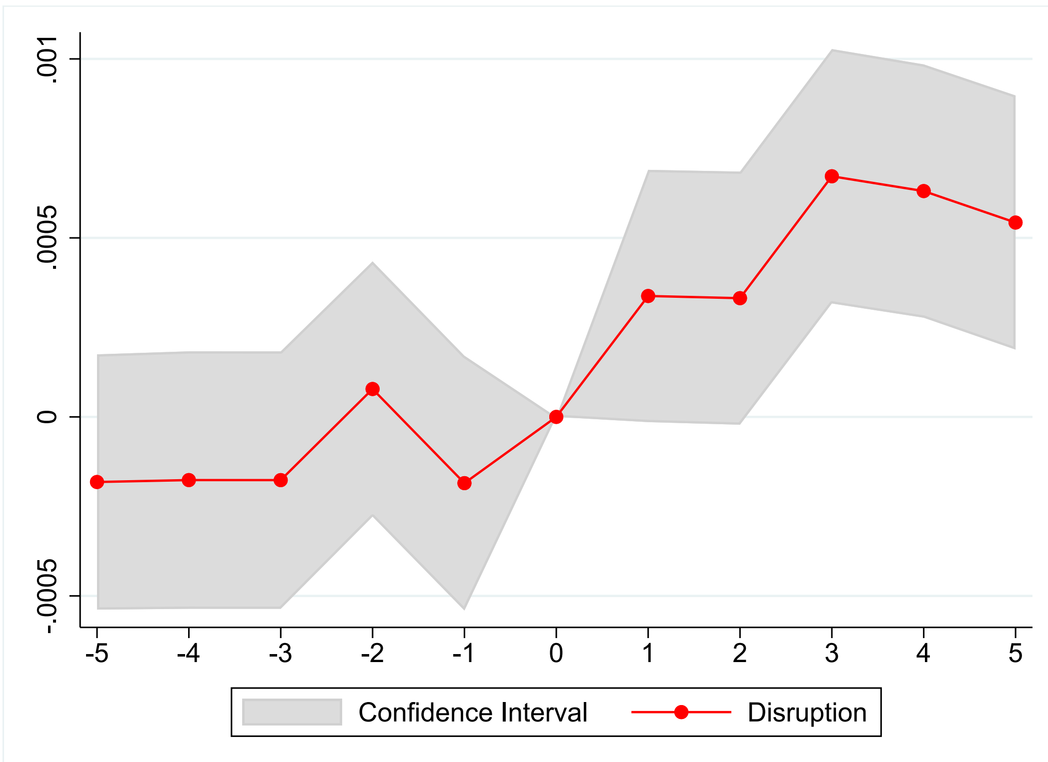


Figure 2: Asset Pricing Signal versus Months of Delay

The figure plots the significance of return predictability for lags of up to 36 months for TNIC disruption and SIC disruption. We first run Fama-MacBeth regressions in which the dependent variable is the monthly stock return in month $t = 0$. We include controls as in Tables 6 and 7. 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 t-statistic versus the number of months of this lag of the disruption period. A t-statistic in excess of 2.0 indicates significant predictability when the disrupted variable is lagged as indicated on the x-axis.

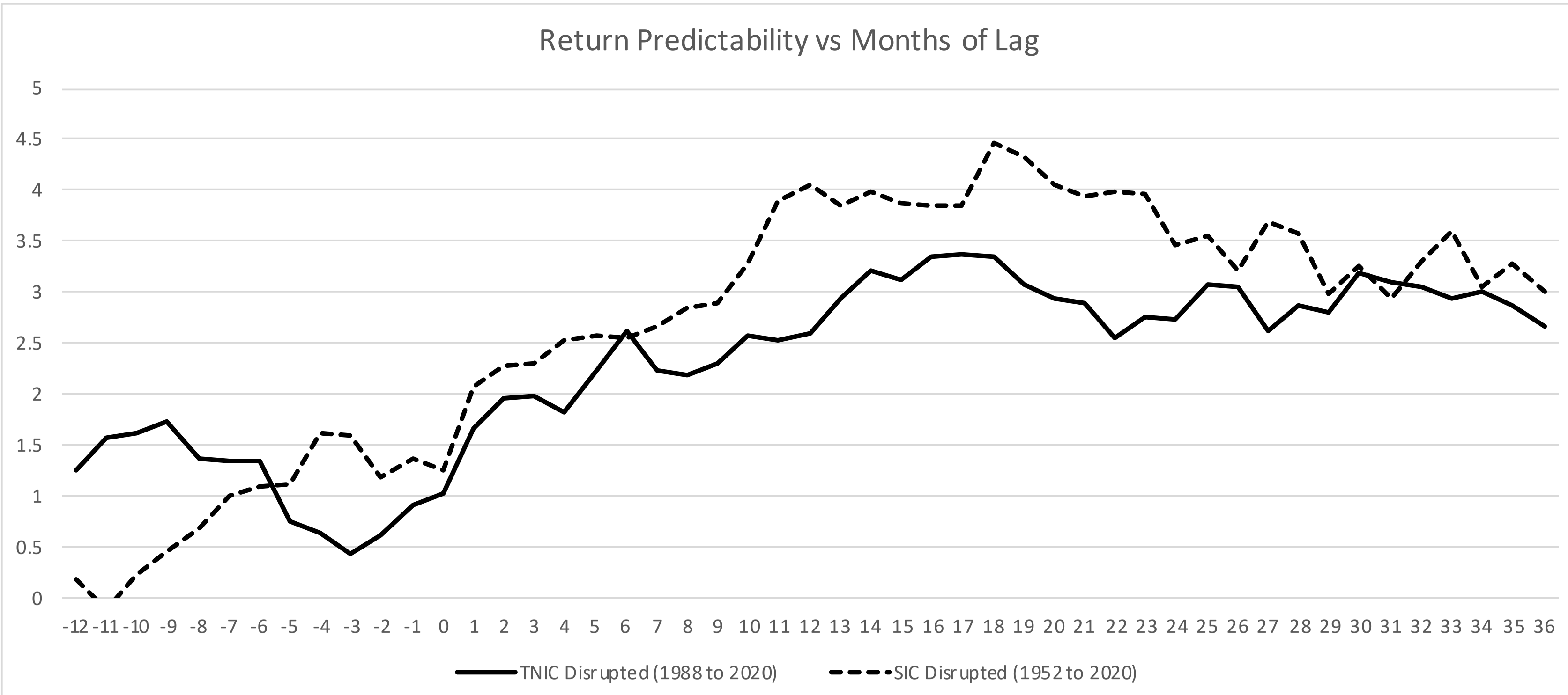
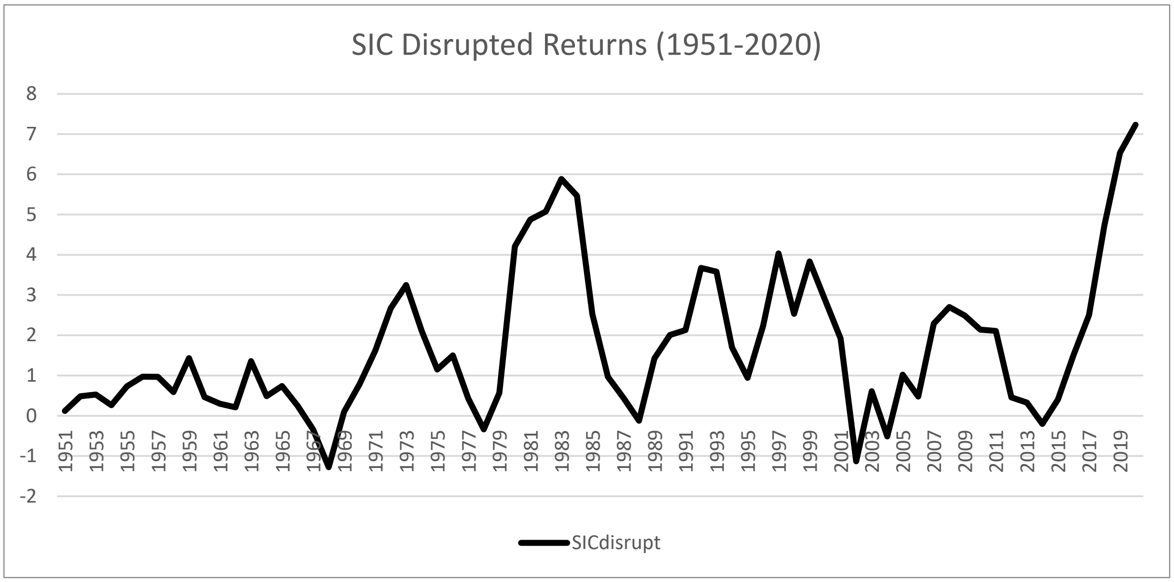


Figure 3: Asset Pricing Signal Over Time

The figure plots the annualized return of portfolios that invest in the TNIC disrupted variable (top figure) and the SIC disrupted variable (lower figure) over our sample period. Portfolio returns are computed using the optimized portfolio method as in Fama (1976) as the slopes (gammas) from the Fama-MacBeth regressions displayed in Tables 6 and 7. 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.



