How Private Companies Win the Market's Attention*

Thomas Bourveau† **Matthias Breuer**‡ **Maximilian Muhn**§

September 7, 2022

Abstract

This paper examines whether private companies use company awards to obtain the market's attention. We use information from the most prominent annual ranking of the fastest-growing private companies in the U.S. and combine those data with historical copies of companies' webpages, job postings, and financial news. We find that companies are more likely to disclose their award and financial performance when they are placed just within a more salient ranking category (top 500) or receive special recognition (top industry award). We also find that these companies receive more (equity) financing and post more job openings after receiving and disclosing the award. Ultimately, these companies tend to have more successful exits and a lower failure rate. Taken together, our paper shows that company awards are an important facilitator helping private companies attract attention in capital, labor, and product markets through the salient disclosure of their financial performance.

Keywords: Private firms; Voluntary disclosure; Rankings; Entrepreneurship

*We thank seminar participants at Chicago Booth and Goethe University Frankfurt for helpful discussions and suggestions. We acknowledge excellent research assistance of Tom Barry and Rongchen Li. This project was supported by the University of Chicago Polsky Center for Entrepreneurship and Innovation. All errors are our own.

†Columbia University, Columbia Business School - tb2797@columbia.edu

‡Columbia University, Columbia Business School - mb4468@gsb.columbia.edu

§University of Chicago, Booth School of Business - maximilian.muhn@chicagobooth.edu

1 Introduction

Small, private businesses are the backbone of the economy. The over 32 million small, private businesses in the United States (U.S.) account for almost half of employment and around half of the country's gross domestic product, and attract ever growing amounts of financial capital (U.S. Small Business Administration, 2021; Kobe and Schwinn, 2018). While the sheer number of private businesses makes this segment important, it also makes it hard for individual companies to attract financial capital, skilled employees, and new business partners to grow their business. To combat the lack of visibility in input and output markets, and allow companies to stand out, information intermediaries such as business newspapers or consultancies publish rankings of the fastest-growing companies (e.g., Financial Times's *The Americas' Fastest Growing Companies* or Deloitte's *Fast 500*).

We examine whether and how companies use company rankings and awards to obtain attention in capital, labor, and product markets. We focus on the *Inc.* magazine's company ranking, the oldest and most prominent ranking of private companies in the U.S. The magazine has published annual rankings of the 500 fastest-growing private companies since the early 1980s (*Inc. 500*), featuring companies such as Microsoft or Morningstar before they eventually became global players. Since 2007, it also provides an expanded ranking, comprising the 5,000 fastest-growing companies (*Inc. 5000*). The *Inc.* ranking is based on companies' three-year revenue growth. To be included in the ranking, companies must submit their tax returns or other (financial) documents to the magazine, and rank among the top 500(0) submitting companies. The final rankings are published online in August and in print in September of the following year, showing the names of the awardees, their ranks, as well as supplemental information (e.g., company profile and revenue growth).[1]

We expect that companies use the ranking of their financial performance to gain market

[1]During our sample period from 2009 to 2018, *Inc.* magazine also disclosed companies' actual revenues. As of 2020, companies can opt out from the public disclosure of this information. Other rankings may (e.g., Financial Times's *The Americas' Fastest Growing Companies*) or may not (e.g., Deloitte's *Fast 500*) require the disclosure of such proprietary information.

participants' attention. If included in the ranking, companies can gain visibility through the magazine's publication of their performance and can advertise their award through their own channels (e.g., corporate websites and job postings). As a result, potential investors in capital markets, employees in labor markets, and business partners in product markets may become aware of the ranked companies.The ranking could thus allow fast-growing companies to stand out from the large number of private companies, increasing their ability to continue their growth through attracting financial capital, skilled labor, and new business partners.

