Exposure to Superstar Firms and Financial Distress

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ABSTRACT

A small minority of highly successful firms (referred to as superstar firms) have captured large market shares and earned massive profits in recent decades. Although various macroeconomic developments, such as an increase in industry concentration, have been attributed to the rise of superstar firms, there is little empirical evidence on how superstars affect individual firms exposed to them in product markets. We conjecture that superstars adversely affect the survival of these firms and provide supporting evidence. Building on recent research that shows that superstar firms are associated with increasing aggregate markups, we identify superstars as firms with the highest markups in the industry and whose industry markup share is increasing over time. We then measure a focal firm's overall exposure to superstars by employing product similarity scores. We document that firms with greater exposure to superstars in product markets are more likely to subsequently file for bankruptcy. We also shed light on the underlying channels through which superstar exposure is associated with bankruptcy and show that firms with the greater exposure exhibit weaker financial performance and greater riskiness. Furthermore, the association between superstar exposure and the likelihood of bankruptcy is concentrated among firms that are less innovative and those that have a weaker access to debt capital, as these firms are less likely to withstand the competitive pressure from superstar firms. Finally, we triangulate our primary evidence by documenting that sophisticated market participants, including dedicated institutional investors, short sellers, and auditors, account for the adverse effects of superstar exposure in their decision-making. Overall, our paper highlights the firm-level consequences of the superstar firm phenomenon, develops a tractable measure of superstar exposure, and documents the positive association between this exposure and firms' financial distress.

Keywords: Superstar Firms; Financial Distress; Bankruptcy; Financial Performance; Innovation; Access to Credit.

1. INTRODUCTION

Technological advances in recent decades have enabled a small minority of highly successful firms to corner large market shares and earn outsized profits. These firms have grown to dominate their industries and the overall economy and thus are known as "superstar firms" (Autor et al. 2020). Emerging research suggests that the rise of superstar firms in recent decades is a likely reason behind the increase in aggregate markups and profitability, rising industry concentration, declining labor share of growth domestic product (GDP), and an increase in the importance of aggregate earnings in explaining individual firms' equity valuations (Autor et al. 2020; Barkai 2020; De Loecker et al. 2020; Sadka et al. 2022).[1] Although these studies attribute several recent macroeconomic developments to the rise of superstar firms, there is little evidence on how superstars affect individual firms that are exposed to them in product markets. We fill this gap by investigating superstars' potential adverse effects on the survival of these firms.

The presence of superstar firms can result in "creative destruction" that can lead to disruptive outcomes for other firms. According to Schumpeter (1934) and Aghion and Howitt (1992), creative destruction entails new innovative economic and technological forces overcoming the existing ones. "Disruptive technology" is a term coined by Christensen (2013) to refer to such new technologies that come to surpass the dominant technologies in specific markets. Some firms exposed to superstars in product markets may be unable to cope with the innovations brought about by superstars due to technological, financial, or management quality reasons (e.g., Tushman and Anderson 1986; Rosenbloom and Christensen 1994; Christensen and Rosenbloom 1995; Gilbert

[1] The use of the term "superstars" in economics dates back to Rosen (1981) who describes and models the superstar phenomenon in the context of outsized income earned by a select few individual performers. We use "superstar firms" and "superstars" interchangeably throughout the paper.

and Bower 2002; Dewald and Bowen 2010; Shivakumar 2017). These firms will thus struggle to compete with superstars and may eventually be driven out of business.

Our proposition that firms with greater exposure to superstars in product markets are more likely to subsequently file for bankruptcy is also supported by institutional evidence. Policymakers are increasingly concerned about the influence of superstar firms on their peers. The US House Antitrust Subcommittee has outlined multiple pieces of legislation targeting dominant technology firms (Reuters Staff 2021). Business press also suggests that superstars may be the reason behind the recent wave of business failures in certain industries (Irwin 2018; Kavoussi 2019). For example, Amazon quintupled its sales between 2010 and 2016 and is alleged to be the driving force behind the "retail apocalypse" that subsequently led to several high-profile brick-and-mortar business bankruptcies (e.g., Thompson 2017). Ride-hailing businesses, such as Uber and Lyft, garnered 70.5% of the total market in 2018, whereas traditional taxi and rental car firms accounted for only 23.5% and 6% of the ground transportation market, respectively (Goldstein 2018). Many argue that firms such as Airbnb have transformed the travel industry, as the share of American travelers using private accommodations quadrupled from 2010 to 2015 (Thompson 2018).

Nonetheless, we acknowledge that despite the economic pressure imposed by superstar firms, they may also provide spillover benefits to other firms. For example, superstar firms may create greater business opportunities by attracting more labor talent and external capital to their industries. In addition, the pressure to innovate in product markets due to superstars' focus on innovation may incentivize other firms to introduce new products and services or to improve their existing offerings (e.g., Lang and Stulz 1992; Chevalier-Roignant et al. 2019). Firms that innovate and successfully adapt can capitalize on these spillover benefits. Therefore, the effect of superstars on the survival of firms exposed to them in product markets is an empirical question.

A key empirical challenge in studying the influence of superstar firms is measuring an individual firm's exposure to superstars. We address this challenge in two steps. In the first step, motivated by Autor et al.'s (2020) idea that superstars are firms that increasingly dominate the product markets, we aim to identify firms that are characterized by both large product market power and an increase in this power over time. However, as Autor et al. (2020) conduct their examination of superstar phenomenon at the industry level, to measure market power at the firm level, we follow the markup-based approach developed by De Loecker and Warzynski (2012) and De Loecker et al. (2020). Specifically, we measure a firm's market power based on its markup amount, defined as the product of the markup ratio (i.e., sales price relative to marginal cost) and sales (see Section 2 and Appendix A for detailed discussion). We then classify a firm as a superstar if (1) its markup amount is in the top 5 percent of firms in its SIC 4-digit industry in a given year, and (2) it experiences an increase in its share of the total SIC 4-digit industry markup amount relative to the previous year. In the second step, to account for the intensity of a focal firm's exposure to different superstar firms, we employ product similarity scores developed by Hoberg and Phillips (2010; 2016) and assign more weight to superstar firms with higher product similarity scores with the focal firm. Last, we assign firms with exposure to at least one superstar into annual decile ranks scaled by 10, such that our measure of superstar exposure takes the value of 0.1 to 1 for firms with superstar exposure, and zero for firms without any exposure to superstars.

To examine whether superstar firms have a detrimental effect on firms exposed to them into product markets, we rely on a sample of US publicly listed firms over the 1988–2018 period. Employing a logit model, we find that firms with greater exposure to superstars are more likely to file for bankruptcy in the following year. In terms of economic significance, firms with the highest exposure to superstars (i.e., firms in the 10^{th} decile of superstar exposure) exhibit a 40% higher odds of bankruptcy compared with those without any superstar exposure. Our findings are robust to the use of the OLS and Cox proportional hazard models, and alternative industry classification. Our findings are further robust to the use of alternative assumptions in identifying superstar firms and alternative proxies for financial distress—performance-based delisting, a broader measure of credit events that includes payment defaults, distressed debt exchanges, and formal restructurings, and credit rating downgrades from an investment grade to a junk. The results remain similar after controlling for variables reflecting industry-level risk and free cash flows, alleviating concerns that the relation between superstar exposure and bankruptcy is driven by time-varying industry-level factors. Collectively, these results indicate that firms with higher exposure to superstar firms in product markets are more likely to suffer financial distress, reflecting a "winner takes all" situation.

We next conduct path analyses (e.g., Bushee and Noe 2000) to explore the channels through which firms' exposure to superstars can affect the likelihood of bankruptcy. We appeal to the Black-Scholes-Merton framework (Merton 1974) that characterizes a firm's equity as a call option on its assets, and posit that a firm's default likelihood is inversely related to its expected asset return and positively related to volatility in asset values. We approximate a firm's asset return by financial performance, including accounting performance and equity returns, and we measure volatility in asset values with stock return volatility. We find that all three measures are positively associated with a firm's bankruptcy likelihood. Using the Sobel test, we also show that the three paths associated with these measures are significant mediating effects, indicating that the documented association between superstar exposure and the likelihood of bankruptcy is mediated by its association with financial performance and stock return volatility. We thus infer that superstar exposure is associated with worse financial performance and greater riskiness, contributing to a higher likelihood of future bankruptcy.

We shed additional light on the accounting performance channel by decomposing return on assets into three components that reflect operating income, interest expense, and other income. We show that the mediating effect of poor accounting performance works through low operating income and high interest expense, with the latter result potentially attributed to superstar exposure leading to greater riskiness, which is reflected in a focal firm's higher cost of debt capital. These findings further suggest that the association between bankruptcy and superstar exposure we document operates through intuitive mediating paths of financial performance and risk.

To further reinforce our inference that exposure to superstars is positively related to bankruptcy likelihood, we conduct two cross-sectional analyses and examine whether this association varies with a focal firm's ability to withstand disruptive effects of this exposure. As discussed earlier, although firms generally face economic pressure due to superstar exposure, some can survive and may even benefit from the competitive pressure from superstars as it will incentivize them to innovate in the product markets. Thus, more innovative firms should be technologically and strategically better able to adapt to competitive pressures from superstars. As expected, we find that the positive association between superstar exposure and future bankruptcy is concentrated among firms that do not engage in innovation activity, which we measure based on research and development (R&D) expenditure and filed patents.

On the other hand, firms with a weaker access to debt capital are likely to have low flexibility to adjust their operating and investing activities to withstand the competitive pressure of superstars.

We thus predict and find that the positive relation between superstar firm exposure and future bankruptcy is concentrated among firms with weaker access to credit, which we measure by lower undrawn revolving credit and lower tangible assets (Sufi 2009; Jiménez et al. 2009; Lins et al. 2010; Falato et al. 2013; Rampini and Viswanathan 2013; DeMarzo 2019).

Because bankruptcy is a critical outcome that affects not only firms and creditors but also all other stakeholders in the firm, in the last set of our analyses, we examine whether sophisticated market participants incorporate a firm's exposure to superstars into their decision-making. We find that analysts do not reflect the detrimental effect of superstar exposure in their recommendations, but short sellers, dedicated institutional investors, and auditors appear to take cognizance of these effects. These findings are in line with prior research that shows that sell-side analysts underreact to or have a tendency to withhold bad news, while short sellers, dedicated institutional investors, and auditors have superior information-processing abilities, allowing them to more accurately assess how superstar exposure affects firms' viability prospects (e.g., McNichols and O'Brien 1997; Khan and Lu 2013; Borochin and Yang 2017; Zimmerman et al. 2023). This evidence that sophisticated market players account for superstar exposure in their decision-making also further supports our primary inference that this exposure increases the likelihood of financial distress.

Our study contributes to the literature on bankruptcy and default prediction (e.g., Beaver 1966; Altman 1968; Altman et al. 1977; Ohlson 1980; Zmijewski 1984; Beaver et al. 2005; Shumway 2001; Chava and Jarrow 2004; Campbell et al. 2008). While prior studies explore primarily accounting and market-based predictors of financial distress, limited attention has been accorded to the effect of broad industry factors or macro-level trends. A notable exception is Amiram et al. (2017) that show that lenders demand higher spreads to bear industry-level risk and that industry characteristics inform lenders about both expected losses and risk premiums. We contribute to prior research by documenting that a firm's exposure to macroeconomic developments—such as the rise of superstar firms—can be an important consideration in assessing the probability of financial distress. Importantly, we further show that the exposure to superstar firms influences financial distress likelihood through financial performance (accounting performance and equity returns) and riskiness channels. We also highlight that the accounting performance channel is attributed to the adverse effect of superstar exposure on a focal firm's operating income and interest expense.