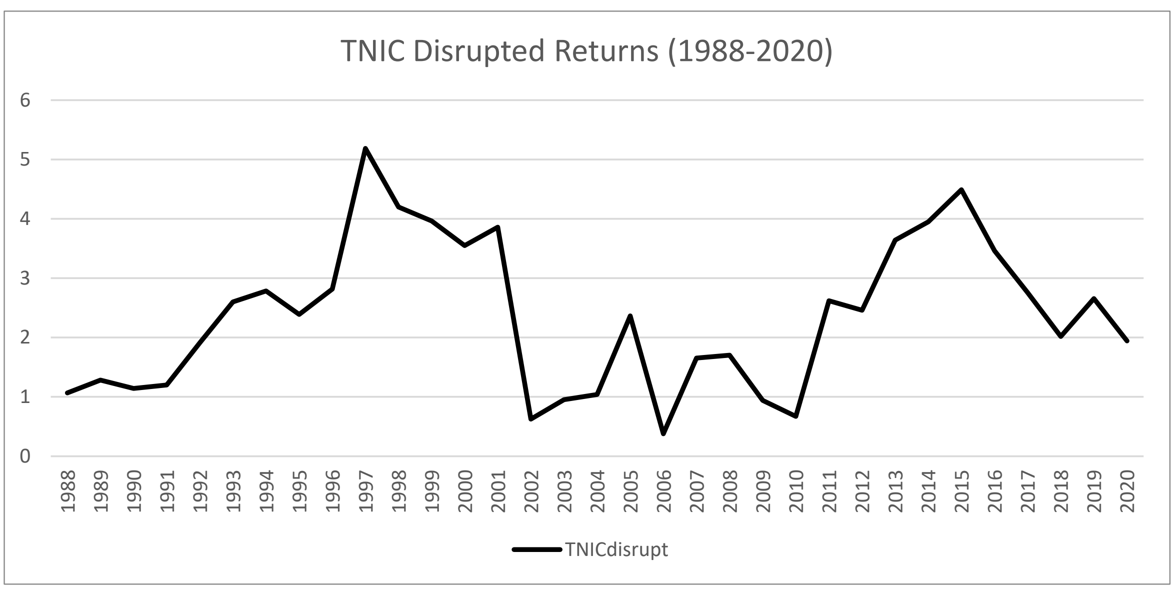


Figure 4: Insider Trading Signal versus Months of Delay

The figure plots the coefficient of Fama-MacBeth regressions of insider trading intensity regressed on either TNIC Disruption or SIC Disruption as in Table 8 . 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.

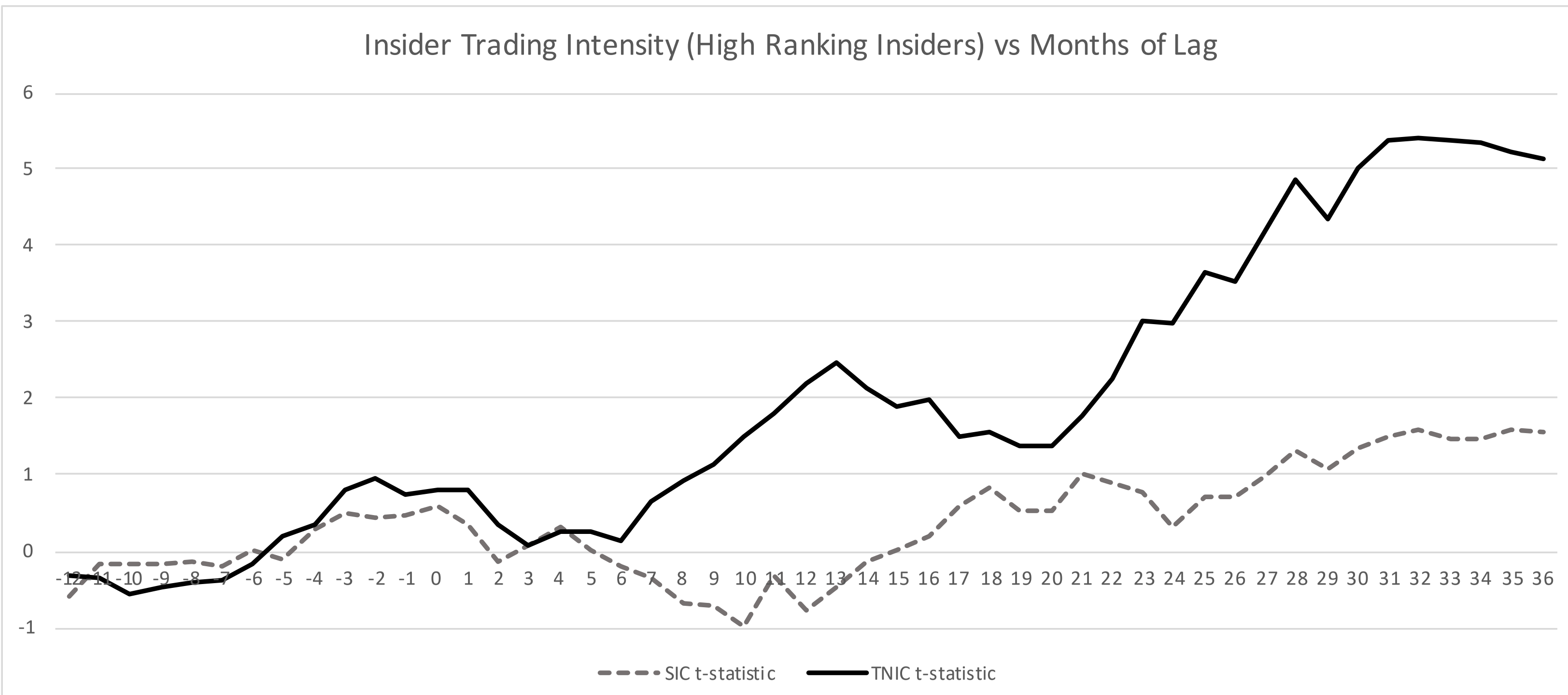


Figure 5: Disruptions, R&D and Acquisitions for Small firms

This figure shows the parallel trends for growth options and investment around the disruption year for small firms. For each firm in our sample, we identify a year as disruption year if: 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 the year three. The figure represents estimates of γ_t from the regression depicted in Equation (8). Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.

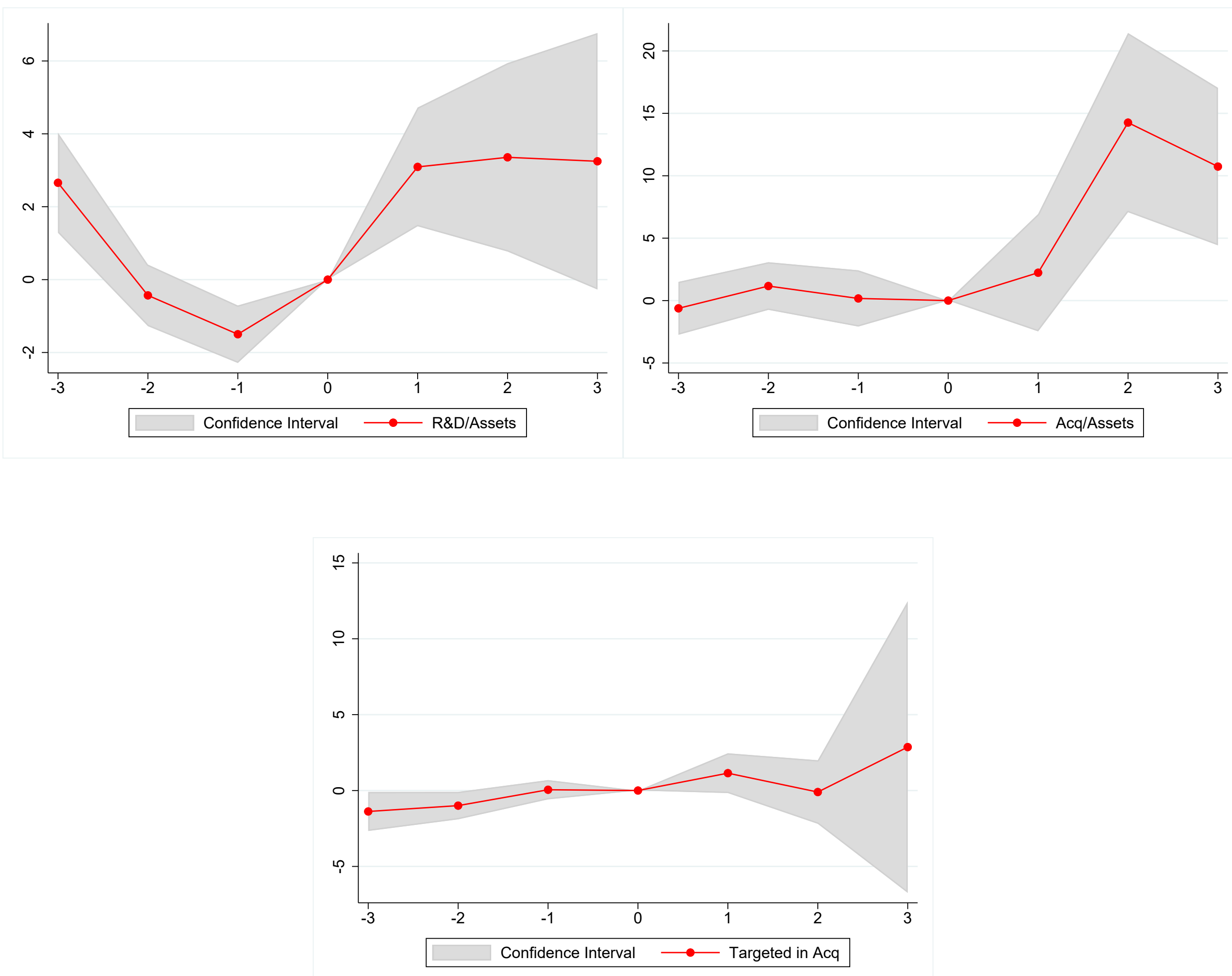
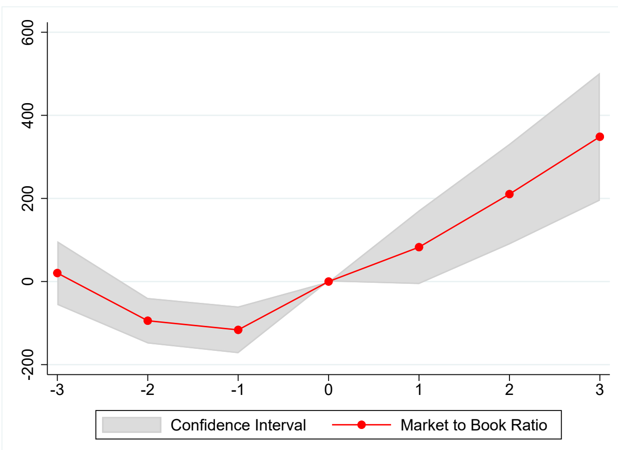
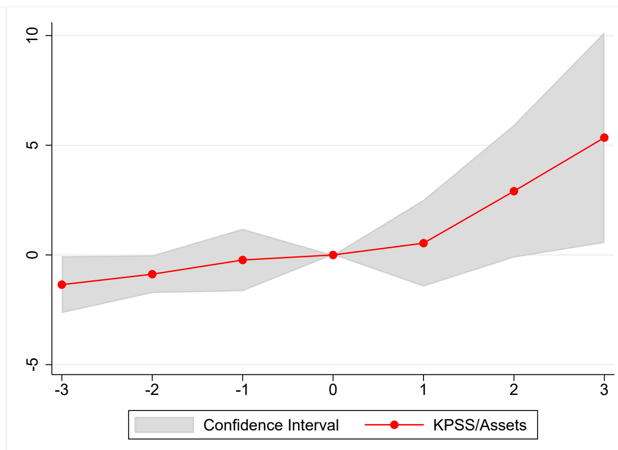