Compared to other forms of attention seeking (e.g., advertising or voluntary disclosure of financial performance), we expect that the ranking may be particularly useful to private companies. The ranking imposes only small direct costs on the companies and also limits indirect costs associated with the disclosure of sensitive information (e.g., proprietary costs) through coarsened information disclosure of ranks and growth percentages instead of detailed tax returns or financial statements. It also likely increases the attention effect by reducing market participants' processing cost through benchmarking companies and selecting a few top performers. Still, it remains an empirical question whether the *Inc.* ranking actually helps companies gain attention and is ultimately desirable to companies. The ranking may not reach a large enough audience to matter or be just one among many rankings, reducing its attention effects. In addition, private companies in the U.S. appear to see little benefit in publishing their financial performance, according to prior literature (e.g., Minnis and Shroff, 2017), casting doubt on the effectiveness of financial disclosures for gaining market attention.

We exploit two stark discontinuities in the *Inc.* ranking to examine whether companies that placed within more salient award categories obtain more attention and better outcomes. First, we compare companies that just made it into the *Inc. 500* ranking with those that placed just outside of the top 500. The latter are only included in the less prestigious and less salient *Inc. 5000* list. Second, we compare companies that receive a special recognition, by virtue of being the highest-ranked company within their industry in a given year, with other companies that exhibit similar overall ranks and revenue growth. The within-industry recognitions are a salient feature of the *Inc. 500* ranking (e.g., allowing a company to label itself the "fastest-growing health care company"). Those two comparisons allow us to plausibly isolate the effect of being recognized with a more salient award while holding fixed the underlying characteristics (e.g., revenue and growth) of companies around the arbitrary award-category discontinuities. This design feature is crucial given that companies with higher ranks, due to better past performance, should be expected to also exhibit a more promising future outlook. Accordingly, comparisons of companies of different ranks threaten to be confounded by differences in companies' qualities and outlooks. Our empirical strategy alleviates this concern by focusing on close rank comparisons around arbitrary award-category discontinuities.

We collect data on fast-growing private companies in the U.S. included in the *Inc.* ranking from various sources. We obtain data on companies' ranks, size (e.g., revenue and employees), growth, and industry from *Inc.* magazine's award lists for the years 2009 to 2018. We complement the magazine data with data on companies' websites, obtained through scraping historical snapshots of corporate websites provided through Archive.org's *Wayback Machine*; data on companies' financial transactions, obtained from *Pitchbook*; and data on companies' labor demand, obtained through historical job postings provided by *Burning Glass Technologies*. Absent centralized business registers for private companies in the U.S., those data are obtained through tracking companies' online footprint and news. They allow measuring companies' advertising of their awards via their websites (e.g., Boulland et al., 2019; Hoberg et al., 2022); companies' access to equity financing via regulatory filings and financial news; companies' labor demand via their job postings (e.g., Hershbein and Kahn, 2018; Forsythe et al., 2020); and companies' success via indicators for large exits ($\leq$ \$5 million deals) (e.g., Kerr et al., 2014) and survival (e.g., active website and not flagged as inactive in Pitchbook or Bureau van Dijk's Orbis database) (e.g., Howell et al., 2020).

We first examine whether companies actively advertise their *Inc.* ranking awards. Using the count of *Inc.* related words on companies' websites, we find that companies just making the *Inc. 500* list are 30 percent more likely to mention the award on their websites than companies just missing the top 500. We also find that companies with industry awards exhibit a higher propensity to mention the award on their websites than otherwise similar companies (e.g., other highly ranked companies). We find similar results for award mentions in companies' job postings. Besides award mentions, we also find that companies in the *Inc. 500* list or with industry awards talk about their financial performance (e.g., "revenue" and "growth") more frequently. Collectively, these results support the notion that companies perceive the *Inc. 500* list and the industry awards as noteworthy distinctions, even relative to making it into the comprehensive *Inc. 5000* list or obtaining a similar *Inc.* rank but without an industry award. They also support the idea that companies actively advertise the awards and their financial performance through various channels (e.g., websites, job postings), likely to attract attention.

We next examine whether awardees gain greater access to capital markets. We find that companies just making the *Inc. 500* list exhibit up to 2.1 (1.3) percent greater funding (equity growth) than companies just missing the top 500. For companies with industry awards, we even find that they exhibit about 5.8 (5.1) percent greater funding (equity growth) than otherwise similar companies. These results suggest that the company awards appear useful in attracting attention from private equity investors, facilitating the access to equity capital. Notably, this effect appears particularly strong for the industry-leader award, suggesting this recognition is particularly salient and effective in attracting attention.

