Creative destruction, stock return volatility, and the number of listed firms

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Abstract

Average idiosyncratic volatility and firm idiosyncratic volatility increase with the number of listed firms. Average industry idiosyncratic volatility increases with the number of listed firms in the industry. We explain the relation between idiosyncratic volatility and the number of listed firms through Schumpeterian creative destruction. We show that Schumpeterian creative destruction increases as the number of listed firms increases. However, there is no consistent evidence of an incremental effect of the number of *non*-listed firms on idiosyncratic volatility either in the aggregate or at the industry level, suggesting that listed firms play a unique role in the dynamism of the economy.

Keywords: Stock return volatility, idiosyncratic risk, creative destruction, firm age, initial public offerings, delists, public listings decline
JEL Classification: G10, G11, G12

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It is well-known that over the last fifty years the number of listed firms in the U.S. follows an inverted U (Doidge, Karolyi, and Stulz, 2016). The number of listed firms peaked in the second half of the 1990s and the number of listed firms today is lower than fifty years ago. Stock return volatility is generally decomposed into systematic volatility and idiosyncratic volatility, where idiosyncratic volatility (IV) measures the volatility of stock returns that cannot be explained by systematic factors. Average IV exhibits temporary spikes associated with crises (Fox, Fox, and Gilson, 2016) that obscure trends. A smoothed measure of average IV follows an inverted U as well. The inverted U of average IV reaches its highest value roughly two years after the inverted U of the number of listed firms reaches its highest value. This close correspondence between the number of listed firms and smoothed average IV has not been investigated in the literature.[1] We find that the relation between changes in smoothed average IV and past changes in the number of listed firms is much stronger than the relation between changes in smoothed average IV and past changes in the number of unlisted firms potentially large enough to be listed. This latter relation has little explanatory power and is not consistently significant. We show that the relation between smoothed average IV and past new listings can be explained by the impact of new listings on creative destruction, so that new listings play an important role in the dynamism of listed firms. Our investigation provides new insights in the dynamics of average IV, the determinants of firm-level IV, the role of IPOs, and the implications of changes in the number of listed and non-listed firms.

Everything else equal, the number of listed firms increases more when the number of net new lists is higher. Greater Schumpeterian creative destruction occurs when there is more firm creation and destruction (Aghion, Akcigit, and Howitt, 2015; Manzzucato and Tancioni, 2005). We expect that, as firms enter public markets, Schumpeterian creative destruction gains strength. This is because new firms challenge established firms and older firms. The future of these innovative young firms is uncertain (Pastor and Veronesi, 2003),

[1] Campbell et al. (2023) have a figure (Figure 9) where they plot firm volatility and the number of stocks. The strong relation we focus on is obscured by the strong spikes in firm volatility arising during crises. They view the plot as supportive of a role in fundamentals for the evolution of firm volatility.

but they make the future of older firms uncertain as well. As a result, IV increases because creative destruction makes the future of firms more uncertain. IV is therefore tied closely to the extent of creative destruction in the economy.[2]

The link between idiosyncratic risk and creative destruction is not new to this paper. In particular, Chun, Kim, Morck, and Yeung (2008) show that creative destruction leads to higher idiosyncratic volatility in the context of the IT revolution. Further, when Chun, Kim, and Morck (2011) measure adoption of the new IT technology by information technology capital intensity, they find support for the view that stock return volatility rises as the new technology propagates across the economy and then ebbs when the new technology becomes widely used. The findings that are new to this paper are: i) establishing the connection between the evolution of IV and the evolution in the number of listings, ii) demonstrating that the connection between the evolution of IV and the number of listed firms exists at the aggregate level, at the industry level, at the firm level, and for both young and older firms, iii) showing that the link between the evolution of IV and the growth in the number of unlisted firms large enough to be potentially listed is much weaker and has little explanatory power, iv) explaining the connection between IV and listings by the relation between growth in the number of firms and creative destruction, v) documenting that past increases in the number of public firms are important for the dynamism of public firms, and vi) showing that past increases in the number of private firms that could potentially enter the public markets have weak effects, if any, on creative destruction in comparison to past increases in the number of public firms.

We show formally using regressions that average IV follows an inverted U shape, and so does the number of listed firms. The inverted U shape is steeper for equal-weighted IV than for value-weighted IV, but the result holds for both IV measures. We then show that smoothed average IV is higher when there are more listed firms and that percentage changes in smoothed average IV are higher when the percentage

[2] Note that a growing literature examines the implications of increases in uncertainty on firm policies. In models using a real option approach, increases in uncertainty can slow creative destruction (Campello, Kankanhalli, and Kim, 2024).

change in listings is higher. It follows from these results that there is a close connection between the time-series dynamics of average IV and the number of listed firms.

We then investigate directly whether the number of listed firms is a proxy for macroeconomic variables that help explain the time-series of average IV. We show that a regression of average IV on lagged market risk, credit spread, the Chicago Fed production index, the NBER indicator for recessions, and the CRSP value-weighted return has an adjusted R-squared of 11% (13%) for equal-weighted (value-weighted) IV. Adding to that regression the number of listed firms increases the adjusted R-squared to 67% (53%) for equal-weighted (value-weighted) IV. It follows that the number of listed firms has considerable explanatory power in regressions attempting to understand the macroeconomic determinants of average IV. The relation between IV and the number of listed firms is not easily explained by the number of listed firms proxying for the state of the economy.

The change in the number of listed firms is the excess of new lists over delists, which we call *net new lists*.[3] As a result, the number of listed firms increases more when there are more new lists than delists. New listings are generally young firms. We would expect average IV to be higher when there are more listed firms during our sample period because there are more listed firms following a period of more net new lists and young firms have higher IV (e.g., Pastor and Veronesi, 2003). Therefore, the relation between average smoothed IV and the number of listed firms could be due to a composition effect: there are more young firms when the number of listed firms is higher.

We find strong evidence against the hypothesis that the relation between IV and the number of listed firms is due primarily to a composition effect. To start with, we find that when we split firms into young firms (those aged five years and less) and old firms (those aged more than five years), the smoothed average IV of both young and old firms has an inverted U shape. The same results hold if we change the threshold for old firms to ten years. A composition effect cannot explain that average IV has an inverted U shape for

[3] There is also a growing literature that examines why the number of listed firms changes and the implications of that change. Though Doidge, Karolyi, and Stulz (2017) focus directly on the number of listed firms, there is a large number of papers that examine the IPO rate over time and why the rate has been low most years since 2000 (see, for instance, Gao, Ritter, and Zhu, 2013, and the review of the IPO literature of Lowry, Michaely, and Volkova, 2017).

both young and old firms. To establish that the IV of old firms is higher when there are more listed firms, we investigate the determinants of firm-level IV during our sample period. If the relation between average IV and the number of listed firms is explained by a composition effect, the number of listed firms should not help explain firm-level IV when we account for firm characteristics as well as macroeconomic variables. We find that the number of listed firms is significantly related to firm-level IV both for young and old firms when we control for firm characteristics, including firm age and size, as well as macroeconomic variables.

Why would older firms have higher idiosyncratic volatility when there are more listed firms? Everything else equal, the number of listed firms increases as more new firms list. Small firms that innovate, which are generally young firms, do so differently from large firms. Small firms are more likely to have major inventions (Akcigit and Kerr, 2018) or radical inventions (Bena, Garlappi, and Grüning, 2016). Strikingly, the number of firms successful at radical innovation peaks in 2001 and evolves similarly to the total number of listed firms (Bena, Garlappi, and Grüning, 2016). These new firms bring with them innovations that threaten older firms. These innovations may or may not scale, which explains why the new firms have high IV. Yet, whether these innovations succeed or not also affects older firms which may have their markets disrupted by successful innovations. As a result, the future of older firms is more uncertain when there are more new firms. This mechanism should be stronger at the industry level than at the aggregate level. If there are many new firms that are spread across industries, the threat of creative destruction in an industry is weaker than if there is a wave of new firms within that industry. If the relation between IV and the number of listed firms is not spurious and is explained by creative destruction, we should find it at the industry level. We therefore investigate whether industry average IV is related to the past net new list rate (defined as net new lists divided by total listings) at the industry level. We find that the increase in industry average IV over a five-year period is related to the increase in listings over that period. We also show that the industry net new listing rate over the last five years predicts the industry's average IV. This evidence shows that the relation between average IV and the number of listed firms is the outcome of an industry-level relation between IV and the rate of arrival of new firms to public markets.

We use other variables that measure changes in listed firms and find similar results. Specifically, we use the *new listing rate*, defined as new listings over listings, the *gross new listing rate*, defined as the sum of new lists and delists over listings, and the *delisting rate*, defined as delists over listings. We find that average IV is related to these measures, but generally much more so for equal-weighted average IV than value-weighted average IV. Such a result does not seem surprising since value-weighted average IV for an industry will reflect the IV of the strongest and largest firms within an industry, which likely are the least affected by creative destruction (Bessen, Denk, Kim, and Righi, 2020).

With greater creative destruction, we would expect variation in firm outcomes to increase. If greater arrival of new firms to public markets corresponds to greater creative destruction, we should see the dispersion of outcomes within industries to be related to the arrival of new firms to public markets. We find that this is the case. As more new firms arrive to public markets within an industry, the within-industry standard deviation of operating income increases. The standard deviation of investment increases as well. Such greater dispersion is what one would expect with greater creative destruction. We would also expect that more past new lists would lead to more delists.

A possible alternative explanation for the relation between the inverted U shape of idiosyncratic volatility and the inverted U shape of the number of listed firms follows from Fama and French (2004). They show that the number of new lists increases in the 1980s and 1990s and that the new lists are increasingly weaker firms. As the market drops after its peak in 2000s, many of these firms delist. To the extent that new lists are weaker and are more adversely affected by the sharp drop in the tech markets of the early 2000s, we could have inverted U shapes for idiosyncratic volatility and the number of listed firms. To ensure that our results are not due to this phenomenon, we provide two pieces of evidence. First, we examine the relation between delists of old firms and past new listings. A positive relation between delists of old firms and past new listings would be expected with the creative destruction explanation that we advance but would not be expected if the decrease in listings is unrelated to creative destruction and caused by delists of weak firms recently listed. We find a strong positive relation between delists of old firms and past new listings. Second, we show that our industry findings hold if we exclude the years from 1998 to 2004 in our regressions. Our evidence supports the existence of a link between the number of listed firms and idiosyncratic volatility separate from the channel presented in Fama and French (2004).

In this study, we only have firm-level data for public firms. It could be that the relation we show between average IV and the number of listed firms is due to a relation between creative destruction and the number of firms in the economy rather than between creative destruction and public firms, so that the number of listed firms proxies for the number of firms in the economy. In this case, there would be nothing special about listings and creative destruction. Census data is available for the number of firms in the aggregate as well as across industries for different firm sizes with size measured by employment. We show that the information in the number of listings is different from the information in the total number of firms in the economy. To conduct this analysis, we need a size benchmark for firms that could potentially have a material impact on creative destruction. We use a 20-employee threshold and a 100-employee threshold to examine whether there is a relation between average IV and the number of firms in the economy at the aggregate level and at the industry level. We find that the extent of creative destruction among public firms is only closely related to the number of public firms during our sample period and not the total number of firms.

Our evidence raises an important question for future work, which is why there is a strong connection between new lists and creative destruction but not between private firm creation and creative destruction. Most private firms are not focused on the type of innovation that impacts an industry, but instead engage in local or industry niche filling. For instance, a new firm could consist of half a dozen restaurants in a town. Such a firm would likely not threaten the position of established firms. With this explanation, the firms that go public are those that are most likely to cause creative destruction. A plausible explanation for this is that more disruptive firms are more likely to exit through an IPO as buying a disruptor might be internally problematic for an established firm and funders of disruptive firms want eventually to cash out. As a result, the option of exit through an IPO is essential for disruptors, and there would be less creative disruption without that option.

The next section provides a summary of the related literature. Section 2 describes our data and how we measure IV. Section 3 shows that average IV and the number of public firms are tightly connected. Section 4 finds that the relation between average IV and the number of public firms is not explained by a composition effect due to the fact that there are more young firms when there are more public firms. Section 5 shows that aggregate and industry average IV are positively related to past aggregate and industry net new lists and documents the role of creative destruction in explaining the relation between IV and the number of listed firms. Section 6 shows that the number of listed firms does not simply proxy for the number of firms in the economy and that the number of public firms explains much more the dynamics of average IV than the number of firms in the economy at the aggregate level or at the industry level. Finally, Section 7 concludes.

1. Literature on the Determinants of Idiosyncratic Equity Volatility

Campbell, Lettau, Malkiel, and Xu (2001, hereafter CLMX) document that idiosyncratic equity volatility more than doubles for the average public U.S. firm from 1962 to 1997. Researchers show that the trend in idiosyncratic risk reverses by 2003 (Brandt, Brav, Graham, and Kumar, 2010). Campbell, Lettau, Malkiel, and Xu (2023) review the evolution of idiosyncratic equity risk and of the literature two decades after their earlier paper.

Since CLMX, much research attempts to explain the high IV during the latter part of the 1990s and the prior increase in IV. The leading explanations advanced in the literature are:

a. **Increase in competition**. This explanation advanced by Comin and Philippon (2005), Gaspar and Massa (2006), and Irvine and Pontiff (2009) predicts that idiosyncratic risk increases with competition.

b. **Schumpeterian creative destruction**. Comin and Philippon (2005) posit that an increase in R&D expenditures leads to Schumpeterian destruction, which creates higher idiosyncratic risk at the firm level. Comin and Mulani (2009) propose a formal model. Chun, Kim, Morck, and Yeung (2008) show that elevated heterogeneity in firm-specific stock returns is associated with industries that make more intense use of IT from 1971 to 2000. They argue that intensified creative destruction can help understand the rise in IV. Chun, Kim, and Morck (2011) hypothesize that the IT revolution can explain both the increase and the decrease in IV as IV should fall as that revolution eventually affects most firms. They find support for this view.

c. **Financial development**. Durnev, Li, Morck, and Yeung (2004) show that more financially developed countries have more heterogeneity in firm-specific stock returns. They advance the explanation that more private information is incorporated in stock prices when financial markets are more developed, so that average IV should increase with financial development. Brown and Kapadia (2007) attribute the increase in IV to the increased willingness of markets to welcome riskier IPOs, which they view as evidence of greater financial development.

d. **Institutional investors**. Bennett and Sias (2006), Malkiel and Xu (2003), and Bennett, Sias, and Starks (2003) attribute the increase in idiosyncratic risk to increased institutional ownership.

e. **Irrational exuberance**. Brandt, Brav, Graham, and Kumar (2010) attribute the high idiosyncratic risk of the late 1990s to "an episodic phenomenon, at least partially associated with retail investors" (p. 863).

f. **Firm age**. Pastor and Veronesi (2003) build a model where investors learn about a firm's long-run profitability over time through Bayesian updating. In such a model, young firms have greater stock return volatility. Fink, Fink, Grullon, and Weston (2010) argue that changes in the age of listed firms explain most of the increase in IV. Bekaert, Hodrick, and Zhang (2012) build on this idea by using a model where idiosyncratic volatility depends on the fraction of young firms among listed firms.

g. **Growth opportunities**. Cao, Simin, and Zhao (2008) posit that in the presence of growth options, shareholders have incentives to take the riskiest projects. Controlling for growth options, they conclude that there is no trend in IV.

h. **Profitability**. Wei and Zhang (2006) show that firm stock volatility is negatively related to return on equity (ROE). They find that the upward trend in average stock return volatility is fully accounted for by a downward trend in ROE and by an upward trend in the volatility of ROE.

i. **Macroeconomic factors**. Bekaert, Hodrick, and Zhang (2012) find that most of the time variation in IV can be accounted for by variation in growth opportunities, market volatility, and the variance premium, which they argue is a business cycle sensitive risk indicator. Fox, Fox, and Gilson (2016) find that average IV increases dramatically during crisis periods.

j. **Firm-specific human capital**. Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) isolate a common component to time-series variation in idiosyncratic risk. The common idiosyncratic volatility (CIV) they identify represents a priced risk factor and is related to cross-sectional household income risk which suggests a real macroeconomic consequence to firm-specific risk.

k. **Network effects**. Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2020) provide evidence that the common factor in the time-series variation of firm idiosyncratic risk is the dispersion of the economy-wide firm size distribution. They develop a model where firms belong to networks of suppliers and customers. Large firms have more diversified networks. When the dispersion of the size distribution increases, shocks are less diversified. They argue that an increase in dispersion can explain the run-up in mean firm volatility in the 1990s. They also conclude that "[t]he changing composition of the universe of public firms could in principle generate the positive comovement between firm size dispersion and firm volatility." (p. 4122). We therefore investigate whether our results can be explained by changes in firm size dispersion. We will show that firm size dispersion is related to average IV in regressions that control for the number of listed firms, but our results are not affected.