Figure 6: Disruptions, Valuation, and Sales for Small Firms

This figure shows the parallel trends for growth options and investment around the disruption year for small firms. For each firm in our sample, we identify a year as disruption year if: 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 the year three. The figure represents estimates of γ_t from the regression depicted in Equation (8). Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.





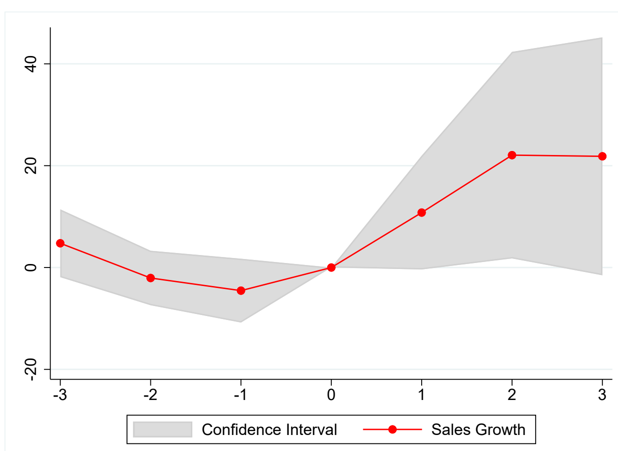


Table 1: **Most Relevant TNIC Sectoral Disruption Firms by Decade**

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.

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

Table 2: **Most Relevant SIC-3 Sectoral Disruption Firms by Decade**

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.

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

Table 2: **Most Relevant SIC-3 Sectoral Disruption Firms by Decade (continued)**

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.

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

Table 3: **Summary Statistics of Stock Return Variables**

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 $t-2$.

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

Table 4: Firm Summary Statistics

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.

Variable	N	Median	Mean	Std. Deviation
Panel A: Firm Characteristics				
Disrupted (SIC)	186,258	-0.00129	-0.00223	0.00258
Disrupted (TNIC)	104,479	-0.00181	-0.00252	0.00221
Log(Assets)	186,258	4.76964	5.03917	2.41604
Log(sales)	186,258	4.54962	4.75006	2.30042
Log(Age)	186,258	2.39790	2.37695	0.83397
Panel B: Investments				
R&D/Assets	186,233	0.00260	0.05857	0.11799
Capital Expenditures/Assets	186,233	0.04304	0.07448	0.09753
Assets Growth	186,233	0.06940	0.12076	0.33330
Log(Scope)	97,917	1.94591	1.78091	0.88770
Panel C: Accounting Performance				
Market to Book	160,269	1.16051	2.27563	4.82650
Sales Growth	184,979	0.08936	0.12731	0.32537
Profitability	185,267	0.11408	0.07489	0.25567
Panel D: Innovation, Acquisitions and Venture Capital				
KPSS/ Assets	186,233	0.00000	0.03633	0.13753
Acquisition Amount/Assets	142,164	0.00000	0.02802	0.14040
Venture Inv./Assets	30,472	0.01127	0.08161	0.18380
Panel E: VSecurity Issuance				
Equity Issues	186,258	0.00110	0.11682	0.49877
Dividend Yields	160,734	0.00000	0.01203	0.02039
Equity Repurchases/Assets	157,866	0.00000	0.00897	0.02505

Table 5: **Product Market Differentiation**

The table displays two panel data regressions in which product market based measures are the dependent variables. TSIMM and Product market-fluidity are firm-year measures of a firm's products market similiarity to its competitors and product market threats from competitors. 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. 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: Log(TSIMM)	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted	7.292***	7.462***	6.374***	8.074***	7.916***	6.283***
	(4.737)	(4.594)	(3.810)	(6.265)	(5.944)	(4.516)
Observations	87,220	80,810	73,486	104,108	87,916	75,358
R-squared	0.039	0.036	0.032	0.062	0.061	0.060
Panel B: Product Market Fluidity						
Disrupted	120.660***	127.666***	93.852***	132.387***	116.030***	82.245***
	(17.753)	(17.789)	(13.674)	(20.571)	(16.450)	(11.215)
Observations	85,127	78,966	71,842	103,687	87,579	75,080
R-squared	0.189	0.191	0.185	0.220	0.212	0.200

Table 6: **Fama MacBeth Regressions (TNIC Disruption)**

The table reports the results of Fama-MacBeth regressions 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. 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 momentum variable is the firm-specific return from month $t-12$ to $t-2$.