We also examine whether awardees demand greater labor inputs. We find that companies just making the *Inc. 500* list exhibit 7.5 percent greater labor demand, as measured by their number of job postings, than companies just missing the top 500. For companies with industry awards, we again find that the award effect is particularly pronounced, amounting to a 19.7 percent increase in labor demand. In light of our previous advertising and capital-access results, the labor results likely reflect at least one of two effects of the awards. For one, the awards can help companies attract skilled employees through more salient job postings.

For another, the awards can help companies grow their business (e.g., in terms of employees) as a result of greater financial resources.

We lastly examine whether awardees are more successful in the future. We find that awardees exhibit larger exits (e.g., IPO or M&A deal sizes) and lower failure rates in the future than other companies with similar ranks and revenue growth at the time of the ranking. This result is most pronounced for companies with industry awards. These companies exhibit a 6.6 percentage points increase in the rate of successful exits and a 6.9 percentage points lower failure rate compared to otherwise similar ones. For companies just making it into the *Inc. 500* ranks, the impact on their future success is less significant or even (statistically) insignificant. The lesser impact is consistent with industry awards providing a greater and more consequential distinction than simply making it into the top 500 list. Collectively, our results suggest that companies appear to actively advertise their awards and financial performance to gain visibility in and access to capital and labor markets. Increased visibility and market access, in turn, betters awardees chances to build a successful business.

Our paper contributes to the literature on private companies, entrepreneurship, and growth (e.g., Minnis, 2011; Haltiwanger et al., 2013; Decker et al., 2014; Kerr et al., 2014; Haltiwanger, 2022; Ewens and Farre-Mensa, 2022). Private companies make up the vast majority of companies in the economy. Despite their prevalence, we know relatively little about private companies in the U.S., especially in comparison to publicly listed companies. This knowledge gap, to no small part, is due to the scarcity of publicly available data on private companies (Crenshaw, 2021). By combing various novel data sources, our paper attempts to fill this data gap for a segment of particular importance: new, fast-growing private companies. Those companies are commonly viewed as key for economic growth. Our study shows though that their growth is held back by limited attention and visibility in input and output markets.

Our paper also contributes to the literature on information disclosure and intermediaries. Fishman and Hagerty (1989) suggest that companies can attract market participants' attention by disclosing their financial performance. In this vein, Ross (1979) shows that especially high-performing (e.g., fast-growing) companies should find it in their best interest to disclose. According to prior literature, however, U.S. private companies do not appear to take advantage of financial disclosure (e.g., Minnis and Shroff, 2017). Our paper highlights that information intermediaries (e.g., newspapers, consultancies, or credit bureaus) can help companies to more effectively use their financial information to attract attention. The intermediaries can increase the attention effects of financial disclosures by facilitating the dissemination of the information (e.g., by creating one central platform, distributing information to subscribers) and enhancing its usefulness (e.g., by harmonizing, certifying, benchmarking, and filtering the data). They can also decrease the costs associated with financial disclosures by providing a free-of-charge distribution of companies' information and aggregating or coarsening the information (e.g., to limit the loss of proprietary information).

Our paper is related to and builds on various streams of the literature. It adds to the growing literature on rankings (e.g., Appel et al., 2016; Kaniel and Parham, 2017; Dessaint and Derrien, 2018; Hartzmark and Sussman, 2019). This literature shows that salient ranks can attract attention and resource flows (e.g., in public capital markets), in line with our results in the important but little studied setting of private companies. In the private company setting, our paper complements concurrent work by Cao (2021), documenting that crowd-sourced product rankings of early-stage companies can act as quality signals and affect companies' capital access. Our paper also relates to the literature on corporate awards and venture competitions. In the context of government grants, Howell (2017) shows that the award money helps companies, whereas, in the context of venture competitions, Howell (2020) shows that it is the quality certification effect that helps companies. In our context of fast-growing company awards, the attention effect appears to matter for companies' success. The importance of attention, especially for fast-growing private companies, is consistent with the emerging literature on processing costs of market participants (e.g., Blankespoor et al., 2020).[2] Given the large number of private companies, it takes a salient feature (e.g., ranking or award) to stand out from the crowd and gain market participants' attention (e.g., Merton, 1987).

