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ABSTRACT

We show that over the past half century innovative disruptions were central to understanding corporate defaults. In a given year, industries experiencing abnormally high VC or IPO activity subsequently see higher default rates, higher segment exits by conglomerates, and higher yields on bonds issued by the firms in these industries. Overall, we find that disruption is a broad phenomenon, negatively affecting incumbent firms across the spectrum of age, valuation, and levers, with the exception of very large and low-leverage firms, which confirms our central hypothesis.

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In this study, we show that innovative disruption—when new or less-established firms gain an advantage from commercial and/or technological innovation (Bower and Christensen 1995, 1996)[1] — is central to understanding corporate defaults. The fact that disruption has been on the rise in the past two decades highlights the importance of this connection. For example, in its "Internet Trends 2018" report, Kleiner Perkins, a leading venture capital (VC) firm, shows that the time it takes for new technologies to become widely adopted has been systematically shrinking since the late 1960s. Rapid and near-universal adoption of social media and smart phones (some of the recent technology-related innovations) illustrate this phenomenon.[2] In line with this observation, academic research has identified several factors that have contributed to the acceleration of

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[1] We use the term "disruption" to represent the general process of less established firms (new entrants or firms with initially low market share, e.g., JetBlue and Southwest in the commercial airline industry) replacing/capturing significant market share from incumbents (Bower and Christensen, 1995). Incumbents are firms experiencing success using established technologies and business models. "Creative destruction" (Schumpeter 1942) and other terms have similar meaning, and we do not attempt to sort out precise relationships among these concepts.

[2] https://www.kleinerperkins.com/perspectives/internet-trends-report-2018/. Although several aggregate indicators including rate of start-up growth and share of scalable companies among start-ups suggest a decline in entrepreneurial activity (www.kauffman.org/kauffman-index), recent efforts to account for entrepreneurial quality indicate substantial heterogeneity across firms and an overall rise in start-up quality (e.g., Guzman and Stern, 2015).

disruption in recent decades including the information-technology revolution (Greenwood and Jovanovic, 1999; Brynjolfson and McAffee, 2012), a rise in VC funding (Kortum and Lerner, 2000; Gompers and Lerner, 2001), the increasing importance of intangible assets (Lev, 2017), and globalization (Melitz, 2003; Mayer, Melitz, and Ottaviano, 2014).

At a high level, disruption captures the idea that some shocks, such as regulation or a new technology, affect incumbent firms in an industry differently than new entrants. Whereas many disruption models involve the notion of an incumbent's exit, in practice, default is a better-defined and more likely event than exit, and this is our primary measure of outcome.[3] (Similar conclusions result when we complement default analysis with data on bond pricing and industry segment exits.)

The conventional wisdom of technology-driven disruption involves new firms run by entrepreneurs with early venture capital (VC) funding and, if they reach or are close to a point where commercial success is realized, listing on the stock market.[4] We use these stylized facts to devise our measures of disruption, which are agnostic about specific causes. Our examination of

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[3] Conceptually, "exit" implies that firm assets are no longer used in the same industry, which can be difficult to capture empirically (e.g., what happens to a firm's assets after a liquidating bankruptcy is not usually tracked). Beyond defaults, we also examine segment exits by conglomerates, a separate measure also related to the theoretical notion of "exit."

[4] For discussions of firm life cycles and initial listings, see, e.g., Jovanovic and Rousseau, 2011; Bernstein, 2015; Hoberg and Maksimovic, 2019; Chen, Hoberg, and Maksimovic, 2020; and Borisov, Ellul, and Sevilir, 2021.

the connection between disruption and credit risk builds on cross-industry differences in the intensity with which incumbent firms experience arrival of disruptive firms as well as time-variation in this intensity within a given industry. We use the flow of Venture Capital investments in an industry over five-year periods leading up to the year of analysis. VC investments enable us to focus specifically on the fastest growing start-ups and an early stage of disruption. However, the success of VC investments is not guaranteed. For example, Harris, Jenkinson, and Kaplan (2014) show that, in the 2000s, the VC industry, on average, underperformed public equity. To ensure that we are looking at industries with successful VC investments, which is embedded in the idea of disruption, we use Burgiss data as a second measure of disruption and zoom in on the realized VC returns in each industry over the preceding five-year period. We then compute the fraction of listed firms in an industry that had an initial public offering (IPO) in the last five years (excluding "reverse LBOs," that is, exits from buyout transactions like HCA, First Data Corp., and JCrew). Some of these IPOs capture successful exits from VC investments, and we show our results to be robust to using only VC-backed IPOs, which captures the prototypical successful VC exit. However, because not all companies pursue formal VC financing, being private does not necessarily mean being backed by VC. This is especially important for the earlier decades of our IPO sample (which goes back to 1970). Adding an IPO-based variable allows us to broaden the source of disruption. Our results are robust to alternative ways of constructing these variables.

One caveat with our industry-based empirical approach is that the scope of disruption may transcend industry classifications. An example is Google's online advertising, which "stole" the advertising market that previously funded local newspapers. Kamarck and Gabriele (2015) report that US newspaper advertising revenue dropped by about half from 2005 to 2010 as local advertising moved online. Also, to the extent that assigning firms to industries is imperfect—industries do not necessarily have clean borders, firms often operate in several industries at once, and so on—our various identification strategies will introduce noise and bias coefficients of interest toward zero.[5] It not being obvious how to improve on this limitation of our analysis, we leave it for future research.

Using VC- and IPO-based measures of disruption to relate new firm arrival to future defaults on corporate bonds issued by firms in a given industry, we document a positive relation between credit risk and measures of new firm entry. Industries with the highest share of VC capital flow and VC success and a high share of IPOs have higher defaults for the 1970-2019 period. In a proportional hazard model with fixed effects for both industries and years, the economic magnitudes are large: for a given industry, an increase in the disruption measure of one standard deviation is associated with increases in the default risk of bonds in the industry of 63%, 480%, and 126% (for VC activity, VC performance, and IPOs, respectively).[6] These results should be interpreted not as estimates of a causal relationship between VC or IPO activity and defaults, but

[5] For much of the analysis we use Fama-French (30) as the industry classification, but our results are robust to alternative industry definitions, in particular, to using fewer, broader industries.

[6] These increases are relative changes in the probability of default the following year. The overall sample baseline is 0.7% year, so these increases correspond to baselines of 1.2%, 4.3%, and 1.7%, respectively. Estimated magnitudes with control variables are lower for the IPO variable, but not for the other two.

rather as consistent with disruption in an industry simultaneously generating success for new firms and distress for incumbents.

VC and IPO intensity can capture important industry-level factors other than disruption. However, most industry shocks—demand shocks (e.g., curtailment of travel during COVID), input supply shocks (e.g., increases in the cost of energy and raw materials), and so on—affect older and newer firms in an industry similarly, that is, these shocks are uniformly positive or negative. Such "standard" shocks lead to a positive correlation between the creditworthiness of incumbent firms and prospects of younger firms.[7] Instead, we are interested in instances in which old firms (incumbents) and entrants in an industry have *opposite* experiences, that is, when one group does well and the other does poorly.[8] The scope for factors other than disruption that can

[7] "Standard" shocks are common in Industrial Organization models such as that of Hopenhayn (1992). In this model, there are demand shocks and cost shocks. Both are "standard" shocks. For example, an increase in demand benefits all firms in an industry. The model has entry costs, and lower entry costs increase the equilibrium arrival of new firms. This is not a dynamic prediction, but a comparative static. Intuitively, the mechanism is similar to a "disruption" shock. We discuss alternative models below.

[8] Some demand shock could affect incumbents and new entrants differentially. For example, changes in demand patterns due to a generational shift, such as Venmo (founded in 2009) gaining market share at the expense of PayPal (founded in 1998) or Poshmark (founded in 2011) gaining market share from Ebay (founded in 1995). In our view, these are examples of disruption: due to a generational shift there is demand

generate opposite experiences for incumbents and new entrants is extremely limited. One can imagine a shock whereby an incumbent suffers an idiosyncratic blow to its reputation of some sort, making its products fall out of favor (so contraction in demand is specific not to the product, but to the incumbent firm). This could cause a reverse causality concern if VC money flows into new firms as a result of market share loss by an incumbent. Reputational scandals are fairly rare, however, and probably not predictable at the horizon needed to create reverse causality in our tests, and therefore unlikely to drive our empirical results. Also, Egan, Matvos, and Seru (2019) and Zingales (2015) point to the financial industry as more problematic than most, and excluding this industry does not significantly affect our results.[9]

Another form of reverse causality is also possible: an anticipated decline in incumbents not driven by disruption spurs the entry of new firms. In this scenario, Google would have been started in part to exploit future challenges that local newspapers were going to face, and the founders of Uber and Lyft would have been motivated by expected performance problems in

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for a modified product and the incumbent is slow to react, enabling a new entrant to gain a substantial share of the market.

[9] Our approach to detecting disruption in the cross-section has multiple advantages; it is easily replicable and can be followed over time. However, although credible, it is neither a comprehensive nor always a precise measure of disruption. Any additional noise will bias our coefficients towards zero, and the presence of standard shocks predicts coefficients of the opposite sign.

rental car firms and local taxi systems. Not surprisingly, this explanation of the origins of entrepreneurship differs from standard accounts, which tend to highlight technological opportunities (e.g., Gompers and Lerner, 2001), capital supply (e.g., Gompers and Lerner, 2000; Kortum and Lerner, 2000; Mollica and Zingales, 2007), and demographics (e.g., Hopenhayn, Neira, and Singhania, 2018) as the core drivers. Moreover, the extent of the entrepreneurs' foresight would have to have been considerable: our analysis documents correlation between VC and IPO activity and defaults five years out.[10] On the other hand, lagged default rates in industries are not correlated with the incidence of VC investments and IPOs.

The fact that several different proxies related to disruption, based on separate data sources, give similar results highlights the robustness of the connection between new firm success and incumbent distress. Nevertheless, we explore several potential concerns and extensions of these results.

We first examine cross-sectional heterogeneity in corporate age, size, and leverage. Because most bonds are issued by mature firms, and new firms use predominantly equity, by construction our analysis captures the impact of disruption on more mature firms. In addition, we confirm that incumbent firms of all ages experience higher default risk in high VC activity and high IPO industries. Similarly, firms with enterprise values up to $10 billion are more prone to defaults in these industries. For leverage, the difference in default rates between high- and low-disruption

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[10] Our key results use cumulative disruption activity measured over *[t-4, t]* to predict default in year *t+1.* (The highest correlation is with defaults at *t+2*, e.g., between IPOs in years 1991-1995 and defaults in 1998.)

industries is detectable for all except the very lowest-leverage firms (less than 10% book leverage). Overall, our finding that disruption is a broad phenomenon that affects incumbents across the spectrum confirms our central hypothesis, but it may be less impactful for very large and low-leverage firms (for which the unconditional default risk is quite low).

Because our main empirical results are identified cross-industry, aggregate movements like financial conditions should not affect them. We also show that our results are not sensitive to inclusion of industry-level valuation measures. Contrary to the financial condition hypothesis, bond spreads are high for high-disruption industries (controlling for time-fixed effects interacted with maturity rating, issue size, and other bond features). In other words, credit markets appear to take disruption risk into account by increasing spreads.

A natural auxiliary prediction, beyond default patterns and pricing of corporate bonds, is that disruption should sometimes affect incumbents in ways less dramatic than default. This can include divesting and closing or shrinking divisions in an affected industry. We collect data on conglomerate divisions and show that divisions do, indeed, disappear more often in industries with higher disruption.