Row	Lag	Disrupted	Momentum	Log B/M	Log Size	Profitability	Investment	# mnths /Obs
(1)	-12 Months	0.076	-0.103	0.347	0.704	-0.339	-0.222	396
		(1.25)	(-0.75)	(5.59)	(10.0)	(-4.03)	(-6.67)	1,167,965
(2)	-10 Months	0.096	-0.086	0.315	0.533	-0.288	-0.214	396
		(1.61)	(-0.62)	(5.19)	(7.28)	(-3.54)	(-6.34)	1,185,584
(3)	-8 Months	0.078	-0.093	0.273	0.373	-0.256	-0.217	396
		(1.36)	(-0.66)	(4.37)	(5.05)	(-3.11)	(-6.51)	1,203,763
(4)	-6 Months	0.073	-0.076	0.227	0.203	-0.219	-0.228	396
		(1.34)	(-0.53)	(3.43)	(2.62)	(-2.79)	(-6.88)	1,222,335
(5)	-4 Months	0.036	-0.074	0.186	0.027	-0.135	-0.226	396
		(0.65)	(-0.51)	(2.82)	(0.32)	(-1.85)	(-6.86)	1,243,086
(6)	-2 Months	0.035	-0.045	0.136	-0.129	-0.082	-0.233	396
		(0.62)	(-0.31)	(2.08)	(-1.53)	(-1.10)	(-6.97)	1,265,522
(7)	0 Months	0.060	0.177	0.136	-0.119	0.177	-0.216	395
		(1.03)	(1.24)	(2.11)	(-1.40)	(2.38)	(-6.43)	1,290,905
(8)	2 Months	0.113	0.191	0.130	-0.094	0.193	-0.202	393
		(1.95)	(1.34)	(1.99)	(-1.13)	(2.60)	(-6.03)	1,268,355
(9)	4 Months	0.101	0.209	0.117	-0.088	0.201	-0.207	391
		(1.81)	(1.48)	(1.81)	(-1.07)	(2.69)	(-6.06)	1,250,466
(10)	6 Months	0.143	0.211	0.111	-0.091	0.207	-0.221	389
		(2.62)	(1.49)	(1.74)	(-1.09)	(2.72)	(-6.36)	1,232,586
(11)	8 Months	0.122	0.206	0.120	-0.069	0.208	-0.234	387
		(2.18)	(1.42)	(1.86)	(-0.85)	(2.68)	(-6.73)	1,213,771
(12)	10 Months	0.147	0.199	0.120	-0.062	0.195	-0.237	385
		(2.57)	(1.32)	(1.86)	(-0.76)	(2.49)	(-6.61)	1,193,781
(13)	12 Months	0.155	0.239	0.120	-0.055	0.183	-0.236	383
		(2.59)	(1.57)	(1.88)	(-0.68)	(2.32)	(-6.58)	1,172,513
(14)	14 Months	0.197	0.253	0.118	-0.043	0.175	-0.236	381
		(3.22)	(1.66)	(1.85)	(-0.54)	(2.17)	(-6.37)	1,150,641
(15)	16 Months	0.199	0.244	0.110	-0.056	0.173	-0.232	379
		(3.33)	(1.60)	(1.72)	(-0.70)	(2.13)	(-6.36)	1,128,868
(16)	18 Months	0.204	0.240	0.098	-0.062	0.172	-0.218	377
		(3.34)	(1.56)	(1.54)	(-0.78)	(2.08)	(-5.95)	1,107,888
(17)	20 Months	0.184	0.206	0.101	-0.036	0.165	-0.222	375
		(2.94)	(1.35)	(1.59)	(-0.46)	(1.96)	(-6.01)	1,087,114
(18)	22 Months	0.159	0.207	0.107	-0.054	0.169	-0.214	373
		(2.55)	(1.34)	(1.69)	(-0.71)	(1.96)	(-5.87)	1,066,630
(19)	24 Months	0.179	0.193	0.107	-0.059	0.149	-0.211	371
		(2.73)	(1.25)	(1.70)	(-0.79)	(1.74)	(-5.67)	1,046,711
(20)	26 Months	0.203	0.175	0.097	-0.062	0.137	-0.220	369
		(3.06)	(1.12)	(1.52)	(-0.82)	(1.57)	(-6.01)	1,027,134
(21)	28 Months	0.190	0.174	0.105	-0.064	0.135	-0.216	367
		(2.86)	(1.12)	(1.64)	(-0.85)	(1.57)	(-5.93)	1,007,982
(22)	30 Months	0.213	0.175	0.106	-0.069	0.140	-0.218	365
		(3.18)	(1.11)	(1.69)	(-0.94)	(1.62)	(-6.08)	989,494
(23)	32 Months	0.195	0.174	0.095	-0.060	0.116	-0.215	363
		(3.06)	(1.10)	(1.48)	(-0.82)	(1.31)	(-6.09)	971,656
(24)	34 Months	0.191	0.141	0.081	-0.073	0.118	-0.204	361
		(3.00)	(0.88)	(1.25)	(-1.02)	(1.32)	(-5.73)	954,064
(25)	36 Months	0.184	0.125	0.095	-0.090	0.127	-0.214	359
		(2.65)	(0.78)	(1.50)	(-1.26)	(1.44)	(-6.01)	936,785

Table 7: **Fama MacBeth Regressions (SIC Disruption)**

The table reports the results of Fama-MacBeth regressions where the monthly firm stock return is the dependent variable. Our period is from June 1951 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. 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 momentum variable is the firm-specific return from month $t-12$ to $t-2$.

Row	Lag	Disrupted	Momentum	Log B/M	Log Size	Profitability	Investment	# mnths /Obs
(1)	-12 Months	0.006	0.539	0.096	-0.315	-0.005	-0.254	822
		(0.17)	(4.93)	(1.94)	(-4.91)	(-0.10)	(-6.59)	1,469,274
(2)	-10 Months	0.008	0.539	0.105	-0.312	0.004	-0.254	824
		(0.23)	(4.90)	(2.12)	(-4.88)	(0.08)	(-6.63)	1,493,166
(3)	-8 Months	0.022	0.536	0.102	-0.308	0.009	-0.265	826
		(0.69)	(4.89)	(2.03)	(-4.80)	(0.19)	(-6.77)	1,517,881
(4)	-6 Months	0.034	0.531	0.108	-0.312	0.011	-0.262	828
		(1.09)	(4.86)	(2.13)	(-4.82)	(0.23)	(-6.77)	1,543,791
(5)	-4 Months	0.051	0.538	0.104	-0.309	0.026	-0.260	830
		(1.62)	(4.92)	(2.07)	(-4.82)	(0.52)	(-6.54)	1,571,896
(6)	-2 Months	0.037	0.508	0.105	-0.318	0.033	-0.279	832
		(1.19)	(4.61)	(2.09)	(-4.96)	(0.66)	(-6.93)	1,602,217
(7)	0 Months	0.039	0.658	0.146	-0.194	0.192	-0.266	833
		(1.24)	(6.11)	(2.90)	(-2.99)	(3.68)	(-6.50)	1,637,396
(8)	2 Months	0.072	0.658	0.148	-0.190	0.206	-0.257	833
		(2.28)	(6.13)	(2.97)	(-2.95)	(4.10)	(-6.28)	1,618,519
(9)	4 Months	0.076	0.676	0.145	-0.188	0.191	-0.258	833
		(2.53)	(6.35)	(2.88)	(-2.94)	(3.72)	(-6.37)	1,604,873
(10)	6 Months	0.083	0.656	0.138	-0.183	0.198	-0.252	833
		(2.56)	(6.28)	(2.79)	(-2.87)	(3.84)	(-6.26)	1,589,410
(11)	8 Months	0.095	0.647	0.136	-0.187	0.183	-0.261	833
		(2.84)	(6.30)	(2.70)	(-2.93)	(3.63)	(-6.44)	1,571,902
(12)	10 Months	0.106	0.614	0.135	-0.196	0.185	-0.249	833
		(3.27)	(6.04)	(2.69)	(-3.06)	(3.68)	(-6.27)	1,552,417
(13)	12 Months	0.132	0.617	0.128	-0.192	0.196	-0.255	833
		(4.04)	(6.07)	(2.54)	(-2.99)	(3.82)	(-6.38)	1,531,205
(14)	14 Months	0.128	0.631	0.134	-0.188	0.201	-0.253	833
		(3.98)	(6.22)	(2.64)	(-2.92)	(3.84)	(-6.35)	1,509,368
(15)	16 Months	0.129	0.640	0.124	-0.197	0.203	-0.256	833
		(3.84)	(6.23)	(2.45)	(-3.08)	(3.94)	(-6.36)	1,487,594
(16)	18 Months	0.145	0.653	0.125	-0.192	0.191	-0.248	833
		(4.47)	(6.32)	(2.48)	(-2.97)	(3.73)	(-6.23)	1,465,874
(17)	20 Months	0.137	0.653	0.134	-0.186	0.202	-0.253	833
		(4.04)	(6.19)	(2.61)	(-2.89)	(3.92)	(-6.43)	1,444,474
(18)	22 Months	0.125	0.640	0.129	-0.196	0.209	-0.254	833
		(3.99)	(6.02)	(2.53)	(-3.04)	(3.93)	(-6.48)	1,423,493
(19)	24 Months	0.113	0.644	0.139	-0.196	0.221	-0.241	833
		(3.46)	(6.06)	(2.72)	(-3.05)	(4.33)	(-6.36)	1,402,856
(20)	26 Months	0.105	0.641	0.134	-0.206	0.216	-0.228	833
		(3.21)	(6.03)	(2.65)	(-3.18)	(4.17)	(-6.05)	1,382,367
(21)	28 Months	0.115	0.644	0.125	-0.203	0.199	-0.229	833
		(3.58)	(5.98)	(2.51)	(-3.14)	(3.87)	(-6.15)	1,362,276
(22)	30 Months	0.110	0.663	0.122	-0.204	0.194	-0.231	833
		(3.24)	(6.11)	(2.47)	(-3.11)	(3.78)	(-6.13)	1,342,676
(23)	32 Months	0.115	0.648	0.112	-0.206	0.177	-0.230	833
		(3.29)	(5.91)	(2.24)	(-3.15)	(3.52)	(-6.10)	1,323,387
(24)	34 Months	0.104	0.628	0.119	-0.205	0.190	-0.226	833
		(3.05)	(5.73)	(2.35)	(-3.13)	(3.84)	(-6.00)	1,304,459
(25)	36 Months	0.104	0.634	0.115	-0.209	0.186	-0.227	833
		(3.01)	(5.85)	(2.28)	(-3.21)	(3.82)	(-6.18)	1,285,872