Our paper also adds to the emerging research on the superstar firm phenomenon. Prior studies examine various reasons contributing to the rise of superstar firms, including changes in the economic environment, such as globalization and favors created by the tax system (e.g., Autor et al. 2020; Gallemore and Maydew 2023). There is also evidence that the rise of superstars explains several puzzling macroeconomic and financial market trends. De Loecker et al. (2020) find a significant increase in aggregate markups in the US, which they mainly attribute to the rise of superstars. Autor et al. (2020), Barkai (2020) and De Loecker et al. (2020) also suggest that the decline in labor share of GDP over time is explained by an increase in sales concentration due to the prominence of superstars in several industries. Sadka et al. (2022) study changes in the earnings-return relationship over time and attribute the rising importance of aggregate earnings in explaining firm-level stock returns to superstars. We add to these studies by exploring the influence of superstars on the financial distress of firms exposed to them in product markets. We also shed light on whether sophisticated market participants—analysts, auditors, short sellers, and dedicated institutional investors—incorporate a firm's exposure to superstars into their decision-making.

Relatedly, in terms of methodological contribution, we propose a tractable method for identifying superstar firms using financial statement data. Although a number of studies employ different strategies to identify superstar firms (e.g., Tambe et al. 2021; Kroen et al. 2022; Gallemore and Maydew 2023), to the best of our knowledge, our study is one of the first to build on the evidence that market power, as captured by markups, is a key element of the superstar phenomenon (De Loecker et al. 2020; De Loecker and Eeckhout 2021).[2] We further develop a measure of product-market exposure to superstars at the firm level. This measure can be adapted by accounting researchers to investigate other firm-level outcomes related to the superstar firm phenomenon. For example, future research can study whether and how superstars affect the information environment of firms exposed to them in the product markets. Exposure to superstar firms may influence firms' financial reporting and voluntary disclosure choices, including the extent of information disclosed and the way it is disseminated to customers, investors, and other stakeholders. Future research can further explore how superstar exposure influences firms' operating, financing, and investing activities, such as product offerings, hiring and recruitment, borrowing, and mergers and acquisitions. Importantly, our measure of superstar exposure can also be relevant for regulators and policymakers in the US and worldwide that debate new regulations to curb the outsize power of superstar firms (e.g., Irwin 2018; Zhai 2021).

[2] Tambe et al. (2021) identify superstars as firms in the top decile of their sample in terms of market value, while Kroen et al. (2022) identify superstars as firms in the top 5 percent of firms in their respective Fama-French industry based on market value. Gallemore and Maydew (2023) identify superstar firms based on size (those with market capitalization or total sales in the top decile of sample firms) and profit margins (those with pretax profits to revenues ratio greater than or equal to 15 percent).

2. Data, Sample, and Variable Measurement

2.1 Data and Sample

We obtain bankruptcy filings data from the New Generation Research's Bankruptcydata.com database. Hoberg-Phillips similarity scores are from the Hoberg-Phillips Data Library.[3] We collect data on firms' accounting information from Compustat, market- and trading-related variables from CRSP, audit opinions from Audit Analytics, and Standard and Poor's credit ratings from Capital IQ. Data used in cross-sectional and supplementary analyses are from a variety of additional sources, including Capital IQ capital structure database, I/B/E/S, Thomson Reuters, Professor Brian Bushee's institutional investor classification data,[4] and Kogan et al. (2017)'s extended dataset on technological innovation resource allocation.[5]

Table 1, Panel A reports the sample construction. We start with 221,923 firm-year observations of US public firms from 1988 to 2018. The sample period begins in 1988 because data on operating cash flows, which is an important potential determinant of financial distress likelihood, is not available prior to 1988. We merge this sample with the CRSP monthly stock file to construct market-based variables, reducing the sample size to 160,856 firm-year observations. We further exclude commercial banks and insurance carriers (SIC codes 60 and 63) because these institutions face a substantially different insolvency resolution processes from firms in other industries, resulting in a sample of 139,987 firm-year observations.[6] After requiring non-missing value for all variables used in our analyses and excluding observations related to bankrupt firms

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[3] https://hobergphillips.tuck.dartmouth.edu
[4] https://accounting-faculty.wharton.upenn.edu/bushee/
[5] https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data
[6] Our inference remains unchanged if we retain commercial banks and insurance companies in the sample.

subsequent to their bankruptcy filing dates, our final sample consists of 116,692 firm-year observations. Panel B presents the sample distribution by year. Panel C shows the sample composition by industry. Our sample has the greatest concentration in the manufacturing industry, followed by the construction, finance and real estate, and wholesale trade industries.

2.2 Measurement of Exposure to Superstar Firms

2.2.1 Identifying Superstar Firms

Our primary variable of interest is "superstar exposure," or the extent to which a firm is exposed to superstars. To construct this variable, we start by identifying superstar firms. Although there is no universally accepted definition of superstar firms at the firm level, Autor et al. (2020) describe firms that *increasingly dominate* the product markets as "superstar firms." Inspired by this idea of increasing power in the product markets, we define superstars conceptually as firms with (i) large product market power, and (ii) increasing market power over time. Autor et al. (2020) conduct their analysis at the industry level, whereas we are interested in firm-level identification of superstars. To identify firms with large market power, we follow De Loecker and Warzynski (2012) and De Loecker et al. (2020) who characterize firms with high markups (i.e., sales price relative to marginal cost) as having large market power. High markups are indicative of a firm's high product market power because they reflect the firm's ability to charge a higher price and extract economic rents from customers (De Loecker et al. 2020). This market power may be driven by a combination of factors, such as product market shares, attributes of products or services offered (e.g., uniqueness and quality), and access to financing.

To estimate firms' markups, De Loecker and Warzynski (2012) and De Loecker et al. (2020) start by estimating markup ratio (*Markup Ratio)* as the product of two components: (i) the inverse of variable cost margin (i.e., $\frac{PQ}{P^V V}$, where P and Q are the price and quantity of output, and P^V and V are the price and quantity of the variable input), and (ii) the output elasticity of the variable input (i.e., the ratio of the percentage change of output Q to the percentage change of the variable input V). Following De Loecker et al. (2020), we measure the former component as the ratio of sales (*Sales*) to cost of goods sold (*COGS*) and assign a value of 0.85 to the latter one, such that *Markup Ratio* is measured by 0.85**Sales/COGS*.[7] Appendix A reports further details of this approach.[8]

Importantly, while *Markup Ratio* captures the concept of product market pricing power, it does not account for the role of a firm's size, which is a critical factor in the characterization of superstars in accordance with Autor et al. (2020). We use Fitbit—a wireless-enabled wearable producer operating in the radio and television broadcasting and communications equipment industry (SIC code=3663)—as an example to illustrate the importance of size in identifying superstar firms. In 2017, Fitbit's *Markup Ratio* was 1.56, whereas the industry giant Apple Inc.'s *Markup Ratio* was 1.48. Although Fitbit's *Markup Ratio* is higher than that of Apple's, Apple wields substantially greater product market influence and thus is more likely to be a superstar firm than its much smaller peer Fitbit (Fitbit was delisted due to an acquisition in 2019). Accordingly, adjusting for a firm's size reduces error in misclassifying small but successful businesses such as Fitbit as superstar firms. Consequently, we follow De Loecker et al. (2020) who weight markup ratio by sales and estimate *Markup Amount* as *Markup Ratio* × *Sales*.

Relying on *Markup Amount* and in line with the insights from Autor et al. (2020) that

[7] In untabulated analyses, we find that all results are similar if the output elasticities are assumed to be time varying and sector specific, as in Fig. 1 of De Loecker et al. (2020).

[8] We thank De Loecker et al. (2020) for sharing their detailed code for replication (available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/5GH8XO).

superstar firms *increasingly dominate* their product markets, we classify a firm as a superstar if the following two conditions are satisfied. First, a firm's *Markup Amount* is among the top 5 percent of the SIC 4-digit industry firms in a given year.[9] When there are fewer than 20 firms in an industry (which means that the top 5 percent is less than one firm), we consider the firm with the largest *Markup Amount* as a superstar firm. Second, we build on the idea that superstar firms become more powerful over time and require a firm to experience an increase in its share of the total SIC 4-digit industry *Markup Amount* relative to the previous year. For example, Apple's *Markup Amount* was in the top 5 percent of the 31 firms in SIC 3663 in 2017 (which satisfies the first condition), and the share of Apple's *Markup Amount* increased from 86.3% in 2016 to 89.5% in 2017 (which satisfies the second one). Thus, we classify Apple Inc. as a superstar firm in 2017.

2.2.2 Calculating A Firm's Product Market Exposure to Superstar Firms

After identifying superstar firms, we measure a focal firm's product market exposure to these firms in all product markets in which it operates. Because a focal firm can be exposed to multiple superstar firms, we estimate the focal firm's overall superstar exposure by aggregating its exposures to individual superstars. Importantly, when aggregating these exposures, we need to account for the intensity of a focal firm's exposure to different superstars, as the focal firm may have different levels of product market overlap with superstar firms. To reflect this variation in exposures, we employ the product similarity scores developed by Hoberg and Phillips (2010; 2016) based on the textual similarity in product descriptions in Item 1 of the 10-Ks between any two firms. Specifically, we sum Hoberg-Phillips pairwise similarity scores between the focal firm and

[9] We use SIC 4-digit code as our industry classification following Autor et al. (2020). In robustness checks reported in Panel B of Table 4, we confirm that our findings are not affected if we focus on the top 5 firms (rather than top 5 percent) or focus on SIC 2-digit (rather than 4-digit) industry.

the superstars it is exposed to (*SuperstarExpo_raw*), which allows us to assign more weight to superstars with higher product similarity scores. [10, 11] Continuing with the Fitbit example, the Hoberg-Phillips database identifies 25 peer firms for Fitbit in 2017, 7 of which are classified as superstars based on the approach outlined in *Section 2.2.1*. The product similarity scores between Fitbit and each superstar firm are 0.066, 0.0225, 0.0183, 0.0124, 0.0095, 0.0043, and 0.0003. Thus, we calculate *SuperstarExpo_raw* for Fitbit as the sum of these scores, which is 0.1333.

Finally, to avoid assigning large weights to a small number of outliers and to facilitate economic interpretation (Dechow and Sloan 1997; Kothari et al. 2005), we transform *SuperstarExpo_raw* into a discrete variable *SuperstarExpo*, which equals the annual decile rank of *SuperstarExpo_raw* scaled by 10 if *SuperstarExpo_raw* is positive, and zero if *SuperstarExpo_raw* is zero. In other words, *SuperstarExpo* takes 11 values between zero and one, such as 0, 0.1, 0.2, to 1.[12] A higher value of *SuperstarExpo* indicates that a focal firm faces greater product market exposure to superstar firms, which suggests greater competitive pressure in the focal firm's product markets.

2.3 Measurement of Other Variables

Our primary outcome variable of interest is the likelihood of business failure of a focal firm. We measure business failure by bankruptcy filings that either require a judicially supervised

[10] If the Hoberg and Phillips database does not contain a pairwise similarity score between a focal firm and a superstar firm, this indicates that these firms' products are sufficiently different and should not be viewed as competing products. In this case, the superstar firm is excluded from the estimation of superstar exposure.