2 Background

2.1 Company Rankings

A variety of company rankings and awards exists. Prominent rankings of public companies include stock market indices such as the *S&P 500* or *FTSE Russell 1000*, which rank companies based on their market value. Other rankings, such as Fortune's *100 Best Companies to Work For* comprise both public and private companies, ranking them based on workplace characteristics and employee satisfaction (Edmans, 2011). There are also several local venture competitions (e.g., by incubators and universities) that rank early-stage companies on their growth prospects and present awards to the highest ranking companies. Winning companies often receive cash prizes or other benefits by the sponsor of the competition (e.g., office space or mentoring).

For early-stage, fast-growing private companies, there are several national and even international rankings. These rankings are typically curated and published by information intermediaries such as business newspapers (e.g., Financial Times) and consultancies (e.g., Deloitte). Unlike local venture competitions or initiatives, they try to provide a more holistic view on an otherwise opaque segment of the market. Notably, the rankings do not entail any direct tangible benefits beyond the "bragging rights" associated with the award. The rankings emerged in the U.S. several decades ago, and have since found widespread imitation around the world (e.g., BRW Fast Starters in Australia; The Globe and Mail Canada's Top Growing Companies; or FT 1000 Europe's Fastest Growing Companies).

[2] There is a growing literature documenting attention effects in capital markets, including, for example, Barber (2007), DellaVigna and Pollet (2009), Da et al. (2011), and Hartzmark (2015).

The *Inc.* magazine publishes the oldest and most prominent ranking of the fastest-growing private companies in the U.S. Since the early 1980s, it provides an annual ranking of the 500 fastest-growing companies. This ranking is based on companies' growth in revenue over the past three years. Using the ranking, companies must submit corresponding financial information (e.g., tax returns) to the magazine. Based on the submitted information, the magazine ranks companies and includes the top 500 companies in its *Inc. 500* list (see Panel A of Appendix A for details on the process). Since 2007, the magazine also provides an extended ranking, including the top 5000 companies in the *Inc. 5000* list. The extension speaks to the popularity of the ranking, but likely also reflects decreasing costs of publication (e.g., due to online dissemination) and the fact that the magazine's readership increases with the number of covered companies.

Every year, the *Inc.* magazine publishes its rankings both online and in a special print issue. The rankings are first released online every August, followed by a print issue released in September (see Panel B of Appendix A for the 2018 issue). The ranking release includes the names of the companies in the top 500(0) lists, their ranks, and supplemental information, including companies' profiles and revenue growth. Until 2020, the magazine also reported companies' actual revenues. Since then, companies can opt out from the public release of this information. The ranking release also includes separate lists of companies ordered by industries (see Panel C of Appendix A). Those lists provide special awards for the highest ranked company in each industry (e.g., "the fastest-growing healthcare company"). Besides those industry-specific awards, the ranking release includes editorial content related to private companies and entrepreneurship (e.g., on generic topics, but also select in-depth success stories of featured companies) and is widely disseminated (e.g., through business news aggregators) to maximize readership.

2.2 Market Attention

Information acquisition, processing, and integration costs limit the attention of market participants, including investors in capital markets, employees in labor markets, and customers in product markets (e.g., Blankespoor et al., 2020). As a result, market participants may not be aware of the investment, employment, or consumption opportunities offered by companies. Merton (1987) and Howell (2020), for example, argue that limited attention of investors reduces companies' capital access. Similarly, Den Haan et al. (2021) and Foster et al. (2016) suggest that high uncertainty and limited information in labor and product markets can hamper companies' hiring and business growth. Notably, those information frictions and resulting limited attention issues are particularly pronounced for young private companies. Given the sheer number of those companies, it is exceedingly costly for market participants to get informed about all new companies. Hence, it is difficult for new companies to stand out and gain attention, even if they offer superior investment, employment, or consumption opportunities.