Table 8: **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

Table 9: **Disruption, R&D, and Acquisitions**

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)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	1.405***	0.588***	0.080	1.672***	1.147***	0.928***
	(9.483)	(4.295)	(0.596)	(12.652)	(7.972)	(6.259)
Disrupted × Large	-1.816***	-1.039***	-0.740***	-0.515***	-0.501***	-0.355***
	(-16.708)	(-10.751)	(-8.054)	(-5.569)	(-5.414)	(-3.723)
Small	0.036***	0.020***	0.012***	0.022***	0.017***	0.013***
	(24.870)	(16.568)	(10.548)	(17.410)	(13.091)	(9.857)
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
Panel B: Acquisition/Assets						
Disrupted × Small	0.194	0.962***	1.304***	1.271***	1.989***	1.030**
	(0.768)	(3.160)	(4.388)	(2.657)	(4.525)	(2.150)
Disrupted × Large	-0.151	0.046	0.179	0.553	0.648*	-0.065
	(-0.673)	(0.205)	(0.868)	(1.401)	(1.948)	(-0.179)
Small	0.014***	0.029***	0.024***	0.028***	0.028***	0.025***
	(5.204)	(9.821)	(8.907)	(9.503)	(9.141)	(7.223)
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
Panel C: Acquired Dummy						
Disrupted × Small	0.440***	0.481***	0.681***	0.058	0.105	0.454
	(2.976)	(2.676)	(3.410)	(0.234)	(0.359)	(1.574)
Disrupted × Large	0.089	0.031	0.282*	-0.018	0.308	-0.126
	(0.520)	(0.176)	(1.766)	(-0.070)	(1.276)	(-0.475)
Small	-0.001	-0.001	-0.002*	-0.001	-0.003**	-0.004**
	(-1.206)	(-0.690)	(-1.734)	(-0.817)	(-1.998)	(-2.406)
Observations	129,961	115,014	102,686	95,916	80,471	68,478
R-squared	0.005	0.006	0.006	0.006	0.006	0.007
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.001	.0011	.0015	.0002	.0003	.0012

Table 10: **Disruption, Valuation and Sales**

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)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	84.856***	54.711***	17.519**	28.484***	38.053***	34.032***
	(9.927)	(6.939)	(2.428)	(5.001)	(6.525)	(5.430)
Disrupted × Large	-56.252***	-22.707***	-21.331***	-4.924	-4.773	-2.027
	(-9.881)	(-5.189)	(-5.233)	(-1.225)	(-1.264)	(-0.519)
Small	1.646***	1.143***	0.708***	0.678***	0.687***	0.577***
	(17.846)	(16.829)	(13.998)	(17.344)	(16.548)	(12.316)
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
Panel B: KPSS/Assets						
Disrupted × Small	2.561***	3.260***	3.999***	2.044***	1.660***	1.284***
	(5.879)	(6.494)	(7.429)	(8.869)	(6.200)	(4.282)
Disrupted × Large	-2.613***	-2.422***	-1.835***	0.537**	-0.160	-1.013***
	(-4.233)	(-3.675)	(-2.787)	(2.166)	(-0.608)	(-3.589)
Small	0.006**	0.007***	0.008***	0.023***	0.025***	0.025***
	(2.211)	(2.725)	(2.684)	(8.405)	(7.913)	(7.109)
Observations	145,698	130,740	118,940	71,774	61,331	53,459
R-squared	0.105	0.121	0.136	0.070	0.077	0.085
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0065	.0083	.0101	.0059	.0047	.0036
Panel C: Sales Growth						
Disrupted × Small	0.203	4.341***	5.250***	0.313	0.501	2.231***
	(0.364)	(7.871)	(9.416)	(0.397)	(0.623)	(2.740)
Disrupted × Large	-3.366***	-0.730*	1.658***	-3.521***	-1.316**	-0.077
	(-7.592)	(-1.651)	(3.647)	(-5.738)	(-2.040)	(-0.118)
Small	0.059***	0.103***	0.078***	0.049***	0.081***	0.068***
	(15.973)	(26.582)	(20.737)	(10.915)	(17.230)	(13.628)
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

Table 11: **Disruption, Performance, and Growth**

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: Profitability	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	-2.255***	0.138	1.503***	-1.727***	-1.016**	-0.543
	(-5.871)	(0.405)	(4.396)	(-4.310)	(-2.443)	(-1.246)
Disrupted × Large	0.918***	0.785***	0.985***	-0.422	-0.626**	-0.370
	(3.529)	(3.161)	(3.979)	(-1.574)	(-2.368)	(-1.362)
Small	-0.019***	0.009***	0.015***	0.001	0.013***	0.011***
	(-6.079)	(3.439)	(6.012)	(0.311)	(4.557)	(3.647)
Observations	184,706	162,939	145,531	102,655	86,763	74,421
R-squared	0.037	0.033	0.040	0.023	0.022	0.023
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	-.0052	.0003	.0035	-.0044	-.0025	-.0013
Panel B: Asset Growth						
Disrupted × Small	3.582***	4.754***	2.104***	1.357*	1.809**	2.636***
	(6.007)	(8.656)	(3.827)	(1.850)	(2.312)	(3.224)
Disrupted × Large	-5.896***	-2.623***	-1.507***	-4.354***	-2.946***	-1.679***
	(-12.388)	(-5.814)	(-3.578)	(-7.227)	(-4.804)	(-2.645)
Small	0.141***	0.132***	0.096***	0.110***	0.111***	0.090***
	(31.769)	(32.919)	(26.338)	(25.242)	(24.805)	(18.480)
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
Panel C: Log(Scope)						
Disrupted × Small	1.622	1.969	3.648**	2.626	3.578**	3.249*
	(1.059)	(1.260)	(2.332)	(1.637)	(2.079)	(1.771)
Disrupted × Large	3.633**	4.364**	3.309*	2.614	2.278	-0.074
	(2.160)	(2.510)	(1.813)	(1.639)	(1.325)	(-0.041)
Small	-0.116***	-0.092***	-0.065***	-0.104***	-0.079***	-0.049***
	(-9.003)	(-6.921)	(-4.692)	(-8.459)	(-5.890)	(-3.314)
Observations	97,576	89,197	80,584	104,108	87,916	75,358
R-squared	0.073	0.073	0.073	0.072	0.073	0.072
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0035	.0042	.0081	.0067	.009	.0081

Table 12: **Disruption and Financing Variables**

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: Equity Issues	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	10.528***	5.608***	0.448	2.476***	1.793***	1.695***
	(13.496)	(9.957)	(0.970)	(5.298)	(3.801)	(3.668)
Disrupted × Large	-7.485***	-2.683***	-1.243***	-0.319	-0.644***	-0.291
	(-13.865)	(-7.926)	(-5.285)	(-1.263)	(-2.871)	(-1.290)
Small	0.208***	0.111***	0.045***	0.058***	0.043***	0.033***
	(25.816)	(22.226)	(14.681)	(19.671)	(15.870)	(11.442)
Observations	185,672	163,765	146,250	104,123	87,929	75,368
R-squared	0.131	0.078	0.026	0.070	0.055	0.044
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0244	.013	.001	.0063	.0045	.0042
Panel B: Equity Outflows						
Disrupted × Small	-0.436***	-0.484***	-0.343***	-0.506***	-0.503***	-0.632***
	(-7.058)	(-7.605)	(-5.304)	(-5.101)	(-4.486)	(-5.137)
Disrupted × Large	-0.181***	-0.132*	-0.021	-0.013	0.083	-0.032
	(-2.639)	(-1.857)	(-0.286)	(-0.137)	(0.844)	(-0.289)
Small	-0.002***	-0.003***	-0.004***	-0.003***	-0.003***	-0.004***
	(-4.332)	(-7.051)	(-6.949)	(-4.081)	(-4.288)	(-4.749)
Observations	185,672	163,765	146,250	104,123	87,929	75,368
R-squared	0.024	0.029	0.032	0.040	0.041	0.041
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	-.001	-.0011	-.0008	-.0013	-.0013	-.0016
Panel D: Venture Inv./ Assets						
Disrupted × Small	-1.100	0.945**	1.311***	-0.459	0.637	2.503***
	(-1.089)	(2.120)	(3.128)	(-0.724)	(1.003)	(3.944)
Disrupted × Large	2.198***	1.404***	0.778***	0.220	0.307	0.460**
	(5.513)	(6.101)	(3.277)	(1.059)	(1.578)	(2.348)
Small	0.030***	0.029***	0.027***	0.005***	0.005***	0.008***
	(8.438)	(8.683)	(7.553)	(2.917)	(2.751)	(4.623)
Observations	30,364	29,066	27,453	39,537	35,834	32,718
R-squared	0.234	0.087	0.049	0.226	0.126	0.081
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	-.0015	.0015	.0023	-.0007	.0011	.0043

Appendix A. Variable definitions

Table A1: Variable definitions

Variable	Definition
Panel A: Financial Characteristics	
Assets	Compustat item AT.
Sales	Compustat item SALE
Profitability	Compustat OIBDP divided by lagged total assets.
M/B Ratio	Compustat sum of market equity (CSHO * PRCC_F), DLC, DLTT, PSTKL, all scaled by lagged book assets.
Sales Growth	Natural logarithm of total sales in the current year t divided by total sales in the previous year t-1.
Log(Age)	Natural logarithm of one plus the current year of observation minus the first year the firm appears in the Compustat database.
Capital Exp./Assets	Compustat CAPX scaled by lagged assets.
Assets Growth	Natural logarithm of total assets in the current year t divided by total assets in the previous year t-1.
Panel B: Innovation, Acquisition & Lawsuit Characteristics	
Disruption	Defined in Section 1
R&D/Assets	Compustat XRD divided by lagged total assets. This variable is set to zero if XRD is missing
Patent App./Assets	The number of patent applications scaled by lagged firm assets.
KPSS/ Assets	Total dollar value of granted patents calculated by the values in KPSS database scaled by lagged assets.
Cites/Assets	Average number of citations that a firm's patents granted in that year received scaled by lagged assets,
Acquisitions/Assets	The total amount of acquisitions divided by lagged firm assets.
Acquired Dummy	Dummy variable equals one if the firm was acquired in that year and zero otherwise.
Panel C: Competition Measures	
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. agreements
Nondisclose	#10K paragraphs mentioning "non-disclose" or "NDA" agreements, all scaled by the total paragraphs in the 10-K.
Log(Scope)	Natural logarithm of firm scope from Hoberg and Phillips (2023).
Venture Inv./Assets	A measure of VC entry in a given firm's product market computed as the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description is most similar to the 10-K business description of the focal firm (using cosine similarities), scaled by focal firm lagged assets.
Noncompete	#10K paragraphs mentioning "non-compete" agreements, all scaled by the total paragraphs in the 10-K.
Equity Issues	Compustat SSTK scaled by lagged assets.
Dividend Yields	Compustat DVC divided by (CSHO * PRCC_F).
Equity Rep./Assets	Compustat PRSTKC scaled by lagged assets.