2. Data and Construction of Volatility Measures and Explanatory Variables

Most of our analyses use a sample that includes all publicly traded U.S. firms for the period January 1978 through December 2020. We use daily data on individual stock returns and market returns from CRSP as well as annual accounting data and firm characteristics from Compustat. Appendix A defines all the variables used in our analysis. For listing variables, we limit our sample to common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3). For measures of IV, we additionally exclude penny stocks with prices less than $1.00 (in January 1997 dollars). We include all industries unless noted otherwise. A recent study (Leippold and Svaton, 2023) argues that microstructure effects explain much of the IV trend highlighted by CMLX. Campbell, Lettau, Malkiel, and Xu (2023) argue that their approach is preferable to the approach recommended by Leippold and Svaton (2023). Moreover, our results hold if we drop the stocks with capitalization below the 20th percentile of NYSE stocks and if we restrict the sample to non-financial firms. The microstructure effects emphasized by Leippold and Svaton (2023) affect mainly the smallest firms, so our conclusions do not depend on these effects.

We use three methods for measuring firm-level IV and market risk. Our first method is based on standard market-model regressions to allow for monthly firm-specific measures of risk following the literature. Specifically, using daily data, we estimate (for each firm and calendar month or year in our sample) the following model:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is firm i's stock return (in excess of the risk-free rate) on day t, and $R_{M,t}$ is the return on the CRSP value-weighted market index (in excess of the risk-free rate) on day t. Our estimate of IV of firm i is the (annualized) standard deviation of the regression residual $\varepsilon_{i,t}$, and our estimate of market risk of firm i is β_i times the (annualized) standard deviation of $R_{M,t}$. We estimate the market model for all firm-months (or in some cases, firm-years) with at least 15 daily return observations available in CRSP and set a small number of observations with idiosyncratic risk less than 0.001 to missing (43 firm-month observations). Estimating this model for all stocks provides a panel of volatility estimates across firms and months (or years) as well as aggregated time-series of market and idiosyncratic risk by averaging the respective firm-level measures by month, year and/or industry, alternatively using equal- and value-weighting.

Our second method utilizes the approach of CLMX to create aggregated time-series for market risk and idiosyncratic risk for all firms. Daily data are used to construct monthly observations. Our third method uses daily observations for the five factors of the Fama French (2015) model (i.e., the excess return on the market, SMB, HML, RMW and CMA), which are available from the Ken French data library.[4] Similar to the estimation of the market model, we regress the daily excess stock return of each firm on the five factors in each calendar month and obtain firm-specific measures of idiosyncratic risk as the annualized standard deviation of the regression residuals.

For macroeconomic variables other than market risk (which we measure by averaging firm-level market risk from the market model or the standard deviation of the return on the CRSP value-weighted index, respectively), we use the credit spread (*Credit Spread*) defined as the difference between Moody's seasoned Baa corporate bond yield and the 10-year U.S. Treasury constant maturity rate, both provided by the Board of Governors of the Federal Reserve System. NBER business cycle dates are from the NBER website. The Chicago Fed National Activity Index (*Chicago Fed Index*) is sourced from the Federal Reserve Bank of Chicago website. The value-weighted stock market return is from CRSP (*CRSP VW Index Return*).

We construct inflation-adjusted market capitalization (*Real Market Capitalization*) by multiplying *market* capitalization from CRSP (constructed as the product of share price and the number of shares outstanding) with the ratio of the All-items Consumer Price Index (CPI) of the month to the CPI of the base period of January 1997 (from the U.S. Bureau of Labor Statistics). We follow Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2020) in computing the dispersion of real market capitalization (*Dispersion Real Market Cap*). The listing age of the firm is measured as the difference in years between the observation date and the date of the first price on CRSP (*Firm Age*). As a measure of illiquidity, we calculate the Amihud (2002) illiquidity measure (*Illiquidity Ratio)* for each firm and month in our sample by taking the average of daily absolute stock returns divided by dollar volume. Poor liquidity in some stocks could cause asynchronous price movements that would affect our regression estimates.

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[4] The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

We define monthly values for firm-level accounting variables of interest by using the most recent annual values, dropping observations for which Compustat data are unavailable. We calculate Tobin's q as the ratio of the market value of total assets (Total Assets – Book Value of Equity + Market Value of Equity) to the book value of Total Assets (*Tobin's Q*). We also scale Selling, General and Administrative Expenses (net of R&D Expenses) and Plant, Property & Equipment by Total Assets (*SG&A Expenses/Total Assets* and *PPE (net)/Total Assets*, respectively). Financial leverage (*Leverage*) is measured as the sum of total debt (long-term debt plus current liabilities) plus preferred stock divided by the market value of the firm's assets (calculated as the sum of market capitalization, preferred stock and total debt). We also calculate the ratio of capital expenditures to total assets (*Capital Expenditures / Total Assets*) and the ratio of research and development (R&D) expenses to total assets (*R&D Expenses / Total Assets*), setting missing values of capital expenditures and R&D expenses to zero. We use the natural logarithm of one plus the ratio of the sum of cash and short-term investments to total assets (*Cash and Short-term Investments / Total Assets*). Return on equity (*ROE*) is calculated as the ratio of net income to shareholders' equity.

We calculate the number of publicly listed firms as the total number of CRSP common stocks listed on NYSE, AMEX or NASDAQ at the end of a calendar month or year. We define young firms as firms with *Firm Age* of less than 5 years. Our sample starts in 1978 to avoid the addition of Nasdaq firms in 1973 causing a shift in the number of firms and the number of firms classified as young. The fraction of young firms in a month is the number of firms that have been listed for less than five years divided by the total number of listed firms. We create four variables capturing changes in the number of listed firms. Specifically, we scale the number of new lists by the end of prior period number of listed firms (*New Lists/Listings*). Similarly, *Delists/Listings* is the ratio of the number of delisted firms and the end of prior period number of listed firms. Finally, we calculate gross and net listing rates using, respectively, the sum and the difference of the number of newly listed firms and delisted firms (*Gross New Lists/Listings* and *Net New Lists/Listings*, respectively). We create these measures for the aggregate market and for each of the 48 Fama-French industries.

We focus on three proxies for the effect of creative destruction at the industry level. First, we calculate the cross-sectional standard deviation of Operating Income/Total assets. Second, we calculate the cross-sectional standard deviation of investment (defined as the sum of R&D Expense and Capital Expenditure) scaled by Total Assets. Third, we use the ratio of delists over listings. These measures are constructed using the universe of firms on Compustat (for accounting measures) by industry (using 48 Fama French industries).

3. Idiosyncratic Volatility over Time

In Figure 1, we use a longer time period than in the remainder of the paper. It starts in January 1963 and ends in December 2020. In Panel A, we plot our estimates of monthly equal-weighted average idiosyncratic equity volatility (IV) and market equity volatility. We see that both market equity volatility and idiosyncratic equity volatility have sharp spikes associated with crises or periods of economic stress. Four such spikes stand out. They occur in 1987, 2000, 2008, and 2020. These episodic volatility spikes obscure trends in the volatility measures. In Panel B, we show the results for the value-weighted IV and the value-weighted market equity volatility. The pattern is similar to the pattern in Panel A. Again, there are large spikes that obscure the long-term trends.

To uncover the long-term trends, we look at smoothed IV measures. In Panel C, we plot the five-year centered moving average of the monthly equal-weighted average IV. In the following, smoothed IV denotes the five-year centered moving average of IV (black line). As is immediately obvious, the equal-weighted average smoothed IV has an inverted U shape. It mostly increases until it reaches a peak in July-August 1999. We also plot the number of listed firms (blue line). As shown by Doidge et al. (2016), the number of listed firms has an inverted U shape as well. The number of listed firms peaks in May-June 1997. The two inverted U shapes are roughly similar, but the number of listed firms peaks shortly before the smoothed equal-weighted average IV. In Panel D, we show the value-weighted average IV and the number of listed firms. The value-weighted average IV also has an inverted U shape that peaks slightly after the number of listed firms. In the remainder of the paper, we examine this relation between average IV and the number of listed firms. Another way to put this is that we want to understand why IV is high when the number of listed firms is high. None of the papers discussed in Section 1 shows how the evolution of IV is like the evolution in the number of listed firms and explains why this is so.

We now turn to the sample period 1978 to 2020 that we use in the remainder of the paper. The reason we drop the period from 1963 to 1977 is that the number of firms increases at the end of 1972 because of the addition of Nasdaq to the data. As a result, a large number of firms with *Firm Age* of zero is introduced in the data, so we would have a large fraction of young firms due to the addition of Nasdaq. By starting the sample in 1978, we can distinguish between young and old firms, where young firms are less than five years on an exchange, without having that distinction affected by when Nasdaq was added to the CRSP data.

We now evaluate the existence of the U-shaped patterns statistically. In Panel A of Table 1, we estimate regressions of the monthly equal-weighted IV and value-weighted IV on indicator variables for five-year periods. The omitted five-year period is 1996-2000. With an inverted U shape for average IV, we would want the coefficients to be negative both before and after the omitted period and we would want the coefficients to increase in absolute value as they move farther in time from the omitted peak period of 1996-2000. In Panel A of Table 1, we show regressions for our three estimates of idiosyncratic equity volatility. The first column uses the market model. We see that average IV increases monotonically towards the omitted period from the beginning and from the end of the sample period, except for the last period. The second column shows the regression when average IV estimates are obtained from the CLMX model. The results are very similar. In the third column, we show results for the Fama-French 5-factor model (Fama and French, 2015). Once more, the results are similar. We then repeat the results for value-weighted average IV. The results are mostly similar, except that there is also a lack of monotonicity from the 1981-1985 period to the 1986-1990 period. In the last column, we show estimates of the same regression for the number of firms (in 1,000s). We again find a monotonic pattern.

As is apparent from Figure 1 and as the literature shows, IV is high in crisis periods. This means that IV is related to aggregate developments in financial markets and in the economy. We now investigate whether the relation between average IV and the number of listed firms shown in Figure 1 can be explained by controlling for macroeconomic variables. We include among our macroeconomic variables a measure of aggregate market risk as average IV is high when aggregate market risk is high (CLMX). We also use as controls the volatility of the CRSP value-weighted market index, an indicator for NBER recessions, the credit spread, the Chicago Fed National Activity Index (the index is high when the economy is doing well), and the return on the value-weighted CRSP index. We treat the dispersion of real market cap as a macroeconomic variable. We use monthly data. We only report the results using the market model to estimate IV as the results are similar for the other measures.

In Panel B of Table 1, we first report the results for our market model measure of equal-weighted average IV and our measure of value-weighted average IV when all variables are observed contemporaneously. The regression in the first column omits the number of firms. We find that the equal-weighted average IV increases with market risk and NBER recessions; it falls with the credit spread and the dispersion of real market cap. The adjusted R-squared is 23% (it is 14% without the dispersion of real market cap). In Column (2), we show estimates of the regression of Column (1) when we add the number of listed firms (in thousands). The number of listed firms has a significant positive coefficient. The adjusted R-squared increases from 23% in the first column to 75% (it is also 75% if we omit the market cap dispersion), indicating that the explanatory power of the number of listed firms is very large. The dispersion of real market cap, market risk, the credit spread, and the indicator for NBER recessions all have significant positive coefficients, while the coefficient on the Chicago Fed index is negative and significant. In the third and fourth columns, we re-estimate the regressions in the first two columns but using the value-weighted average IV. The results are similar except that the dispersion of real market cap does not have a significant coefficient in the regression that includes the number of firms. The adjusted R-squared without the number of listed firms is higher at 24%, and the adjusted R-squared with the number of listed firms is lower at 61%. There is still an extremely large increase in the adjusted R-squared. A concern is that the macroeconomic variables might be affected by the level of IV. One way to address this concern is to lag the macroeconomic variables.

We do so in the last 4 columns. We again find a strong relation between the level of average IV and the number of firms controlling for macroeconomic variables.

The relation shown in Figure 1, Panels C and D, is statistically significant and it holds using changes as well. To examine the statistical significance of the connection between the two inverted U shape patterns shown in Figure 1, we use annual data and regress smoothed average IV on the number of listed firms lagged three years (so that the measurement of the number of firms is not made inside the moving average window). This regression approximates the relation shown in Panel C of Figure 1 and we report the results in Panel C of Table 1. We first show estimates using the smoothed, equal-weighted IV average. We start with a regression in levels. We find a strong relation between smoothed IV and the lagged number of listed firms. The coefficient on the lagged number of listed firms is highly significant and the adjusted R-squared is 75%. Next, we re-estimate the regression but use percentage changes of smoothed average IV and percentage changes of the number of firms. The regression coefficient is positive and significant as expected. Not surprisingly, the adjusted R-squared is lower as it drops to 21%. We then turn to estimating the same regressions for smoothed, value-weighted average IV. We find similarly strong results for the level of average IV, but the positive coefficient is only significant at the 10% level for percentage changes of value-weighted average IV.

Our evidence in this section shows a strong relation between average IV and the number of listed firms. This relation is not explained by the changes in the dispersion of real market cap. We further show in Internet Appendix Table 1 that there is no relation between changes in average IV and lagged changes in the dispersion of real market cap dispersion. As shown in Internet Appendix Figure 1, while real market cap dispersion increases with average IV during the runup of average IV, it does not fall after the peak of average IV and hence does not capture the decrease in average IV.

4. Is It a Composition Effect Due to New Lists?

The number of listed firms at time *t* is the number of listed firms at an earlier time plus the sum of the net new lists from that earlier time to time *t*. For the number of listed firms to be high at *t* compared to time

$t-j$, the sum of the net new lists between $t-j$ and t has to be high. In contrast, if the number of listed firms at t is lower than at $t-j$, the sum of the net new lists has to be negative. For net new lists to be positive, new firms have to be listed in excess of listed firms dropping out of the exchanges. It follows that, everything else equal, the number of firms is high when there are more recently listed firms. As already discussed, young firms have higher idiosyncratic volatility. Recently listed firms have high IV because young firms have high IV. Hence, the result we find could simply be a composition effect. We show in this section that this is not the case.

We first show that smoothed average IV is related to past changes in the number of listings. In Panel A of Table 2, we show estimates of a regression of percentage changes in smoothed average IV on percentage changes in the number of listed firms using annual data and five lags. We report two sets of results for each regression. The first set of results uses five lags of percentage changes in the number of listed firms. With these results, the first two lags overlap with the equal-weighted average IV used to construct the five-year centered moving average. The second set of results eliminates this overlap and only uses the last three lags. With both sets of results, we find that the sum of the coefficients is significantly positive. We then do the same for the value-weighted average IV. In that case, we find the sum of the coefficients to be significantly positive when we use five lags but not when we use three lags.

In Panel B, we estimate changes in average IV over a five-year period over contemporaneous changes in listings measured over twelve-month periods. We use monthly data and use Newey West standard errors with 59 lags. We estimate these regressions for different measures of the change in listings (listing variables). The measures for the change in listings are scaled by the number of listings at the beginning of the twelve-month period. The first column uses net new lists/listings. One coefficient is significantly positive, none is significantly negative, and the sum of the coefficients is positive with a *p*-value of 1%. It follows that average IV increases when there are more new lists. In the next column, we use gross new lists/total listings. Gross new lists are defined as the sum of new lists and delists. It is a measure of churn among listed firms but not a proxy for the change in the number of public firms. We find that all coefficients except one are positive, but no coefficient is significantly different from zero. The sum of the coefficients is significantly positive. We then turn to new lists as our listing variable. We find that all coefficients but one are positive, one coefficient is significantly positive, and none is significantly negative. The sum of the coefficients is positive and significant with a *p*-value of 2%. Lastly, we use as our listing variable delists/listings. One coefficient is significantly positive and two are significantly negative. The sum of the coefficients is insignificantly different from zero. Results are similar when we use the value-weighted average IV except that the sum of the coefficients for gross new lists is not significantly different from zero.