In theory, companies can gain the market's attention through disclosure of value-relevant information (e.g., Ross, 1979; Grossman, 1981; Milgrom, 1981). The disclosure (e.g., of companies' revenue growth) can reduce information acquisition costs, thereby increasing attention by market participants (e.g., Fishman and Hagerty, 1989). In practice, however, it appears that most private companies in the U.S. do not take advantage of public disclosure to gain attention (e.g., Minnis and Shroff, 2017). Their reluctance to disclose financial information likely reflects that the attention benefits are limited. For one, in the absence of a centralized disclosure platform and harmonized reporting standards, the disclosure of company-specific information through company-specific channels (e.g., companies' websites) likely does not reduce information acquisition costs markedly (e.g., Christensen et al., 2017; Kim and Kim, 2020). For another, even if disclosure reduces information acquisition costs, disclosure still requires market participants to expand substantial information processing and integration costs to be effective in generating awareness. Thus, the benefits of public disclosure are likely limited, especially for the many new, private companies. At the same time, the costs of disclosure are likely most pronounced for those companies. While dispersed employees and customers may not pay much attention to the new companies' disclosure, larger competitors likely do (e.g., Bernard, 2016; Breuer et al., 2022). As a result, disclosure of financial information may impose notable proprietary costs on young private companies.

Company rankings, such as the *Inc. 500*, can possibly act as an alternative mechanism to gain the market's attention. Compared to companies' financial disclosure, company rankings may come with greater attention benefits and lower costs for new, private companies. The rankings can increase the attention benefits by providing a centralized platform (e.g., a well-known magazine and search-engine optimized website) through which harmonized information (e.g., revenue growth) is provided to interested market participants. These features reduce information acquisition and processing costs. The rankings also explicitly benchmark companies (e.g., through the ranks) and focus on a select set of top performing companies (e.g., the top 500). Those features further reduce information acquisition, processing, and even integration costs. Thus, the rankings can be expected to more effectively increase the market's attention, compared to companies' disclosure. At the same time, the rankings also reduce the costs incurred by new companies. Companies must only disclose their proprietary financial information to the ranking organization, not the public. The ultimate ranking only publishes coarsened information (e.g., ranks and growth), rather than financial details (e.g., tax returns).

Despite the potential advantages of company rankings over company disclosure as a means to gain attention, it remains an empirical question whether companies actually use company rankings with the goal to gain attention, and whether the rankings are effective in achieving that goal. The rankings may not be credible (e.g., due to the limited verification of company information), not be salient enough (e.g., due to a multitude of competing rankings), and/or primarily benefit the ranking organization (e.g., through increased readership of family and friends of ranked companies) instead of the ranked companies.

3 Identification

3.1 Research Designs

We make use of two stark discontinuities in the *Inc.* magazine's rankings to identify whether companies in more salient award categories advertise their awards and benefit from them to a greater extant than otherwise similar companies. To capture companies' advertising of their salient awards, we examine whether they disclose their awards on their corporate websites and in their job postings. To capture attention benefits from the salient awards, we examine whether companies obtain easier access to external capital (e.g., more equity funding), exhibit greater labor demand (e.g., more job postings), and experience greater business success (e.g., large exits or longer survival). We discuss the measurement of these outcomes in detail in the next section (3.2). In this section, we describe how we use the discontinuities in the *Inc.* rankings in our research designs to try to identify the impact of the company awards.

In our first research design, we compare the outcomes (e.g., equity financing) of companies that just make it into the top 500 with those companies that rank just outside of the top 500. The former companies are part of the prestigious *Inc. 500* list, whereas the latter companies are only included in the less prestigious and less salient *Inc. 5000* list. Thanks to the existence of the *Inc. 5000* list (since 2007), we can observe the exact ranks for both, companies within the top 500 as well as those just outside of those ranks.[3] Thus, we can restrict our attention to companies within a given bandwidth of the top 500 cutoff, with companies within the top 500 representing our treatment group and those just outside of those ranks representing our control group. Companies in those two groups starkly differ in the salience of the company list that they are included in (*Inc. 500* vs. *Inc. 5000*), but are otherwise reasonably comparable, especially after controlling for companies' rank (or revenue growth), the assignment variable used by the magazine in classifying the companies.

[3] *Inc.* magazine doesn't maintain records of company ranks for those companies that did not make it into the top 500 prior to 2007.