Table A2: **Fama MacBeth Regressions (TNIC Disruption) (Small vs Big)**

This table reports robustness to Table 6 where the only change made is we document the disrupted coefficients separately for small vs big firms (above vs below median ex-ante market cap in the given month). We thus add the interaction between the big and small indicators and our disruption variable (and include a control for the indicator. The table reports the results of Fama-MacBeth regressions 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. The final two 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). The alpha is estimated as the intercept of the portfolio return on the 5 q-factor model from Hou et al. (2015) (we thank Lu Zhang for providing the factor data on his website).

Row	Lag	Disrupted x Small	Disrupted x Big	Big	Mom-entum	Log B/M	months /Obs	Disrupted x Small Alpha	Disrupted x Big Alpha
(1)	-12 Months	-0.045	0.182	0.231	-0.109	0.345	396	-0.021	0.135
		(-0.67)	(2.79)	(2.46)	(-0.80)	(5.57)	1,167,965	(-0.36)	(2.58)
(2)	-10 Months	0.016	0.169	0.209	-0.090	0.313	396	0.047	0.144
		(0.23)	(2.73)	(2.30)	(-0.65)	(5.17)	1,185,584	(0.86)	(2.98)
(3)	-8 Months	0.012	0.137	0.173	-0.096	0.272	396	0.055	0.115
		(0.18)	(2.33)	(1.85)	(-0.68)	(4.36)	1,203,763	(0.95)	(2.41)
(4)	-6 Months	0.033	0.110	0.205	-0.076	0.225	396	0.057	0.086
		(0.51)	(2.01)	(2.27)	(-0.53)	(3.42)	1,222,335	(0.99)	(1.91)
(5)	-4 Months	-0.000	0.067	0.140	-0.074	0.184	396	0.025	0.048
		(-0.01)	(1.26)	(1.49)	(-0.52)	(2.80)	1,243,086	(0.41)	(1.04)
(6)	-2 Months	0.025	0.042	0.198	-0.044	0.134	396	0.044	0.006
		(0.37)	(0.76)	(2.34)	(-0.30)	(2.05)	1,265,522	(0.71)	(0.13)
(7)	0 Months	0.058	0.059	0.044	0.178	0.135	395	0.070	0.012
		(0.81)	(1.05)	(0.53)	(1.24)	(2.09)	1,290,905	(1.15)	(0.25)
(8)	2 Months	0.096	0.128	0.061	0.191	0.129	393	0.125	0.084
		(1.39)	(2.28)	(0.77)	(1.34)	(1.98)	1,268,355	(1.97)	(1.61)
(9)	4 Months	0.081	0.120	0.008	0.210	0.117	391	0.081	0.059
		(1.19)	(2.21)	(0.09)	(1.48)	(1.80)	1,250,466	(1.34)	(1.19)
(10)	6 Months	0.146	0.148	0.092	0.214	0.110	389	0.119	0.070
		(2.20)	(2.74)	(1.11)	(1.50)	(1.72)	1,232,586	(2.15)	(1.43)
(11)	8 Months	0.086	0.158	0.034	0.206	0.120	387	0.034	0.080
		(1.23)	(2.92)	(0.43)	(1.43)	(1.85)	1,213,771	(0.57)	(1.55)
(12)	10 Months	0.119	0.178	0.030	0.200	0.119	385	0.050	0.070
		(1.63)	(3.22)	(0.38)	(1.32)	(1.85)	1,193,781	(0.75)	(1.40)
(13)	12 Months	0.125	0.189	0.041	0.239	0.119	383	0.075	0.075
		(1.70)	(3.25)	(0.55)	(1.57)	(1.87)	1,172,513	(1.17)	(1.49)
(14)	14 Months	0.196	0.205	0.052	0.253	0.117	381	0.131	0.109
		(2.47)	(3.58)	(0.69)	(1.67)	(1.82)	1,150,641	(1.62)	(2.20)
(15)	16 Months	0.201	0.198	0.090	0.243	0.109	379	0.151	0.099
		(2.66)	(3.50)	(1.22)	(1.59)	(1.70)	1,128,868	(2.18)	(1.98)
(16)	18 Months	0.241	0.174	0.070	0.239	0.096	377	0.189	0.061
		(3.22)	(2.93)	(0.94)	(1.56)	(1.51)	1,107,888	(2.92)	(1.09)
(17)	20 Months	0.223	0.152	0.058	0.206	0.099	375	0.176	0.051
		(2.94)	(2.54)	(0.76)	(1.35)	(1.57)	1,087,114	(2.77)	(0.91)
(18)	22 Months	0.199	0.125	0.059	0.207	0.105	373	0.155	0.016
		(2.54)	(2.11)	(0.74)	(1.33)	(1.66)	1,066,630	(2.24)	(0.28)
(19)	24 Months	0.232	0.136	0.073	0.194	0.105	371	0.221	0.052
		(2.83)	(2.19)	(0.93)	(1.25)	(1.67)	1,046,711	(3.17)	(0.92)
(20)	26 Months	0.260	0.161	0.070	0.176	0.095	369	0.268	0.094
		(3.19)	(2.58)	(0.90)	(1.13)	(1.49)	1,027,134	(3.80)	(1.59)
(21)	28 Months	0.239	0.148	0.017	0.174	0.103	367	0.217	0.093
		(2.91)	(2.38)	(0.22)	(1.11)	(1.60)	1,007,982	(3.07)	(1.56)
(22)	30 Months	0.266	0.169	0.033	0.174	0.104	365	0.221	0.101
		(3.28)	(2.66)	(0.41)	(1.11)	(1.66)	989,494	(3.34)	(1.58)
(23)	32 Months	0.243	0.157	0.064	0.174	0.092	363	0.194	0.068
		(3.17)	(2.56)	(0.84)	(1.10)	(1.44)	971,656	(3.11)	(1.15)
(24)	34 Months	0.244	0.142	0.053	0.141	0.080	361	0.167	0.040
		(3.26)	(2.29)	(0.72)	(0.88)	(1.23)	954,064	(2.58)	(0.66)
(25)	36 Months	0.213	0.152	-0.005	0.124	0.095	359	0.154	0.044
		(2.64)	(2.24)	(-0.06)	(0.78)	(1.49)	936,785	(2.29)	(0.73)

Table A3: **Fama MacBeth Regressions (SIC Disruption) (Small vs Big)**

This table reports robustness to Table 7 where the only change made is we document the disrupted coefficients separately for small vs big firms (above vs below median ex-ante market cap in the given month). We thus add the interaction between the big and small indicators and our disruption variable (and include a control for the indicator. The table reports the results of Fama-MacBeth regressions where the monthly firm stock return is the dependent variable. Our period is from June 1951 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. The final two 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 investable portfolios, see Back et al. (2015) for example). The alpha is estimated as the intercept of the portfolio return on the 5 q-factor model from Hou et al. (2015) (we thank Lu Zhang for providing the factor data on his website).