[11] We use the product similarity scores from Hoberg and Phillips' (2016; 2020) TNIC-3 database to measure superstar exposures, as it is the most granular level at which these data are available. Our main inference is robust when we measure superstar exposure based on whether there is *at least one* superstar firm in the SIC 4-digit industry (Table 4, Panel B) rather than relying on the Hoberg and Phillips similarity scores to calculate intensity in exposure to superstars.

[12] Alternatively, we create annual decile ranks among all observations. About 20% of observations do not face superstars, so the bottom decile has too many observations, whereas the second lowest decile contains too few observations. Our inference remains unchanged even with this alternative measure.

reorganization process (i.e., a Chapter 11 process) or a liquidation (i.e., a Chapter 7 process). A bankruptcy filing is typically a measure of last resort—financial distress is so severe that a firm cannot restructure its operations and finances out of court and must resort to a court-supervised procedure. We define *Bankrupt* as an indicator variable that equals to one if a firm declares bankruptcy in year *t+1*, and zero otherwise. In robustness checks we use several alternative financial distress proxies. *PerformDelist* is an indicator variable that equals one if the firm is delisted due to issues related to poor financial performance in year *t+1*, and zero otherwise (Shumway 1997). *Default* is an indicator variable that equals one if credit default events (i.e., payment defaults, distressed debt exchanges, and formal restructurings) are reported on the firm's obligations in the Moody's default and recovery database in year *t+1*, and zero otherwise. *RatingDown* is an indicator variable that equals one if a firm's credit rating is downgraded in year *t+1* from an investment grade (i.e., BBB- and above) to a junk grade (i.e., below BBB-).

In line with prior research (e.g., Ohlson 1980; Zmijewski 1984; Shumway 2001; Gutierrez et al. 2020), our empirical analyses control for variables associated with corporate bankruptcy, including the relative market capitalization (*Relative Market Cap*), market-adjusted returns (*Market-adj Return*), idiosyncratic volatility of stock returns (*Sigma*), return on assets (*ROA*), leverage ratio (*Leverage*), working capital ratio (*Working Capital*), current ratio (*Current*), cash holding (*Cash*), operating cash flow (*OCF*), log of total assets (*Size*), negative equity (*Negative Equity*), Big-4 auditors (*Big4*), and investment grade ratings (*Investment Grade*). Appendix B provides detailed variable definitions.

2.4 Descriptive Statistics

Table 2, Panel A presents descriptive statistics of our primary variables. The average of

SuperstarExpo is 0.350. The mean bankruptcy filing frequency (*Bankrupt*) is 0.7%, which is comparable to the mean of 0.64% from 1963 to 1998 as reported in Campbell et al. (2008). The means for our alternative financial distress proxies, *PerformDelist*, *Default*, and *RatingDown* are 2.3%, 0.3%, and 1.6%, respectively. In terms of control variables, the means of the relative market capitalization (*Relative Market Cap*), market-adjusted returns (*Market-adj Return*), idiosyncratic volatility of stock returns (*Sigma*), return on assets (*ROA*), leverage ratio (*Leverage*), working capital ratio (*Working Capital*), current ratio (*Current*), cash holding (*Cash*), operating cash flow (*OCF*), and log of total assets (*Size*) are -10.76, -0.119, 0.128, -0.050, 0.504, 0.241, 2.664, 0.132, 0.078, and 5.636, respectively. About 3.4% of sample observations have negative equity (*Negative Equity*), 82.9% have Big-4 auditors (*Big4*), and 8.2% have investment grade ratings (*Investment Grade*).[13] These descriptive statistics are largely comparable to those in Shumway (2001) and Gutierrez et al. (2020). Table 2, Panels B and C further provide the averages for *Bankrupt* by year and by industry, respectively. The proportion of sample firms filing for bankruptcy ranges from 0.2% in 2005 to 2.0% in 2000. The Mining and Wholesale Trade sectors exhibit the highest bankruptcy proportion in our sample (1.3% of the firm-years in those industries).

3. MAIN RESULTS

3.1. Superstar Exposure and Future Bankruptcy

We estimate the relation between a firm's future bankruptcy outcome and its exposure to superstar firms using the following logit model:

$$Bankrupt_{i,t+1} = \lambda_t + \beta_0 SuperstarExpo_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}, \qquad (1)$$

[13] Only 18.2% of our sample firm-years have S&P credit ratings. Among those, 44.8% are rated investment grade.

where i indexes firms, and t indexes time. Our primary variables, *SuperstarExpo* and *Bankrupt*, are discussed in detail in Sections 2.2 and 2.3, respectively. We follow prior research to control for variables associated with corporate bankruptcy (e.g., Ohlson 1980; Zmijewski 1984; Shumway 2001; Gutierrez et al. 2020), including *Relative Market Cap*, *Market-adj Return*, *Sigma*, *ROA*, *Leverage*, *Working Capital*, *Current*, *Cash*, *OCF*, *Size*, *Negative Equity*, *Big4*, and *Investment Grade*, as defined previously. To further control for time-variant macroeconomic factors, we include year fixed effects.[14] We cluster standard error at the firm level and winsorize all continuous variables at the 1st and the 99th percentiles. β_0 is the coefficient of interest that estimates the effect of a firm's exposure to superstar firms on its bankruptcy likelihood.

Panel A of Table 3 presents the estimation results of model (1). Column 1 only includes the main variable of interest (*SuperstarExpo*), column 2 adds all control variables, and column 3 further includes year fixed effects. In all three columns, the coefficient on *SuperstarExpo* is positive and statistically significant at the 1% level, suggesting that a focal firm's future bankruptcy likelihood is positively associated with its exposure to superstar firms. Further, the statistical significance and economic magnitude of the coefficient on *SuperstarExpo* is stable across the three columns (*Coeff*. = 0.344, 0.310, 0.334 in columns 1 to 3; all with *t*-statistics in the range of 2.9 to 3.5), indicating that the documented effect is not sensitive to the inclusion or exclusion of those covariates.

In terms of economic significance, the coefficient of 0.334 in column 3 corresponds to an odds ratio of 1.40 (i.e., *exp*(0.344)). In other words, we observe 40% higher odds of bankruptcy in

[14] In untabulated analyses, we find our inferences robust to replacing year fixed effects with the yield on US treasury securities at 10-year constant maturity, obtained from the St. Louis FED Economic Research Center.

the next year for firms within the top decile of *SuperstarExpo* compared to those without any exposure to superstars. In terms of the area under the ROC curve (AUROC), the incremental effect of *SuperstarExpo* in column 3 is about 0.1%, which is around a half of the incremental increase in AUROC due to the inclusion of *ROA* in the model (0.19%), and about a quarter of the incremental increase in AUROC due to the inclusion of *Market-adjusted Return* (0.41%), both of which are well-established covariates in bankruptcy prediction models (e.g., Gutierrez et al. 2020).

The coefficients on control variables are largely consistent with those reported in prior studies (e.g., Ohlson 1980; Zmijewski 1984; Shumway 2001; Gutierrez et al. 2020). Future bankruptcy is negatively associated with relative market capitalization, market-adjusted returns, return on assets, working capital, cash, operating cash flows, and investment-grade ratings, and positively associated with the idiosyncratic volatility of stock returns, leverage ratio, and size.[15]

We further test the intertemporal stability and significance of our coefficient of interest on *SuperstarExpo* using the "expanding windows" approach. Specifically, we start the sample in 1988 and end it in 1989 and then sequentially expand the sample by ending it in 1990, 1991 . . . , and 2018, respectively. We conduct the regression analysis for each of these sequentially expanded samples. We report the results in Panel B of Table 3. The magnitude of the coefficients on *SuperstarExpo* stays within the 0.180 to 0.409 range, with the mean of 0.282 and a *t*-statistic of 24.5. This evidence suggests that our coefficient of interest is relatively stable and significantly different from zero, further supporting our primary findings.

[15] The conflicting signs on relative market capitalization (*Market Cap*) and total assets (*Size*) reflect non-linearity of the size effect and are consistent with prior literature that includes both variables to proxy of market and accounting factors (e.g., Gutierrez et al. 2020).

3.2. Robustness Analyses

Table 4 presents the results of robustness analyses. Panel A provides the results of the tests that employ alternative design choices. To address concerns over potential omitted variables that are industry specific and time invariant, we add the SIC-2 industry fixed effects and find that the inferences are unchanged (column 1).[16, 17] To mitigate the incidental parameter problem (e.g., Lancaster 2000; Greene 2008), we employ an OLS model and find our results to be robust (column 2). The inferences are further robust to the use of a Cox proportional hazard model (column 3), which does not assume proportional odds and can capture time-varying hazard ratios. Next, because our main sample includes all firms, we partition the sample by whether a focal firm is identified as a superstar firm. Columns 4 and 5 confirm that the main effect is due to the subsample of non-superstar firms, further supporting our inference that firms exposed to superstars are more likely to experience future bankruptcy. In addition, the results are robust to clustering standard errors by firm and year, and by industry and year (columns 6 and 7, respectively).

Panel B provides the results using alternative measures of a firm's exposure to superstar firms. Our main measure of the superstar firm exposure is constructed using a two-step approach described in Section 2. We next evaluate sensitivity of our results to the use of alternative assumptions in both steps. First, our inferences are unchanged if we identify superstar firms as (i) the five largest firms in terms of markups in an SIC 4-digit industry (column 1), (ii) the top 5

[16] We do not include industry fixed effects in our main analyses as our primary construct of interest—exposure to superstars—may be related to industry factors (Autor et al. 2020).

[17] It is worth noting that the number of observations is smaller after controlling for SIC 2-digit industry. This is because there are no bankruptcy cases in a few small SIC 2-digit industries and therefore those observations are not used in the estimation. Similarly, in column 5 of this panel, we lose many superstar observations because in many years there are no superstar firms going bankrupt, and thus all superstar observations in those years are not used in the estimation.

percent of firms in an SIC 2-digit industry (column 2), and (iii) as the top 1 or 10 percent of firms in terms of markups in an SIC 4-digit industry (columns 3 and 4, respectively). Second, we find similar results if we measure exposure to superstars based on an indicator for whether there is at least one superstar firm in an SIC 4-digit industry (column 5). Third, our inferences remain unchanged when we require the SIC 4-digit industries to have at least 20 firms (column 6) or 100 firms (column 7). Panel C presents the results using alternative ways to measure financial distress as described in Section 2.3, including *PerformDelist*, *Default*, and *RatingDown*. Columns 1 to 3 show that *SuperstarExpo* is positively related to the likelihood of future performance-based delisting, credit default events, and downgrades to "junk" credit ratings.[18]

Finally, we consider alternative explanations for our results. Table 3 shows that the magnitude and significance of *SuperstarExpo* remains stable after we include year fixed effects, suggesting that correlated macro shocks are unlikely to significantly alter our inferences. Importantly, we also control for SIC 2-digit industry fixed effects in column 1 in Panel A of Table 4 and find similar results, indicating that time-invariant industry factors are unlikely to explain our results. However, to the extent that the prevalence of superstars may be an industry-level phenomenon, we further investigate two alternative explanations based on time-varying industry-level factors. First, firms in industries with greater exposure to superstar firms may invest in inherently riskier projects and this could be associated with a higher bankruptcy likelihood. Second, business models of firms in industries with greater superstar exposure can be associated

[18] We lose some observations because we require one extra year of data in constructing those dependent variables. The sample in column 3 is much smaller because (1) only 18.2% of our sample firm-years have S&P credit ratings, (2) we require that a firm has S&P credit rating in both the current year and the next year, and (3) those years without any bankruptcies in the sample with S&P credit ratings are excluded from the analyses.

with inherently low free cash flows due to higher investment and operational needs. Thus, firms in such industries may be more likely to experience financial distress (Hillegeist et al. 2004). Although these risk and free-cash-flow explanations are not mutually exclusive from the superstar firms' effect, to ensure that our results are not attributed to these two alternative industry-level explanations, we include additional controls for industry risk and free cash flow in model (1).