Lastly, patent rates provide important complementary evidence as they enable us to link an observed rise in distress to technological development. Moreover, patent results are unlikely to reflect macro variables given the long delays involved in patenting. Patents can in principle be used both by entrants to disrupt incumbents and by incumbents to protect against disruption, and we filter patents with individual filers as a proxy for non-incumbent inventions. We find that future default rates are higher when many patents are filed in an industry, when patents are highly cited, and when patent filing is by individuals as opposed to firms. The latter result, especially, points to how new technology capture in patents can help new firms disrupt incumbents. Patent results highlight the role of technology as the root cause of disruption. This is in line with anecdotes indicating that technology in general and the Internet specifically have played a large role in disruption and increased firm turnover in many industries. However, patents capture certain types of innovation (innovations that can be patented and when patenting is chosen by the inventor), and other channels of disruption are possible.[11]

The central contribution of our paper is to show that disruption is an important explanation of defaults in an industry. Our results are consistent with the finding that industry productivity growth is related to entry and exit (e.g., Goolsbee and Syverson, 2008; Melitz Polanec, 2015; Decker, Haltiwanger, Jarmin, and Miranda, 2017) and industry transformation involving divergent outcomes for new firms that benefit and old firms that suffer (a pattern in telecommunications documented by Olley and Pakes, 1996). To put this result in an I/O context, industry default dynamics in our sample period are driven more by disruption shocks (as in Olley and Pakes, 1996) than by standard shocks (as in Hopenhyan, 1992).

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[11] For example, in the airline industry, the conventional wisdom is that many legacy airlines suffered from high labor costs, lack of flexibility, and poor operating efficiency sustainable, in part, due to low competition consequent to regulatory barriers to entry. The success of some of the new entrants, therefore, was at least in part facilitated by deregulation. We explore some of these other channels in this paper, but ultimately do not take a stand on the precise founts of disruption.

Our results also point to the fact that disruption has a different impact on different classes of investors and securities markets. Although innovation may benefit entrepreneurs (Kaplan and Rauh, 2009; Kogan, Papanikolau, Seru, and Stoffman, 2017), and investors in startups (Kaplan and Schoar, 2005), it might not benefit investors more broadly (see also Döttling and Perotti, 2018).[12] For retail investors with limited opportunities to invest in young firms and startups (because VC funds do not raise funding from public sources), the greatest financial impact of disruption may be losses in publicly traded securities to which their access is not restricted. Greenwood and Jovanovic (1999) make a similar point, comparing the distribution of public stock equity returns to entrepreneurial rents. Overall, this implies that financial markets may amplify the distributional impact of disruption on labor markets (Acemoglu and Autor, 2011; Autor et al., 2017). Just as low-skilled workers may see unfavorable labor income trends as technology drives disruption, small investors who invest in public bond markets but not VC may lose out financially for the same reasons.[13]

Our results also have implications for understanding corporate credit markets by providing one mechanism behind the industry default correlation (e.g., Das, Duffie, Kapadia, and Saita, 2007). Disruption may help explain tougher corporate credit rating standards in terms of financial

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[13] Pension funds (as a group) are, though, the largest fund contributors to the private equity industry, and to VC, in particular. There is substantial heterogeneity across pension funds in terms of engagement, allocation choices, and investment success in the private equity field. For a review, see Ivashina and Lerner (2019).

ratios (Blume, Lim, and Mackinlay, 1998; Baghai, Servaes, and Tamayo, 2014). For any current performance indicator (low-leverage, high-interest coverage, and so on), the risk that an issuers' market position and earnings power will deteriorate due to the entry of new firms has increased. For example, in 2013 Fitch claimed that Apple did not deserve an AA credit rating because of the "inherent business risk that overshadows a significant liquidity cushion." In addition, if disruption has an economy-wide component, for example, reflecting broad technological shifts, fixed income markets may face structurally higher default rates when disruption accelerates. This may be reflected in broader portfolio return structures.

Our study contributes to several strands of the literature including studies of disruption and of the concentration of credit defaults (among them the papers cited above). Our work also closely relates to the literature on the competitive effects of IPOs, and the studies by Hsu, Reed, and Rocholl (2010) and Spiegel and Tookes (2020), in particular. Hsu et al. (2014) show that IPO events contain negative news for existing public firms in an industry, whereas Spiegel and Tookes (2020) show IPOs to be responses to industry conditions, that is, they point to causality in opposite directions. Importantly, in both of these papers IPOs are a central mechanism through which the effects occur. Because we are interested in the broader disruption phenomenon, we use IPOs as one of the signs that an industry is experiencing disruption. The different perspectives lead to several important measurement and interpretation differences, which do not allow us to generalize the findings in these previous studies to the question we study here.

The rest of the paper is structured as follows. Section 2 describes the data used in the analysis. Section 3 presents the results and explores alternative explanations. The final section concludes the paper.

I. Data

This study employs multiple data sources including Mergent FISD, Compustat, CapitalIQ, VentureXpert, Burgiss, Pitchbook, and data from the U.S. Patent and Trademark Office.

We examine three different metrics of increase in credit risk. We look first at bond defaults. Data on corporate bond histories, from Mergent FISD, covers the sample between 1970 and 2019. We drop all convertible bonds from the sample because these bonds have different return properties (they contain embedded equity options) that affect pricing and ratings treatment. (There being few convertible bonds, including or excluding them does not noticeably affect our results.) We construct a bond-year panel of every issued bond that is not matured, reorganized, called, or exchanged. Default is defined by Mergent as a bond being "reorganized," which includes bankruptcy, but also other types of defaults. Common bond exchanges are not classified as reorganizations. We use the Default table for exact dates. Our tests of defaults are run at the firm-year level, and we use the max operator to aggregate defaults across multiple bonds of a single issuer: a default on azny outstanding bond in the following year is considered a default event. This reflects the reality that most corporate credit has cross-default contract terms, meaning a default on one instrument triggers a technical default on others.[14] We exclude bonds issued by firms with IPOs in the last five years because we use IPO firms as an important explanatory

[14] In previous versions of this paper, tests were at the bond-year level. Results were similar; the norm is that all of an issuer's bonds report defaults in the same year. We have also used averages when aggregating bonds of the same issuer. This does not change our results.

variable (see below). This excludes less than 1% of observations, reflecting the modest role of recent IPO firms in the bond market.

We use segment data from Compustat to measure industry-segment exits. Segment data is reported for 70% of the companies in Compustat. We use Business Segments, which are "[a]n industry segment or product line reported by a company." We define a segment exit as a segment not being reported in the following year as long as the same firm (gvkey) still reports segments the following year. Disappearing segments may reflect asset sales, liquidations, sale of a division (e.g., to private equity), or simply shrinking (small segments are not reported). The data covers 10-20 thousand segments annually since 1977 (we lag the outcome variable, i.e., a segment disappearing in 1978 is related to characteristics in 1977). The average number of segments is three (for a firm-year reporting segments). On average, 10%-15% of segments disappear in any given year. A third of segments belong to firms reporting a single segment. We collect size and profitability measures as follows: the log of revenues (winsorized below -3), the log of assets (winsorized below -3), and the ratio of net income to revenues (winsorized below -1 and above 1). We also rank segments by sales within a firm-year. An indicator called Core Segment is created if the segment industry coincides with the firm's main industry (this may be true for more than one segment). Segment accounting data is available mostly from 1999 and onwards.

We run several regressions with bonds' yield to maturity at issue as the dependent variable. This data is also collected from Mergent. Pricing tests are implemented at the bond level (the issuer level makes less sense for prices as bonds are issued at different times and with different terms, which will result in different pricing). We use both yield to maturity and yield spread as reported by Mergent relative to a similar duration treasury bond. Using primary issues rather than secondary market prices avoids double counting the same bond, and sidesteps issues with liquidity and trading micro structure in the bond market.

Our main explanatory variables are measures of disruption at the industry level. By construction, industry classifications are central to our analysis as they underpin the incumbent market leaders and entry/growth activity of disruptors (as a group). The limitations of the standard industry classifications (SIC) might be particularly problematic for our analysis. For example, large, established companies likely operate in more than one segment. This could result in superficial industry reclassifications (Chen, Cohen, and Dong, 2016) or erroneous assignments, leading us to associate a firm with the wrong level of disruption activity. To minimize these problems, we use risk-based industry groupings downloaded from Kenneth French's website. In particular, in the regression analysis we use Fama-French 30 industry classifications.

We employ three approaches to measuring disruption in the cross-section of industries: VC capital flow, high VC performance, and IPO share.

VC capital flow—For VC capital flow, we use VentureXpert investments by industry (see, e.g., Kaplan and Lerner, 2016). We calculate the dollar amount invested in each industry and year accumulated over rolling five-year periods, and use the log. Our VentureXpert sample ends in 2018. We match all independent variables to corporate bond defaults in the following year (the idea is that VC investment amounts in 2010-2014 predict defaults in 2015).

VC performance—For returns, we use Burgiss data for the "venture capital" segment (buyouts are excluded from our subset). Burgiss, the state-of-the-art data source for private equity performance, covers several investment strategies in the alternative space and has been used in numerous recent studies (for details, see Harris, Jenkinson, and Kaplan, 2014)). To measure performance, we use total value relative to paid in capital, also known as TVPI or "multiple," a common performance metric in the private capital industry. We use the year of the fund vintage, that is, the year of the fund's first investment. In a representative case, most investments occur in the first half of the fund's life. Typically, there is significant leadtime between the beginning of the conversation with an entrepreneur and the actual investment. Moreover, it is common, at least since the early 2000s, for growth and later stage venture capital funds to take a view of the industries most attractive for investment and specialize ahead of time. Consequently, although not a precise timing variable, fund vintage is a reasonable proxy. As an example, if a fund's vintage is 2014, and 2x return was realized in 2019 through sale of the portfolio to a strategic buyer, we consider 2014 the relevant year for our analysis. As with the other variables, we construct the performance-based variables using a five-year rolling window and taking a simple average of multiples in a given industry. Our benchmark results are obtained using the global VC investments sample. In the robustness tests, we limit the data to U.S.-domiciled target firms and early-stage investments.

Researchers do not have direct access to the Burgiss data, and only receive variables constructed using at least five funds and twenty portfolio investments. Given that our variables are defined at the industry level, these data filters can be significantly binding in any given year, especially in the earlier part of the sample. A rolling-window approach helps to overcome this constraint partially, but this is also why we use VentureXpert for capital flows. That said, our results robust to using Burgiss data for capital flows as well.

IPO share—Highly successful new firms often become public. We look at the share of IPOs in a given industry, that is, the number of IPOs as a fraction of the total number of public firms in an industry measured over a five-year rolling window. We exclude reverse LBOs, exits from buyout transactions identified using the Pitchbook database, which provides for newly listed firms an "[i]ndicator if a company had a buyout status before its IPO." Although buyouts often undertake significant operational changes, post-buyout firms are probably rarely disruptive at a level that would matter for our purposes (for a discussion of reverse LBOs, see Cao and Lerner, 2009). As an alternative, we use only VC-backed IPOs as identified by Ritter (2015).[15] Our base IPO-share variable is a simple count. In the robustness results, we use Compustat data to weight recent IPO firms by market capitalization and revenue.