Row	Lag	Disrupted x Small	Disrupted x Big	Big	Mom-entum	Log B/M	months /Obs	Disrupted x Small Alpha	Disrupted x Big Alpha
(1)	-12 Months	0.038	-0.024	-0.028	0.537	0.094	822	-0.017	-0.038
		(0.96)	(-0.65)	(-0.51)	(4.92)	(1.89)	1,469,274	(-0.37)	(-0.78)
(2)	-10 Months	0.027	-0.013	0.002	0.535	0.104	824	0.016	-0.022
		(0.72)	(-0.38)	(0.04)	(4.87)	(2.09)	1,493,166	(0.32)	(-0.47)
(3)	-8 Months	0.058	-0.009	0.008	0.532	0.099	826	0.073	-0.015
		(1.51)	(-0.26)	(0.15)	(4.86)	(1.99)	1,517,881	(1.60)	(-0.34)
(4)	-6 Months	0.081	-0.006	0.010	0.527	0.104	828	0.095	-0.005
		(2.11)	(-0.16)	(0.19)	(4.82)	(2.05)	1,543,791	(1.96)	(-0.12)
(5)	-4 Months	0.092	0.011	0.050	0.534	0.102	830	0.095	0.001
		(2.43)	(0.33)	(0.91)	(4.89)	(2.03)	1,571,896	(2.04)	(0.01)
(6)	-2 Months	0.075	0.002	0.075	0.506	0.104	832	0.096	-0.012
		(2.08)	(0.07)	(1.41)	(4.60)	(2.06)	1,602,217	(2.04)	(-0.27)
(7)	0 Months	0.070	0.014	0.016	0.656	0.144	833	0.089	0.001
		(1.94)	(0.38)	(0.30)	(6.10)	(2.85)	1,637,396	(1.76)	(0.01)
(8)	2 Months	0.096	0.050	0.006	0.654	0.145	833	0.108	0.030
		(2.69)	(1.32)	(0.11)	(6.09)	(2.90)	1,618,519	(2.13)	(0.61)
(9)	4 Months	0.118	0.034	-0.006	0.673	0.140	833	0.080	0.005
		(3.38)	(0.98)	(-0.12)	(6.33)	(2.78)	1,604,873	(1.77)	(0.12)
(10)	6 Months	0.117	0.048	0.001	0.653	0.136	833	0.106	0.055
		(3.05)	(1.34)	(0.02)	(6.26)	(2.73)	1,589,410	(2.26)	(1.23)
(11)	8 Months	0.131	0.057	-0.005	0.643	0.134	833	0.119	0.060
		(3.28)	(1.55)	(-0.09)	(6.26)	(2.66)	1,571,902	(2.45)	(1.30)
(12)	10 Months	0.161	0.049	0.008	0.611	0.133	833	0.127	0.035
		(4.21)	(1.39)	(0.14)	(6.01)	(2.65)	1,552,417	(2.86)	(0.79)
(13)	12 Months	0.197	0.065	0.016	0.615	0.127	833	0.162	0.057
		(4.89)	(1.81)	(0.30)	(6.05)	(2.51)	1,531,205	(3.77)	(1.30)
(14)	14 Months	0.201	0.054	0.014	0.627	0.133	833	0.185	0.051
		(5.08)	(1.52)	(0.26)	(6.18)	(2.62)	1,509,368	(3.93)	(1.13)
(15)	16 Months	0.186	0.073	0.013	0.636	0.123	833	0.153	0.038
		(4.62)	(2.02)	(0.24)	(6.19)	(2.42)	1,487,594	(3.13)	(0.84)
(16)	18 Months	0.193	0.093	0.021	0.649	0.123	833	0.136	0.054
		(4.81)	(2.59)	(0.38)	(6.29)	(2.43)	1,465,874	(2.91)	(1.19)
(17)	20 Months	0.181	0.096	0.041	0.651	0.132	833	0.142	0.054
		(4.59)	(2.56)	(0.75)	(6.18)	(2.58)	1,444,474	(2.84)	(1.09)
(18)	22 Months	0.172	0.078	0.045	0.637	0.127	833	0.144	0.048
		(4.55)	(2.22)	(0.85)	(5.99)	(2.50)	1,423,493	(2.78)	(1.03)
(19)	24 Months	0.163	0.063	0.061	0.639	0.138	833	0.132	0.027
		(4.06)	(1.69)	(1.13)	(6.03)	(2.71)	1,402,856	(2.36)	(0.54)
(20)	26 Months	0.149	0.066	0.043	0.633	0.132	833	0.126	0.047
		(3.72)	(1.79)	(0.78)	(5.97)	(2.61)	1,382,367	(2.24)	(0.96)
(21)	28 Months	0.156	0.078	0.053	0.643	0.125	833	0.118	0.061
		(3.96)	(2.12)	(0.98)	(5.98)	(2.51)	1,362,276	(2.18)	(1.30)
(22)	30 Months	0.147	0.077	0.055	0.659	0.119	833	0.137	0.065
		(3.64)	(2.05)	(1.04)	(6.08)	(2.42)	1,342,676	(2.28)	(1.33)
(23)	32 Months	0.160	0.066	0.048	0.645	0.112	833	0.119	0.041
		(3.92)	(1.72)	(0.91)	(5.89)	(2.24)	1,323,387	(2.19)	(0.82)
(24)	34 Months	0.139	0.064	0.048	0.627	0.118	833	0.087	0.038
		(3.53)	(1.66)	(0.86)	(5.73)	(2.33)	1,304,459	(1.59)	(0.80)
(25)	36 Months	0.147	0.061	0.049	0.631	0.113	833	0.114	0.049
		(3.55)	(1.58)	(0.92)	(5.84)	(2.25)	1,285,872	(2.05)	(0.99)

Table A4: **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

6.1 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.

6.2 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 6.1 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.

Figure A1: 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 A4 . 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.

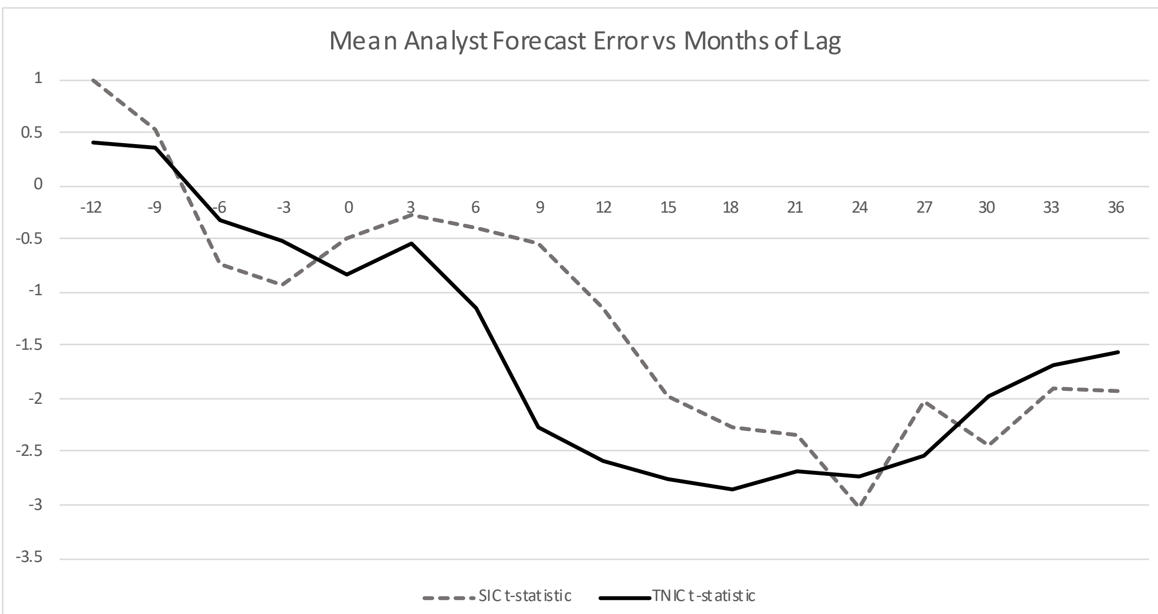


Table A5: **Disruption, Valuation and Sales (Firms With Highly-Cited Patents Removed)**

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) and 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)
Small	1.627***	1.124***	0.658***	0.687***	0.671***	0.595***
	(17.427)	(16.478)	(13.425)	(18.658)	(16.938)	(13.702)
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
Panel B: KPSS/Assets						
Disrupted × Small	1.960***	2.367***	2.827***	1.026***	0.790***	0.654***
	(5.278)	(5.627)	(6.357)	(6.751)	(4.504)	(3.337)
Disrupted × Large	-2.028***	-1.945***	-1.539***	0.277*	-0.055	-0.411***
	(-4.063)	(-3.595)	(-2.913)	(1.941)	(-0.388)	(-2.609)
Small	0.002	0.004*	0.004*	0.014***	0.013***	0.012***
	(1.053)	(1.779)	(1.780)	(7.326)	(6.658)	(5.617)
Observations	139,595	124,082	112,039	67,993	57,436	49,577
R-squared	0.093	0.102	0.113	0.055	0.058	0.059
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.005	.0061	.0073	.003	.0023	.0019
Panel C: 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)
Small	0.059***	0.103***	0.077***	0.048***	0.087***	0.073***
	(15.611)	(25.947)	(19.797)	(10.207)	(17.278)	(13.664)
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

Table A6: **Disruption, R&D, and Acquisitions (Firms With Highly-Cited Patents Removed)**

The table displays three panel data regressions in which restructurings variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021) and 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)
Small	0.035***	0.019***	0.011***	0.019***	0.015***	0.011***
	(23.822)	(15.593)	(9.199)	(15.423)	(11.662)	(8.560)
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
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)
Small	0.015***	0.027***	0.023***	0.028***	0.028***	0.024***
	(5.557)	(9.373)	(8.414)	(9.427)	(9.157)	(7.071)
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
Panel C: Acquired Dummy						
Disrupted × Small	0.447***	0.519***	0.706***	0.077	0.047	0.403
	(2.987)	(2.858)	(3.467)	(0.301)	(0.157)	(1.385)
Disrupted × Large	0.204	0.164	0.320**	0.066	0.406*	-0.072
	(1.280)	(0.963)	(2.025)	(0.252)	(1.668)	(-0.270)
Small	-0.001	-0.002	-0.002	-0.000	-0.003**	-0.004***
	(-1.036)	(-1.418)	(-1.517)	(-0.302)	(-2.296)	(-2.762)
Observations	124,273	109,059	96,676	90,945	75,548	63,730
R-squared	0.005	0.006	0.006	0.006	0.007	0.006
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.001	.0012	.0016	.0002	.0001	.0011