It follows from Table 2 that long-period changes in average IV are related to contemporaneous changes in the number of listed firms. The number of listed firms increases with the number of new lists and falls with the number of delists. New lists are younger firms than the typical listed firm. As a result, there should be a relation between the number of listed firms and the average age of firms. Using listing age, we divide firms between young and old firms based on *Firm Age* so that young firms are listed for five years or less and old firms are listed for more than five years. In Panel A of Figure 2, we show that the number of young firms increases sharply over our sample period before peaking in December 1996. In contrast, the evolution of the number of old firms is much more subdued. In Panel B, we show that the ratio of the equal-weighted average IV of young firms over the equal-weighted average IV of old firms does not change much over time as it is typically greater than 1.2 and less than 1.4. In comparison, the ratio of the number of young firms to the number of old firms exhibits much variation. It peaks in October 1987 at 0.936, so that there are almost as many young firms as old firms at that time. The ratio then falls before reaching another peak in December 1996 at 0.880. The ratio has its lowest value in March 1978 at 0.144. Its lowest value after the peak in December 1996 is 0.182 in early 2013. It follows from this that the evolution of the fraction of young firms does not match the evolution of the smoothed equal-weighted average IV as smoothed average IV does not peak in 1987. Internet Appendix Figure 2 shows in Panels A and B that our conclusions are similar if we use ten years as the threshold for old firms. Note that when we use the ten-year threshold, our sample starts in 1983 so that we do not have a discontinuity in the number of old firms because of the addition of the Nasdaq data.

The fact that the ratio of the average IV of young firms to the average IV of old firms does not exhibit the same pattern as the ratio of young firms to old firms suggests that the volatility of young firms moves like the volatility of old firms. We verify this in Panel C of Figure 2. In that panel, we see that the smoothed equal-weighted average IV of young firms as well as the smoothed equal-weighted average IV of old firms exhibit the same inverted U-shaped pattern. Consequently, the U-shaped pattern cannot be due to a composition effect caused by the shifting age composition of listed firms. The results for value-weighted IV are shown in Panel D. We see there that the smoothed, average value-weighted IV for old firms exhibits much less variation than the smoothed, average value-weighted IV for young firms. These results hold as well when we define old firms as those that are more than ten years old as shown in Panel C of Internet Appendix Figure 2.

Figure 2 suggests that the number of listed firms should be helpful in explaining the IV of both young and old firms. However, Kahle and Stulz (2017) show that firm characteristics are quite different in the 2000s than they are at the beginning of our sample. As discussed in Section 2, it is well-known that firm characteristics are related to IV. Illiquid firms and small firms tend to have higher IV. So do highly levered firms. Firms with higher R&D have higher IV (Comin and Philippon, 2005, and Bartram, Brown, and Stulz, 2012). So do firms with higher cash holdings. Hence, it could be that the number of firms proxies for other firm characteristics than firm age, so that when we control for firm characteristics the number of firms may no longer be significant. We show that firm characteristics alone or firm characteristics together with macroeconomic variables cannot explain the relation between the number of firms and IV. Our regressions include all firms but those in the Fama-French 48 classification for utilities and financial firms because they include regulated firms. Our regressions include industry fixed effects.

Table 3 shows the results. We report results separately for young firms and old firms to show that the IV of both types of firms is related to the number of firms. We use annual data and lag the macroeconomic variables and firm characteristics by a year. We also use industry fixed effects using the 48 Fama and French industries. The standard errors are clustered by year and firm. Panel A presents the results for young firms and Panel B for old firms. The first column shows a regression of firm IV on macroeconomic variables. We find that a firm's IV is negatively related to the credit spread and positively related to market risk. We add the number of firms in the second column. We find that the number of firms has a positive coefficient that is highly significant. The coefficient on market risk loses significance and the coefficient on the credit spread switches signs. The adjusted R-squared increases from 7% to 16%. Turning next to firm characteristics, we show in the third column the coefficients for a regression of IV on firm characteristics. The coefficients on the characteristics are those generally found in the literature. IV increases with Tobin's Q, leverage, R&D, capital expenditures, and cash holdings. It falls with market capitalization, plant, property, and equipment, and ROE. We then add the number of firms in the fourth column. We find that firm IV increases with the number of firms when we control for a broad range of firm characteristics. In this regression, illiquidity becomes significantly negative. All other coefficients are of the same sign and significant as in the third column. The adjusted R-squared increases when we add the number of firms from 31% to 36%. In the fifth column, we have both macroeconomic variables and firm characteristics. We then add the number of firms in the sixth column. Again, the number of firms has a positive and significant coefficient and the adjusted R-squared increases from 33% to 38%.

We now turn to Panel B. In that panel, we estimate the same regressions for old firms. The coefficients on macroeconomic variables and on firm characteristics have mostly, but not always, the same sign and significance for old firms as for young firms. The coefficients on the number of firms are always positive and significant, but they are smaller than in the regressions for young firms. The increase in the adjusted R-squared is also smaller than for the regressions with young firms. Internet Appendix Table 2 shows that the results of Panel B hold when the threshold for old firms is ten years instead of five years.

It follows from this section that the relation between IV and the number of firms cannot be explained by a composition effect. Importantly, the IV of both old firms and new firms is higher when the number of firms is higher – even after controlling for firm age. Any explanation for this relation must therefore show why the IV of both new and old firms are higher when there are more listed firms.

5. Creative Destruction, New Lists, and Firm Volatility

We have now shown that the relation between the number of firms and average IV is not due to a composition effect and it holds in changes, so that it is unlikely to be explained by common trends. In this section, we investigate a simple explanation for the relation. This explanation is that creative destruction is greater when there are more new firms. Such an explanation has a strong foundation in the literature: new firms challenge existing ones with new technologies or business models. Hence, as there are more new firms, we expect more firms to be challenged. New firms may or may not succeed in their challenge, which makes their stock price more volatile. Older firms may repel the challenge or succumb to it. This means that the existence of challengers makes older firms more volatile. If our explanation is correct, it should apply at the industry level. A concern with industry-level results is that industries might evolve similarly during the period of peak IV, so that industry-level results might not be really different from the aggregate results. To address this concern, we estimate all the regressions using industry data omitting 1998-2003 and show the estimates in the internet appendix. All our results hold up if we omit the period from 1998 to 2003. We first show how industry average IV is related to the number of firms in an industry. We then turn to showing how creative destruction is related to the number of firms.

5.a. Industry IV and Industry Number of Firms

With the creative destruction hypothesis, we expect smoothed average IV to be related to the number of firms and to past new lists at the industry level. The dynamics of the number of listed firms differ across industries, so that a common explanation having to do with aggregate trends is unlikely to explain these dynamics. We use the Fama-French 48 industries as our industries but omit industries that include regulated firms (utilities, banking, insurance, real estate, etc.). As already mentioned, the issue with banking and utilities firms is that entrance in these industries is often regulated. We investigate first whether our earlier results hold at the industry level. In Panel A of Table 4, we use yearly data and estimate a regression of the percentage change in the industry-level smoothed average IV on the percentage change in the number of listed firms in the industry, using five lags. We use Driscoll-Kray (1998) standard errors with five lags. The results in the first column show that four of the five coefficients on lags are significant and positive. No coefficient is significantly negative. The sum of the coefficients is positive and significant at the 1% level. In the second column, we estimate the same regression but omit the first two lags since these lags overlap with IV values used to compute the smoothed average IV. We find similar results. In the third and fourth columns, we estimate the same regressions using smoothed value-weighted average IV. Though the sum of the coefficients is always positive, it is not significantly different from zero. The weaker results for value-weighted average IV are to be expected if the relation between net new lists and IV is due to creative destruction. A value-weighted index reflects the most highly valued firms, which are the ones that are most resistant to creative destruction (for example, by using their large size to acquire innovative new companies). As a result, we would expect the relation between net new lists and value-weighted IV at the industry level to be weak.

We then show how changes in the listing variables are related to contemporaneous changes in average IV at the industry level as we did in Panel B of Table 2 for aggregate IV. We use monthly data. We again use five lags, with each corresponding to a twelve-month sum of the listing variables. Standard errors are Driscoll-Kraay (1998) with 59 lags. The results are reported in Panel B of Table 4. As for the aggregate, we find a strong relation between net new lists and the change in average IV using the Fama-French industries (excluding utilities and financials). We also find a significant relation both for gross new lists and new lists, but not for delists. The relation between listing variables and average IV is weaker when we use value-weighted industry portfolios, but it is significant for net new lists and for new lists.

In Panel C of Table 4, we investigate whether listing changes can help predict future average IV at the industry level. We use monthly data and regress the one-year moving average IV on lagged twelve-month sums of our listing variables. We use Driscoll and Kray standard errors with 11 lags. In these regressions, we see that future industry average IV is positively related to all the listing variables for equal-weighted average IV and for value-weighted average IV. While gross new listings and delists do not explain contemporaneous changes in IV in Panel B of Table 4, they predict higher future average IV. Lastly, we estimate the regressions of Panel C for old firms. We show the results in Panel D of Table 4. We find that the listing variables predict future IV for old firms. As shown in Internet Appendix Table 3, similar results hold if we require old firms to be more than ten years old. These results are consistent with the creative destruction explanation for the relation between listings and average IV.

It follows from this analysis that changes in industry equal-weighted average IV are strongly related to changes in the number of firms in the industry. Industry average IV increases more when there are more recent new lists. Similarly, a greater arrival of new lists predicts higher future volatility. This latter result holds for the sample as a whole as well as for old firms. Consequently, old firms' IV in an industry is affected by the arrival of new firms in the industry. This is the case using value-weighted IV as well, but some results are weaker or not significant when we use value-weighted IV, which is to be expected as value-weighted IV puts the most weight on the most valuable firms. We now turn to show that indicia of creative destruction are higher following greater arrival of new firms.

5.b. Creative Destruction and New Lists

Creative destruction means that new firms entering an industry cause existing firms to either compete and adapt, or lose. We therefore expect more cross-sectional variability in performance and investment within an industry if there is more creative destruction. For our reasoning to be correct, we must show that there is a relation between average IV and our indicia of creative destruction. These indicia are measures of cross-sectional variability of operating income to assets and investment to assets. We use annual data at the industry level and regress the average industry IV on industry indicia of creative destruction and industry fixed effects. Table 5 shows that there is a strong relation between our indicia of creative destruction and average IV at the industry level. We find in all cases a positive significant coefficient, so that more creative destruction is accompanied by higher IV. This result holds for both equal-weighted IV and value-weighted IV.

We now turn to regressions that regress the five-year percentage change in the indicia of creative destruction in year t on five lags of our listing variables. We show the results in Table 6. We use annual data and industry fixed effects. We show results for the whole sample first and then for old firms. Starting with the whole sample, we first report the regression for the standard deviation of operating income to assets. We find that the percentage change in the standard deviation is positively related to lags of net new lists. We then find a similar result for the standard deviation of investment to total assets. Up to now, we have used the whole sample in Table 6. However, one might be concerned that there is a mechanical element in our results. The argument would be that new firms are different and so adding more new firms to the industry mix would increase the cross-sectional variation within an industry. To avoid this possible mechanical relation, we show results only for old firms. If we estimate regressions using our indicia of creative destruction on lags of the net new list rate, the new firms are not included in the estimate of the indicia of creative destruction for old firms. We find that the percentage change in the standard deviation of operating income over assets for old firms over five years is positively related to the net new list annual rates over those five years. We then find the same results for the standard deviation of investment to total assets for old firms. In Internet Appendix Table 4, we show results for old firms when we require old firms to be more than ten years old. The results are similar.

Another approach to show that the greater arrival of new firms leads to more creative destruction is to examine whether more firms are delisted following the arrival of more new firms. We show in Table 7 regressions of the sum of delists over months t to t+11 scaled by the number of listed firms in month t–1 regressed on the twelve-month sums of new lists for the last five years using the whole sample first. We use industry fixed effects. We find a strong positive relation between new lists and future delists since the sum of the coefficients on the listing variables is positive and significant. However, this evolution might reflect the arrival of weak new lists that die quickly (Fama and French, 2004). We therefore repeat our estimation focusing on old firms instead (second column). Now, the dependent variable is the sum of delists of old firms for months t to t+11 scaled by the number of listed old firms in month t–1. We again find a strong relation. In Internet Appendix Table 5, we estimate the relation for old firms requiring old firms to be more than ten years old. We find similar results.

In this section, we have shown that average IV is positively related to lagged new listings at the industry level. We explain this by the fact that new listings result in creative destruction. We show that indicia of creative destruction at the industry level are positively related to the arrival of new firms in the industry.

6. Is There Something Special about New Public Firms?

So far in this paper, we have focused on the number of listed firms and changes in the number of listed firms. Therefore, we cannot tell whether creative destruction results from the arrival of new firms listed on the stock market or from the creation of new firms in general. Suppose that a constant fraction of new firms created eventually goes public. With our regressions, the listing rate could proxy for the aggregate rate of firm creation at an earlier time. In this case, our results would not be about listed firms but about aggregate firm creation. Whether a firm is listed or not would not affect creative destruction. We therefore investigate whether the aggregate rate of firm creation has information for average IV that the rate of new lists does not have and whether it affects the creative destruction proxies for public firms.

We use data from the U.S. Census Bureau's Statistics of U.S. Businesses (SUSB) to measure the number of firms in the economy.[5] With these data, we can only compute the net change in the number of firms and cannot compute separately the number of firms created and the number of firms that died. Most non-public firms have few employees, so that it would not make sense for them to be listed and it would be improbable that they would have a creative destruction impact. It is not clear, however, what the size threshold should be for our analysis. We conduct our analysis with two different thresholds: 20 and 100 employees. Panel A of Figure 3 plots the number of Census firms using the 20-employees threshold and the equal-weighted average IV. We see that the number of Census firms evolves very differently from the number of listed firms. There is no inverted U shape. The number of Census firms at the end of our sample period is substantially larger than the number of Census firms at the beginning of our sample period. Panel B of Figure 3 uses the 100-employees threshold and shows similar results.

[5] For additional details of this data set see https://www.census.gov/programs-surveys/susb.html.

To examine whether there is a relation between average IV and the number of Census firms, we estimate separate regressions with levels and percentage changes of smoothed average IV (using a five-year moving average) and the aggregate number of firms like we did in Panel C of Tables 1 and Panel A of Table 2 for listed firms. These regressions use annual data; the standard errors are Newey-West with five lags. We use alternatively the 20-employees threshold and the 100-employees threshold.

Panel A of Table 8 replicates the regressions of Panel C of Table 1 with Census variables. The dependent variable is the five-year smoothed average IV. In the first five Columns, we use the equal-weighted average. We show the results for regressions with dependent and independent variables in levels (percent changes) in the top (bottom) panel. We start with a discussion of the results for levels. In Column (1), we use the level of the number of listed firms at lag 3. We find a significant positive coefficient and an adjusted R-squared of 75%. In Column (2), we use the level of the number of Census firms at lag 3 using the 20-employees threshold. The coefficient is statistically insignificant and the regression has no explanatory power. Results in Column (3) for Census firms with at least 100 employees are similar. Lastly, in Columns (4) and (5) we include the number of public firms and the number of Census firms. Both the number of public and Census firms are significant, but the increase in the adjusted R-squared of Column (1) from adding the number of Census firms is trivially small. It follows that there is no evidence of a relation between average IV and the number of Census firms in regressions that use only the number of Census firms. While the number of Census firms is significant in regressions that also include the number of listed firms, its explanatory power is minimal. In the next five columns, we re-estimate the regressions using the smoothed value-weighted IV as the dependent variable. The results are similar, except that the number of Census firms is less significant compared to the regressions with equal-weighted IV when including both listed firms and Census firms. Turning to the percentage change results, we find that the number of listed firms is positive and significant for regressions with both equal- and value-weighted IV, while the number of Census firms is never significant. It follows from this evidence that there is no relation between the change in average IV and the change in the number of Census firms at the three-year lag.

While there is a close relation between changes in smoothed average IV and the increase in listings at the three-year lag, there is no reason for the same lag to be important for the increase in the number of Census firms. We estimate regressions with more lags in Panel B of Table 8 like we did in Panel A of Table 2, but now we also add lagged percentage changes in the number of Census firms. When using equal-weighted IV and the 20-employees threshold for Census firms, we find that the sum of the lags is significant whether we use five lags or three lags. However, the adjusted R-squared is more than twice as high for the regressions using listed firms. The results are much weaker when we use the 100-employees threshold. In that case, the sum of the lags is significant for five lags but not three. When we include both lags for listings and lags for Census firms, we find that the sum of the coefficients is significant for Census firms for five lags when the threshold is 20 employees and when it is 100 employees, while it is never significant when we use only three lags. In contrast, the sum of the coefficients for listed firms is always significant. Results using value-weighted IV are generally similar but weaker, with the number of Census firms never significant.