We perform several other focused tests to get closer to the sources of innovations. In particular, we look at patent filings and citations. We collected data on US patents from the U.S. Patent and Trademark Office. More than 7 million patents were filed in the 1955-2016 period. We categorize patents into NAICS industry codes using a process described in Appendix A. We assign patents to the year in which they are filed (not granted), and count citations of patents with truncation at year five. Over the long timespan of our sample, we observe trends in patent filings, grants, and citations as well as cross-industry differences (Lerner and Seru, 2017). Because our analysis includes year- and industry-fixed effects, we believe we are able to produce a useful cross-industry measure of innovation.[16]

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[15] The data can be downloaded from Jay Ritter's website (https://site.warrington.ufl.edu/ritter/ipo-data/).

[16] Although matching of patent filings to individual non-public corporations would allow better tests of the disruption hypothesis, such matching currently appears difficult given limited data availability.

Throughout the analysis, we use a number of control variables in addition to fixed effects. Using Mergent, we collect the following variables that measure bond characteristics: amount of bond (issue amount in millions of dollars), callability, seniority, maturity, and presence of covenants. Independent variables (e.g., bond seniority) are calculated as equal-weighted averages for each firm-year. We also match bond issuers to Compustat using the CRSP-Compustat merged database. Including these variables reduces the sample size considerably. Firm-level variables from Compustat include sales (*revt*), book assets (*at*), market value (*mkvalt*), leverage ((*dlc* + *dltt*)/*at*), enterprise value (*mkvalt* + *dltt* + *dlc*), and ROA (*ebit* /*at*). Summary statistics for these and other variables are reported in Table I. We lag all time-varying independent variables relative to bond default outcomes.

[TABLE I]

II. Empirical tests

II.A Basic evidence of disruption

The core insight of our paper is the connection between industry disruption and the structural shift in corporate defaults. We begin by providing anecdotal evidence of the underlying channel of disruption. It is well known (and ought to be the case) that credit quality deterioration is a function of firms' financial health (e.g., Altman, 1968). Among the factors that might drive poor financial performance are shrinking demand and industry-wide rising costs (what we have termed a "standard" shock). For our hypothesis, however, it is important to show that loss of market share to new entrants lies at the heart of declining revenue. To see this more clearly, we decompose EBITDA growth for firm i operating in industry J in the following way:

$$\Delta EBITDA_{i} = \Delta(Revenue_{i} * Margin_i) \quad (1)$$

$$= \Delta\big(Market\ size_J * Revenue\ market\ share_i * Margin_i\big)$$

$$\approx \Delta Market\ size_J + \Delta Revenue\ market\ share_{i} + \Delta Margin_i.$$

For disruption to have an effect on corporate defaults, it is not essential to look at growing markets (i.e., $\Delta Market\ size_J > 0$). Reallocation of revenue share from incumbents to disruptors could take place in a stale or declining industry, the tobacco industry being one example.[17] The prediction for the EBITDA margin ($\Delta Margin_i$) is also ambiguous. Although disruptors could be more efficient at cost management, it is likely that to a large degree this would be passed on to the consumer. Notably, despite consistent and staggering revenue growth, Amazon's profit margin was miniscule until recently. But ultimately, disruptive changes must be reflected in the rising leader's gain in market share at the expense of the incumbent ($\Delta Revenue\ market\ share_{i} > 0$). As noted in the introduction, we are interested in the opposite experiences of disrupting and incumbent firms. Our main results look at the credit quality of incumbent firms. Here we look at the root of profitability decline with an emphasis on the "top line" of financial performance.

The U.S. commercial airline industry illustrates the connection between the entry of new firms and incumbents' loss of market share and profitability and subsequent defaults.[18] The airline industry is a good case because the main service of passenger airlines is homogenous, market size

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[17] See "Big Tobacco Has Caught Startup Fever," *Bloomberg*, March 8, 2017.

[18] Another tangible example of an industry experiencing disruption when new firms introduce new technologies or new business models is book selling; off-line bookstores suffered considerably from Amazon's growth (Borders filed for bankruptcy in 2011).

is relatively inflexible, and market shares are accurately tracked by the U.S. Department of Transportation, which reports passenger miles flown. It also happens to be an industry that has experienced considerable disruption. Many U.S. airlines including United (founded 1926), TWA (founded 1924), American (founded 1936), Delta (founded 1924), Northwest (founded 1926), ATA (founded 1973), and World Airways (founded 1948) have defaulted on their debt. Importantly, this happened after they lost market share to new entrants to the industry, such as Southwest (founded in 1968) and JetBlue (founded in 1998). This is shown in Figure 1.

Figure 1, Panel A reports market share for all airlines that have defaulted (including declaring bankruptcy). Panel B shows the two airlines that gained market share. The figure illustrates a pattern indicative of industry disruption: the fast growth of small and new firms occurs in parallel with the gradual loss of market share by incumbent leaders. Loss of market share eventually damages incumbents' performance to the point of defaulting on debt obligations or even declaring bankruptcy while the new firms continue to grow. At least in part, this case also illustrates the connection between private capital and IPO activity as lead indicators of disruptors' success; Jetblue was VC-funded when it started in 1998 and was taken public in 2002.

[FIGURE 1]

In case of the airlines, we can look at the product they sell, which is passenger miles. Although ideal, this is not realistic for a broader set of industries. To generalize this point, we follow the EBITDA decomposition presented in (1). Credit quality is measured using credit rating downgrades because this enables us to capture the evolution of revenue share following a credit event, as firms usually remain in the sample after a downgrade (whereas many defaults are associated with firms dropping out). Downgrades indicate a rise in the risk that the issuer will default on its debt obligations (e.g., Hilscher and Wilson, 2017). In a given year, for a given industry, rated firms are divided into those that were downgraded (column (1)), those that saw no change (column (2)), and those that were upgraded (column (3)).[19] We treat firms with credit ratings as mature firms. "Young firms" are defined as firms that had an IPO within the last five years (column (4)).

The results in Table II indicate that downgraded firms tend to have declining market share and falling profitability. Defaulted firms (a subset of downgrades) see especially steep drops in market share. As one would expect, upgraded firms perform better on all dimensions. The focus is on younger firms that, in line with our hypothesis, show a substantial gain in revenue market share. Although the annual revenue market share growth for downgraded firms is -4.2%, recently listed firms show an average gain of 12.2%, which substantially exceeds the 6.5% market share gain for upgraded firms.

[TABLE II]

To understand better whether the loss of market share by mature firms is tied to the market share gained by younger firms, we look, in Figure 2, at the change in revenue market share for young (on the left) and mature (on the right) firms. Firms are sorted in terciles based on the distribution of years since IPO. The figure is further broken down by the degree to which industries have been disrupted; light bars indicate stable industries, dark bars disrupted industries. To classify the degree of industry disruption, for every year we do a sort based on the

[19] In our main analysis, the unit of observation will be bonds, but here we look at firms, as we are interested in illustrating aggregate effects at the industry level.

fraction of firms that had an IPO in the past five years. For example, in 1995, for each industry we take the number of firms that had an IPO between 1991 and 1995 and scale it by the total number of firms in that industry in 1995. We then group the industries in terciles. Because this exercise is repeated for each year from 1970 to 2014, the same industry could be allocated to different terciles over time. The sizes of the bars correspond to the average three-year forward change in revenue market share. That is, for each firm we compute:

$$Revenues_{i,t+3} \Big/ \sum_{J} Revenues_{i,t+3} - Revenues_{i,t} \Big/ \sum_{J} Revenues_{i,t} \ .$$

Figure 2 indicates that, in high-IPO industries, in sharp contrast to firms in industries with low IPO share, disrupting firms gain market share while the stakes of the more mature firms shrink. This relates to Hsu, Reed, and Rocholl (2010), who document that IPOs are associated with a loss of market value for incumbents in the same industry, and to Eisdorfer and Hsu (2011), who argue that technological change may force firms to take on more risk.

[FIGURE 2]

II.B Disruption measures and default risk

We now turn to establishing whether measures of disruption predict defaults in an industry. Our main hypothesis is that VC activity or many IPOs are signs of disruptive pressure on incumbents, and associated with a higher default frequency going forward. We compute the disruption variables over [*t-4, t*] period; defaults are measured in *t+1*. The source of identification is variation in the disruption measure—VC capital flow, VC performance, and IPO share—across industries and within a particular industry over time; that is, all regressions include year- and industry-fixed effects. The dependent variable "default" (D_i), according to Mergent, is a dummy equal to 100 if one or more of a corporation's outstanding bonds is restructured, and 0 otherwise. Throughout, we double cluster errors on industry-year (the key dimension, as our explanatory variable of interest varies at this level) and issuer (for a given firm defaults tend to coincide in time for all outstanding bonds).

In Table III, we report estimated coefficients using a linear probability model (columns (1)-(3)) and proportional hazard model (columns (4)-(6)). Linear probability models are easy to interpret, but offer a poor fit when the mean of the dependent variable is close to zero (or one). Proportional hazard models naturally handle probabilities (which are bound between zero and one), and allow independent variables to have a smaller absolute impact on observations when the conditional probability is close to zero or one. This is relevant in a default setting, most firm-years having less than 1% conditional probability, but some having much higher default risk. The hazard model also allows time-series dependence and time-dependence (see Shumway, 2001). We therefore use the proportional hazard models in other tests of defaults once the linear model has been shown for baseline tests in Table III. We include industry and year fixed effects to control for aggregate conditions and generic industry risk levels (e.g., Helwege and Kleiman, 1996). In all statistical models, the coefficients on disruption measures are positive. In the proportional hazard models, and in most cases in the linear probability models, the coefficients are statistically significant, indicating that high VC activity, strong VC performance, and high IPO activity are associated with a high level of defaults in an industry.

Point estimates are economically large for two of the three specifications: a change of one standard deviation in the disruption variables is associated with an increase in expected annual default probability of 0.1%, 0.5%, and 0.6% in columns (1), (2), and (3), respectively, which can be compared to the sample average of around 1%.[20] This corresponds to an increase in the five-year default risk from 4.9% to 7.1%.[21] For comparison, the historical five-year default rates for Baa, Ba, and B rated corporate bonds were 2.6%, 8.6%, and 20.0%, respectively, based on Moody's (2017).[22]

The incidence of defaults on corporate bonds may reflect many factors at both the industry and firm level. In Table III, Panel B, we introduce additional controls for bond characteristics (size, indicator for whether the bond is callable, covenant indicator, seniority, and maturity at issue) and issuer (indicator for whether the firm is publicly listed). Many of the controls are significantly related to default rates. The coefficients on the disruption variables are positive and significant in all the regressions with more controls, and have similar magnitude.

The pattern of clustered periods with higher-than-normal defaults in an industry is well known (see, e.g., Azizpour, Giesecke, and Schwenkler, 2018; Das et al., 2007). A key point of this literature is that debtors in a given industry tend to default close in time, beyond what can be explained by

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[20] For column (1), 0.134*1.022=0.14. For column (2), 0.093*4.993=0.46. For column (3), 4.822*0.124=0.60.

[21] These numbers are calculated as follows: $4.9\% = 1 - (1 - 1.01\%)^5$ where 1.01% is the sample average annual default probability and 5 is the number of years; $7.1\% = 1 - (1 - 1.01\% - 0.46\%)^5$ where 0.46% is the product of 0.093 (the coefficient in Table 3 Panel A Column 2, in %) and 4.993 (the variable's standard deviation).