Table A7: **Disruption, Performance, and Growth (Firms With Highly-Cited Patents Removed)**

The table displays three panel data regressions in which accounting performance variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021) and 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: Profitability	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	-2.055***	0.127	1.442***	-1.598***	-0.800*	-0.489
	(-5.272)	(0.367)	(4.191)	(-3.979)	(-1.938)	(-1.116)
Disrupted × Large	0.734***	0.658***	0.856***	-0.703***	-0.850***	-0.597**
	(2.733)	(2.591)	(3.349)	(-2.617)	(-3.165)	(-2.136)
Small	-0.016***	0.010***	0.016***	0.005*	0.018***	0.016***
	(-5.096)	(3.944)	(6.371)	(1.733)	(6.234)	(5.013)
Observations	170,390	148,908	131,923	92,248	76,889	65,107
R-squared	0.036	0.032	0.040	0.021	0.021	0.022
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	-.0048	.0003	.0034	-.0042	-.0021	-.0013
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)
Small	0.140***	0.132***	0.097***	0.111***	0.113***	0.094***
	(30.984)	(32.223)	(25.441)	(24.402)	(23.614)	(18.319)
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
Panel C: Log(Scope)						
Disrupted × Small	1.937	2.138	3.202**	1.890	2.343	2.587
	(1.261)	(1.372)	(2.050)	(1.187)	(1.368)	(1.423)
Disrupted × Large	4.570***	4.561***	3.082*	3.209**	2.350	-0.577
	(2.789)	(2.700)	(1.739)	(2.029)	(1.396)	(-0.323)
Small	-0.123***	-0.099***	-0.069***	-0.108***	-0.081***	-0.048***
	(-9.370)	(-7.398)	(-4.928)	(-8.572)	(-5.913)	(-3.197)
Observations	87,980	79,812	71,515	93,613	77,968	65,978
R-squared	0.072	0.072	0.071	0.072	0.073	0.073
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0043	.0048	.0074	.005	.0062	.0068

Table A8: **Disruption and Financing Variables (Firms With Highly-Cited Patents Removed)**

The table displays three panel data regressions in which accounting performance variables are the dependent variables. We drop all firms with breakthrough patents listed in Kelly et al. (2021) and 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: Equity Issues	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Disrupted × Small	10.486***	5.670***	0.460	2.348***	1.638***	1.853***
	(13.020)	(9.798)	(0.989)	(5.007)	(3.538)	(4.119)
Disrupted × Large	-8.019***	-2.905***	-1.128***	-0.256	-0.614***	-0.321
	(-13.992)	(-8.126)	(-4.698)	(-1.001)	(-2.784)	(-1.369)
Small	0.210***	0.114***	0.044***	0.056***	0.041***	0.031***
	(24.873)	(21.545)	(13.534)	(18.816)	(15.176)	(10.746)
Observations	171,311	149,695	132,605	93,627	77,980	65,988
R-squared	0.129	0.077	0.025	0.071	0.055	0.044
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	.0248	.0138	.0011	.0062	.0043	.0049
Panel B: Equity Outflows						
Disrupted × Small	-0.355***	-0.416***	-0.282***	-0.446***	-0.414***	-0.585***
	(-5.865)	(-6.595)	(-4.405)	(-4.651)	(-3.836)	(-4.936)
Disrupted × Large	-0.132*	-0.085	-0.008	-0.064	-0.017	-0.174
	(-1.940)	(-1.219)	(-0.116)	(-0.694)	(-0.179)	(-1.590)
Small	-0.002***	-0.003***	-0.003***	-0.002***	-0.002***	-0.003***
	(-3.529)	(-6.797)	(-6.525)	(-3.331)	(-3.050)	(-3.259)
Observations	171,311	149,695	132,605	93,627	77,980	65,988
R-squared	0.020	0.024	0.027	0.038	0.038	0.037
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	-.0008	-.001	-.0007	-.0012	-.0011	-.0015
Panel D: Venture Inv./ Assets						
Disrupted × Small	-0.331	1.183**	1.695***	-0.206	0.918	2.639***
	(-0.299)	(2.507)	(4.006)	(-0.330)	(1.449)	(4.007)
Disrupted × Large	2.471***	1.858***	1.111***	0.429**	0.720***	0.895***
	(6.080)	(7.712)	(4.356)	(1.981)	(3.399)	(4.210)
Small	0.031***	0.029***	0.028***	0.005***	0.005**	0.006***
	(7.858)	(7.643)	(6.913)	(3.024)	(2.456)	(3.089)
Observations	26,516	25,350	23,850	34,972	31,501	28,566
R-squared	0.240	0.086	0.050	0.234	0.136	0.083
$\beta_{Disrupted \times Small} \times \Delta Disrupted$	-.0005	.002	.0033	-.0003	.0016	.0048

Figure A2: Disruptions, Valuation, and Sales (Large Firms)

This figure shows the parallel trends for growth options and investment around the disruption year. For each firm in our sample, we identify a year as disruption year if: 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 the year three. The figure represents estimates of γ_t from the regression depicted in Equation (8). Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.

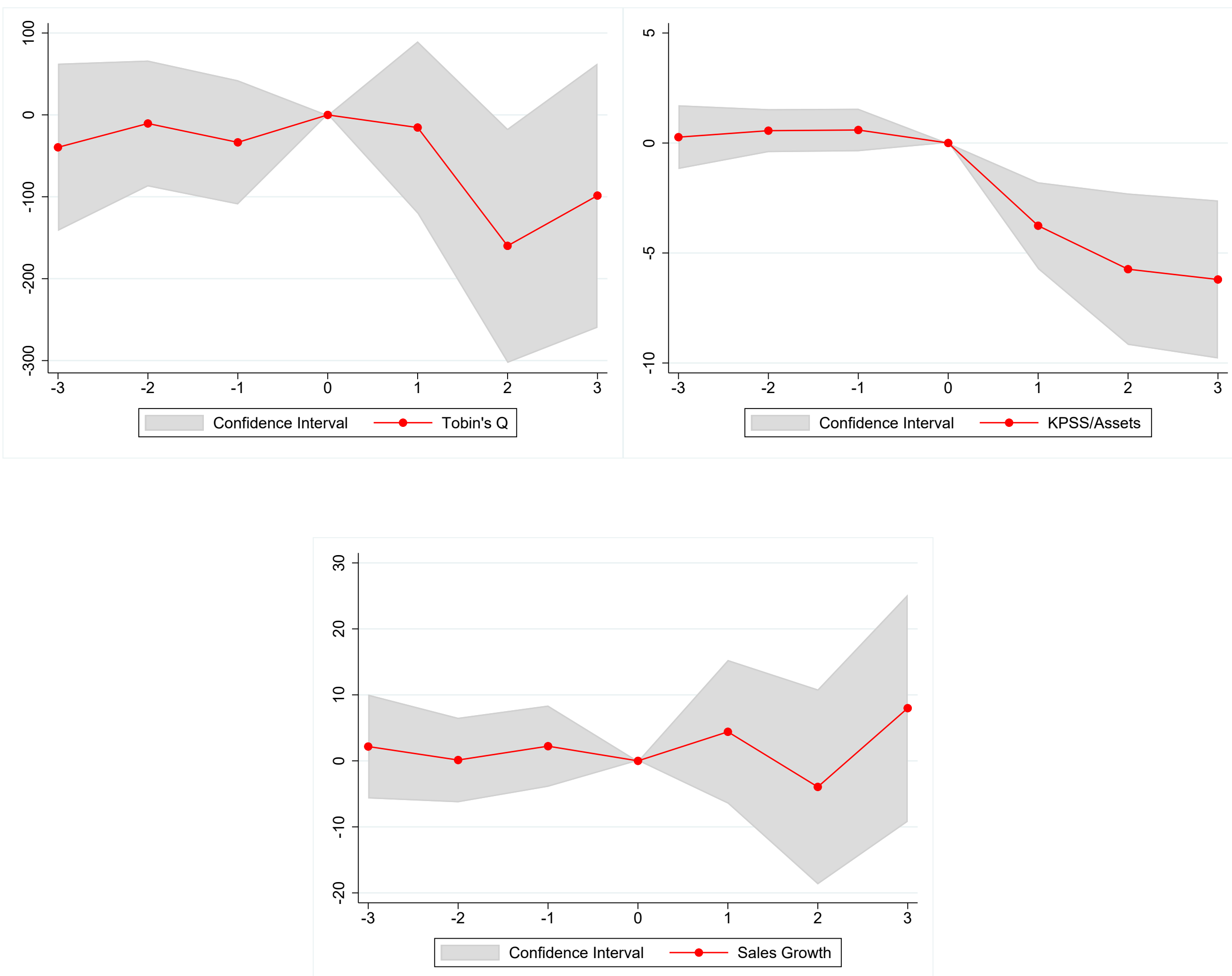


Figure A3: Disruptions, R&D and Acquisitions (Large Firms)

This figure shows the parallel trends for growth options and investment around the disruption year. For each firm in our sample, we identify a year as disruption year if: 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 the year three. The figure represents estimates of γ_t from the regression depicted in Equation (8). Gray lines indicate the 90% confidence interval. All variables are defined in detail in Appendix A.