We now repeat the regressions of Panel A of Table 4 using Census data at the industry level in Panel C of Table 8. We only show the results for equal-weighted IV. As discussed earlier, we do not expect significance at the industry-level for value-weighted IV regressions. The Census makes data available at the 4-digit NAICS industry level. We map NAICS-4 industries to the SIC-4 industries most common among firms with the same non-missing NAICS-4 code. If we cannot find a mapping for NAICS-4, we alternatively use mappings based on the most common SIC-4 code for 3-digit, 2-digit, or 1-digit NAICS codes, respectively. Subsequently, we map 4-digit SIC codes into the 48 Fama-French industries used earlier. We reproduce the results for the listed firms from Panel A of Table 4. The dependent variable in our regressions is the percentage change in the five-year moving average of IV centered at t. We use yearly observations. We show results for five yearly lags and three yearly lags in turn. We estimate our regressions for the 20-employees threshold and for the 100-employees threshold.

For equal-weighted IV in the top panel, Columns (1) and (2) repeat the results for listed firms from Panel A of Table 2. Columns (3) and (4) report results for five and three lags for Census firms using the

20-employees threshold. We find that the sum of the coefficients is positive and significant for the five lags regression but not the three lags regression. The adjusted R-squared is much higher for the regressions using listed firms again. Further, the standard deviation of the percentage change in listings is approximately three times the standard deviation of the percentage change in the number of Census firms. As a result, the economic significance of the regression coefficient for a one-standard deviation increase in the percentage change in the number of listed firms on smoothed average IV is approximately 25% larger than the economic significance of the regression coefficient for the percentage change in the number of Census firms.

In Columns (5) and (6), we estimate the same results for the 100-employees threshold and find similar results. In Column (7), we show results for five lags where we include both listed firms and Census firms and the threshold is 20 employees. In that case, the sum of the coefficients is significant for listed firms but not for Census firms. When we use the 100-employees threshold in Column (8), we find the same. Lastly, when we estimate regressions with three lags in Columns (9) and (10), coefficients are again only significant for listed firms while not for Census firms. In summary, when we use both listed firms and Census firms, the coefficient on listed firms is significant but the coefficient on Census firms is not.

We next investigate whether the measures of creative destruction for listed firms are related to past changes in the number of Census firms. In Table 9, we regress our measures of creative destruction on the percentage change in the number of listed firms and of Census firms using the 20-employee threshold and the 100-employee threshold for Census firms. There is a significant relation between the change in the number of listed firms and the change in the measures of creative destruction for both measures of creative destruction irrespective of the threshold for Census firms. The only regression with a significant relation for Census firms is with the standard deviation of investment to total assets for the 20-employees threshold, but the sum of the coefficients for Census firms in that regression is negative.

Overall, the results in this section show that the relation between the percentage change in IV and the percentage change in the number of listed firms holds up when we add the percentage change in the number of Census firms to the regression. While the percentage change in the number of Census firms is significant in some regressions, the results are not consistent and generally the explanatory power of the percentage change in the number of Census firms is low compared to the explanatory power of the percentage in the number of listed firms. We also fail to find a reliable relation between the number of Census firms and our measures of creative destruction. Together these results suggest that the number of listed firms, as opposed to total firms, plays an important role in how creative destruction affects IV.

7. Conclusion

In this paper, we document that there is a close connection between the number of public firms and idiosyncratic volatility. We show that this relation is not spurious. It is not due to young firms or to the period around the internet bubble. We then proceed to explain this relation. We argue that when more firms enter the markets, there is more creative destruction. With more creative destruction, the value of incumbent firms is more uncertain, so that their idiosyncratic volatility is higher. This is the case for older firms since these older firms might be challenged by the firms that enter the markets. We find that this is the case at the industry level. Further, at the industry level, greater past growth in listed firms implies greater cross-sectional variation in operating performance and investment. Again, we find that this result holds when we consider only older firms. Lastly, we find that with more creative destructions, old firms are more likely to delist.

Our evidence shows a strong connection between changes in the number of public firms and creative destruction, but we fail to find evidence of a strong connection between changes in the number of Census firms and creative destruction. With the data available to us, we must leave a full explanation of the role of public markets for creative destruction to future work. However, our study provides useful indications about the importance of the availability of the IPO exit for private firms for creative destruction. The peak number of public firms during our sample period is approximately 7,500. The peak number of Census firms with more than 20 employees is approximately ten times more, or 740,000. The peak number of Census firms with more than 100 employees is approximately 190,000. The firms that are public are therefore a tiny fraction of the Census firms. They are not selected randomly. Most private firms are unlikely to threaten public firm incumbents. Rather, these firms fill in geographic or industry niches. For instance, a new drycleaning operation with 30 employees and several stores might be created. It would have no measurable impact on established public firms. To explain our evidence, it must be that the firms going public have a much higher likelihood of generating creative destruction than the firms that stay private. This result raises two questions about the role of public firms. First, why is it that firms that are more likely to contribute to creative destruction choose to go public? Second, do these firms contribute more to creative destruction because they go public?

Existing literature suggests that the firms that contribute more to creative destruction are likely to be venture funded. It is also the case that venture-funded firms seek an exit that enables their funders to cash out. Startups that contribute more to creative destruction may be more likely to exit through an IPO to maximize the value of their business model since incumbents may not want to acquire a firm that could be internally disruptive. With this view, there is a close connection between the ability of firms to exit through an IPO and creative destruction, and it provides further support to Black and Gilson (1998) who argue that a healthy public market is key for a healthy venture industry. Absent the availability of an IPO exit, we would see fewer startups that contribute much to creative destruction.

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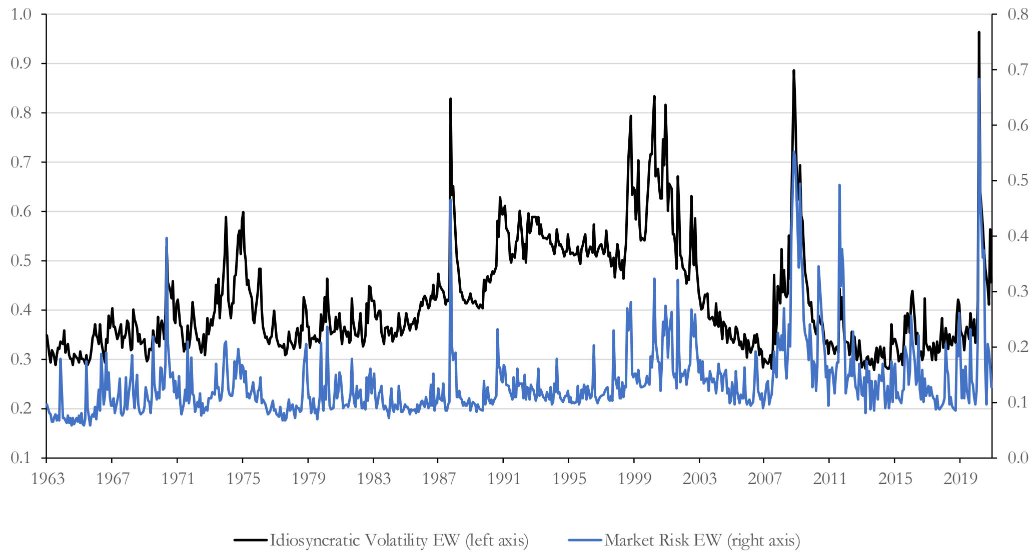
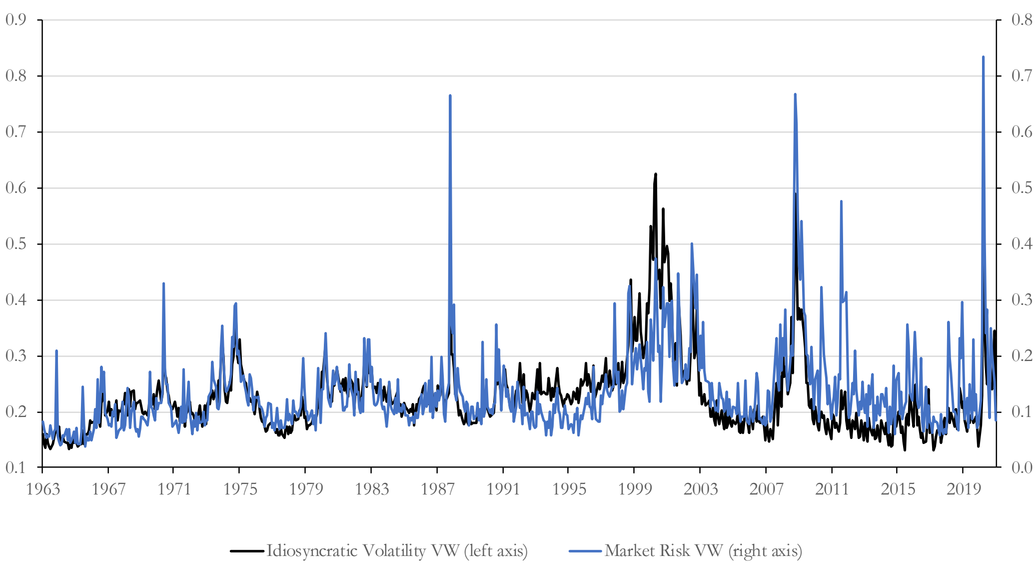
Figure 1: Idiosyncratic Volatility and Listings over Time

The figure shows monthly aggregate average idiosyncratic volatility (IV) for U.S. firms over time. In particular, Panels A and B show monthly equal- and value-weighted averages, while Panels C and D show centralized, 5-year moving averages of equal- and value-weighted IV, respectively. Panels A and B also show monthly equal- and value-weighted averages of market risk from the market model, while Panels C and D also show the number of listed firms. IV is estimated using the market model for each month using daily returns. Average IV is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). The number of listed firms is the number of common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar month. The sample period is 1963 to 2020.

Panel A: Equal-weighted Idiosyncratic Volatility and Market Risk



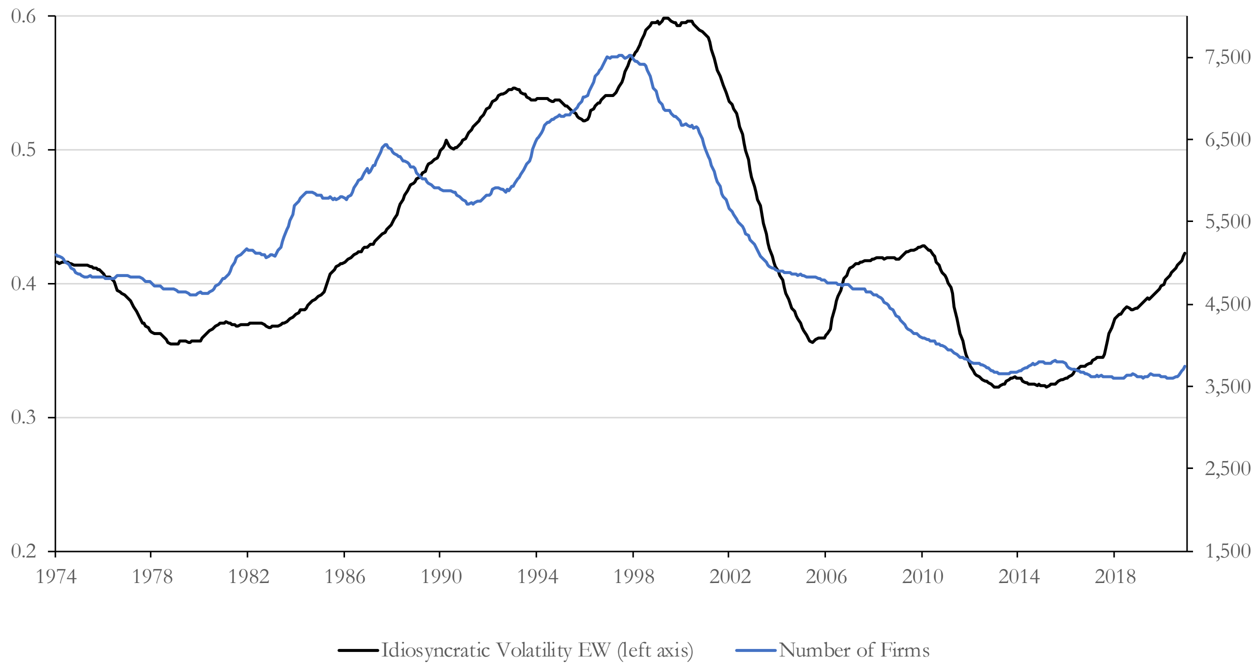
Panel B: Value-weighted Idiosyncratic Volatility and Market Risk



(continued)

Figure 1: Idiosyncratic Volatility and Listings over Time (continued)

Panel C: Smoothed Equal-weighted Idiosyncratic Volatility and Number of Listed Firms



Panel D: Smoothed Value-weighted Idiosyncratic Volatility and Number of Listed Firms

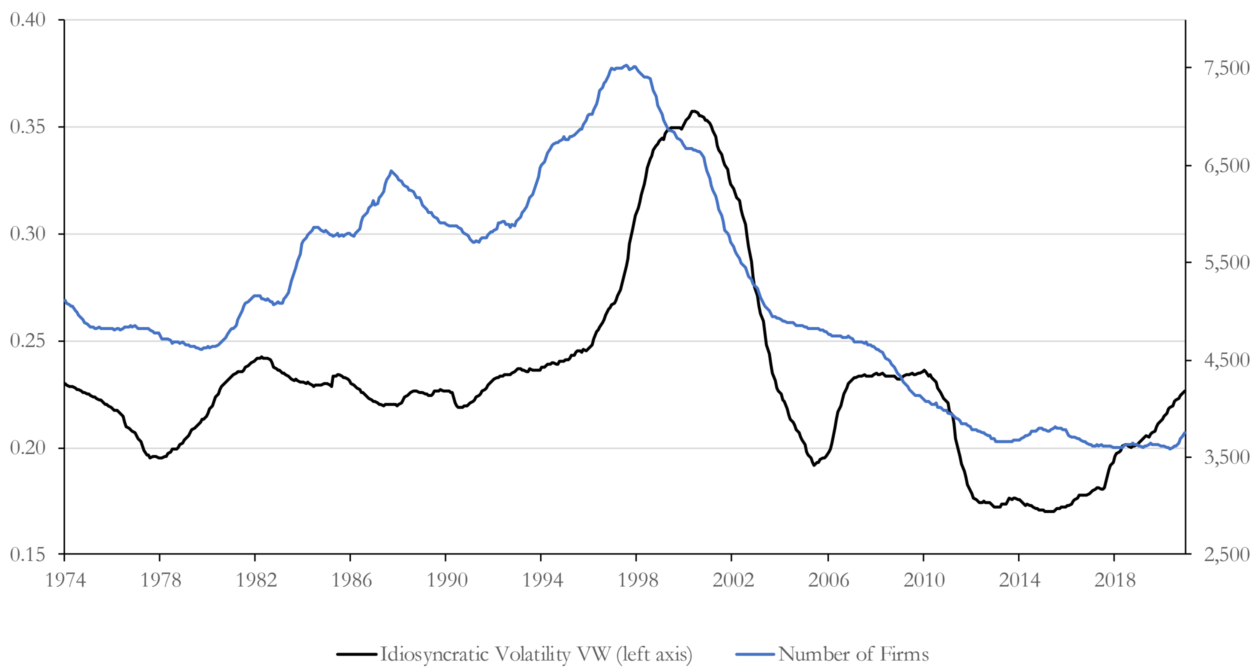
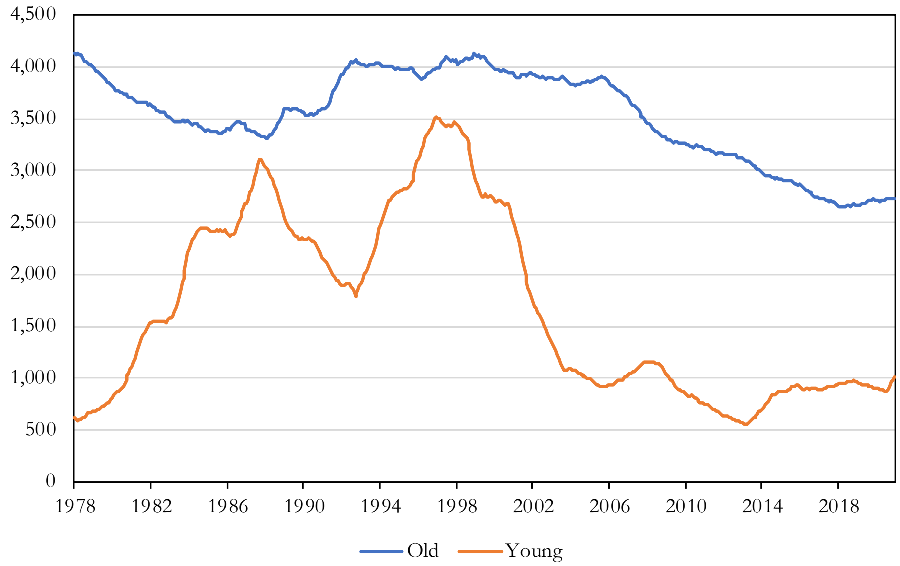


Figure 2: Number, Fraction, and IV of Young Firms vs. Old Firms

The figure shows centralized, 5-year moving averages of monthly idiosyncratic volatility (IV) as well as the fraction and number of young and old firms over time. In particular, Panel A shows the number of listed firms separately for young firms and old firms. Panel B shows the ratio of the number of young and old firms and the ratio of the equal-weighted IV of young and old firms. Panel C shows the average equal-weighted IV of young and old firms. Panel D shows the average value-weighted IV of young and old firms. IV is estimated using the market model for each month using daily returns. IV is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). The number of firms is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar month. Young firms are firms with age of less or equal to 5 years; old firms are firms with age greater than 5 years. The sample period is 1978 to 2020.