[22] The IPO boom in the late 1990s may constitute noise for our analysis in the sense that many of the firms listing at the time posed less threat of disruption than in normal times. Indeed, if we drop the period 1995-99, the coefficient estimate rises (not reported).

economy-wide factors. In general, this coincidence of defaults can reflect either contagion (default by firm 1 causes firm 2 to struggle) or some latent factors. Clearly, disruption belongs to the second category, and offers one potential mechanism behind industry-level correlation of defaults. Other mechanisms may also be operational, and default caused by disruption could be exacerbated by contagion (e.g., due to industry fire sales or through an impact on joint suppliers).[23]

[TABLE III]

II.C Alternative ways of measuring disruption

In Table IV, we explore alternative ways of measuring new firms' significance to an industry. This table reports results from proportional hazard models like those reported in Table III, Panel A, columns (4)-(6); only the coefficient of interest, that is, the coefficient of the proxy for disruption, is reported. In rows (1) and (2), we use Burgiss data to construct the VC capital flow variable. Due to the filter required by Burgiss, we use a dummy variable instead. In row (1), VC active industry is defined as any industry-year with at least $25 million 2015 US dollars of VC investment in the prior five-year period. In row (2), the threshold is $100 million 2015 US dollars.

We next vary the sample used to calculate VC performance, first by restricting it to investments in early stage VC targets (as classified by Burgiss), and then by restricting it to U.S. investment targets. Both restrictions reduce the number of observations slightly, reflecting the filters Burgiss employs to guarantee anonymity.

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[23] Disruption also offers one possible reason why recoveries are depressed in industries with poor recent stock performance, as documented by Acharya, Bharath, and Srinivasan (2007).

Rows (5)-(7) in Table IV examine three variations on the IPO Share variable. First, only firms with VC-backing prior to listing are counted. Second, IPO Share is value-weighted by enterprise value, and third, value-weighted by revenue.

[TABLE IV]

In general, the results using alternative measures of disruption show that industry-years with more recent VC and IPO activity are followed by elevated default rates for bonds issued by firms in the industry under a range of plausible variations in variable definitions. The parameter estimates remain economically large. This is consistent with the hypothesis that exposure to industry disruption is an important driver of credit risk.

II.D Heterogeneity

The results in the earlier tables establish that industries that attract VC activity, and in which a large share of listed firms have recent IPO dates, tend to see an elevated incidence of corporate bond defaults, holding year and industry fixed. This is consistent with the disruption hypothesis: successful entry of new firms is connected with deteriorating performance of incumbent firms in an industry. An important issue is which firms default. For example, elevated default rates associated with leverage or underperformance of new firms would not fit the disruption hypothesis. So it is critical to look at cross-sectional patterns. First, we examine a non-parametric setting for firm age, size, and leverage. Results are shown in Figure 3, in which each panel plots the univariate relationship between default risk and a key variable (age, size, and leverage) for high and low industry-year disruption activity as defined by VC capital flow and IPO share. The cutoff for high and low IPO share is 15% (this reduces the sample by about half) and for VC activity \$100 million invested (in 2015 dollars). For each panel, default risk is connected to the underlying variable with local polynomial fits, separately for industry-years with high and low disruption rates. A 95% confidence interval is plotted around each estimated fit. The distribution of the running variable is also plotted behind each fit so that economically important regions (in which the mass of firms is relatively larger) can be easily identified.

[FIGURE 3]

As expected, the risk of default is highest for young firms (Panel A), for small firms (Panel B), and especially for highly levered firms (Panel C). Default probabilities are always higher in high VC activity years than in low VC activity years and in high-IPO industry-years than in low-IPO industry-years. This is basically the same finding as reported in Table III in a regression setting, but these figures also demonstrate cross-sectional heterogeneity. The (absolute) difference in default probability (between high and low VC industry-years and between high and low IPO industry-years) peaks for young firms, moderate size firms, and high leverage firms. For VC activity, the confidence intervals are non-overlapping for young firms (up to 10 years since listing), for levered firms (above 0.7), and for intermediate sizes. For IPO activity, the 90% confidence intervals of point estimates for the default risk are non-overlapping for most levels, but not for the oldest (25+ years), largest ($5B+ enterprise value), and least levered (<10% book leverage) firms.

These results suggest that disruption hurts many, but not all firms. The most established firms may be immune.[24]

An alternative way of analyzing cross-sectional heterogeneity within industries is by splitting samples, and we turn to this in Table V. We separately estimate the baseline regressions for young and old firms, for small and large firms (measured by their bond debt outstanding), for Investment Grade and High Yield firms, for non-deregulated industries, and for non-finance industries. As in Figure 3, the motivation for these splits is as follows. Disruption involves not just failing startups or young firms, but more widespread incidences of default. Firm age and size are proxies for incumbency. By splitting the sample along these dimensions, we can see which firms are affected.

In Table V, the coefficients of interest (the reported coefficients) are similar for younger and older firms and somewhat higher for the largest firms than for smaller firms (not statistically significant). Because these are coefficients from a proportional hazard model, they should be understood in a relative sense. The point estimate for the largest firms implies a greater relative increase in default risk when IPOs are high, but the baseline default risk for large firms is lower, and the absolute increase is therefore likely smaller as well (Figure 4, Panel B also suggests that the absolute difference is largest for small or intermediate size firms). Table V also compares High Yield and Investment Grade firms. The point estimate is larger for IG firms (not significantly

[24] It is noteworthy that in Figure 3, Panel C, the distribution of leverage has more weight on high values for high-IPO industry-years. This may reflect the endogeneity of leverage choices (see, e.g., Almazon, de Motta, and Titman, 2015 and He and Matvos, 2016).

different). This result also suggests that the impact of disruption is felt widely, even among firms with lower ex-ante risk of default. Taken together, Table V and Figure 3 should give a good sense of how disruption operates across firm types: large relative increases in default risk for strong, mature firms, and large absolute increases for smaller, younger firms.

The next two rows in Table V are focused on the source of disruptive pressure. Although, as noted in the introduction, we do not take a firm stand on causes of disruption, here and in what follows we provide some evidence on this matter. In particular, we exclude industries that experienced considerable deregulation, that is, Fama-French 30 industries classifications "Transportation," "Petroleum and Natural Gas," and "Communication." The last row shows the main result excluding firms in "Banking, Insurance, Real Estate, Trading," Although banking is heavily regulated and many new regulations have recently been imposed on the sector, there have also been important instances of deregulation over the long sample period employed in this study. That the results with these exclusions still show a strong connection between IPO share and defaults indicates that deregulation is not the sole, nor probably the main, factor behind our findings.

[TABLE V]

Overall, the consistent message of a number of econometric specifications, alternative variables that capture the success of new firms, and various controls and subsamples is that new firm success in an industry tends to be associated with hardship for incumbent firms. This is the key hypothesis regarding disruption: new firms succeed at the expense of incumbents. Our results suggest that this is empirically important in the United States in recent decades.

II.E Patents

Patents are an interesting variable to consider in the context of disruption, both because they may reflect disruptors' technological edge or the potential for new technology to enable disruption, and because public firms' patents are known to be valuable in the eyes of financial markets (Kogan, Papanikolau, Seru, and Stoffman, 2017). Patenting activity can help firms preserve their competitive position (Hsu et al., 2014), and also have the advantage over spending-based measures from Compustat that they measure results, not effort (Lerner and Seru, 2017).

Based on this, we use patent data to construct an output-based proxy for technological innovation. We associate patents with industries through product classification codes. Because many patents are associated with more than one industry, we have a large count of patents for each industry. The number of patents filed has a strong positive time trend, but because we include time-fixed effects this should not affect our results. We also count total citations of patents in an industry, and citations of the most cited patent in an industry. Following the procedure described in Appendix A, we separate patents filed by individuals from those filed by firms. We think of patents filed by individuals as more likely to generate disruption and firm-filed patents to be more likely to help incumbents protect their competitive position.

We present regressions with patent measures as explanatory variables together in Table VI. In the first three columns, we use the firm default model (similar to the one used in Table III, column (3)), and in the last three columns the bond-pricing model (similar to Table IX, column (1)). The benefit of bond prices at issue is that they contain information about market perceptions of bond credit-risk. We discuss this in more detail in Section II.H, where we provide pricing results for our main disruption variables. For many of these regressions, there is a positive association between patent counts and citation counts in an industry and both future defaults and spreads on newly issued bonds. Additionally, there appears to be a strong divergence between the two types of patents, those filed by individuals being associated with defaults and especially with large spreads, those filed by firms being associated with a low incidence of defaults and small bond spreads. This is consistent with the idea that patents originated by incumbents (defined here as bond issuers in an industry) *reduce* disruption. New technology that originates outside incumbents is associated with higher defaults (and more expensive bonds), as predicted by the disruption hypothesis.

[TABLE VI]

II.F Robustness of the results and alternative drivers of default risk

In Table VII, we examine several broad trends that may affect the rate of disruption as well as affect defaults through other channels including financial conditions and technological change.[25] This is motivated both by concerns about alternative explanations for our main findings and by a desire to understand the drivers of default risk, controlling for other drivers may improve our ability to identify the impact of disruption. Note, however, that because all regressions include time fixed effects, we are most interested in trends and mechanics that affect industries differentially. For example, the relationship between disruption and IPOs could have changed over our sample for several reasons that have little to do with the disruption itself. This includes increases in the supply of private capital (Kahle and Stulz, 2017), in filing requirements resulting

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[25] See Slatter and Lovett (1999), Eisdorfer and Hsu (2011), and Altman, Hotchkiss, and Wang (2019) for additional long-term drivers of trends in corporate default.

from the Sarbanes-Oxley Act (Gao, Ritter, and Zhu, 2013), and in use of intangibles as collateral (Stulz, 2018). If a structural break in IPO volume constitutes a level shift, the year fixed effects would deal fairly well with that and our regressions might be more or less unaffected. However, we want to investigate some specific explanations that could be correlated with industry-level IPO activity.

We first consider financial conditions. There is more IPO activity in industries with high valuations (e.g., Schultz, 2003). If high industry valuations are also associated with higher defaults, IPO activity might simply proxy for stock market price levels in our regressions. By controlling for valuation ratios, we can more confidently ascribe our results to the arrival of new firms to the stock market and not aggregate conditions. We use two common measures of valuation, market-to-book and enterprise value to EBITDA, using aggregate data for all firms in an industry in a given year (averages or medians give similar results).

We also want to control for technology. There is little doubt that technological opportunities are key to startup activity, VC investment, many IPOs and, eventually, the product market success of many new firms. New firms may be more willing or better able to exploit new technologies (e.g., Bower and Christensen, 1996; Brezis, Krugman, and Tsiddon, 1991). However, new technology is also developed and employed by many incumbent firms. Technological advances might *directly* affect default rates (Eisdorfer and Hsu, 2011) due, for example, to risk associated with the adaptation of new technologies (Pástor and Veronesi, 2009) or changes in the extent of economies of scale (Kretschmer, Miravete, and Pernías, 2012) or in the need to standardize output (Katz and Shapiro, 1986).

One way to examine a direct impact of new technology on default rates is to measure technological change and include it in default prediction models. We start with the most conventional proxy for technological development, R&D spending. We aggregate R&D spending by industry-year and normalize by industry sales (results using alternative normalizations like industry assets and EBIDTA are similar). In addition to concerns about measurement noise, there are clearly conflicting predictions. If R&D spending is a sign of technological change that enables entry and competition with incumbents, it will be associated with defaults. If, on the other hand, R&D spending erects barriers to entry, it may be associated with incumbent market power (see, e.g., Autor et al., 2017). Presumably, both types of R&D may be captured in our variable.

A large share of recent disruption is connected in some way to information technology, and R&D may not capture this well. For example, a significant portion of spending may be on purchases of IT equipment rather than R&D. To address this, we collect data on IT spending from input-output tables for the U.S. economy. These data start in 2002. In the reported results, we compare 2002 IT spending levels to defaults in years preceding 2002, but the results are similar if we restrict the sample to 2002 forward.