Panel D of Table 4 presents the results of these analyses.[19] Columns 1 and 2 show that our inferences are unchanged when we respectively control for an industry's average idiosyncratic volatility of stock returns (*Sigma_Ind*), as well as the sensitivity risk (*Sensitivity Risk*), which is the sensitivity of an industry to external economic forces, measured as the forward-looking correlation between industry-level earnings growth and aggregate GDP growth, as suggested by Amiram et al. (2017). We further control for the industry-level free cash flows (*FCF*) in column 3 and find that the coefficient on *SuperstarExpo* remains largely unchanged in terms of the economic and statistical significance. These results indicate that even after controlling for industry-level risk and cash flows, firms with greater exposure to superstars exhibit a higher bankruptcy likelihood.

Taken together, the results in Table 4 show that our inferences are robust to various empirical specifications, variable measurements, and are not due to alternative explanations.

3.3. Path Analyses

To identify potential channels through which superstar exposure is associated with the probability of bankruptcy, we conduct path analysis. As Jollineau and Bowen (2023) explain, path analysis "provides a visual portrayal of hypothesized relationships and the equations that underly

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[19] We lose some observations due to constructing additional variables in columns 2 and 3.

them." In particular, we seek to examine how a firm-level observable outcome, future bankruptcy, is associated *directly* with another firm-level observable phenomenon of interest—exposure to superstars, or associated *indirectly* through superstar exposure's effects on some identified *mediating* variables. Importantly, we use path analysis not to identify causal relations or test specific hypotheses, but to provide a validation check that superstar exposure's effect on future bankruptcy operates through intuitive associations with several firm-level mediating variables.

To identify the mediating variables, we appeal to the Black-Scholes-Merton framework (Merton 1974) that characterizes a firm's equity as a call option on its assets. Default occurs when a firm's asset value falls below a certain default threshold (that is equal to the contractual value of liabilities coming due). Under this framework, a firm's default likelihood is inversely related to its expected asset return and positively related to volatility in asset values. We approximate a firm's asset return by financial performance, including accounting performance (*ROA*) and equity returns (*Market-adj Return)*, and we measure volatility in asset values with equity returns volatility (*Sigma*). Intuitively, a firm's bankruptcy likelihood is expected to be negatively associated with financial performance and positively associated with risk.

Following Bushee and Noe (2000), we first separately regress *ROA, Market-adj Return,* and *Sigma* on our measure of superstar exposure, *SuperstarExpo*. These regressions capture the associations between superstar exposure and financial performance and risk-mediating variables. Next, we regress future bankruptcy (*Bankrupt*) on *SuperstarExpo*, as well as the three mediating variables (*ROA, Market-adj Return,* and *Sigma*).[20] Based on these two steps, we estimate the

[20] As these variables are considered key predictors in conventional bankruptcy-prediction models, we control for them in our baseline model following Gutierrez et al. (2020). For this path analysis, we exclude these three variables in the

association between future bankruptcy and superstar exposure that operate through the identified mediators (i.e., indirect effects), as well as the association that operate independently of the identified mediators (i.e., the direct effect). The direct effect reflects an aggregation of other channels that are not explicitly specified as mediators (including unobserved factors). We are thus able to quantify the portion of the association between future bankruptcy and superstar exposure that is mediated through financial performance and risk.

Table 5, Panel A presents the results. Columns 1 to 3 show that superstar exposure is significantly associated with lower *ROA,* lower *Market-adj Return,* and higher *Sigma.* Column 4 includes all three variables, and future bankruptcy continues to be negatively related to *Market-adj Return* and *ROA* and positively related to *Sigma.*[21] We next calculate the portion of the association between superstar exposure and future bankruptcy that is mediated through financial performance and risk. Figure 1, Panel A provides a path analysis diagram to illustrate the relative size of the direct and mediating effects in the association between superstar exposure and bankruptcy. To facilitate economic interpretation, we follow Bushee and Noe (2000) and standardize the regression coefficients by dividing them by the ratio of the respective dependent variable's standard deviation to the independent variable's standard deviation. For example, to get the standardized coefficient of *SuperstarExpo* on *Bankruptcy*, we take the coefficient of *SuperstarExpo* in column 4 of Table 6, Panel A (0.002), and divide it by the ratio of the standard deviation of *Bankruptcy* (0.085) to that of *SuperstarExpo* (0.350), both tabulated in Panel A of

bankruptcy prediction model but use them as paths through which a firm's superstar exposure relates to future bankruptcy.

[21] It is worth noting that we have to use OLS in path analysis. As a result, Column 4 is comparable to Column 2 in Panel A of Table 4 (i.e., the one using OLS) rather than to Column 3 in Panel A of Table 3 (i.e., the one using Logit).

Table 2. The resulted value of 0.0083 is the direct effect of *SuperstarExpo* on *Bankruptcy.* Similarly, we calculate the standardized coefficients of *SuperstarExpo* on *SIGMA, Market-adj Return,* and *ROA* as 0.1069, -0.0591, and -0.0780, respectively, and the standardized coefficients of those three mediating variables on *Bankruptcy* as 0.0698, -0.0890, and -0.0254, respectively. To obtain the mediating effects of *SIGMA, Market-adj Return,* and *ROA*, we multiply the standardized coefficients on *SuperstarExpo* (columns 1–3) by the standardized coefficients on *SIGMA, Market-adj Return,* and *ROA* (column 4), and obtain their mediating effects of 0.0075, 0.0053, and 0.0020.

In terms of economic significance, the mediating effect through accounting performance *ROA* (0.0020) represents about 24% of the size of the direct effect (0.0083). In addition, the mediating effects through *Market-adj Return* (0.0053) and *SIMGA* (0.0075) are also substantial in magnitude and represent 64% and 90% of the size of the direct effect, respectively. We use the Sobel test (Sobel 1982; 1986) to evaluate the statistical significance of these mediated effects and find that *all three* mediators are statistically significant at the 1% level. The path analysis results suggest that a firm's exposure to superstar firms is associated with its poorer financial performance (in terms of both accounting performance and equity returns) and greater risk, contributing to a higher likelihood of future bankruptcy.

Next, we attempt to further understand the effect of accounting performance (*ROA*) by examining its components. We decompose *ROA* into three components, including the operating income (*EBITOA*), interest expense (*IntExpOA*), and other income (*OtherIncomeOA*), such that $ROA = EBITOA - IntExpOA + OtherIncomeOA.$ We control for the other two mediators (*Market-adj Return* and *SIGMA*). Table 5, Panel B presents the results of these analyses. Columns

1 to 3 show that a firm's exposure to superstar firms is negatively associated with *EBITOA,* positively associated with *IntExpOA,* and insignificantly related to *OtherIncomeOA,* respectively. In column 4, *Bankruptcy* is negatively associated with *EBITOA* and *OtherIncomeOA,* and positively associated with *IntExpOA.* The relation between *Bankruptcy* and *OtherIncomeOA*, while not a focus of our investigation, is intuitive and indicates that higher non-operating earnings are associated with lower distress risk.

Figure 1, Panel B plots a path analysis diagram to illustrate the paths through these three components. The results show that the mediating effect of *ROA* works mostly through *EBITOA* and *IntExpOA*; this effect through *EBITOA* (0.0009) and *IntExpOA* (0.0005) represents 10.5% and 6.6% of the size of the direct effect, respectively. Thus, the accounting performance channel reflects that superstar exposure is associated with low operating income and high interest expense. The results concerning interest expense are likely explained by the exposure to superstars increasing a focal firm's risk, which is reflected in its difficulty in accessing low-cost financing. [22]

Collectively, the results of the path analysis in Table 5 provide us with some comfort that the relation that we observe in our primary analyses between bankruptcy and superstar exposure operates through the intuitive mediating paths of financial performance and risk.

4. SUPPLEMENTARY ANALYSES

4.1 Cross-Sectional Results

Although our main results show the on-average adverse effects of exposure to superstars, we further examine cross-sectional heterogeneity in this effect. For example, some firms exposed to

[22] We thank an anonymous referee for suggesting this link between superstar firms and the cost for a focal firm of accessing the credit markets.

superstars can still survive and may even enjoy positive spillover effects, offsetting the potential adverse effects brought about by superstars. Specifically, we explore a focal firm's innovation activity. Some firms may be able to thrive under the competitive pressure from superstars by innovating in product markets. For example, these firms may be forced to compete with superstars by introducing new products or by improving existing offerings (Lang and Stulz 1992; Chevalier-Roignant et al. 2019). Firms with higher R&D expenditures generally invest more in innovation. If such investments are successful, these firms should be able to develop patents for their products and processes. Thus, we proxy for innovation activity using R&D expenditures and filed patents. We expect superstar firms' disruptive effects to be concentrated among firms without R&D expenditures and those that do not file patents (i.e., those firms that do not invest in innovation).

Table 6, Panel A presents the results. Columns 1 and 2 present subsample analyses based on R&D expenditures (innovation input), and columns 3 and 4 present the analyses based on patents (innovation output).[23] As innovation activity itself may be related to the likelihood of bankruptcy, we further control for R&D expenditure intensity (*R&DIntensity*) and the number of patents (*LnPatent*) in our regressions in columns 1 and 3.[24] Columns 1 and 2 show that the coefficient on *SuperstarExpo* is only positive and statistically significant in column 2, suggesting that superstar firms' effect on the bankruptcy likelihood of firms exposed to them is concentrated among firms with no R&D expenditure, while such an effect is mitigated for firms with R&D activity. In terms of economic significance, in the subsample without R&D expenses, we observe 53% higher odds

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[23] As discussed earlier, we lose some observations in each subsample because there are no bankruptcy cases in some years within a subsample, and therefore those observations are not used in the estimation.

[24] We note that the coefficient on *R&DInt* is positive, while that on *LnPatent* is negative. We conjecture that this is because R&D expenditures reflect risky innovation inputs and are therefore positively related to future bankruptcy, while patents reflect successful innovation outputs, which are negatively related to future bankruptcy.

(= exp(0.425) – 1) of bankruptcy in the next year for firms within the top decile of *SuperstarExpo* compared to those without any exposure to superstars. To test the difference in coefficients on *SuperstarExpo* across subsamples, we use a bootstrapping method following Da et al. (2011) and Shroff et al. (2014). We find that the coefficients on *SuperstarExpo* are significantly different between columns 1 and 2 ($p = 0.039$).

Similarly, columns 3 and 4 indicate that the relation between future bankruptcy and superstar exposure is concentrated among firms without patenting activity in column 4. In terms of economic significance, in the subsample without patents, we observe 49% higher odds (i.e., exp(0.400) – 1) of bankruptcy in the next year for firms within the top decile of *SuperstarExpo* compared to those without any exposure to superstars. Interestingly, the negative coefficient in column 3 suggests that the superstar exposure could have beneficial spillover effects for firms that are sufficiently innovative and able to develop patents. We conjecture that such positive spillover effects may be a combined result of the competitive pressure to develop new offerings, industrywide learning, and nurturing and retention of talent (we leave it for future research to explore these channels). Using a bootstrapping procedure, we find that the coefficients on *SuperstarExpo* are significantly different between columns 3 and 4 ($p < 0.001$). These results further suggest that innovation affects firms' ability to withstand the pressures brought about by superstars.