Panel A: Number of Firms



Panel B: Ratio of Number and EW IV of Young and Old Firms

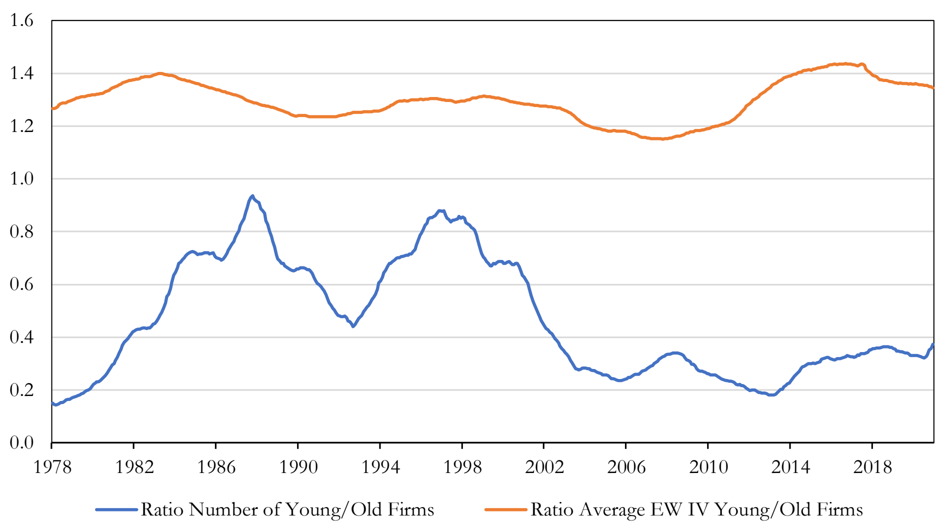


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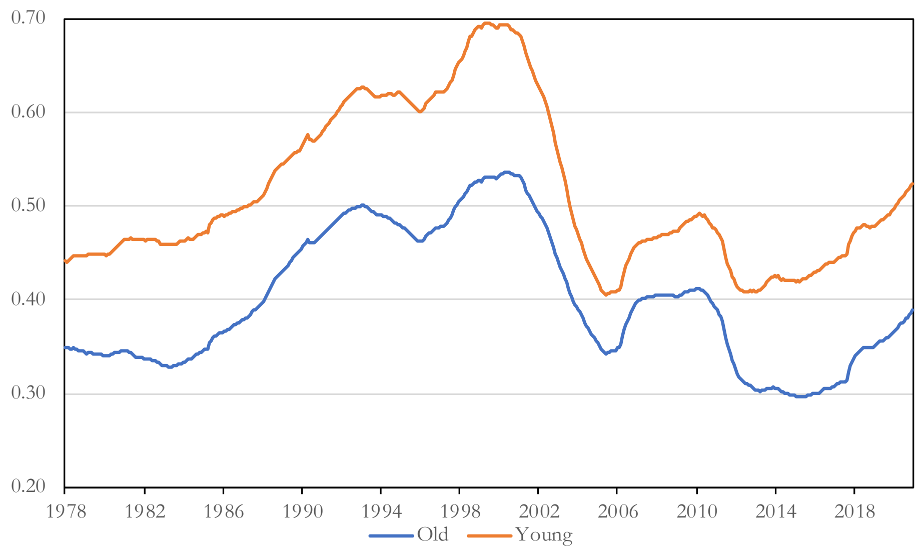
Figure 2: Number, Fraction, and IV of Young Firms vs. Old Firms (continued)

Panel C: Equal-weighted Idiosyncratic Volatility



Panel D: Value-weighted Idiosyncratic Volatility

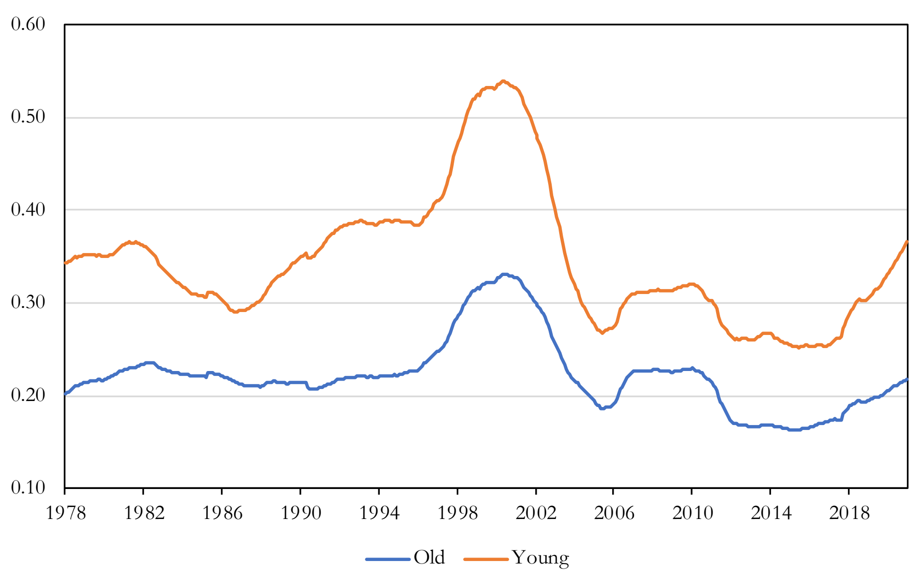
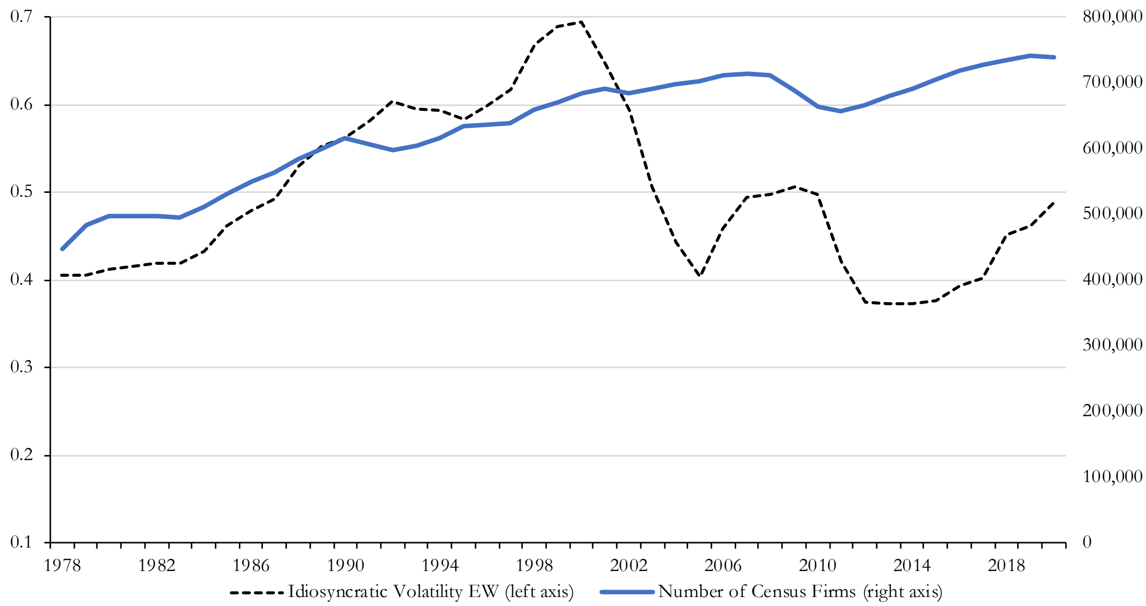


Figure 3: Idiosyncratic Volatility and Number of Census Firms over Time

The figure shows annual idiosyncratic volatility (IV) of listed firms and the number of Census firms over time. IV is estimated using the market model for each calendar year using daily returns. The figure shows the centered, 5-year moving average of equal-weighted IV. It also shows the annual number of Census firms with at least 20 (Panel A) and 100 (Panel B) employees reported by the U.S. Census, respectively. IV is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). The sample period is 1978 to 2020.

Panel A: Census Firms with at least 20 Employees



Panel B: Census Firms with at least 100 Employees

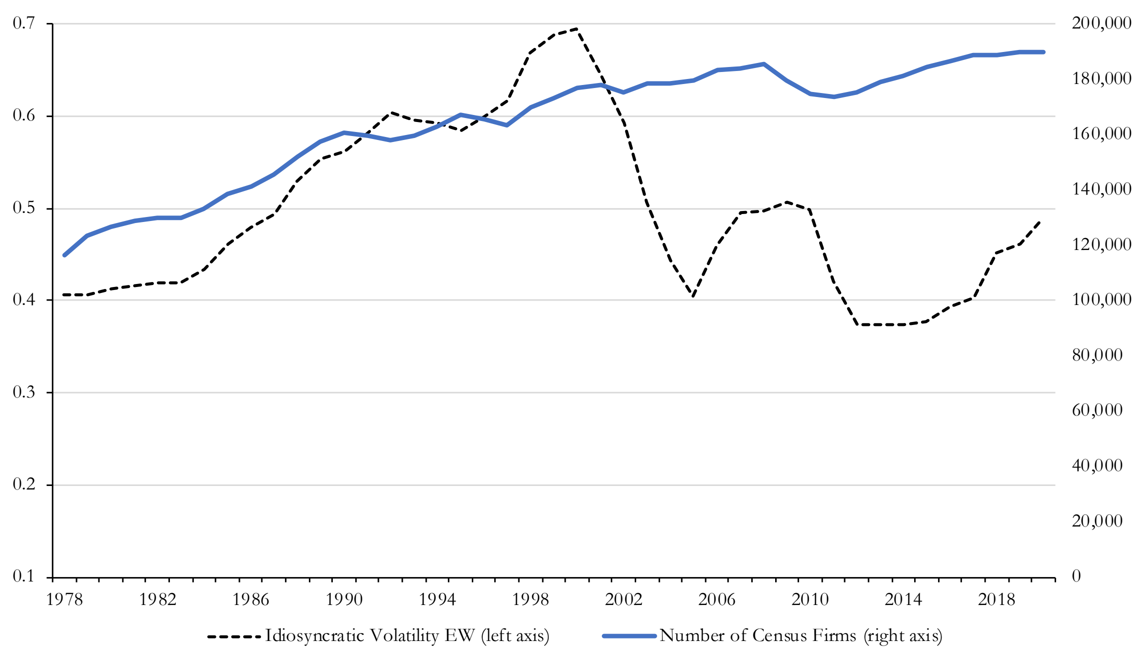


Table 1: Time-Series Regressions of Idiosyncratic Volatility and Number of Firms

The table shows results from time-series regressions with equal- and value-weighted idiosyncratic volatility (IV) and the number of listed firms. In particular, Panel A is based on regressions of alternatively monthly average IV and the number of listed firms on indicator variables for 5-year periods, with 1996-2000 as the omitted period captured by the regression intercept. IV is measured using three methods: the market model, the CLMX model, or the Fama-French 5-Factor Model. IV is estimated for each month using daily returns. In Panel B, the monthly equal- or value-weighted average of the natural logarithm of IV is regressed on the number of listed firms, (the natural logarithms of) dispersion in real market capitalization, and a range of macro variables, namely the equal- or value-weighted average of the natural logarithm of market risk from the market model, the credit spread, an indicator variable for NBER recessions, the Chicago Fed Index, and the CRSP value-weighted return. IV and market risk are estimated using the market model for each month using daily returns. Regressors are alternatively contemporaneous or lagged. In Panel C, the annual levels or percentage changes in equal- and value-weighted centralized, 5-year moving averages of IV are regressed on the levels and percentage changes of the number of firms lagged by 3 years with standard errors based on Newey-West (1987) with 5 lags. IV is estimated using the market model for each calendar year using daily returns. The table reports regression coefficients and associated *p*-values, the regression (adjusted) R-Squared, and the number of observations. IV is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). The number of listed firms (in 1,000s) is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar month or year. The dispersion in real market capitalization is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) at of the end of the calendar year. The sample period is 1978 to 2020.

Panel A: 5-year Indicator Variables

	Equal-weighted Idiosyncratic Volatility						Value-weighted Idiosyncratic Volatility							
	Market Model		CLMX Model		Fama-French 5-Factor Model		Market Model		CLMX Model		Fama-French 5-Factor Model		Number of Firms	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Years 2016-2020	-0.205	[0.00]	-0.235	[0.00]	-0.195	[0.00]	-0.130	[0.00]	-0.132	[0.00]	-0.120	[0.00]	-3.477	[0.00]
Years 2011-2015	-0.262	[0.00]	-0.290	[0.00]	-0.235	[0.00]	-0.158	[0.00]	-0.149	[0.00]	-0.134	[0.00]	-3.348	[0.00]
Years 2006-2010	-0.166	[0.00]	-0.176	[0.00]	-0.153	[0.00]	-0.098	[0.00]	-0.092	[0.00]	-0.087	[0.00]	-2.680	[0.00]
Years 2001-2005	-0.148	[0.00]	-0.160	[0.00]	-0.133	[0.00]	-0.088	[0.00]	-0.091	[0.00]	-0.076	[0.00]	-1.870	[0.00]
Years 1991-1995	-0.046	[0.00]	-0.068	[0.00]	-0.035	[0.00]	-0.096	[0.00]	-0.090	[0.00]	-0.077	[0.00]	-0.847	[0.00]
Years 1986-1990	-0.123	[0.00]	-0.143	[0.00]	-0.107	[0.00]	-0.107	[0.00]	-0.093	[0.00]	-0.088	[0.00]	-1.054	[0.00]
Years 1981-1985	-0.217	[0.00]	-0.241	[0.00]	-0.190	[0.00]	-0.100	[0.00]	-0.087	[0.00]	-0.082	[0.00]	-1.704	[0.00]
Years 1978-1980	-0.223	[0.00]	-0.253	[0.00]	-0.197	[0.00]	-0.120	[0.00]	-0.107	[0.00]	-0.099	[0.00]	-2.440	[0.00]
Intercept	0.587	[0.00]	0.639	[0.00]	0.512	[0.00]	0.332	[0.00]	0.317	[0.00]	0.279	[0.00]	7.114	[0.00]
R^2	0.50		0.46		0.57		0.31		0.32		0.37		0.93	
Observations	516		516		516		516		516		516		516	

(continued)

Table 1: Time-Series Regressions of Idiosyncratic Volatility and Number of Firms (continued)

Panel B: Macroeconomic Variables

	Contemporaneous Regressors								Lagged Regressors							
	Equal-weighted IV				Value-weighted IV				Equal-weighted IV				Value-weighted IV			
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Number of Firms (1,000s)			0.189	[0.00]			0.178	[0.00]			0.190	[0.00]			0.179	[0.00]
Dispersion Real Market Cap (log)	-0.116	[0.00]	0.021	[0.03]	-0.112	[0.00]	0.016	[0.20]	-0.088	[0.00]	0.049	[0.00]	-0.077	[0.00]	0.052	[0.00]
Market Risk (log)	0.305	[0.00]	0.236	[0.00]	0.243	[0.00]	0.178	[0.00]	0.212	[0.00]	0.143	[0.00]	0.128	[0.00]	0.063	[0.02]
Credit Spread	-0.042	[0.02]	0.038	[0.00]	0.009	[0.65]	0.084	[0.00]	-0.042	[0.03]	0.038	[0.00]	0.014	[0.50]	0.090	[0.00]
NBER Recessions	0.110	[0.00]	0.147	[0.00]	0.167	[0.00]	0.202	[0.00]	0.135	[0.00]	0.172	[0.00]	0.194	[0.00]	0.228	[0.00]
Chicago Fed Index	-0.005	[0.59]	-0.010	[0.09]	-0.005	[0.68]	-0.009	[0.28]	-0.005	[0.63]	-0.010	[0.15]	0.003	[0.77]	-0.001	[0.93]
CRSP VW-Return	0.370	[0.12]	0.191	[0.16]	-0.092	[0.72]	-0.261	[0.16]	-0.247	[0.32]	-0.428	[0.01]	-0.673	[0.01]	-0.844	[0.00]
Intercept	0.791	[0.00]	-1.752	[0.00]	-0.063	[0.76]	-2.453	[0.00]	0.312	[0.12]	-2.238	[0.00]	-0.670	[0.00]	-3.074	[0.00]
Adjusted R^2	0.23		0.75		0.24		0.61		0.16		0.68		0.16		0.54	
Observations	516		516		516		516		515		515		515		515	