Regressions with additional control variables are reported in Table VII. The VC and IPO variables remain positive predictors of default. Market to book is negatively related to defaults in two of three regressions – high valuations are associated with fewer future defaults. The other financial variable has a positive coefficient – high valuations are associated with more defaults. We conclude that, for this sample, IPOs in our regressions likely do not capture industry-specific financial conditions. The R&D variable is not related to defaults, whereas the level of IT spending is a negative predictor of defaults, suggesting that incumbent advantage may be increased in industries with high IT-spending. However, the magnitude is small.

[TABLE VII]

The robustness tests point to a few additional factors that may be associated with future defaults in an industry. However, related measures point in different directions, which does not suggest any coherent explanation for defaults. Most important, these regressions suggest that industry VC and IPO variables are not less likely to relate to default risk because they capture general financial or technological conditions in an industry. This is an industry-level analysis. Measurement of firms' technological edge is provided by patent data. We return to this in Section 3.7 below.

II.G The risk of segment exits

Multi-division firms can shrink, sell, or liquidate a business division without defaulting on any debt. Segment data provides an alternative window for examining the threat disruption poses for such firms. We expect high IPO and VC industries to have higher rates of segment exits, just as defaults increase in such industries. To test this, we identify segment exits using Compustat. We regress an indicator for segment exits on a measure of disruption (IPO share or VC activity) on firm-year as well as industry and year fixed effects. Importantly for interpretation, firm-year fixed effects eliminate any overall group level patterns, effectively comparing divisions of the same firm operating in separate industries. Tests include these fixed effects.[26] We report results in Table VIII. In columns (1) and (2), IPOs measure disruption, in columns (3) and (4), venture capital. In columns (1) and (3), there are no controls except fixed effects; columns (2) and (4) include three measures of segment performance (which reduces sample size). The unconditional probability of segment exit is 12%-14%, depending on the exact sample. Disruption measures are associated with high segment exit rates. In column (1), raising the IPO share by 13% (a standard deviation) predicts a higher exit probability of 6%, about half the unconditional mean.

[TABLE VIII]

The results for segment exits are consistent with the results for defaults. High IPO and VC industries experience subsequent increases in both defaults and segment exits. These are quite distinct – defaults involve interactions with investors, segment exits business sales, closures, etc. – but both sets of results are consistent with the idea that entry is associated with problems for incumbents.

II.H The pricing of credit risk associated with disruption

Does the corporate bond market understand the risks associated with industries experiencing disruption and, if so, does it adjust bond prices accordingly? This is the focus of Table IX. If financial markets appreciate the risks associated with the arrival of new firms, we expect bonds

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[26] Because there are a large number of fixed effects for firm-years, all tests in Table 8 employ linear probability models. For example, in Table 8, column (1), there are 95,501 fixed effects. Other functional forms work less well than linear models in such settings.

issued by firms in industries with many IPOs to fetch higher yields. We test this prediction in a cross-sectional regression of yield to maturity at issue, controlling for the level and slope of yield curves with fixed effects as well as for bond characteristics like seniority and credit rating at issue. Specifically, we interact year-fixed effects with bond maturity, maturity squared, and ratings. These controls should capture variation in the market pricing of bonds affecting the slope and shape of the yield curve as well as variation in risk premia for bonds with different horizons (see, e.g., Helwege and Turner, 1999). We also include separate fixed effects for the exact month of issue to capture creation in overall market conditions. We control for bond size as well as indicators for whether a bond is callable, has covenants, and is senior.

The dependent variable is yield spread, reported by Mergent FISD. This variable compares the yield of a bond to that of a treasury bond with similar maturity. If disruption raises credit risk, yield spreads should rise and we would expect the coefficient on the IPO variable to be positive. Results are presented in Table IX. Overall, the bond-pricing model performs fairly well: the *R*-squared is above 75% in all specifications. The regression reported in column (1) indicates that bonds in high-IPO industries have moderately higher yields at issue: increasing the IPO variable by one standard deviation is associated with a seven basis points higher yield spread ($= 53.8$ bps $*$ 0.13). This positive association between IPOs and bond yields implies that the bond market prices the default risk associated with the arrival of new firms. Controls for bond characteristics enter with the predicted sign: unrated and callable bonds have higher, bonds with covenants and senior bonds lower, yields.

[TABLE IX]

In column (2), we allow the coefficient on IPOs to vary between investment-grade and high-yield bonds. Because the majority of defaults are in high yield bonds, we may expect the price impact to be larger there. Indeed, in this specification we cannot reject zero pricing impact for investment-grade bonds, whereas the effect is large and significant for high-yield bonds: 33 basis points higher yield per standard deviation of IPOs.

Perhaps rating agencies realize how credit risk is affected by disruption and adjust their ratings downward for bonds in highly exposed industries. If so, controlling for credit rating should reduce or eliminate the coefficient on IPOs in the yield regression. In column (3), we introduce ratings-notch-fixed effects (i.e., separate for AAA, AA+, AA, AA-, A+ and so on) interacted with year-fixed effects. In this regression, the pricing impact of IPOs remains similar and significant (the magnitude is 5 basis points of yield per standard deviation), suggesting that rating agencies have not completely captured disruption risk in credit ratings.[27]

We next examine the timing of the yield premium for high-IPO industries. In particular, we are concerned that the premium is identified in early periods when the scale of IPOs and defaults tends to be lower. In column (4), in which all bond issues before 2000 are excluded, the price magnitude is comparable to the results for the full sample. In column (5), we allow all control variables to have different coefficients by year, which allows callability, covenants, and so forth to

[27] Macro factors are absorbed by the time series fixed effects. We have also experimented with allowing macro factors to have separate effects on different industries. This introduces additional coefficients, but results are largely similar (two coefficients of interest were not significant when we allowed industry-specific slopes on inflation, GDP growth, a recession indicator, and credit spreads).

have different price impacts under different market conditions. Including these additional control interactions pushes the R-squared close to 85%. The coefficient on the IPO variable remains similar.

Overall, the results suggest that firms exposed to disruption—captured as industries in which a higher share of listed firms had a recent IPO—pay slightly higher yields when issuing bonds. This evidence is consistent with the hypothesis that the corporate bond market considers disruption a risk factor for companies and asks for higher yields as compensation. The long-term asset pricing consequences of this finding are beyond the scope of the present study.

III. Conclusions

A standard model of industry dynamics suggests that industry shocks affect firms symmetrically. For example, demand may rise or input costs fall for all industry firms. Under disruptive innovation, in contrast, new firms rise to industry leadership positions, resulting in worse performance and higher credit risk for incumbent firms. We test this hypothesis in U.S. corporate bond markets to determine which model works better in recent decades.

We show that industries with higher VC and IPO activity subsequently see higher default rates, controlling for time- and industry-fixed effects. In other words, the success of new firms is associated with pressure on incumbents. This fits the disruptive model of industry shocks. The bond market appears to perceive disruption as a risk, and bonds issued in high-VC and high-IPO industries have higher yields.

At the end of our sample, a forward-looking forecast using the IPO variable points to high disruption going forward (the IPO rate is high at the sample end, but lower than the exceptional years in the late 1990s), whereas VC-funding forecasts high disruption (many industries are close to all-time-high VC investment at the end of our sample). Against this background, the consequences of our findings are numerous and diverse. First, they suggest that the rise in bond credit risk may continue if disruption remains high. Second, disruption, apart from producing large gains for entrepreneurs and investors with access to VC funds, may also have large negative return implications for bond investors. To the extent that bonds are widely held, often by pension funds and retirees, the distributional consequences of this would appear adverse. Just as disruption may exacerbate inequality through labor markets, it may do so through financial markets. Third, our findings suggest that time-series patterns in aggregate default rates at longer horizons than business cycles are economically important. Finally, we acknowledge important caveats, among them that disruptive shocks may not always predominate. Perhaps large changes in technology in the last few decades have created an environment in which disruption is more prevalent than at other times.

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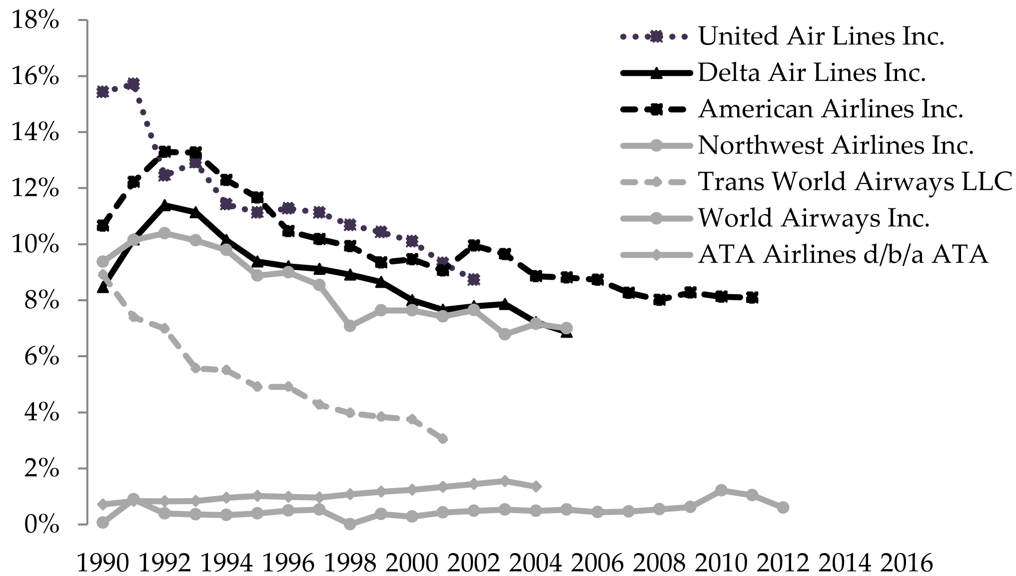
FIGURE 1: U.S. AIRLINE INDUSTRY MARKET SHARES. The figure shows market shares of domestic U.S. passenger airline routes for publicly listed airline companies based on Department of Transportation statistics for passenger miles. Panel A shows airlines that have defaulted on debt obligations (including bankruptcies). Panel B shows the two airlines without defaults. After default, market shares are no longer tracked. Data on defaults and bankruptcy filings are from Mergent FISD and Compustat.

Panel A. Incumbent airline market shares (until date of default)



Panel B. New airline market shares

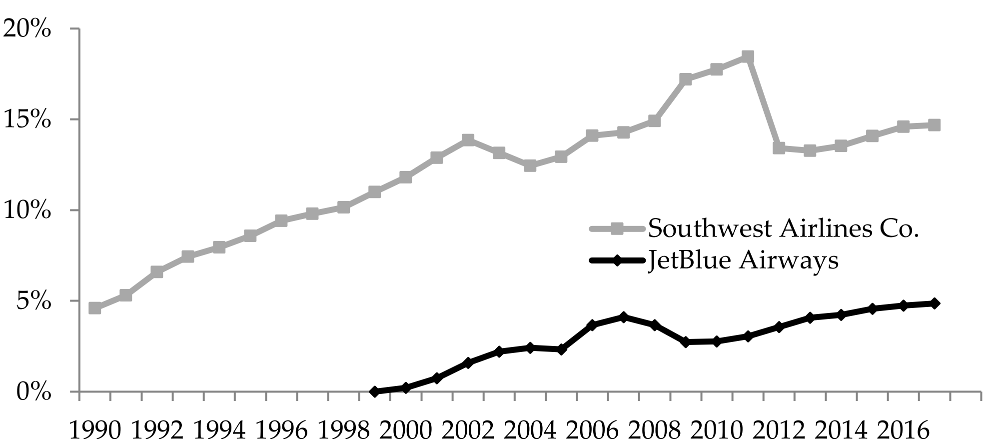


FIGURE 2: FIRM REVENUE MARKET SHARE CHANGES (PERCENTAGE POINTS) IN HIGH- AND LOW-ENTRY INDUSTRIES. The figure shows revenue market share changes over a 3-year window for Compustat firms sorted by (i) the fraction of firms in the industry with recent IPO dates, and (ii) firm age (defined as time since IPO). Market share changes are aggregated for all firms in a size group.