On the other hand, we expect that firms with low flexibility to adjust their operating and investing activities are less likely to be able to navigate superstars' disruptive effects. In particular, firms with weaker access to credit have lower ability to obtain additional financing, which is likely to impede their ability to adjust their operations and investments to superstar firms' competitive pressure. We thus expect the effect of superstar exposure to be concentrated among firms with weaker access to credit, which we proxy for by the size of a focal firm's undrawn revolving credit and its tangible assets. Revolving credit lines can be used by firms to alleviate liquidity problems (Sufi 2009; Jiménez et al. 2009; Lins et al. 2010; Kizilaslan and Mathers 2014; Zhao et al. 2014). Firms with a lower undrawn portion of the revolving credit in place should have less financial flexibility to adapt to the shocks induced by superstar firms (as they cannot simply draw upon the credit line when in need of additional liquidity). Further, firms with a lower tangible asset base exhibit lower financial flexibility due to their lower ability to raise additional debt financing by pledging their assets as collateral or by having a lower ability to conduct asset sales (e.g., Almeida and Campello 2007; Falato et al. 2013; Rampini and Viswanathan 2013; DeMarzo 2019; Donaldson et al. 2019, 2020; Benmelech et al. 2020).

Panel B of Table 6 shows the results. Columns 1 and 2 present the subsample analyses based on undrawn revolving credit; columns 3 and 4 present the analyses based on the extent of tangible assets in place. [25] Because access to credit can itself be related to future bankruptcy likelihood, we further control for the size of undrawn credit availability (*LnUndrawn*) and tangible assets (*LnTangible*) in the regressions.[26] We find that the coefficient on *SuperstarExpo* is insignificant (significant) in column 1 (2) where the undrawn revolving credit is higher (lower) than the annual sample median, and insignificant (significant) in column 3 (4) where the tangible assets are higher (lower) than the annual sample median. In terms of economic significance, in the subsample with

[25] In columns 1–2, we only use those observations for which the undrawn credit amount is available from the CIQ capital structure database. In columns 3–4, we lose 5,373 observations due to missing tangible assets in Compustat. Results are very similar if we replace those missing values with zero.

[26] We note a significant and positive coefficient on *LnTangible*. We conjecture that this is because industries with the highest tangible assets, such as mining, wholesale trading, and transportation & public utilities, are also the ones with the highest likelihood of bankruptcy. Indeed, controlling for SIC 2-digit industry fixed effects, the correlation between *Bankrupt* and *LnTangible* becomes significantly negative.

low available revolving credit (low tangible assets), we observe 46% (51%) higher odds of bankruptcy in the next year for firms within the top decile of *SuperstarExpo* compared to those without any exposure to superstars. Using a bootstrapping approach, we further find that the difference in the coefficient on *SuperstarExpo* is insignificant between columns 1 and 2 (p = 0.204), but significant between columns 3 and 4 (p = 0.055). These findings provide some evidence that access to credit plays an important role in moderating the relation between superstar exposure and firms' future bankruptcy likelihood.

Taken together, the findings in Table 6 supplement our primary findings and suggest that the adverse effect of exposure to superstars on future bankruptcy likelihood is mitigated for those firms that are able to innovate and those with better access to debt financing.

4.2 Superstar Exposure and Sophisticated Market Participants

Although bankruptcy is a rare event, it is highly significant for stakeholders of public firms. An interesting and relevant extension of our main analyses is whether sophisticated market participants are aware of a firm's exposure to superstar firms and its adverse effects, and hence, incorporate this exposure in their decision-making. Market participants' perceptions of the relation between bankruptcy risk and superstar exposure can provide complementary insights about extensiveness and the importance of the superstar phenomenon.

We consider four types of sophisticated market participants whose information acquisition activity is well documented in the prior literature: financial analysts (e.g., Bradshaw et al. 2017; Gibbons et al. 2021), short sellers (e.g., Dechow et al. 2001; Boehmer et al. 2020), dedicated institutional investors (e.g., Bushee and Noe 2000; Borochin and Yang 2017), and auditors (e.g., DeFond and Zhang 2014; Zimmerman et al. 2023). To make sure that all information related to a firm's superstar exposure is publicly available, we study decisions by these market participants one year after the current fiscal year-end.

To examine whether sophisticated market participants incorporate superstar exposure in their decision-making, we regress these participants' decision outcomes on our measure of superstar exposure, using the following regression model:

$$Outcome_{i,t+1} = \lambda_t + \beta_0 SuperstarExpo_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}, \quad (2)$$

where $Outcome_{i,t+1}$ represents one of the sophisticated market players' decision outcomes as of the next fiscal year end $t+1$. We define four outcome variables as follows: $BuyRec\%_{i,t+1}$ is the proportion of analysts' buy recommendations among all recommendations outstanding for the firm at the fiscal year end $t+1$. $ShortRatio_{i,t+1}$ is the short interest ratio (shares shorted scaled by total shares outstanding) at the fiscal year end $t+1$. $DedicateInst\%_{i,t+1}$ is the proportion of shares that are held by dedicated institutional investors at the fiscal year end $t+1$. $Going\_Concern_{i,t+1}$ is an indicator that equals one if the auditor issues a going concern opinion at the fiscal year end $t+1$, and zero otherwise. We use OLS regressions for the first three specifications with continuous dependent variables ($BuyRec\%_{i,t+1}$, $ShortRatio_{i,t+1}$, and $DedicateInst\%_{i,t+1}$) and a Logit regression when an indicator variable, $Going\_Concern_{i,t+1}$, is the dependent variable. To address the concern that these outcomes may reflect the effect of actual bankruptcies rather than the impact of superstar exposure, we exclude observations of firms that have already filed for bankruptcy by the date when we measure the dependent variable.

Table 7 reports the estimated coefficient, β_0, for the various market participants. In column 1, we find that a firm's superstar exposure exhibits no significant relation with the proportion of sell-side analysts' *Buy* recommendations, suggesting that analysts do not seem to incorporate this information into their decision-making.[27] This evidence is consistent with prior literature that documents that sell-side analysts tend to underreact to or withhold bad news (e.g., McNichols and O'Brien 1997; Hong et al. 2000; Easterwood and Nutt 1999; Hugon and Muslu 2010).

In contrast, columns 2 to 4 show that a firm's superstar exposure is positively correlated with short interest, negatively related to dedicated institutional ownership, and positively related to auditors' likelihood of issuing going concern opinions. In terms of economic significance, short sellers have 0.3 percentage points higher short interest (representing 7.6% of the sample mean of 3.9 percentage points), dedicated institutions have 0.3 percentage points lower ownership (representing 12.5% of the sample mean of 2.4 percentage points), and auditors have 24% higher odds (i.e., exp(0.214) – 1) of issuing going concern opinions in the next year for firms within the top decile of *SuperstarExpo* compared to those without any exposure to superstars. These results suggest that short sellers, dedicated investors, and auditors likely recognize the adverse effect of superstars on firm performance, consistent with prior research suggesting that these market participants are sophisticated users of firm-specific information. Specifically, the evidence on short sellers is consistent with their superior information processing abilities (e.g., Dechow et al. 2001; Drake et al. 2011; Engelberg et al. 2012; Khan and Lu 2013; Boehmer et al. 2020). The evidence on dedicated institutional investors is in line with their ability in choosing profitable investing opportunities (e.g., Ke and Ramalingegowda 2005; Borochin and Yang 2017). The evidence

[27] We have smaller sample sizes in this table partly because we exclude observations that have filed for bankruptcy by the date when we measure the dependent variables. An additional reason for sample attrition for columns 1, 2, and 4 is the availability of dependent variables. Specifically, we cannot construct *BuyRec%* ($ShortRatio_{i,t+1}$) [$Going\_Concern_{i,t+1}$] for firms without analyst coverage (when short interest data is not available for NASDAQ firms prior to 2002) [when going concern opinion information is not available in Audit Analytics prior to 2000].

concerning auditors' going-concern assessments is aligned with auditors' ability to acquire and process relevant information about their clients (e.g., Cassell et al. 2011; Gutierrez et al. 2020; Zimmerman et al. 2023).

Overall, our findings in Table 7 show that short sellers, dedicated investors, and auditors are aware of the potentially adverse effects of superstar exposure and adjust accordingly their assessment of firms' viability prospects. This evidence that sophisticated market players account for superstar exposure in their decision-making also provides an important validation to our primary inference that this exposure is positively associated with firms' financial distress.

5. CONCLUSION

Our study provides timely evidence on superstar firms' disruptive effects on firms exposed to them in product markets. We utilize financial statements data to identify superstar firms and construct a novel measure of a focal firm's exposure to superstar firms. Using this measure, we document that firms with greater exposure to superstars are more likely to file for bankruptcy. We conduct complementary analyses to shed light on the channels through which superstar exposure affects bankruptcy likelihood. Path analyses show that firms with superstar exposure exhibit weaker financial performance and greater riskiness, contributing to higher bankruptcy likelihood. We supplement these findings by demonstrating that superstar firms' disruptive effects are mitigated for firms engaging in innovation but are exacerbated when firms have weaker access to debt financing. Collectively, our results suggest that although superstars are the driving force behind technological and economic progress over the recent decades, their power adversely affects the financial viability of firms exposed to them in product markets.

Building on the firm-level superstar exposure measure proposed in our study, future research can further explore how superstars affect various aspects of firms' operating, financing, investing and innovation activities. In addition, little is known about how the increasing dominance of superstar firms influences how firms communicate with their customers, capital providers, and other stakeholders. Finally, while we provide some evidence that dedicated investors, auditors, and short sellers account for firms' exposure to superstars in their decision-making, future studies can further examine in detail how sophisticated market participants assess the positive and adverse effects of exposure to superstars.

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APPENDIX A: The De Loecker et al. (2020) Approach for Estimating Markups

We provide the basic intuition behind the approach used by De Loecker and Warzynski (2012) and De Loecker et al. (2020) for estimating markups in this appendix. For further details, please refer to Section II.A of De Loecker et al. (2020). [28]

Intuitively, this approach assumes that a firm faces a constrained optimization problem: it minimizes total costs while achieving a certain level of production. More formally, De Loecker et al. (2020) define markup $\mu = \frac{P}{c}$, where *P* is the sales price and *c* is the marginal cost. They assume that the production technology is $Q(.) = Q(\Omega, V, K)$, where Ω, V, and K reflect productivity, variable input, and capital stock. As a result, the total cost of production is $P^V V + rK + F$, where P^V is the price of variable input, r is the cost of capital, and F is the fixed cost. To minimize the production cost given that the production is at least as large as $\bar{Q}$, they consider the following Lagrangian function: $L(V, K, \lambda) = P^V V + rK + F - \lambda(Q(.) - \bar{Q})$.[29] The Lagrange multiplier λ mathematically captures the marginal change in production costs if the production constraint $\bar{Q}$ changes marginally by one unit. In other words, it is essentially a direct measure of the marginal cost of input, or the "shadow price" (see Dixit 1990). Recall that markup is $\mu = \frac{P}{c}$. Therefore, substituting the shadow price λ for c, markup can be estimated as $\mu = \frac{P}{\lambda}$.