Panel C: Moving Averages

	Equal-weighted IV				Value-weighted IV			
	5-year Central Moving Average		Percent Change of 5-year Central Moving		5-year Central Moving		Percent Change of 5-year Central Moving Average	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Number of Firms (1,000s, lagged 3yr)	0.070	[0.00]			0.037	[0.00]		
Percent Change Number of Firms (lagged 3yr)			0.624	[0.01]			0.637	[0.10]
Intercept	0.130	[0.02]	0.010	[0.31]	0.070	[0.13]	0.006	[0.65]
R^2	0.75		0.21		0.62		0.13	
Observations	40		39		40		39	

Table 2: Time-Series Regressions with Multiple Lags and Listing Variables

The table shows results from time-series regressions of equal- and value-weighted idiosyncratic volatility (IV) on alternative listing variables. Panel A regresses the percentage change in the centered, 5-year moving average of annual equal- or value-weighted IV on the percentage change in the number of listed firms for lags of 1 to 5 years. IV is estimated using the market model for each calendar year using daily returns. Standard errors are based on Newey West (1987) with 5 lags. In Panel B, the change from month *t*–60 to month *t* in the monthly equal- or value-weighted average IV is regressed on listing rates over prior 12-month periods based on net new lists (the difference of new listings and delists), gross new lists (the sum of new listings and delists), new lists, or delists. IV is estimated using the market model for each month using daily returns. Standard errors are based on Newey West (1987) with 59 lags. The table reports regression coefficients and associated *p*-values, the regression R-Squared, and the number of observations. It also reports the sum of the coefficients of the listing variables, and a test of it being equal to zero. IV is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). The number of firms, net new lists, gross new lists, new lists, and delists is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar month or year. The sample period is 1978 to 2020.

Panel A: Number of Listed Firms

	Percentage Change in 5-year Central Moving Average							
	Equal-weighted IV				Value-weighted IV			
	(1)		(2)		(1)		(2)	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Percent Change Number of Firms (lag 1)	0.076	[0.56]			-0.030	[0.88]		
Percent Change Number of Firms (lag 2)	0.581	[0.10]			0.888	[0.05]		
Percent Change Number of Firms (lag 3)	0.273	[0.08]	0.546	[0.06]	0.203	[0.37]	0.576	[0.13]
Percent Change Number of Firms (lag 4)	0.161	[0.20]	0.217	[0.10]	0.178	[0.47]	0.224	[0.25]
Percent Change Number of Firms (lag 5)	-0.138	[0.70]	-0.069	[0.84]	-0.205	[0.64]	-0.073	[0.86]
Intercept	0.014	[0.19]	0.011	[0.30]	0.012	[0.43]	0.008	[0.61]
Sum Coef Listing Variables	0.953		0.693		1.034		0.726	
p-value (Test Sum of Coefficients)	[0.00]		[0.01]		[0.03]		[0.13]	
R^2	0.37		0.24		0.31		0.16	
Observations	37		37		37		37	

(continued)

Time-Series Regressions with Multiple Lags and Listing Variables (continued)

Panel B: Net New Lists, Gross New Lists, New Lists, and Delists

	Change in IV from t-60 to t															
	Equal-weighted Idiosyncratic Volatility								Value-weighted Idiosyncratic Volatility							
	Net New Lists/Listings		Gross New Lists/Listings		New Lists /Listings		Delists /Listings		Net New Lists/Listings		Gross New Lists/Listings		New Lists /Listings		Delists /Listings	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Listing Variable (t-11 to t)	-0.092	[0.86]	0.105	[0.87]	-0.171	[0.79]	-1.046	[0.40]	-0.226	[0.49]	0.222	[0.63]	-0.172	[0.68]	-0.096	[0.89]
Listing Variable (t-23 to t-12)	-0.449	[0.11]	0.920	[0.22]	0.037	[0.93]	3.613	[0.00]	-0.498	[0.09]	0.651	[0.23]	-0.099	[0.78]	3.256	[0.00]
Listing Variable (t-35 to t-24)	0.389	[0.24]	0.543	[0.21]	0.627	[0.19]	0.860	[0.37]	0.322	[0.21]	0.318	[0.43]	0.443	[0.27]	-0.191	[0.71]
Listing Variable (t-47 to t-36)	0.614	[0.11]	0.041	[0.93]	0.632	[0.18]	-1.525	[0.05]	0.650	[0.02]	0.137	[0.55]	0.646	[0.07]	-1.454	[0.03]
Listing Variable (t-59 to t-48)	1.297	[0.00]	-0.382	[0.70]	0.843	[0.02]	-3.808	[0.01]	0.791	[0.01]	-0.518	[0.42]	0.424	[0.22]	-2.364	[0.02]
Intercept	0.011	[0.61]	-0.193	[0.10]	-0.150	[0.08]	0.160	[0.13]	0.001	[0.94]	-0.132	[0.15]	-0.100	[0.08]	0.067	[0.28]
Sum Coef Listing Variables	1.760		1.226		1.968		-1.906		1.039		0.810		1.243		-0.848	
p-value (Test Sum of Coefficients)	[0.01]		[0.05]		[0.02]		[0.14]		[0.02]		[0.15]		[0.05]		[0.24]	
R^2	0.29		0.12		0.19		0.33		0.30		0.13		0.16		0.42	
Observations	456		456		456		456		456		456		456		456	

Table 3: Firm-level Panel Regressions of Idiosyncratic Volatility on Firm Characteristics

The table shows results from panel regressions of the natural logarithm of annual firm-level idiosyncratic volatility (IV) on the lagged number of listed firms, lagged macro-economic variables, and lagged firm characteristics. Panel A is based on young firms (age less than or equal to 5 years), while Panel B is based on old firms (age greater than 5 years). IV is estimated using the market model for each calendar year using daily data. The number of firms, credit spread, an indicator variable for NBER recessions, and the Chicago Fed Index are as of the last month of the calendar year, while the natural logarithm of market risk is the standard deviation of the monthly CRSP value-weighted index return, and the CRSP value-weighted return is cumulative over the year. The natural logarithm of the Amihud illiquidity ratio, SG&A expenses (scaled by total assets), R&D expenses (scaled by total assets), capital expenditures (scaled by total assets), and ROE are the average of the monthly values over the calendar year, while the natural logarithm of real market capitalization, the natural logarithm of firm age, the natural logarithm of Tobin's Q, leverage, PPE (net) (scaled by total assets), and the natural logarithm of cash and short-term investments (scaled by total assets) are as of the last month of the calendar year. The regressions include industry fixed effects. Standard errors are clustered by firm and year. The table reports regression coefficients and associated *p*-values, the adjusted regression R-Squared, and the number of observations. The sample consists of all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). We drop firms in Fama French 48 industries Utilities, Banking, Insurance, Real Estate, Trading, and Miscellaneous. The number of firms is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3). The sample period is 1978 to 2020.

Panel A: Young Firms

	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Number of Firms (lagged)			0.177	[0.00]			0.117	[0.00]			0.142	[0.00]
Market Risk (CRSP VW Index) (log) (lagged)	0.156	[0.07]	0.023	[0.66]					0.094	[0.31]	-0.002	[0.97]
Credit Spread (lagged)	-0.098	[0.06]	0.069	[0.07]					-0.077	[0.19]	0.048	[0.34]
NBER Recessions (lagged)	-0.008	[0.96]	-0.046	[0.75]					-0.131	[0.49]	-0.132	[0.42]
Chicago Fed Index (lagged)	-0.080	[0.37]	-0.046	[0.50]					-0.132	[0.17]	-0.095	[0.23]
CRSP VW-Return (lagged)	0.109	[0.68]	-0.022	[0.90]					0.044	[0.88]	-0.036	[0.87]
Illiquidity Ratio (log) (lagged)					-0.001	[0.94]	-0.026	[0.03]	-0.003	[0.81]	-0.022	[0.04]
Real Market Capitalization (log) (lagged)					-0.125	[0.00]	-0.139	[0.00]	-0.128	[0.00]	-0.139	[0.00]
Firm Age (log) (lagged)					-0.035	[0.23]	-0.031	[0.20]	-0.033	[0.20]	-0.029	[0.19]
Tobin's Q (log) (lagged)					0.053	[0.02]	0.036	[0.06]	0.059	[0.00]	0.050	[0.00]
Leverage (lagged)					0.200	[0.00]	0.218	[0.00]	0.195	[0.00]	0.207	[0.00]
SG&A Expenses / Total Assets (lagged)					-0.017	[0.49]	-0.006	[0.81]	-0.019	[0.46]	-0.009	[0.71]
R&D/Total Assets (lagged)					0.139	[0.07]	0.116	[0.11]	0.115	[0.10]	0.101	[0.12]
PPE (net) / Total Assets (lagged)					-0.223	[0.00]	-0.230	[0.00]	-0.221	[0.00]	-0.222	[0.00]
Capital Expenditures/Total Assets (lagged)					0.432	[0.00]	0.389	[0.00]	0.416	[0.00]	0.367	[0.00]
Cash and Short-term Investments/Total Assets (log) (lagged)					0.232	[0.00]	0.244	[0.00]	0.224	[0.00]	0.220	[0.00]
ROE (lagged)					-0.271	[0.00]	-0.283	[0.00]	-0.270	[0.00]	-0.275	[0.00]
Adjusted R^2	0.07		0.16		0.31		0.36		0.33		0.38	
Observations	22,267		22,267		22,267		22,267		22,267		22,267	

(continued)

Table 3: Firm-level Panel Regressions of Idiosyncratic Volatility on Firm Characteristics (continued)

Panel B: Old Firms

	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Number of Firms (lagged)			0.136	[0.00]			0.079	[0.00]			0.089	[0.00]
Market Risk (CRSP VW Index) (log) (lagged)	0.120	[0.15]	0.020	[0.68]					0.044	[0.54]	0.004	[0.94]
Credit Spread (lagged)	-0.108	[0.06]	-0.003	[0.95]					-0.063	[0.23]	-0.014	[0.75]
NBER Recessions (lagged)	-0.028	[0.86]	-0.110	[0.40]					-0.146	[0.33]	-0.165	[0.21]
Chicago Fed Index (lagged)	-0.123	[0.18]	-0.125	[0.09]					-0.155	[0.07]	-0.155	[0.04]
CRSP VW-Return (lagged)	-0.057	[0.81]	-0.048	[0.76]					-0.064	[0.77]	-0.035	[0.85]
Illiquidity Ratio (log) (lagged)					-0.019	[0.14]	-0.046	[0.00]	-0.022	[0.08]	-0.045	[0.00]
Real Market Capitalization (log) (lagged)					-0.161	[0.00]	-0.187	[0.00]	-0.166	[0.00]	-0.187	[0.00]
Firm Age (log) (lagged)					-0.108	[0.00]	-0.094	[0.00]	-0.107	[0.00]	-0.094	[0.00]
Tobin's Q (log) (lagged)					0.179	[0.00]	0.163	[0.00]	0.189	[0.00]	0.174	[0.00]
Leverage (lagged)					0.426	[0.00]	0.417	[0.00]	0.407	[0.00]	0.405	[0.00]
SG&A Expenses / Total Assets (lagged)					-0.006	[0.76]	-0.006	[0.75]	-0.007	[0.71]	-0.007	[0.73]
R&D/Total Assets (lagged)					0.569	[0.00]	0.524	[0.00]	0.522	[0.00]	0.477	[0.00]
PPE (net) / Total Assets (lagged)					-0.083	[0.03]	-0.100	[0.01]	-0.070	[0.07]	-0.086	[0.02]
Capital Expenditures/Total Assets (lagged)					0.453	[0.00]	0.347	[0.00]	0.400	[0.00]	0.293	[0.00]
Cash and Short-term Investments/Total Assets (log) (lagged)					-0.002	[0.97]	0.049	[0.17]	-0.009	[0.84]	0.044	[0.20]
ROE (lagged)					-0.251	[0.00]	-0.257	[0.00]	-0.264	[0.00]	-0.268	[0.00]
Adjusted R^2	0.08		0.15		0.48		0.50		0.49		0.51	
Observations	88,385		88,385		88,385		88,385		88,385		88,385	

Table 4: Industry Panel Regressions

The table shows results from panel regressions of average idiosyncratic volatility (IV) on alternative listing variables at the industry level (48 Fama French industries). Panel A regresses the percentage change in the centered, 5-year moving average of alternatively equal- and value-weighted IV on the percentage change in the number of listed firms for lags of 1 to 5 years. IV is estimated using the market model for each calendar year using daily returns. Standard errors are based on Driscoll and Kraay (1998) with 5 lags. In Panel B, the change from month *t*–60 to month *t* in the monthly equal- or value-weighted average IV is regressed on listing rates over prior 12 months periods based on alternatively net new lists (the difference of new listings and delists), gross new lists (the sum of new listings and delists), new lists, and delists. IV is estimated using the market model for each month using daily returns. Standard errors are based on Driscoll and Kraay (1998) with 59 lags. In Panel C, the moving average over months *t* to *t*+11 of the monthly equal- or value-weighted average of IV is regressed on listing rates over prior 12 months periods based on alternatively net new lists, gross new lists, new lists, and delists. The regression includes industry fixed effects. Standard errors are based on Driscoll and Kraay (1998) with 11 lags. The regressions in Panel D are the same as in Panel C, but the sample is limited to old firms (age greater than 5 years). The table reports regression coefficients and associated *p*-values, the (adjusted) regression R-Squared, and the number of observations. It also reports the sum of the coefficients of the listing variables and a test of it being equal to zero. IV is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). We drop firms in Fama French 48 industries Utilities, Banking, Insurance, Real Estate, Trading, and Miscellaneous. The number of firms in an industry is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar month or year, respectively. The number of net new lists, gross new lists, new lists, and delists is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3). The sample period is 1978 to 2020.