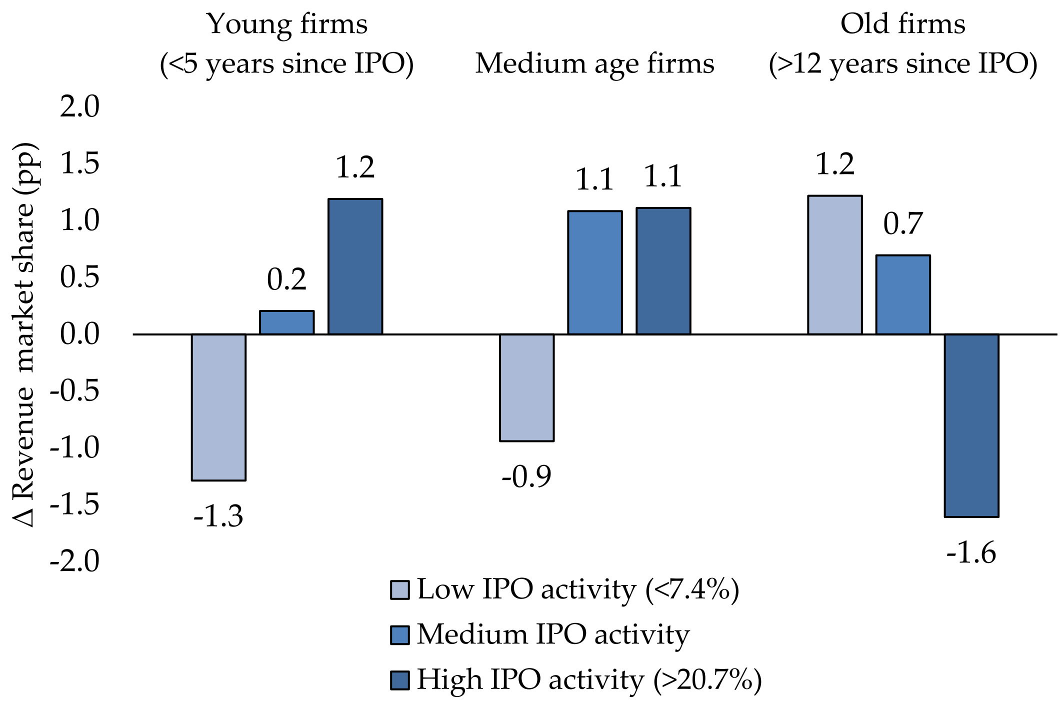
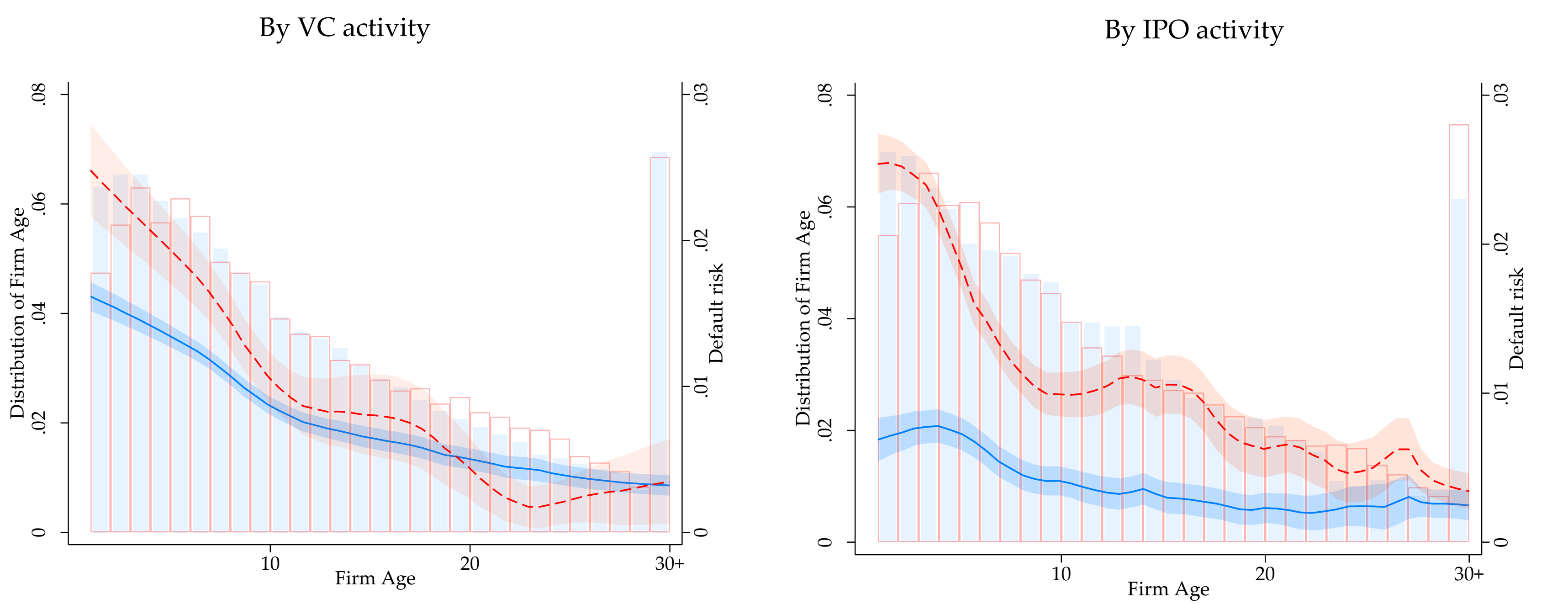
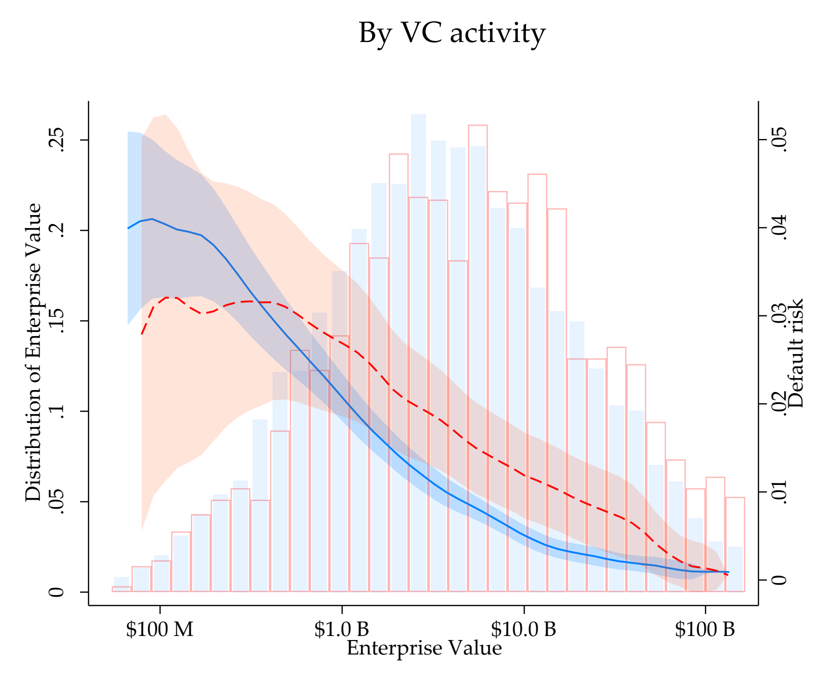


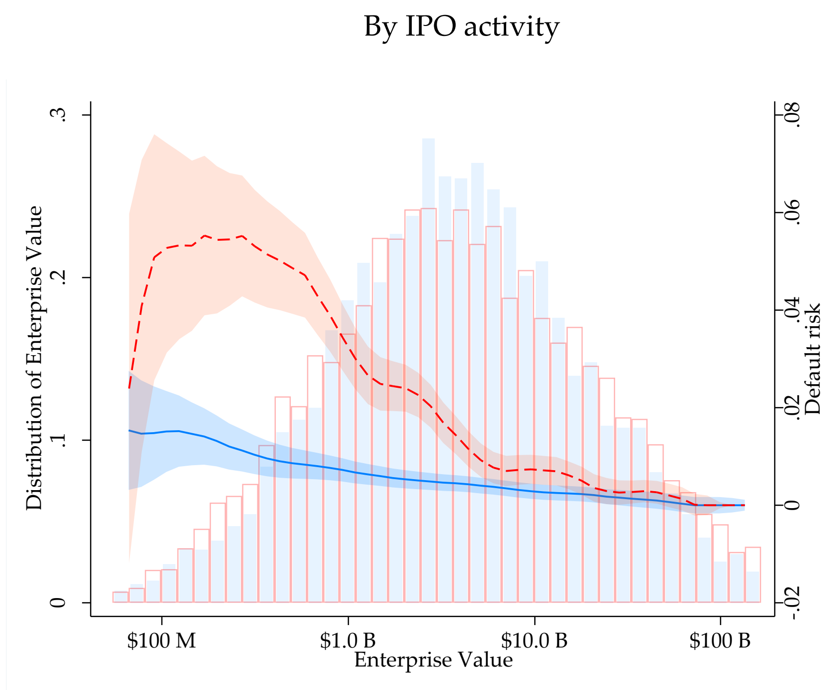
FIGURE 3: DEFAULT PROBABILITY IN HIGH AND LOW DISRUPTED INDUSTRIES BY FIRM CHARACTERISTICS. The figure shows the relation between unconditional probability of firm default in a given year (right axis) and lagged firm age (Panel A), firm size (Panel B), and book leverage (Panel C). Age is the maximum number of years since the firm appears in Compustat or Mergent databases. Firm size is the sum of market capitalization and debt measured in 2015 dollars. Leverage is the ratio of book debt to total assets. The distribution of each independent variable is shown in the histogram (left axis). High IPOs means 15% or more; High VC means $100 million invested (in 2015 dollars). A local polynomial smooth of default risk is plotted separately for industry-years with high (red) and low (blue) disruption. Two-sided 90% confidence intervals are indicated for each line.