Next, De Loecker et al. (2020) use the first-order condition with respect to the variable input V, to obtain $\frac{P^V}{\lambda} = \frac{\partial Q(.)}{\partial V}$. Upon multiplying $\frac{V}{Q}$ to both sides of the equation, it becomes $\frac{\partial Q(.)}{\partial V}\frac{V}{Q} = \frac{1}{\lambda}\frac{P^V V}{Q}$.

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[28] De Loecker et al. (2020) also discuss two other approaches—the "demand approach" and the "accounting approach." The demand approach requires complicated assumptions about the demand curve and the structure of competition (pages 569-570) and hence is not followed in that paper or by us. The accounting approach assumes a constant return to scale (CRS)—in other words, it assumes that the average and marginal costs are the same. However, as discussed later, when De Loecker et al. (2020) fix the output elasticity at 0.85, the accounting and the production approaches are virtually identical, and they find that their results are very similar under either approach. We follow De Loecker et al. (2020) rather than using the accounting approach as we do not know ex ante whether their theoretically preferred production approach and the simpler accounting approach would lead to similar inferences.

[29] The Lagrangian function approach is widely used in managerial economics for optimization problems that involve fixed resource constraints. The Lagrangian function essentially combines the objective function and the resource constraint into a single equation. The Lagrangian multiplier has an interesting and important interpretation: it measures the change in the objective function for each unit change in the resource constraint. Thus, in a cost minimization problem subject to a production output constraint, the Lagrangian multiplier (also known as the shadow price), reflects the marginal increase production cost for each unit of relaxation in the production output constraint.

The left-hand side, which they label as θ^v, is the output elasticity of variable input *V*. As a result, they can solve $\lambda = \frac{1}{\theta^v}\frac{P^V V}{Q}$. Given that $\mu = \frac{P}{\lambda}$, they obtain $\mu = \theta^v \frac{PQ}{P^V V}$.

Following De Loecker et al. (2020), we use *Sales* and *COGS* from Compustat to measure *PQ* and $P^V V$, respectively. De Loecker et al. (2020) show various specifications for estimating θ^v. They conclude that the pattern of markups is similar when they fix the output elasticity to be time-invariant, with an average of 0.85, and conclude that the rise in markups is not due to the change in the estimated output elasticity and that the output elasticities vary very little over time (page 577). In untabulated analyses, we also confirm that our results remain similar if we use an alternative approach to estimate the output elasticity θ^v, such as using a sector-year-specific Cobb-Douglas production function illustrated in Appendix A of De Loecker et al. (2020).

APPENDIX B: Variable Definitions

Bankrupt	An indicator variable that equals one if the firm files bankruptcy in year *t+1*, and zero otherwise.
Big4	An indicator variable that equals one if the firm employs a big-4 auditor in year *t*, and zero otherwise.
$BuyRec\%_{t+1}$	The percentage of buy recommendations among all outstanding recommendations on a firm at the fiscal year end *t+1*.
Cash	Cash holding level, measured as the ratio of the firm's cash and cash equivalents (*CH*) to total assets (*AT*) at the fiscal year end. Missing *CH* is replaced with zero.
Current	Current ratio, measured as the firm's current assets (*ACT*) to current liabilities (*LCT*) at the fiscal year end. Missing *ACT* is replaced with zero. If *LCT* is missing, we calculate the ratio using total liabilities (*LT*) as we cannot replace the denominator with zero.
$DedicateInst\%_{t+1}$	The percentage of shares held by dedicated institutional investors (Bushee 1998) among all shares outstanding for a firm based on the 13F filing date immediately prior to the fiscal year end *t+1*.
Default	An indicator variable that equals one if the firm experiences adverse credit events, including payment defaults, distressed debt exchanges, and formal restructurings, as reported in Moody's Default & Recovery Dataset in year *t+1*.
EBITOA	The ratio of earnings before interest and tax (EBIT) to total assets (AT) measured at the fiscal year end.
FCF	The aggregate free cash flow (*OANCF – CAPX*) for all businesses reported in Compustat in an SIC-4 industry, scaled by lagged aggregate total assets; accounting variables are obtained from Compustat $$FCF_{j,t} = \frac{\sum_{i \in j}(OANCF - CAPX)_{i,t}}{\sum_{i \in j} AT_{i,t-1}},$$ where *j* denotes the SIC-4 industry, *i* denotes the firm, *t* denotes the year; $\sum_{i \in j}(OANCF - CAPX)_{i,t}$ is the aggregate free cash flow for all public firms in Compustat that operate in the SIC-4 industry *j* for year *t* ; $\sum_{i \in j} AT_{i,t-1}$ are the lagged total assets for all firms operating in the SIC-4 industry *j*.
$GoingConcern_{t+1}$	An indicator that equals one if the auditor issues a going concern opinion in the next fiscal year ended *t+1*.
IntExpOA	The ratio of interest expense (XINT) to total assets (AT) measured at the fiscal year end.
Investment Grade	An indicator variable that equals one if the outstanding credit rating prior to the fiscal year end is an investment grade, and zero otherwise.
Leverage	Leverage ratio, measured as the ratio of the firm's total liabilities (*LT*) to total assets (*AT*) at the fiscal year end.
LnPatents	The log of one plus the number of patents filed by the company in a given fiscal year, as provided by Kogan et al. (2017). Available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data
LnTangible	The log of one plus tangible assets (i.e., the sum of inventory and net PP&E) at the fiscal year end, as reported in Compustat.

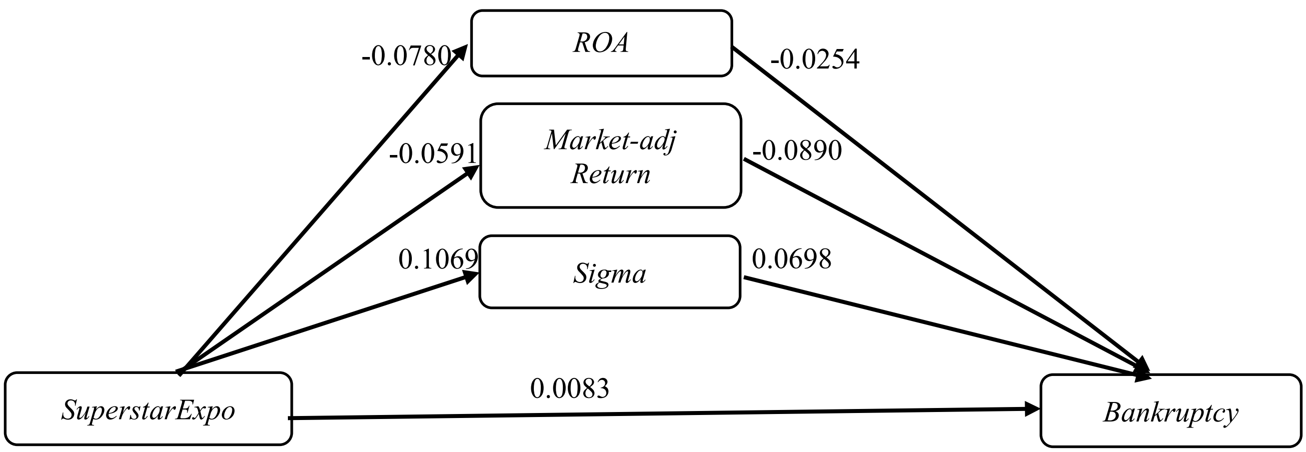
LnUndrawn	The log of one plus the undrawn portion of revolving credit (*UndrawnCrdtPortionRevolvingCrdt* in Capital IQ Capital Structure Summary database). As this variable is only available from 2003 to 2018, we only use those observations that are matched with CIQ capital structure database.
Market-adj Return	Market-adjusted returns, measured as the firm's cumulative returns less the market's cumulative returns over the 12 months leading up to the filing date.
Negative Equity	An indicator variable that equals one if the firm's total liabilities (*LT*) exceed total assets (*AT*), and zero otherwise.
OCF	Operating cash flow, measured as the ratio of the firm's cash flow from operating activities (*OANCF*) to total assets (*AT*) at the fiscal year end. Missing *OANCF* is replaced with zero.
OtherIncomeOA	The ratio of other income excluding *EBITOA* and *InExpOA* (= ROA – EBITOA + IntExpOA) to total assets (AT) measured at the fiscal year end.
PerformDelist	An indicator variable that equals one if the firm is delisted due to issues related to poor financial performance in year t+1, and zero otherwise. We collect delisting data from CRSP, and identify performance-related delisting following Shumway (1997).
RatingDown	An indicator variable that equals one if the firm's credit rating is downgraded in year *t+1* from investment grade rating to junk.
Relative Market Cap	Relative market capitalization, measured as the natural logarithm of the ratio of the firm's market capitalization to the CRSP total market capitalization at the month-end prior to the filing date for year *t*.
ROA	Return on assets ratio, measured as the ratio of the firm's net income (*NI*) to total assets (*AT*) at the fiscal year end.
R&DIntensity	R&D expenses scaled by revenue at the fiscal year end, as reported in Compustat.
Sensitivity Risk	The sensitivity risk measure suggested by Amiram et al. (2017), measured as the forward-looking correlation between industry-level earnings growth and aggregate GDP growth using the five-year rolling correlation from *t-1* to *t+3*.
$ShortRatio_{t+1}$	The percentage of shares sold short among all shares outstanding for a firm based on the settlement date immediately prior to the fiscal year end *t+1*.
Sigma	Standard deviation of residuals, estimated by regressing firms' monthly returns on market returns for the 12 months leading up to the filing date for year *t*.
Sigma_Ind	The average *Sigma* of all firms in an SIC-4 industry.
Size	Firm size, measured as the natural logarithm of the firm's total assets (*AT*) at the fiscal year end.
SuperstarExpo_raw	The number of superstar firms (*Superstar*) that a peer firm is exposed to, weighted by the product similarity score developed by Hoberg and Phillips (2010; 2016).
SuperstarExpo	A variable that equals the annual decile rank of *SuperstarExpo_raw* scaled by 10 for firms exposed to superstars, and equals zero for firms without any exposure to superstar firms.

SuperstarExpo_ SIC2	Superstar exposure rank, calculated similar to *SuperstarExpo*, except that superstars are defined as *the top 5 percent of firms* in an SIC 2-digit industry rather than in an SIC 4-digit industry.
SuperstarExpo_Top 1%	Superstar exposure rank, calculated similar to *SuperstarExpo*, except that the superstar firms are defined as the top 1 percent rather than the top 5 percent firms in the *SIC 4-digit* industry.
SuperstarExpo_Top 10%	Superstar exposure rank, calculated similar to *SuperstarExpo*, except that the superstar firms are defined as the top 10 percent rather than the top 5 percent firms in the *SIC 4-digit* industry.
SuperstarExpo_Top5	Superstar exposure rank, calculated similar to *SuperstarExpo*, except that the superstar firms are defined as *the biggest five firms* rather than the top 5 percent firms in the *SIC 4-digit* industry.
WithSuperstar	An indicator variable that equals one if at least one firm in the SIC 4-digit industry is defined as *Superstar*.
Working Capital	Working capital ratio, measured as the ratio of the firm's current assets (*ACT*) adjusted by current liabilities (*LCT*) to its total assets (*AT*) at the fiscal year end. Missing *ACT* and *LCT* are replaced with zero.