Panel A: Moving Averages

	Percentage Change in 5-year Central Moving Average							
	Equal-weighted Idiosyncratic Volatility				Value-weighted Idiosyncratic Volatility			
	(1)		(2)		(1)		(2)	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Percent Change Number of Firms (lag 1)	0.078	[0.01]			0.057	[0.09]		
Percent Change Number of Firms (lag 2)	0.088	[0.06]			0.091	[0.10]		
Percent Change Number of Firms (lag 3)	0.088	[0.00]	0.106	[0.00]	0.071	[0.12]	0.087	[0.11]
Percent Change Number of Firms (lag 4)	0.051	[0.07]	0.065	[0.06]	0.035	[0.43]	0.048	[0.32]
Percent Change Number of Firms (lag 5)	0.007	[0.82]	0.017	[0.58]	0.009	[0.84]	0.018	[0.65]
Intercept	0.008	[0.45]	0.007	[0.59]	0.007	[0.63]	0.005	[0.72]
Sum Coef Listing Variables	0.313		0.188		0.263		0.153	
p-value (Test Sum of Coefficients)	[0.01]		[0.01]		[0.12]		[0.22]	
R^2	0.09		0.05		0.05		0.02	
Observations	1,554		1,554		1,554		1,554	

(continued)

Table 4: Industry Panel Regressions (continued)

Panel B: Net New Lists, Gross New Lists, New Lists, and Delists

	Change in IV from t-60 to t															
	Equal-weighted Idiosyncratic Volatility								Value-weighted Idiosyncratic Volatility							
	Net New Lists/Listings		Gross New Lists/Listings		New Lists/Listings		Delists/Listings		Net New Lists/Listings		Gross New Lists/Listings		New Lists/Listings		Delists/Listings	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Listing Variable (t-11 to t)	-0.010	[0.90]	0.127	[0.15]	0.040	[0.71]	0.257	[0.05]	-0.085	[0.27]	0.097	[0.17]	-0.022	[0.74]	0.273	[0.06]
Listing Variable (t-23 to t-12)	0.019	[0.76]	0.178	[0.01]	0.124	[0.09]	0.252	[0.01]	-0.065	[0.33]	0.089	[0.13]	0.000	[1.00]	0.229	[0.05]
Listing Variable (t-35 to t-24)	0.167	[0.03]	0.102	[0.05]	0.187	[0.04]	-0.036	[0.72]	0.113	[0.03]	0.037	[0.39]	0.109	[0.10]	-0.073	[0.27]
Listing Variable (t-47 to t-36)	0.212	[0.03]	0.035	[0.61]	0.170	[0.10]	-0.237	[0.17]	0.177	[0.02]	0.033	[0.43]	0.156	[0.04]	-0.205	[0.06]
Listing Variable (t-59 to t-48)	0.316	[0.01]	-0.048	[0.71]	0.194	[0.01]	-0.436	[0.15]	0.200	[0.09]	-0.054	[0.53]	0.113	[0.21]	-0.314	[0.15]
Intercept	0.008	[0.70]	-0.056	[0.17]	-0.047	[0.23]	0.014	[0.66]	0.001	[0.95]	-0.031	[0.28]	-0.026	[0.35]	0.004	[0.84]
Sum Coef Listing Variables	0.703		0.393		0.714		-0.200		0.339		0.202		0.356		-0.090	
p-value (Test Sum of Coefficients)	[0.01]		[0.04]		[0.01]		[0.70]		[0.08]		[0.15]		[0.07]		[0.77]	
R^2	0.08		0.03		0.06		0.04		0.06		0.02		0.03		0.05	
Observations	19,152		19,152		19,152		19,152		19,152		19,152		19,152		19,152	

Panel C: Predictive Regressions

	Moving Average of Idiosyncratic Volatility (months t to t+11)															
	Equal-weighted Idiosyncratic Volatility								Value-weighted Idiosyncratic Volatility							
	Net New Lists/Listings		Gross New Lists/Listings		New Lists/Listings		Delists/Listings		Net New Lists/Listings		Gross New Lists/Listings		New Lists/Listings		Delists/Listings	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Listing Variable (t-11 to t)	-0.027	[0.74]	0.240	[0.00]	0.136	[0.16]	0.470	[0.00]	-0.077	[0.11]	0.150	[0.00]	0.038	[0.35]	0.349	[0.00]
Listing Variable (t-23 to t-12)	0.022	[0.76]	0.203	[0.00]	0.153	[0.12]	0.330	[0.00]	-0.023	[0.62]	0.104	[0.00]	0.051	[0.32]	0.216	[0.00]
Listing Variable (t-35 to t-24)	0.128	[0.04]	0.178	[0.00]	0.219	[0.01]	0.137	[0.06]	0.093	[0.01]	0.080	[0.01]	0.127	[0.01]	0.015	[0.77]
Listing Variable (t-47 to t-36)	0.218	[0.00]	0.212	[0.00]	0.307	[0.00]	0.038	[0.68]	0.148	[0.00]	0.098	[0.00]	0.181	[0.00]	-0.050	[0.39]
Listing Variable (t-59 to t-48)	0.237	[0.00]	0.160	[0.00]	0.295	[0.00]	-0.020	[0.84]	0.120	[0.02]	0.042	[0.21]	0.125	[0.05]	-0.062	[0.29]
Sum Coef Listing Variables	0.578		0.993		1.110		0.955		0.262		0.474		0.524		0.467	
p-value (Test Sum of Coefficients)	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
R^2	0.33		0.43		0.41		0.32		0.34		0.38		0.36		0.35	
Observations	19,152		19,152		19,152		19,152		19,152		19,152		19,152		19,152	

(continued)

Table 4: Industry Panel Regressions (continued)

Panel D: Predictive Regressions for Old Firms

	Moving Average of Idiosyncratic Volatility (months t to t+11)															
	Equal-weighted Idiosyncratic Volatility								Value-weighted Idiosyncratic Volatility							
	Net New Lists/Listings		Gross New Lists/Listings		New Lists/Listings		Delists/Listings		Net New Lists/Listings		Gross New Lists/Listings		New Lists/Listings		Delists/Listings	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Listing Variable (t-11 to t)	-0.093	[0.21]	0.156	[0.01]	0.030	[0.73]	0.424	[0.00]	-0.098	[0.03]	0.130	[0.00]	0.010	[0.81]	0.342	[0.00]
Listing Variable (t-23 to t-12)	-0.041	[0.52]	0.135	[0.01]	0.059	[0.49]	0.305	[0.00]	-0.039	[0.36]	0.091	[0.01]	0.032	[0.51]	0.212	[0.00]
Listing Variable (t-35 to t-24)	0.057	[0.29]	0.117	[0.02]	0.128	[0.11]	0.141	[0.03]	0.075	[0.04]	0.061	[0.03]	0.103	[0.03]	0.012	[0.81]
Listing Variable (t-47 to t-36)	0.130	[0.02]	0.156	[0.00]	0.207	[0.01]	0.075	[0.34]	0.111	[0.01]	0.070	[0.00]	0.135	[0.01]	-0.037	[0.50]
Listing Variable (t-59 to t-48)	0.204	[0.00]	0.143	[0.01]	0.269	[0.00]	-0.020	[0.81]	0.108	[0.02]	0.028	[0.38]	0.109	[0.07]	-0.071	[0.18]
Sum Coef Listing Variables	0.258		0.706		0.693		0.924		0.157		0.380		0.389		0.458	
p-value (Test Sum of Coefficients)	[0.03]		[0.00]		[0.00]		[0.00]		[0.02]		[0.00]		[0.00]		[0.00]	
R^2	0.32		0.38		0.36		0.35		0.33		0.35		0.33		0.36	
Observations	19,146		19,146		19,146		19,146		19,146		19,146		19,146		19,146	

Table 5: Industry Panel Regressions with IV and Creative Destruction Proxies

The table shows results from panel regressions of annual idiosyncratic volatility (IV) on alternative proxies for creative destruction at the industry level (48 Fama French industries). In particular, the dependent variable is the equal- and value-weighted average of IV, while the independent variables are the cross-sectional standard deviations of alternatively operating income/total assets or investment/total assets. Investment is the sum of capital expenditure and R&D expenses. The independent variables are either contemporaneous or lagged by one year. Proxies for creative destruction are based on accounting data of all firms in Compustat and assigned to the calendar with its most overlap. The regressions include industry fixed effects. Standard errors are clustered by industry and year. The table reports regression coefficients and associated *p*-values, the (adjusted) regression R-Squared, and the number of observations. IV is estimated using the market model for each calendar year using daily returns. It is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). We drop firms in Fama French 48 industries Utilities, Banking, Insurance, Real Estate, Trading, and Miscellaneous. The sample period is 1978 to 2020.

	Equal-weighted IV				**Value-weighted IV**			
	(1)		(2)		(1)		(2)	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Standard Deviation of Operating Income/Total Assets	0.683	[0.00]			0.249	[0.01]		
Standard Deviation of Investment/Total Assets			0.955	[0.00]			0.394	[0.05]
Adjusted R^2	0.29		0.25		0.28		0.27	
Observations	1,806		1,806		1,806		1,806	
Standard Deviation of Operating Income/Total Assets (1 year Lag)	0.700	[0.00]			0.263	[0.00]		
Standard Deviation of Investment/Total Assets (1 year Lag)			1.130	[0.00]			0.469	[0.02]
Adjusted R^2	0.29		0.26		0.28		0.27	
Observations	1,764		1,764		1,764		1,764	

Table 6: Industry Panel Regressions of Proxies for Creative Destruction on Listing Variables

The table shows results from panel regressions of annual proxies for creative destruction on alternative listing variables at the industry level (48 Fama French industries). Proxies for creative destruction are the cross-sectional standard deviation of operating income/total assets and investment/total assets within an industry, alternatively based on all firms or old firms (firm age greater than 5 years). Investment is the sum of capital expenditure and R&D expenses. Proxies for creative destruction are based on accounting data of all firms in Compustat and assigned to the calendar with its most overlap. Proxies of creative destruction in year *t* are regressed on net new listing rates lagged by 1 to 5 years. The annual number of net new lists during the calendar year and the number of listings at the end of the prior calendar year is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3). The regressions include industry fixed effects. Standard errors are based on Driscoll and Kraay (1998) with 5 lags. The table reports regression coefficients and associated *p*-values, the (adjusted) regression R-Squared, and the number of observations. It also reports the sum of the coefficients of the listing variables, and a test of it being equal to zero. We drop firms in Fama French 48 industries Utilities, Banking, Insurance, Real Estate, Trading, and Miscellaneous. The sample period is 1978 to 2020.

	All Firms				Old Firms			
	Percentage Change from t-5 to t							
	Standard Deviation of Operating Income/Total Assets		Standard Deviation of Investment/Total Assets		Standard Deviation of Operating Income/Total Assets		Standard Deviation of Investment/Total Assets	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Net New Lists/Listings (*t*-1)	0.823	[0.01]	0.777	[0.00]	0.656	[0.02]	0.521	[0.00]
Net New Lists/Listings (*t*-2)	0.227	[0.25]	0.376	[0.01]	0.487	[0.04]	0.431	[0.00]
Net New Lists/Listings (*t*-3)	0.047	[0.85]	0.263	[0.07]	0.065	[0.45]	0.380	[0.00]
Net New Lists/Listings (*t*-4)	0.093	[0.66]	0.291	[0.18]	0.334	[0.05]	0.226	[0.26]
Net New Lists/Listings (*t*-5)	0.226	[0.22]	0.004	[0.98]	0.386	[0.10]	0.211	[0.22]
Sum Coef Listing Variables	1.416		1.712		1.928		1.769	
p-value (Test Sum of Coefficients)	[0.04]		[0.00]		[0.00]		[0.00]	
Adjusted R^2	0.07		0.08		0.06		0.06	
Observations	1,554		1,554		1,554		1,554	

Table 7: Industry Panel Regressions with Delists and Lagged New Lists

The table shows results from panel regressions of monthly delisting rates on lagged new listing rates at the industry level (48 Fama French industries). In particular, the sum over months *t* to *t*+11 of delists scaled by the number of firms in month *t*–1 is regressed on new listing rates over prior 12 months periods. Delisting rates are alternatively based on all firms or old firms (firm age greater than 5 years). The number of new lists and delists during the calendar year and the number of listings at the end of the prior calendar year is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3). The regressions include industry fixed effects. Standard errors are based on Driscoll and Kraay (1998) with 11 lags. The table reports regression coefficients and associated *p*-values, the (adjusted) regression R-Squared, and the number of observations. It also reports the sum of the coefficients of the listing variables and a test of it being equal to zero. We drop firms in Fama French 48 industries Utilities, Banking, Insurance, Real Estate, Trading, and Miscellaneous. The sample period is 1978 to 2020.

	Delists (months *t* to *t*+11)/Listings (*t*–1)		Delists of Old Firms (months *t* to *t*+11)/Listings of Old Firms (*t*–1)	
	Coef	*p*-value	Coef	*p*-value
New Lists/Listings (t-11 to t)	-0.007	[0.81]	0.025	[0.51]
New Lists/Listings (t-23 to t-12)	0.038	[0.15]	0.027	[0.46]
New Lists/Listings (t-35 to t-24)	0.041	[0.13]	-0.005	[0.81]
New Lists/Listings (t-47 to t-36)	0.044	[0.04]	0.004	[0.83]
New Lists/Listings (t-59 to t-48)	0.111	[0.00]	0.118	[0.00]
Sum Coefs Listings Variables	0.226		0.168	
p-value (Test Sum Coefs Listing Variables)	[0.00]		[0.00]	
R^2	0.11		0.11	
Observations	19,152		19,147	

Table 8: Regressions with Census Firms

The table shows results from regressions with average idiosyncratic volatility (IV) and the number of listed and Census firms. Panels A and B estimate time-series regressions. In particular, in Panel A annual levels and percentage changes in centralized, 5-year moving equal- and value-weighted IV are regressed on levels and percentage changes in the number of listed firms and the number of Census firms lagged by 3 years. In Panel B, annual percentage changes in centralized, 5-year moving equal- and value-weighted IV are regressed on percentage changes in the number of listed firms and the number of Census firms lagged by 1 to 5 years. IV is estimated using the market model for each calendar year using daily data. It is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). The number of listed firms is based on the number of common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar year. The number of Census firms applies alternatively a threshold of 20 and 100 employees. The panels report regression coefficients and associated *p*-values, the regression adjusted R-Squared, and the number of observations. Separately for listed firms and Census firms, Panel B also reports the sum of the coefficients of the listing variables, and a test of it being equal to zero. Standard errors based on Newey-West (1987) with 5 lags. Panel C estimates panel regressions at the industry level (48 Fama French industries). In particular, it regresses percentage changes in the centered, 5-year moving average of equal-weighted IV on percentage changes in the number of listed and Census firms for lags of 1 to 5 years. IV is estimated using the market model for each calendar year using daily data. It is based on all common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) excluding penny stocks with prices less than $1.00 (in January 1997 dollars). The number of listed firms is based on the number of common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar year. The number of Census firms applies alternatively a threshold of 20 and 100 employees. The panel reports regression coefficients and associated *p*-values, the adjusted regression R-Squared, and the number of observations. Separately for listed firms and Census firms, it reports the sum of the coefficients of the listing variables and a test of it being equal to zero. Standard errors are based on Driscoll and Kraay (1998) with 5 lags. We drop firms in Fama French 48 industries Utilities, Banking, Insurance, Real Estate, Trading, and Miscellaneous. The sample period is 1978 to 2020.

Panel A: Time-series Regressions with Single Lag

	5-year Central Moving Average																			
	Equal-weighted Idiosyncratic Volatility										Value-weighted Idiosyncratic Volatility									
	(1)		(2)		(3)		(4)		(5)		(1)		(2)		(3)		(4)		(5)	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Average Idiosyncratric Volatility (t)																				
Number of Listed Firms (lag 3)	0.070	[0.00]					0.074	[0.00]	0.075	[0.00]	0.037	[0.00]					0.039	[0.00]	0.039	[0.00]
Number of Census Firms > 20 (lag 3)			-0.068	[0.72]			0.223	[0.02]					-0.033	[0.76]			0.119	[0.09]		
Number of Census Firms > 100 (lag 3)					-0.282	[0.70]			0.893	[0.02]					-0.196	[0.64]			0.411	[0.13]
Intercept	0.130	[0.00]	0.546	[0.00]	0.550	[0.00]	-0.032	[0.68]	-0.039	[0.61]	0.070	[0.01]	0.285	[0.00]	0.296	[0.00]	-0.016	[0.77]	-0.008	[0.89]
Adjusted R^2	0.75		-0.02		-0.02		0.77		0.78		0.61		-0.02		-0.02		0.63		0.62	
Observations	40		40		40		40		40		40		40		40		40		40	
Percentage Change in Average Idiosyncratic Volatility (t-1 to t)																				
Percent Change Number of Listed Firms (lag 3)	0.624	[0.00]					0.597	[0.00]	0.608	[0.00]	0.637	[0.02]					0.610	[0.03]	0.625	[0.03]
Percent Change Number of Census Firms > 20 (lag 3)			0.825	[0.11]			0.694	[0.13]					0.811	[0.22]			0.678	[0.28]		
Percent Change Number of Census Firms > 100 (lag 3)					0.785	[0.16]			0.688	[0.18]					0.617	[0.40]			0.517	[0.46]
Intercept	0.010	[0.31]	-0.004	[0.73]	-0.004	[0.78]	0.001	[0.95]	0.001	[0.93]	0.006	[0.63]	-0.008	[0.64]	-0.005	[0.77]	-0.002	[0.87]	0.000	[0.99]
Adjusted R^2	0.19		0.04		0.03		0.22		0.21		0.11		0.01		-0.01		0.12		0.10	
Observations	39		39		39		39		39		39		39		39		39		39	

(continued)

Table 8: Regressions with Census Firms (continued)
Panel B: Time-series Regressions with Multiple Lags