Panel A. Firm age and default risk in high (red, dashed) and low (blue) disruption industries

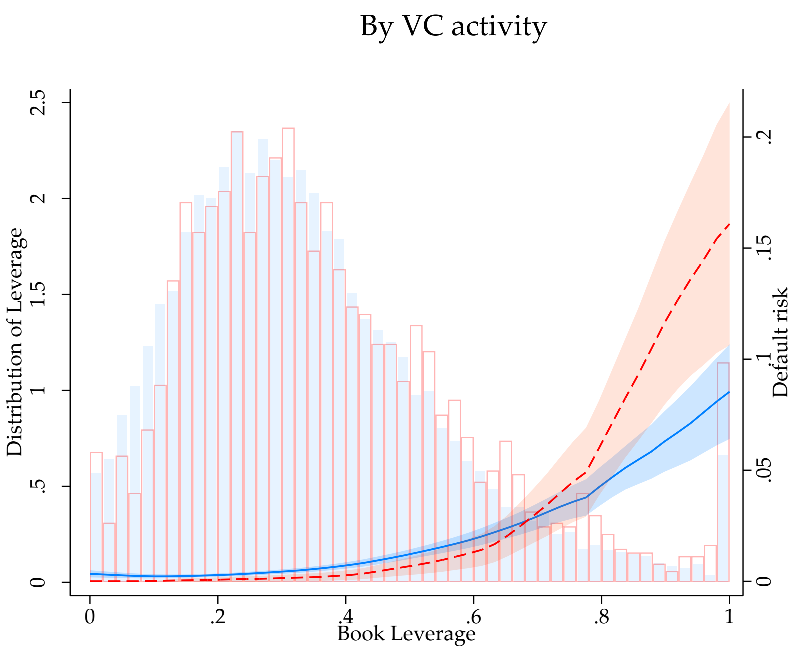


Panel B. Enterprise value and default risk in high (red, dashed) and low (blue) disruption industries





Panel C. Book leverage and default risk in high (red, dashed) and low (blue) disruption industries



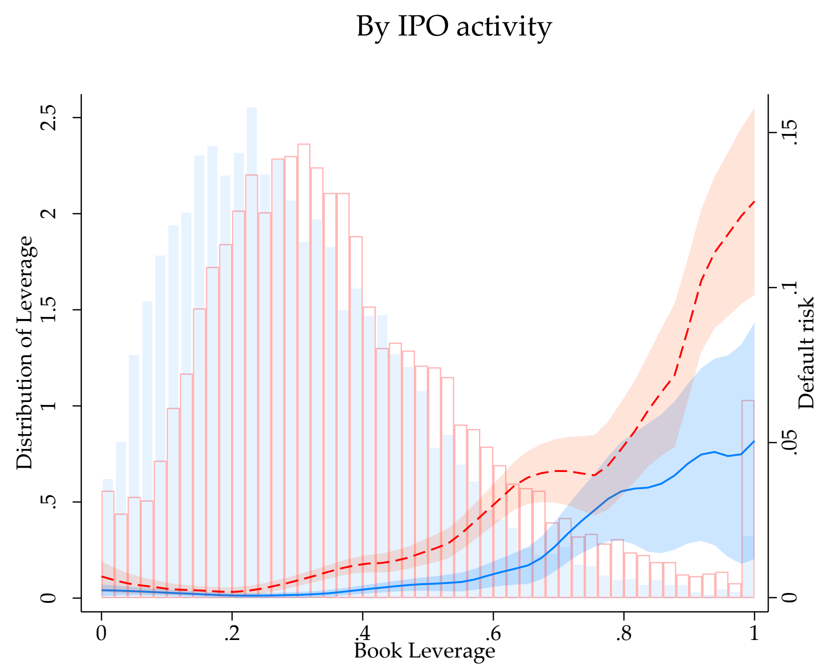


TABLE I – SAMPLE OVERVIEW

Summary statistics for data sets used in regressions. Panel A reports bond features, Panel B data from the panel regressions of default risk and variables collected at industry level. In Panel A, observations are individual bonds at issue. In Panel B, observations represent issuer-year. (When an issuer has more than one outstanding bond at a given time, the average value across bonds is used.) The data set starts in 1970. Bond rating at issue is the median of ratings issued by S&P, Moody's, and Fitch. Bond restructuring includes bankruptcies, distressed exchanges, and other default outcomes. VC capital flow data is from VenturXpert and captures five-year aggregates. The alternative VC capital flow variables, which are indicators constructed using data from Burgiss, capture five-year periods when investment exceeds a threshold. *VC performance* refers to TVPI and is from Burgiss. Early stage is a subset of VC investments. U.S. refers to VC target domicile. IPO *share* is the fraction of firms in the industry with an IPO in the last five years, excluding reverse LBOs. VC-backed IPO is based on Jay Ritter's data for IPOs. The last two variables in Panel B show a value-weighted share using enterprise value and revenues.

Panel A. Bond cross-section

Variable	10th percent	25th percent.	Mean	75th percent.	90th percent.	Std dev.	Obs.
Treasury spread (bps)	0	0	167	225	457	201	37,823
Value (M$)	0.25	1.5	210.9	207	500	1,483	140,752
Callable	0	0	0.505	1	1	0.500	140,753
Covenants	0	0	0.204	0	1	0.404	140,753
Senior	0	1	0.892	1	1	0.310	140,753
Maturity at issue	0.5	1.0	6.6	10.0	15.0	7.9	140,651
Rating at issue (num.)	1	1	6.6	9.5	14.5	4.4	75,671
Rating at issue	AAA	AAA	A	BBB	B+	-	75,671

Panel B. Bond issuer panel

Variable (Unit: issuer*year)	10th perc.	25th perc.	Mean	75th perc.	90th perc.	Std dev.	Obs.
Restructuring	0	0	1.01	0	0	9.99	142,349
VC capital flow ($ million)	31.7	454	7,311	5,866	17,841	19,060	124,412
VC capital flow, log	-0.097	0.641	1.230	1,848	2.427	1.022	121,328
I(VC capital flow over $25 million)	0	0	0.111	0	1	0.315	142,349
I(VC capital flow over $100 million)	0	0	0.108	0	1	0.310	142,349
VC performance	0.976	1.248	3.608	3.248	6.385	4.993	46,513
VC performance, early stage only	0.997	1.000	4.418	3.871	21.180	6.179	29,683
VC performance, U.S. only	0.977	1.248	3.518	3.455	6.146	3.956	26,732
IPO share	0.042	0.096	0.174	0.227	0.337	0.124	126,181
IPO share, VC-backed	0	0	0.097	0	0	0.297	126,181
IPO share (Enterprise Value)	0.014	0.032	0.083	0.121	0.165	0.071	126,181
IPO share (Revenue)	0.012	0.027	0.080	0.115	0.176	0.066	126,181

TABLE II – CREDIT QUALITY AND CHANGES IN FINANCIAL PERFORMANCE

This table shows a decomposition of earnings before interest, tax, depreciation, and amortization (EBITDA) for Compustat firms. All changes are one-year. Columns (1)-(3) separate firms into those that experience a downgrade, no change, or upgrade in their S&P long–term credit rating (unrated firms are excluded). Column (4) looks at defaults (a subset of column (1)). The "young firms" sample in column (4) includes firms (both rated and unrated) within five years of IPO. All changes are in real terms (adjusted with the CPI deflator from the U.S. Bureau of Labor Statistics). Market size is the log of total industry sales (all Compustat firms in the same FF30 industry). Market share refers to the log of a firm's share of the total sales of all Compustat firms in the same FF 30 industry. EBITDA margin is the log of EBITDA divided by revenue. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Variable	Downgrade (1)	No change (2)	Upgrade (3)	*t*-stat. (3) – (1)	Young firms (4)	*t*-stat. (4) – (1)	Defaults (5)	*t*-stat. (5)-(2)
EBITDA decomposition:								
Δ Market size (log)	0.2%	2.8%	3.6%	15.8 ***	3.8%	27.4 ***	4.3%	1.6
Δ Market share (log)	– 4.2%	2.3%	6.5%	9.8 ***	12.2%	45.0 ***	-26.2%	-9.1 ***
Δ EBITDA margin (log)	– 10.5%	0.5%	519%	14.8 ***	-3.5%	10.5 ***	-0.1%	-0.0

TABLE III – DISRUPTION AND CREDIT RISK

This table presents linear probability (OLS) and proportional hazard models of corporate bond defaults from 1970-2019. Each observation is a firm-year. The dependent variable is equal to 100 if, in the following year (t+1), a firm had a bond restructured according to Mergent-FISD, and 0 otherwise. *VC capital flow* refers to aggregate investment in an industry in the preceding five years. *VC performance* is the average multiple (that is, ratio of the total value of remaining funds and distributions to paid in capital). *IPO share* refers to the number of IPOs in an industry in the last five years, excluding reverse LBOs. In Panel (B), control variables are *Bond debt* (logs) and *Publicly listed* (an indicator), and a series of averages across all of an issuer's outstanding bonds at year-end: *Callable*, *Covenant*, *Senior*, *Senior secured*, *Maturity at issue*, *Time to maturity remaining*. Control variables are measured in the preceding year or in the preceding five-year period (VC variables), and are described in Table 1. For proportional hazard models, coefficients (not hazard ratios) are reported, i.e., a value of zero corresponds to no effect. Standard errors (in parentheses) are clustered by issuer and industry-year. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Panel A. No control variables

Dependent variable	Default $_{t+1}$, {0,100}					
Mean	1.078	1.171	1.051	1.072	1.209	1.045
	(1)	(2)	(3)	(4)	(5)	(6)
Model	OLS	OLS	OLS	Prop. Hazard	Prop. Hazard	Prop. Hazard
Industry VC capital flow	0.134	-	-	0.143**	-	-
	(0.133)			(0.066)		
Industry VC performance	-	0.093***	-	-	0.066***	
		(0.025)			(0.011)	
Industry IPO share	-	-	4.822***	-	-	2.269***
			(1.597)			(0.421)
Year F.E./Industry F.E.	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	120,738	46,513	125,013	106,640	40,348	109,902
R-squared	0.013	0.019	0.015	-	-	-

Panel B. With additional control variables

Dependent variable	Default $_{t+1}$, {0,100}					
Mean	1.018	1.177	1.054	1.075	1.215	1.055
	(1)	(2)	(3)	(4)	(5)	(6)
Model	OLS	OLS	OLS	Prop. Hazard	Prop. Hazard	Prop. Hazard
Industry VC capital flow	0.121	-	-	0.137**	-	-
	(0.131)			(0.066)		
Industry VC performance	-	0.094***	-	-	0.067***	-
		(0.024)			(0.011)	
Industry IPO share	-	-	4.632***	-	-	2.327***
			(1.470)			(0.423)
Bond debt outstanding, log	0.016	0.012	0.009	0.058**	0.025	0.049
	(0.023)	(0.040)	(0.018)	(0.031)	(0.056)	(0.031)
Callable (share)	0.501***	0.290	0.506***	0.492***	0.371**	0.487***
	(0.108)	(0.190)	(0.103)	(0.105)	(0.180)	(0.104)
Covenants (share)	0.359***	0.359**	0.351***	0.215***	0.160	0.222***
	(0.079)	(0.139)	(0.078)	(0.077)	(0.118)	(0.077)
Senior (share)	-0.248**	-0.304	-0.213*	-0.128	0.134	-0.144
	(0.127)	(0.197)	(0.126)	(0.283)	(0.712)	(0.278)
Senior Secured (share)	0.466***	0.477	0.500***	0.353	0.570	0.339
	(0.180)	(0.352)	(0.169)	(0.288)	(0.721)	(0.284)
Initial tenor	-0.012***	-0.030***	-0.034***	-0.049***	-0.028*	-0.051***
	(0.004)	(0.010)	(0.007)	(0.012)	(0.016)	(0.012)
Remaining maturity	-0.012***	-0.013***	-0.011***	-0.028***	-0.043***	-0.027***
	(0.004)	(0.005)	(0.004)	(0.008)	(0.016)	(0.008)
Year F.E./Industry F.E.	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	120,738	46,308	124,402	105,170	40,152	108,314
R-squared	0.017	0.022	0.018	-	-	-