Figure 1: Path Analyses on Mediating Channels through which Superstar Exposure Affects Future Bankruptcy

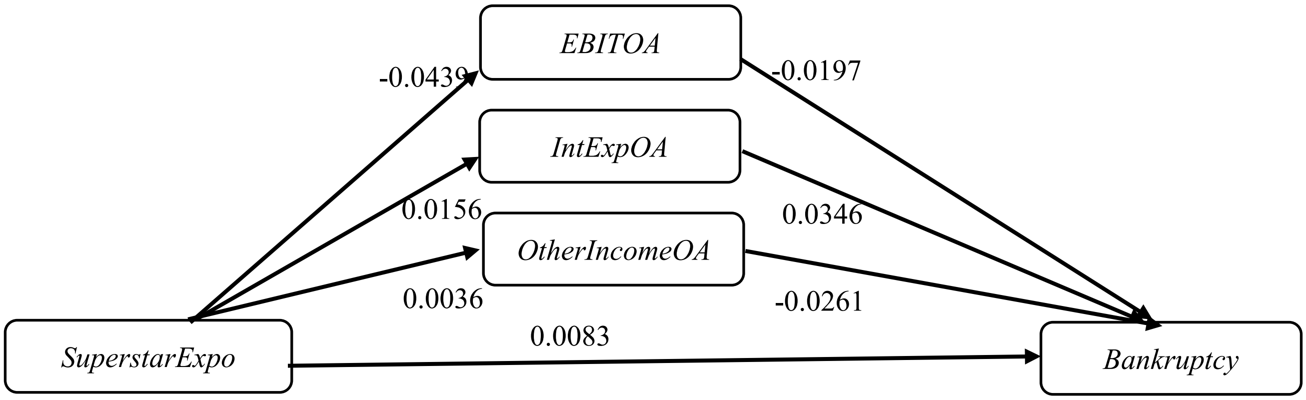
This figure illustrates the relative size of the direct effect and the various mediating effects discussed in *Section 3.3 Path Analyses*. We report the estimated coefficients in Table 5 and calculate the relative size of superstar exposure's direct and mediating effects on future bankruptcy. Panel A illustrates three potential mediating channels—financial performance (*ROA* and *Market-adj Return*), and risk (*Sigma*). Panel B focuses on the accounting performance (*ROA*) channel and illustrates the paths through which accounting performance's (*ROA*'s) three components—operating income (*EBITOA)*, interest expense (*IntExpOA)*, and other (*OtherIncomeOA*)—affect the likelihood of future bankruptcy. We use the Sobel test to evaluate the statically significance of the calculated effect sizes.

Panel A. Performance and Risk



<u>Direct and Indirect Effects:</u>
*SuperstarExpo ➔ Bankruptcy = 0.0083***
*SuperstarExpo ➔ ROA ➔Bankruptcy = 0.0020****
*SuperstarExpo ➔ Market-adj Return ➔Bankruptcy = 0.0053****
*SuperstarExpo ➔ Sigma ➔Bankruptcy = 0.0075****

Panel B. Decomposition of Accounting Performance (*ROA*)



<u>Direct and Indirect Effects:</u>
*SuperstarExpo ➔ Bankruptcy = 0.0083***
*SuperstarExpo ➔ EBITOA ➔Bankruptcy = 0.0009****
*SuperstarExpo ➔ IntExpOA ➔Bankruptcy = 0.0005***
SuperstarExpo ➔ OtherIncomeOA ➔Bankruptcy = 0.0001

Table 1: Sample Construction and Distribution

This table presents the sample construction procedure in Panel A, and the distributions by year and by industry in Panels B and C, respectively.

Panel A. Sample Construction Procedure

Procedure	Sample
Compustat universe data (1988–2018)	221,923
Merge with CRSP PERMNO	160,856
Exclude banks and insurance companies (SIC 60 and 63)	139,987
Exclude observations with missing test and control variables	116,731
Exclude observations that filed bankruptcy earlier in the sample	116,692

Panel B. Sample Distribution by Year

Year	Freq.	Percent	Cum. Percent	Year	Freq.	Percent	Cum. Percent
1988	2,027	1.74	1.74	2004	3,817	3.27	60.43
1989	3,187	2.73	4.47	2005	3,760	3.22	63.65
1990	3,224	2.76	7.23	2006	3,716	3.18	66.83
1991	3,386	2.90	10.13	2007	3,660	3.14	69.97
1992	3,564	3.05	13.19	2008	3,439	2.95	72.92
1993	4,006	3.43	16.62	2009	3,237	2.77	75.69
1994	4,283	3.67	20.29	2010	3,160	2.71	78.40
1995	4,683	4.01	24.30	2011	3,084	2.64	81.04
1996	5,186	4.44	28.75	2012	3,037	2.60	83.64
1997	5,361	4.59	33.34	2013	3,141	2.69	86.34
1998	5,198	4.45	37.80	2014	3,300	2.83	89.16
1999	5,101	4.37	42.17	2015	3,261	2.79	91.96
2000	5,043	4.32	46.49	2016	3,153	2.70	94.66
2001	4,509	3.86	50.35	2017	3,131	2.68	97.34
2002	4,108	3.52	53.87	2018	3,099	2.66	100
2003	3,831	3.28	57.16		116,692	100	

Panel C. Sample Distribution by Industry

Industry Category	SIC Code	Freq.	Percent	Cum. Percent
A. Agriculture, Forestry, & Fishing	01-09	342	0.29	0.29
B. Mining	10-14	6,948	5.95	6.25
C. Construction	15-17	19,490	16.70	22.95
D. Manufacturing	20-39	31,849	27.29	50.24
E. Transportation & Public Utilities	40-49	11,579	9.92	60.17
F. Wholesale Trade	50-51	12,855	11.02	71.18
G. Retail Trade	52-59	11,922	10.22	81.40
H. Finance & Real Estate	61, 62, 64-67	15,996	13.71	95.11
I. Services	70-89	5,597	4.80	99.90
J. Other	91-99	114	0.10	100
Total		116,692	100	

Table 2: Descriptive Statistics

This table reports the summary statistics for variables used in the main analyses. Panel A presents the summary statistics for bankruptcy, superstar exposure, and control variables. Panels B and C provide the means for bankruptcy by year and by industry, respectively. All variables are defined in Appendix B.

Panel A. Full Sample

N=116,692	Mean	STD	P5	P25	P50	P75	P95
Bankrupt	0.007	0.085	0.000	0.000	0.000	0.000	0.000
SuperstarExpo	0.350	0.350	0.000	0.000	0.300	0.700	1.000
PerformDelist	0.023	0.150	0.000	0.000	0.000	0.000	0.000
Default	0.003	0.054	0.000	0.000	0.000	0.000	0.000
RatingDown	0.016	0.126	0.000	0.000	0.000	0.000	0.000
Relative MarketCap	-10.76	1.994	-13.97	-12.20	-10.82	-9.426	-7.284
Market-adj Return	-0.119	0.539	-1.122	-0.370	-0.065	0.184	0.695
Sigma	0.128	0.088	0.036	0.067	0.105	0.162	0.302
ROA	-0.050	0.269	-0.585	-0.045	0.028	0.069	0.160
Leverage	0.504	0.264	0.110	0.302	0.500	0.671	0.938
Working Capital	0.241	0.261	-0.080	0.014	0.201	0.421	0.731
Current	2.664	2.978	0.000	1.069	1.842	3.134	8.213
CASH	0.132	0.171	0.001	0.017	0.064	0.178	0.508
OCF	0.078	0.077	0.000	0.000	0.065	0.120	0.226
SIZE	5.636	2.126	2.314	4.040	5.531	7.133	9.360
Negative Equity	0.034	0.180	0.000	0.000	0.000	0.000	0.000
Big4	0.829	0.376	0.000	1.000	1.000	1.000	1.000
Investment Grade	0.082	0.274	0.000	0.000	0.000	0.000	1.000

Panel B. Mean Bankruptcy by Year

Year	*Bankrupt*
1988	0.004
1989	0.011
1990	0.015
1991	0.008
1992	0.007
1993	0.004
1994	0.006
1995	0.005
1996	0.006
1997	0.009
1998	0.008
1999	0.011
2000	0.020
2001	0.013
2002	0.010
2003	0.005

Year	*Bankrupt*
2004	0.005
2005	0.002
2006	0.004
2007	0.007
2008	0.013
2009	0.003
2010	0.004
2011	0.003
2012	0.002
2013	0.005
2014	0.006
2015	0.006
2016	0.005
2017	0.004
2018	0.006
All	0.007

Panel C. Mean Bankruptcy by Industry

Industry Category	SIC Code	*Bankrupt*
A. Agriculture, Forestry, & Fishing	01-09	0.006
B. Mining	10-14	0.013
C. Construction	15-17	0.006
D. Manufacturing	20-39	0.006
E. Transportation & Public Utilities	40-49	0.009
F. Wholesale Trade	50-51	0.013
G. Retail Trade	52-59	0.004
H. Finance & Real Estate	61, 62, 64-67	0.006
I. Services	70-89	0.006
J. Other	91-99	0.000
All		0.007

Table 3: Exposure to Superstar Firms and Future Bankruptcy Outcome

$$Bankrupt_{i,t+1} = \lambda_t + \beta_0 SuperstarExpo_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}. \qquad (1)$$

This table presents logit regression results of the relation between a firm's future bankruptcy in year *t+1* and its exposure to superstar firms. *Panel A* provides the main results. Column 1 reports the baseline results. Column 2 includes control variables. Column 3 adds year fixed effects. *Panel B* presents the coefficient on *SuperstarExpo* estimated using an expanding window approach. We estimate *SuperstarExpo* with the regression specification of Panel A, column 3 using various sample periods. We start the sample period in 1988 and end it in 1989, and then sequentially expand the sample end to 1990, 1991, and . . . 2018. We report the means and standard deviations of these coefficients, and *t*-statistics that test whether the average coefficients are significantly different from zero. All variables are defined in Appendix B; standard errors are clustered at the firm level; *t*-statistics are in parentheses. * *p*-value < 0.1, ** *p*-value < 0.05, *** *p*-value < 0.01 (two-sided tests).