	Percentage Change in IV (t-1 to t) in 5-year Central Moving Average																			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Equal-weighted Idiosyncratic Volatility																				
Percentage Change Number of Listed Firms (lag 1)	0.076	[0.56]											0.101	[0.51]	0.125	[0.44]				
Percentage Change Number of Listed Firms (lag 2)	0.581	[0.10]											0.681	[0.11]	0.565	[0.10]				
Percentage Change Number of Listed Firms (lag 3)	0.273	[0.08]	0.546	[0.06]									0.187	[0.22]	0.266	[0.06]	0.648	[0.04]	0.653	[0.04]
Percentage Change Number of Listed Firms (lag 4)	0.161	[0.20]	0.217	[0.10]									-0.048	[0.80]	0.025	[0.91]	0.041	[0.87]	0.130	[0.57]
Percentage Change Number of Listed Firms (lag 5)	-0.138	[0.70]	-0.069	[0.84]									-0.264	[0.34]	-0.250	[0.42]	-0.148	[0.59]	-0.176	[0.54]
Percentage Change Number of Census Firms > 20 (lag 1)					0.980	[0.03]							-0.049	[0.93]						
Percentage Change Number of Census Firms > 20 (lag 2)					0.753	[0.21]							1.221	[0.08]						
Percentage Change Number of Census Firms > 20 (lag 3)					0.795	[0.25]	1.655	[0.03]					0.759	[0.36]			1.511	[0.11]		
Percentage Change Number of Census Firms > 20 (lag 4)					-0.414	[0.63]	-0.880	[0.27]					-0.264	[0.74]			-0.686	[0.41]		
Percentage Change Number of Census Firms > 20 (lag 5)					0.226	[0.61]	0.201	[0.62]					0.210	[0.62]			-0.059	[0.87]		
Percentage Change Number of Census Firms > 100 (lag 1)									1.177	[0.01]					0.445	[0.08]				
Percentage Change Number of Census Firms > 100 (lag 2)									0.344	[0.60]					0.413	[0.50]				
Percentage Change Number of Census Firms > 100 (lag 3)									0.825	[0.20]	1.070	[0.12]			0.904	[0.26]			0.996	[0.18]
Percentage Change Number of Census Firms > 100 (lag 4)									-0.144	[0.82]	-0.247	[0.65]			-0.063	[0.91]			-0.098	[0.86]
Percentage Change Number of Census Firms > 100 (lag 5)									-0.079	[0.85]	-0.199	[0.65]			-0.240	[0.53]			-0.544	[0.20]
Intercept	0.014	[0.19]	0.011	[0.30]	-0.019	[0.13]	-0.004	[0.72]	-0.016	[0.31]	0.000	[1.00]	-0.008	[0.46]	-0.002	[0.86]	0.002	[0.76]	0.008	[0.43]
Sum Coef Listing Variables Listed	0.953		0.693										0.657		0.730		0.541		0.607	
Sum Coef Listing Variables Census					2.339		0.976		2.124		0.624		1.877		1.460		0.766		0.354	
p-value (Test Sum of Coefficients Listed)	[0.00]		[0.01]										[0.10]		[0.06]		[0.09]		[0.06]	
p-value (Test Sum of Coefficients Census)					[0.00]		[0.08]		[0.01]		[0.36]		[0.01]		[0.06]		[0.27]		[0.62]	
Adjusted R^2	0.27		0.17		0.14		0.04		0.07		-0.01		0.32		0.25		0.20		0.17	
Observations	37		37		37		37		37		37		37		37		37		37	
Value-weighted Idiosyncratic Volatility																				
Percentage Change Number of Listed Firms (lag 1)	-0.030	[0.88]											-0.053	[0.83]	-0.032	[0.90]				
Percentage Change Number of Listed Firms (lag 2)	0.888	[0.05]											1.037	[0.03]	0.862	[0.04]				
Percentage Change Number of Listed Firms (lag 3)	0.203	[0.37]	0.576	[0.13]									0.206	[0.35]	0.369	[0.06]	0.676	[0.09]	0.683	[0.10]
Percentage Change Number of Listed Firms (lag 4)	0.178	[0.47]	0.224	[0.25]									0.001	[1.00]	0.082	[0.83]	0.076	[0.83]	0.174	[0.57]
Percentage Change Number of Listed Firms (lag 5)	-0.205	[0.64]	-0.073	[0.86]									-0.279	[0.48]	-0.228	[0.61]	-0.118	[0.75]	-0.129	[0.75]
Percentage Change Number of Census Firms > 20 (lag 1)					0.803	[0.25]							-0.769	[0.34]						
Percentage Change Number of Census Firms > 20 (lag 2)					0.494	[0.57]							1.248	[0.22]						
Percentage Change Number of Census Firms > 20 (lag 3)					0.986	[0.29]	1.596	[0.10]					0.777	[0.45]			1.364	[0.31]		
Percentage Change Number of Census Firms > 20 (lag 4)					-0.659	[0.56]	-1.003	[0.35]					-0.564	[0.61]			-0.784	[0.51]		
Percentage Change Number of Census Firms > 20 (lag 5)					-0.047	[0.92]	-0.066	[0.88]					0.008	[0.99]			-0.362	[0.49]		
Percentage Change Number of Census Firms > 100 (lag 1)									0.872	[0.18]					-0.318	[0.58]				
Percentage Change Number of Census Firms > 100 (lag 2)									-0.129	[0.90]					-0.025	[0.98]				
Percentage Change Number of Census Firms > 100 (lag 3)									0.875	[0.32]	0.877	[0.31]			0.907	[0.44]			0.710	[0.52]
Percentage Change Number of Census Firms > 100 (lag 4)									-0.381	[0.65]	-0.405	[0.61]			-0.460	[0.55]			-0.266	[0.73]
Percentage Change Number of Census Firms > 100 (lag 5)									-0.528	[0.26]	-0.604	[0.19]			-0.642	[0.18]			-0.977	[0.05]
Intercept	0.012	[0.43]	0.008	[0.61]	-0.014	[0.52]	-0.002	[0.91]	-0.003	[0.91]	0.006	[0.76]	0.004	[0.83]	0.019	[0.47]	0.006	[0.70]	0.015	[0.34]
Sum Coef Listing Variables Listed	1.034		0.726										0.911		1.053		0.634		0.728	
Sum Coef Listing Variables Census					1.578		0.527		0.710		-0.133		0.700		-0.538		0.218		-0.533	
p-value (Test Sum of Coefficients Listed)	[0.03]		[0.13]										[0.13]		[0.07]		[0.27]		[0.20]	
p-value (Test Sum of Coefficients Census)					[0.21]		[0.47]		[0.64]		[0.88]		[0.61]		[0.76]		[0.81]		[0.59]	
Adjusted R^2	0.20		0.08		-0.02		-0.01		-0.07		-0.03		0.16		0.12		0.07		0.07	
Observations	37		37		37		37		37		37		37		37		37		37	

(continued)

Table 8: Regressions with Census Firms (continued)
Panel C: Industry Panel Regressions

	Percentage Change in IV (t-1 to t) in 5-year Central Moving Average																			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Equal-weighted Idiosyncratic Volatility																				
Percentage Change Number of Listed Firms (lag 1)	0.072	[0.04]											0.071	[0.04]	0.072	[0.04]				
Percentage Change Number of Listed Firms (lag 2)	0.101	[0.04]											0.090	[0.07]	0.094	[0.06]				
Percentage Change Number of Listed Firms (lag 3)	0.080	[0.00]	0.103	[0.01]									0.063	[0.02]	0.066	[0.02]	0.101	[0.01]	0.101	[0.01]
Percentage Change Number of Listed Firms (lag 4)	0.053	[0.05]	0.068	[0.04]									0.043	[0.19]	0.041	[0.20]	0.061	[0.13]	0.065	[0.08]
Percentage Change Number of Listed Firms (lag 5)	0.003	[0.92]	0.013	[0.70]									0.000	[1.00]	-0.006	[0.87]	0.009	[0.78]	0.007	[0.83]
Percentage Change Number of Census Firms > 20 (lag 1)					0.212	[0.02]							0.136	[0.14]						
Percentage Change Number of Census Firms > 20 (lag 2)					0.196	[0.05]							0.160	[0.10]						
Percentage Change Number of Census Firms > 20 (lag 3)					0.039	[0.44]	0.154	[0.04]					0.013	[0.84]			0.099	[0.30]		
Percentage Change Number of Census Firms > 20 (lag 4)					-0.062	[0.58]	-0.015	[0.88]					-0.052	[0.61]			-0.029	[0.78]		
Percentage Change Number of Census Firms > 20 (lag 5)					-0.025	[0.69]	0.011	[0.84]					-0.040	[0.42]			-0.007	[0.89]		
Percentage Change Number of Census Firms > 100 (lag 1)									0.200	[0.01]					0.142	[0.04]				
Percentage Change Number of Census Firms > 100 (lag 2)									0.133	[0.11]					0.097	[0.29]				
Percentage Change Number of Census Firms > 100 (lag 3)									0.072	[0.22]	0.127	[0.07]			0.061	[0.37]			0.089	[0.29]
Percentage Change Number of Census Firms > 100 (lag 4)									-0.033	[0.67]	-0.021	[0.77]			-0.043	[0.59]			-0.038	[0.61]
Percentage Change Number of Census Firms > 100 (lag 5)									0.002	[0.97]	0.025	[0.63]			-0.017	[0.77]			0.015	[0.78]
Intercept	0.008	[0.45]	0.007	[0.59]	0.005	[0.68]	0.005	[0.71]	0.005	[0.68]	0.005	[0.71]	0.008	[0.44]	0.008	[0.44]	0.007	[0.59]	0.007	[0.59]
Sum Coef Listing Variables Listed	0.310		0.183										0.267		0.267		0.172		0.173	
Sum Coef Listing Variables Census					0.359		0.150		0.374		0.131		0.216		0.241		0.064		0.066	
p-value (Test Sum of Coefficients Listed)	[0.01]		[0.02]										[0.05]		[0.05]		[0.07]		[0.06]	
p-value (Test Sum of Coefficients Census)					[0.02]		[0.23]		[0.03]		[0.36]		[0.30]		[0.27]		[0.70]		[0.69]	
Adjusted R^2	0.09		0.05		0.05		0.01		0.04		0.01		0.11		0.11		0.05		0.05	
Observations	1,443		1,443		1,443		1,443		1,443		1,443		1,443		1,443		1,443		1,443	

Table 9: Industry Panel Regressions of Proxies for Creative Destruction on Listing Variables

The table shows results from panel regressions of annual proxies for creative destruction on the number of listed and Census firms at the industry level (48 Fama French industries). Proxies for creative destruction are the cross-sectional standard deviation of operating income/total assets and investment/total assets within an industry. Investment is the sum of capital expenditure and R&D expenses. Proxies for creative destruction are based on accounting data of all firms in Compustat and assigned to the calendar year with its most overlap. Percentage changes in proxies of creative destruction from year *t*–5 to year *t* are regressed on percentage changes in the number of listed and Census firms in an industry lagged by 1 to 5 years. The number of listed firms is based on common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, or Nasdaq (CRSP exchange codes 1, 2, and 3) as of the end of the calendar year. The number of Census firms uses a threshold of alternatively 20 and 100 employees. The regressions include industry fixed effects. The table reports regression coefficients and associated *p*-values, the (adjusted) regression R-Squared, and the number of observations. Separately for listed firms and Census firms, it reports the sum of the coefficients of the listing variables, and a test of it being equal to zero. Standard errors are based on Driscoll and Kraay (1998) with 5 lags. We drop firms in Fama French 48 industries Utilities, Banking, Insurance, Real Estate, Trading, and Miscellaneous. The sample period is 1978 to 2020.

	Census Firms >=20				Census Firms >=100			
	Percentage Change from t-5 to t							
	Standard Deviation of Operating Income/Total Assets		Standard Deviation of Investment/Total Assets		Standard Deviation of Operating Income/Total Assets		Standard Deviation of Investment/Total Assets	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
Percent Change Listed Firms Year *t*-1	0.601	[0.00]	0.673	[0.00]	0.587	[0.00]	0.664	[0.00]
Percent Change Listed Firms Year *t*-2	0.249	[0.10]	0.308	[0.00]	0.243	[0.08]	0.302	[0.00]
Percent Change Listed Firms Year *t*-3	0.196	[0.52]	0.218	[0.04]	0.225	[0.45]	0.217	[0.04]
Percent Change Listed Firms Year *t*-4	-0.003	[0.99]	0.316	[0.11]	0.023	[0.93]	0.298	[0.13]
Percent Change Listed Firms Year *t*-5	0.268	[0.17]	0.206	[0.07]	0.254	[0.17]	0.151	[0.15]
Percent Change Census Firms Year *t*-1	-0.315	[0.61]	-0.273	[0.48]	0.182	[0.60]	-0.013	[0.97]
Percent Change Census Firms Year *t*-2	1.088	[0.01]	0.544	[0.10]	0.300	[0.51]	0.122	[0.62]
Percent Change Census Firms Year *t*-3	0.428	[0.26]	-0.099	[0.65]	0.137	[0.66]	-0.274	[0.11]
Percent Change Census Firms Year *t*-4	0.018	[0.95]	-0.726	[0.04]	0.198	[0.56]	-0.298	[0.27]
Percent Change Census Firms Year *t*-5	-0.823	[0.08]	-1.046	[0.01]	-0.130	[0.65]	-0.306	[0.11]
Sum Coef Listing Variables Listed	1.311		1.721		1.331		1.632	
Sum Coef Listing Variables Census	0.395		-1.599		0.687		-0.768	
p-value (Test Sum of Coefficients Listed)	[0.04]		[0.00]		[0.03]		[0.00]	
p-value (Test Sum of Coefficients Census)	[0.66]		[0.00]		[0.38]		[0.15]	
Adjusted R^2	0.08		0.10		0.08		0.09	
Observations	1,443		1,443		1,443		1,443	

Appendix A: Variable Definitions

The table shows the variables used in the paper and their definitions.

Variable	Definition
Panel A: Listing Variables	
Delists /Listings	Number delisted firms/Number of listed firms (end of prior period)
Gross New Lists/Listings	(Number of newly listed firms + Number of delisted firms)/Number of listed firms (end of prior period)
Net New Lists/Listings	(Number of newly listed firms - Number of delisted firms)/Number of listed firms (end of prior period)
New Lists /Listings	Number of new lists/ Number of listed firms (end of prior period)
Number of Firms	For listed firms, this is the number of common stocks (share code 10 and 11) on NYSE, AMEX, and Nasdaq (exchange code 1, 2, and 3) as of the end of the calendar month or year. For Census firms, this is the number for firms with at least 20 and 100 employees, respectively.
Panel B: Macroeconomic variables	
Chicago Fed Index	Chicago Fed National Activity Index: Total (CFNAITot). We use a regression analysis to construct values of CFNAITot prior to March 1967 using available subcomponents.
Credit Spread	Difference between Moody's seasoned Baa corporate bond yield provided by Board of Governors of the Federal Reserve System, averages of business days (H.15 release) (BAA) and Constant maturity 10-year U.S. Treasury yield provided by Board of Governors of the Federal Reserve System, averages of business days (H.15 release) (GS10)
CRSP VW-Return	Return on CRSP value-weighted stock market index (incl. dividends)
Dispersion Real Market Cap (log)	Natural logarithm of the cross-sectional standard deviation of real market capitalization
Market Risk (CRSP VW Index)	Standard deviation of monthly returns of CRSP value-weighted index during calendar year
NBER Recessions	Indicator variable with value equal to 1 for months during an NBER-dated recession; 0 otherwise.
Panel C: Firm-level variables	
Capital Expenditures/Total Assets	Capital Expenditures/Total Assets
Cash and Short-term Investments/Total Assets	Cash and Short-term Investments / Total Assets
Firm Age	Difference in years between the observation date and the date of the first price on CRSP.
Idiosyncratic Risk (CLMX Model)	Idiosyncratic risk from CLMX model using daily returns in a month
Idiosyncratic Risk (Fama-French 5-Factor Model	Idiosyncratic risk from Fama French 5-factor model
Idiosyncratic Risk (Market Model)	Idiosyncratic risk from market model
Illiquidity Ratio	Monthly average of (Absolute Stock Return/Stock Trading Volume)
Investment/Total Assets	(Capital Expenditure + R&D Expenses)/Total Assets
Leverage	(Total Debt + Preferred Stock) / (Total Debt + Preferred Stock + Market Capitalization)
Market Risk (Market Model)	Market risk from market model using daily returns in a month
Operating Income/Total Assets	Operating Income/Total Assets
PPE (net) / Total Assets	Plant, Property & Equipment (net)/Total Assets
R&D Expenses/Total Assets	R&D Expenses/Total Assets
Real Market Capitalization	Market capitalization in millions of 1997 dollars
ROE	Return on Equity (Net Income/Shareholders' Equity)
SG&A Expenses / Total Assets	SG&A Expenses (net of R&D Expenses) / Total Assets
Tobin's Q	(Total Assets – Book Value of Equity + Market Value of Equity)/Total Assets
Total Debt	Current Liabilities + Long-Term Debt