TABLE IV – ALTERNATIVE MEASURES OF DISRUPTION

This table reports results from proportional hazard models like those reported in Table 3, Panel A, columns (4)-(6). Each result in rows (1) through (7) corresponds to a separate regression. In rows (1) and (2), VC active industry is defined as any industry-year with at least $25 million and $100 million 2015 U.S. dollars (respectively) of VC investment in the prior five-year period (both conditional on Burgiss filters discussed in the data section). In row (3), late-stage VC is excluded. In row (4), only U.S.-based VC targets are used to measure VC returns. In row (5), we only use VC-backed IPOs according to Ritter's (2015) classification. In row (6), IPO share is weighted by enterprise value (market cap plus book value of debt), in row (7) by revenue. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

	Independent variable	Coeff.	Obs.
(1)	Industry VC capital flow ($25 million threshold)	0.729***	115,296
		(0.149)	
(2)	Industry VC capital flow ($100 million threshold)	0.708***	115,296
		(0.164)	
(3)	Industry VC performance, early stage	0.039***	25,698
		(0.150)	
(4)	Industry VC performance, U.S. targets only	0.108***	22,918
		(0.020)	
(5)	Industry IPO share (VC-backed)	2.309***	109,902
		(0.424)	
(6)	Industry IPO share (Enterprise value)	6.596***	109,902
		(1.943)	
(7)	Industry IPO share (Revenue)	3.914***	109,902
		(0.706)	

TABLE V – DISRUPTION AND CREDIT RISK: HETEROGENEOUS EFFECTS

This table presents regression results for various subsamples. Regressions use proportional hazard models based on those reported in Table 3, Panel A, columns (4)-(6). Each cell of the table reports the coefficient of interest from a separate regression. The $500 million cutoff is measured in 2015 US dollars. Standard errors (in parentheses) are clustered by issuer and industry-year. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

		Industry VC capital flow (1)	Industry VC performance (2)	Industry IPO share (3)
By age:				
Old	At least seven years since IPO or first bond issue	0.074	0.046***	0.551
		(0.107)	(0.017)	(0.816)
Young	At most six years since IPO or first bond issue	0.160*	0.071***	2.806***
		(0.083)	(0.015)	(0.514)
By size:				
Large	At least $500 million of bond debt outstanding	0.249**	0.073***	3.617***
		(0.108)	(0.016)	(0.645)
Small	Less than $500 million of bond debt outstanding	0.010	0.064***	0.836
		(0.086)	(0.017)	(0.594)
By credit quality:				
IG	Average bond rating BBB- or above	1.316***	-	6.592***
		(0.518)		(2.181)
HY	Average bond rating BB+ or below	0.041	0.065***	2.087***
		(0.073)	(0.012)	(0.495)
By industry type:				
Not deregulated	Excludes "Transportation," "Petroleum and Natural Gas," and "Communication"	0.596***	0.064***	1. 887***
		(0.139)	(0.011)	(0.464)
Non-financials	Excludes "Banking, Insurance, Real Estate, Trading"	0.531***	0.066***	2.363***
		(0.134)	(0.011)	(0.418)

TABLE VI – DISRUPTION AND PATENTING ACTIVITY

This table presents two sets of results. Columns (1)-(4) build on the results in Table 3, column (3) (proportional hazard model) for the 1970-2019 sample of corporate bond defaults. Columns (5)-(8) build on the results in Table 9, column (1) for bond yields. However, instead of share of IPOs we look at the role of patents and patent citations as a measure of disruption in the industry. Standard errors are clustered by industry-year and issuer. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Dependent variable	Default_{t+1}				Bond yield spread			
Mean	0.983	0.983	1.017	0.983	175.1	175.1	175.1	175.1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patents (log)	0.032	-	-	-	16.31***	-	-	-
	(0.281)				(0.186)			
Patent citations (log)	-	0.317	-	-	-	15.47***	-	-
		(0.387)				(1.88)		
Patents, individual filer (log)	-	-	0.270***	-	-	-	15.47***	-
			(0.092)				(1.89)	
Patents, corporate filer (log)	-	-	-0.217***	-	-	-	- 94.84***	-
			(0.065)				(9.14)	
Citations, most cited patent (log)	-	-	-	-0.045	-	-	-	82.18***
				(0.094)				(14.16)
Controls (Table 3, column (3))	Yes	Yes	Yes	Yes	-	-	-	-
Controls (Table 9, column (1))	-	-	-	-	Yes	Yes	Yes	Yes
Year & Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,715	80,715	80,715	80,715	24,588	24,588	24,563	24,563
Issuer clusters	9,213	9,213	9,213	9,213	6,196	6,196	6,195	6,195

TABLE VII – DISRUPTION AND CREDIT RISK: SENSITIVITY TO INDUSTRY CHARACTERISTICS

This table reports results with additional industry-level control variables. Regressions are based on those reported in Table 3, Panel B, columns (4)-(6). Industry Market-to-Book is the aggregate ratio of total industry market value of equity plus book value of debt to industry total book value of debt and equity. Industry EV-to-EBITDA is the aggregate ratio of market value of equity plus book value of debt to EBITDA. R&D spending is the total reported in Compustat for the industry in a year, normalized by total reported sales for firms in the industry. IT spending is the computer hardware and software share of industry expenses from U.S. input-output tables, matched to FF30 industries. Firm level control variables are described in Table 3. Standard errors (in parentheses) are clustered by issuer and industry-year. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Dependent variable		Default $_{t+1}$	
Mean	0.989	1.068	0.961
	(1)	(2)	(3)
Model	Prop. Hazard	Prop. Hazard	Prop. Hazard
Industry VC capital flow	0.130*	-	-
	(0.074)		
Industry VC performance	-	0.054***	-
		(0.013)	
Industry IPO share	-	-	1.317**
			(0.552)
Industry Market-to-Book	-0.563***	-0.073	-0.556***
	(0.169)	(0.332)	(0.168)
Industry EV-to-EBITDA	0.031***	0.015	0.025***
	(0.008)	(0.014)	(0.008)
R&D spending	8.79	32.92	14.55
	(9.86)	(20.91)	(10.33)
IT spending	-1.743*	-1.878	-1.800**
	(0.888)	(1.160)	(0.887)
Year F.E./Industry F.E.	Yes/Yes	Yes/Yes	Yes/Yes
Firm-level Control Variables	Yes	Yes	Yes
Observations	92,321	32,481	94,999

TABLE VIII – SEGMENT EXITS

This table presents the results of linear probability models of segment exits. Data is collected from Compustat Business Segment Data for the period 1977-2019. The unit of observation is a segment-year. The dependent variable (segment exit) is a dummy equal to 1 if a segment is no longer being reported in the following year (but the firm still reports segments the following year), and 0 otherwise. Control variables are based on segment assets, sales, and operating income. *Segment Sales Rank* is defined within firm-year. *Core Segment* is a dummy equal to 1 if the segment is the same as the firm-level industry classification. In regressions with control variables (columns (3)-(6)), independent variable outliers are dropped. Standard errors are clustered by firm and year. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Dependent variable	Segment Exit					
Mean	0.169	0.143	0.175	0.140	0.134	0.144
	(1)	(2)	(3)	(4)	(5)	(6)
Model	OLS	OLS	OLS	OLS	OLS	OLS
Industry VC capital flow	0.029***	-	-	0.013***	-	-
	(0.003)			(0.005)		
Industry VC performance	-	0.001	-	-	-0.004	-
		(0.003)			(0.005)	
Industry IPO share	-		0.043*	-	-	0.049
			(0.027)			(0.052)
Segment sales (log)	-	-	-	0.006***	0.004**	0.002
				(0.002)	(0.002)	(0.002)
Segment assets (log)	-	-	-	-0.015***	-0.013***	-0.012***
				(0.002)	(0.002)	(0.001)
Segment sales rank	-	-	-	0.006***	0.027	0.006***
				(0.002)	(0.025)	(0.002)
Core segment	-	-	-	-0.024***	-0.023***	-0.028***
				(0.004)	(0.006)	(0.006)
Operating income	-	-	-	-0.013**	-0.046***	-0.029***
				(0.005)	(0.011)	(0.007)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	353,242	74,786	300,308	86,532	41,057	80,018
R-squared	0.561	0.512	0.585	0.504	0.517	0.585

TABLE IX – DISRUPTION AND BOND YIELDS

Linear regression of corporate bond yield spreads to maturity at issue. Each observation is one corporate bond issuance. The spread is the yield in basis points above a treasury benchmark, as reported in Mergent FISD. Convertible bonds are excluded. Control variables except bond face value (log, in 2015 dollars) are indicator variables. Unrated, Callable, and Covenants are also indicators. Face value is the log of the amount issued. Other control variables are described in Table 1. High yield is dummy variable equal to 1 if the bond had a median credit rating below BBB- at issue. Standard errors are clustered by industry-year and issuer. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Dependent variable	Yield to Maturity			Yield Spread		
Mean	8.206	6.069	8.515	173.6	246.2	168.5
	(1)	(2)	(3)	(1)	(2)	(3)
Model	OLS	OLS	OLS	OLS	OLS	OLS
Industry VC capital flow	0.253**	-	-	26.84***	-	-
	(0.130)			(8.42)		
Industry VC performance	-	0.037	-	-	1.039	-
		(0.044)			(0.810)	
Industry IPO share	-	-	3.267***	-	-	176.2***
			(0.590)			(24.9)
Control variables:	Yes	Yes	Yes	Yes	Yes	Yes
Year-month of issue F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E. x Maturity	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E. x Maturity sq.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87,012	26,268	78,343	40,146	16,184	35,186
R-squared	0.491	0.352	0.482	0.358	0.278	0.389

APPENDIX A: CLASSIFYING FIRM AND INDIVIDUAL PATENT APPLICANTS

Patent filings were collected from the U.S. Patent and Trademark Office database. Our starting sample of U.S. patents published from 1955-2016 had 7,349,389 observations. All patents are assigned International Patent Classification (IPC) codes, which, according to the World Intellectual Property Organization, "[provide] for a hierarchical system of language independent symbols for the classification of patents and utility models according to the different areas of technology to which they pertain." Because IPC codes are different from the SIC, NAICS, and Fama-French industry codes we use in our analysis, to use IPC codes in the analysis we need to map each code to a standard industry classification. Another challenge is that individual patents are often associated with more than one IPC code (the average is 20), reflecting the multiple possible commercial uses of the fundamental ideas captured in patents. We translate IPC codes to the International Standard Industrial Classification (ISIC) Rev. 2 codes, which we then translate in successive steps to ISIC Rev. 3, ISIC Rev. 4, and eventually to NAICS codes. We sum the number of patents by 2-digit NAICS code and year. Although this process involves multiple steps, several are fairly simple (involving similar industry categories).

We also classified patents into those filed by individuals and those filed by business firms (corporations). We classify filers as corporations if the name of the filer includes any of the following terms.

AIRCRAFT	HOLDING	OPTICAL
AMERICA	INC	PETROLEUM
AMERICAN	IND	PRODUCTS
AUTOMATIC	INDUSTRIES	RESEARCH
CHEM	INSTRUMENTS	SEMICONDUCTOR
CHEMICAL	INTELLECTUAL	SOLUTIONS
CO	INTERNACIONAL	SYSTEMS
COMPANY	INTERNATIONAL	TECH
CORP	LABORATORIES	TECHNOLOGIES
DEVELOPMENT	LIMITED	TECHNOLOGY
DEVICES	LLC	TELEGRAPH
ELECTRIC	LTD	TELEPHONE
ELECTRONICS	MATERIALS	TRUST
ENERGY	MEDICAL	TRUSTEES
ENG	MFG	UNION
ENGINEERING	MICROELECTRONICS	UNITED
GLOBAL	MICROSOFT	UNIV
GMBH	MOTORS	USA
GROUP	OPERATIONS	

This list was developed manually by looking at the three hundred most frequent terms in the name field.