Panel A. Main Results

	(1)	(2)	(3)
SuperstarExpo	0.344***	0.310***	0.334***
	(3.533)	(2.904)	(3.079)
Relative Market Cap		-0.463***	-0.614***
		(-12.173)	(-14.477)
Market-adj Return		-1.054***	-0.924***
		(-14.081)	(-11.568)
Sigma		2.633***	2.243***
		(7.300)	(5.816)
ROA		-0.285**	-0.663***
		(-2.213)	(-4.843)
Leverage		2.016***	1.650***
		(9.461)	(7.337)
Working Capital		-0.544**	-0.615**
		(-2.173)	(-2.454)
Current		0.003	0.019
		(0.123)	(0.794)
Cash		-2.006***	-1.193***
		(-5.280)	(-3.146)
OCF		-6.625***	-6.245***
		(-6.850)	(-6.592)
Size		0.362***	0.578***
		(11.193)	(14.350)
Negative Equity		-0.310**	-0.163
		(-1.995)	(-1.039)
Big4		0.314***	-0.023
		(3.081)	(-0.222)
Investment Grade		-1.090***	-1.125***
		(-3.214)	(-3.322)
Obs.	116,692	116,692	116,692
Year FE	N	N	Y
Pseudo R^2	0.001	0.276	0.290

Panel B. Estimation Using an Expanding Windows Approach

Sample Period Ends in *Year*	Coefficient on *SuperstarExpo*	Sample Period Ends in *Year*	Coefficient on *SuperstarExpo*
1989	0.281	2004	0.18
1990	0.375	2005	0.182
1991	0.369	2006	0.229
1992	0.381	2007	0.256
1993	0.336	2008	0.266
1994	0.409	2009	0.272
1995	0.246	2010	0.306
1996	0.234	2011	0.31
1997	0.293	2012	0.298
1998	0.346	2013	0.292
1999	0.273	2014	0.298
2000	0.204	2015	0.297
2001	0.188	2016	0.287
2002	0.191	2017	0.323
2003	0.193	2018	0.334

Mean	0.282
Std Dev	0.063
t-statistic	24.5

Table 4: Robustness Analyses

This table presents the results of robustness analyses. In Panel A, we examine the robustness of our findings to alternative research design choices. In column 1, SIC-2 industry fixed effects are added. In columns 2 and 3, the OLS and Cox models are employed, respectively. In columns 4 and 5, the analyses are conditioned on whether the firm is a superstar. In columns 6 and 7, standard errors are clustered by firm and year and by industry and year, respectively. In Panel B, we examine the robustness of our findings to alternative measures of a firm's exposure to superstars. We employ two steps in constructing this measure. In Step 1, we identify superstar firms. In Step 2, we calculate a focal firm's exposure to superstar firms. Columns 1–4 focus on Step 1. In column 1, the dependent variable *SuperstarExpo_Top5* is based on the definition of superstar firms as the biggest five firms in the SIC-4 industry. In column 2, the dependent variable *SuperstarExpo_SIC2* is based on the definition of superstar firms as the top 5 percent firms in the SIC-2 industry. In columns 3 and 4, the dependent variable *SuperstarExpo_Top1(10)%* is based on the definition of superstar firms as the top 1 (10) percent firms in the SIC-4 industry. Column 5 focuses on Step 2; in this column the dependent variable *WithSuperstar* is an indicator variable that equals one if there is at least one firm in the focal firm's SIC 4-digit industry that is defined as *Superstar*. Columns 6 and 7 relate to both steps and require the sample to comprise firms whose SIC-4 industries have at least 20 firms and 100 firms, respectively. In Panel C, we examine the robustness of our findings to alternative measures of financial distress. In column 1, the dependent variable *PerformDelist* is an indicator variable that equals one if the firm is delisted due to issues related to poor financial performance. In column 2, the dependent variable *Default* is an indicator variable that equals one if a firm experiences a credit default event. In column 3, the dependent variable *RatingDown* is an indicator variable that equals one if a firm's credit rating is downgraded from an investment grade to a junk grade. In Panel D, we examine the robustness of our findings to alternative explanations. In columns 1 and 2, additional control variables (*Sigma_Ind* and *Sensitivity_Risk*) are added to address the industry risk explanation. In column 3, an additional control variable (*FCF*) is added to address the cash flow explanation. All additional variables are defined in Appendix B; standard errors are clustered at the firm level (except for columns 6 and 7 of Panel A); *t*-statistics are in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01 (two-sided tests).

Panel A. Alternative Research Design Choices

	Additional Fixed Effects	Models		Subsamples		Clustering	
	Industry	OLS	Cox	Non-Superstar Firms	Superstar Firms	Firm & Year	Industry & Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SuperstarExpo	0.271**	0.002**	0.309***	0.332***	0.051	0.334***	0.334***
	(2.318)	(2.275)	(3.165)	(3.025)	(0.076)	(3.307)	(2.811)
Obs.	115,638	116,692	116,692	110,180	2,182	116,692	116,692
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Adjusted/Pseudo R^2	0.321	0.040	0.365	0.284	0.509	0.290	0.290

Panel B. Alternative Measures of Exposure to Superstar Firms

	Alternative Ways to Identify Superstar Firms				*Alternative Way to Capture Exposure*	*Subsamples (SIC-4 Industry Size)*	
	Top 5 firms in SIC-4	Top 5% firms in SIC-2	Top 1% firms in SIC-4	Top 10% firms in SIC-4		≥ 20 Firms	≥ 100 Firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SuperstarExpo_Top5	0.519***						
	(4.551)						
SuperstarExpo_SIC2		0.291**					
		(2.534)					
SuperstarExpo_Top1%			0.371***				
			(3.471)				
SuperstarExpo_Top10%				0.270**			
				(2.469)			
WithSuperstar					0.219***		
					(2.711)		
SuperstarExpo						0.422***	0.676**
						(2.604)	(2.196)
Obs.	116,692	116,692	116,692	116,692	116,692	62,130	21,721
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.292	0.290	0.291	0.290	0.290	0.283	0.350

Panel C. Alternative Measures of Future Negative Outcomes

Dependent variable=	*PerformDelist*	*Default*	*RatingDown*
	(1)	(2)	(3)
SuperstarExpo	0.158**	0.464**	0.407**
	(2.201)	(2.530)	(2.282)
Obs.	98,914	98,914	8,037
Controls	Y	Y	Y
Year FE	Y	Y	Y
Pseudo R^2	0.203	0.215	0.138

Panel D. Alternative Risk and Free-Cash-Flow Explanations

	Risk Explanation		Free-Cash-Flow Explanation
	(1)	(2)	(3)
SuperstarExpo	0.304***	0.333***	0.332***
	(2.792)	(3.073)	(3.063)
Sigma_Ind	2.547***		
	(2.763)		
Sensitivity Risk		0.094	
		(1.223)	
FCF			-0.863**
			(-2.061)
Obs.	116,692	116,673	116,662
Controls	Y	Y	Y
Year FE	Y	Y	Y
Pseudo R^2	0.291	0.291	0.291

Table 5: Path Analyses

This table presents the results of path analyses that illustrate the channels through which superstar exposure affects firms' likelihood of future bankruptcy. Panel A explores three potential paths, including financial performance in terms of accounting performance (*ROA*) and market-adjusted returns (*Market-adj Return)*, and firm-level risk (*Sigma*). Panel B focuses on the accounting performance (*ROA*) channel, and further decomposes *ROA* into three components, including the operating income (*EBITOA*), interest expense (*IntExpOA*), and others income (*OtherIncomeOA*). In both panels, we use OLS regressions and follow the research design in Bushee and Noe (2000). Specifically, we first separately regress the various path variables on superstar firms' exposure (*SuperstarExpo*), and then we regress the likelihood of future bankruptcy (*Bankrupt)* on *SuperstarExpo* as well as the path variables. We calculate the relative size of the direct and the various mediating effects, which we report in Figure 1. All variables are defined in Appendix B; standard errors are clustered at the firm level; *t*-statistics are in parentheses. * *p*-value < 0.1, ** *p*-value < 0.05, *** *p*-value < 0.01 (two-sided tests).

Panel A. Financial Performance and Risk

Dependent variable=	*ROA*	*Market-adj Return*	*Sigma*	*Bankrupt*
	(1)	(2)	(3)	(5)
SuperstarExpo	-0.060***	-0.091***	0.027***	0.002**
	(-20.701)	(-18.526)	(29.960)	(2.275)
ROA				-0.008***
				(-3.714)
Market-adj Return				-0.014***
				(-16.290)
Sigma				0.067***
				(12.945)
Obs.	116,692	116,692	116,692	116,692
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adjusted R^2	0.401	0.233	0.342	0.040

Panel B. Decomposition of Accounting Performance

Dependent variable=	*EBITOA*	*IntExpOA*	*OtherIncomeOA*	*Bankrupt*
	(1)	(2)	(3)	(4)
SuperstarExpo	-0.030***	0.001***	0.001	0.002**
	(-12.055)	(3.676)	(0.964)	(2.207)
EBITOA				-0.007***
				(-2.970)
IntExpOA				0.131***
				(5.118)
OtherIncomeOA				-0.023***
				(-4.922)
Market-adj Return	0.102***	0.000	0.028***	-0.013***
	(53.746)	(1.026)	(27.247)	(-16.084)
Sigma	-0.467***	0.011***	-0.066***	0.065***
	(-30.370)	(9.456)	(-8.193)	(12.684)
Obs.	116,692	116,692	116,692	116,692
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adjusted R^2	0.497	0.509	0.054	0.041

Table 6: Cross-Sectional Analyses

This table presents the results of cross-sectional analyses. Panel A provides the cross-sectional results using firms' innovation activity as the partition. We partition the sample by innovation input (i.e., whether the firm incurs research and development expenditures) in columns 1 and 2. We partition the sample by innovation output (i.e., whether the firm files at least one patent) in columns 3 and 4. Panel B provides the cross-sectional results based on firms' access to credit. We partition the sample by whether a firm's undrawn portion of the revolving credit is above the annual sample median in columns 1 and 2. We partition the sample by whether a firm's tangible assets are above the annual sample median in columns 3 and 4. All variables are defined in Appendix B; standard errors are clustered at the firm level; *t*-statistics are in parentheses. * *p*-value < 0.1, ** *p*-value < 0.05, *** *p*-value < 0.01 (two-sided tests).

Panel A. Innovation Activity

	Innovation Input		Innovation Output	
Subsample=	With *R&D*	Without *R&D*	With *Patents*	Without *Patents*
	(1)	(2)	(3)	(4)
SuperstarExpo	0.006	0.425***	-0.900*	0.400***
	(0.029)	(3.358)	(-1.719)	(3.626)
	coeff. diff = 0.419		*coeff. diff* = 1.300	
	p-value = 0.039		*p*-value < 0.001	
R&DIntensity	0.677***	-		
	(2.692)			
LnPatent			-0.332***	-
			(-2.701)	
Obs.	49,911	66,773	21,985	85,887
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Pseudo R^2	0.311	0.285	0.405	0.274

Panel B. Access to Credit

Subsample=	Revolving Credit Availability		Tangible Assets	
	High *Available Credit*	Low *Available Credit*	High *Tangible Assets*	Low *Tangible Assets*
	(1)	(2)	(3)	(4)
SuperstarExpo	0.112	0.380*	0.024	0.411**
	(0.409)	(1.753)	(0.164)	(2.394)
	coeff. diff = 0.268		*coeff. diff* = 0.387	
	p-value =0.204		*p*-value = 0.055	
LnUndrawn	0.047	0.046		
	(0.494)	(0.666)		
LnTangible			0.552***	0.422***
			(5.211)	(6.789)
Obs.	25,089	26,950	55,651	55,668
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Pseudo R^2	0.485	0.335	0.369	0.242

Table 7: Are Market Participants Aware of Firms' Exposure to Superstars?

This table explores whether sophisticated market participants incorporate firms' exposure to superstars into their decision-making. In column 1, the dependent variable *BuyRec%* is the proportion of equity analysts' "buy" recommendations over all outstanding recommendations. In column 2, the dependent variable *ShortRatio* is short interest ratio. In column 3, the dependent variable *DedicateInst%* is the proportion of dedicated institutional ownership. In column 4, the dependent variable *Going_Conern* is an indicator variable reflecting auditors' going concern opinion. All these four dependent variables are measured at the fiscal year end *t+1*. We use OLS regression in columns 1–3 and Logit in column 4. All variables are defined in Appendix B; standard errors are clustered at the firm level; t statistics are in parentheses. * *p*-value < 0.1, ** *p*-value < 0.05, *** *p*-value < 0.01 (two-sided tests).

Dependent variable= ($Outcome_{i,t+1}$)	$BuyRec\%_{t+1}$ (1)	$ShortRatio_{t+1}$ (2)	$DedicateInst\%_{t+1}$ (3)	GCO_{t+1} (4)
SuperstarExpo	0.000	0.003***	-0.003**	0.214**
	(0.052)	(2.578)	(-2.486)	(2.022)
Obs.	71,836	74,611	109,609	61,634
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo/Adjusted R^2	0.102	0.104	0.024	0.329