Using a difference-in-differences approach, we examine whether treated companies that make it into the top 500 in a given ranking year experience different changes compared to control companies that fell just outside of the top 500. This approach allows us to flexibly control for companies' differential ranks and correlated cross-sectional differences (e.g., their three-year revenue growth) via company-fixed effects. As a new company ranking is published every year, we additionally have multiple staggered treatment events. For each event (i.e., annual ranking), we have a new cohort of treated and control companies. Some companies of the treatment cohort for a given ranking may have been treated before already, while some are newly treated (i.e., included in the top 500 for the first time). We accommodate this feature by using a stacked event-window design, which includes observations within a five-year event window for all companies within a given bandwidth for a given ranking year.

To examine the treatment effects of being included in the top 500 list (e.g. Focke et al., 2017), we estimate variants of the following regression equation:

$$\begin{aligned} Log(Outcome_{c,t,y}) = {} & \beta_1 Post\_Award_{t,y} \times Inc\_500\_M_{c,y} \\ & + \beta_2 Post\_Award_{t,y} \times Log(\#\ Employees_{c,y}) \\ & + \beta_3 Post\_Award_{t,y} \times Log(Revenue_{c,y}) \\ & + \alpha_{c,y} + \alpha_{t,i,y} + \epsilon_{c,t,y} \end{aligned} \tag{1}$$

where *Log(Outcome)* is the natural logarithm of the outcome of interest (e.g., equity capital access) of company c, in ranking cohort y, at time t; *Post_Award* is an indicator that takes the value of one for time periods after the ranking year ($t > y$) (and zero otherwise); *Inc_500_M* is an indicator that takes the value of one if a company c is included in the top 500 list in a given ranking year y (and zero otherwise); *Log(# Employees)* is the natural logarithm of the number of employees plus one of company c at the time of the ranking year y; *Log(Revenue)* is the natural logarithm of revenue plus one of company c at the time of the ranking year y; $\alpha_{c,y}$ is a fixed effect for company c and ranking cohort/year y; and $\alpha_{t,i,y}$ is a fixed effect for industry i and ranking cohort y at time t. To account for potential dependence in the error term ($\epsilon_{c,t,y}$) and our treatment, we cluster standard errors by company c.

The coefficient of interest in the above equation is β_1 which captures differential changes experienced by treated companies (i.e., those inside the top 500) relative to control companies (i.e., those outside of the top 500) around the ranking release. The other coefficients in the equation capture the associations between our outcomes of interest and the control variables. The controls include interactions between the post-ranking indicator and companies' size (e.g., employees and revenue). Those interactions allow for differential trends of companies of different size around the ranking year. The controls also include company-cohort fixed effects and industry-cohort-time fixed effects. The former focuses our estimation on within-company changes around a given ranking release. The latter controls for any industry-wide time trends experienced by companies in a given ranking release (i.e., cohort) over the five-year event window.[4] Finally, to limit differences between treatment and control companies, we estimate the above equation for companies within a narrow bandwidth around the top 500 cutoff. In the broadest specification, we use a +/-500 ranks bandwidth (i.e., ranks 1 to 1,000), whereas we limit it to a +/-100 ranks bandwidth in the narrowest specification (i.e., ranks 400 to 600).

In our second research design, we compare companies that receive a special recognition by virtue of being the highest ranked company within their industry in a given year, with other companies that exhibit similar overall ranks and revenue growth. The special recognition is a salient award, designating one company in each industry as the fastest growing companies in that industry (e.g., the fastest-growing healthcare company). Besides providing a salient recognition, this industry-specific recognition is appealing because it allows controlling for the company's actual overall rank. As a result, we can compare companies with special recognition to companies with exactly the same company rank and very similar three-year revenue growth, but without a special recognition (e.g., because other companies grew even

[4]This flexible time effect subsumes the post-ranking ($Post\_Award$) main effect.

more in the respective industry).

To examine the treatment effects of receiving a special industry recognition, we estimate variants of the following regression equation:

$$\begin{aligned} Log(Outcome_{c,t,y}) = \; & \beta_1 Post\_Award_{t,y} \times Top\_Industry_{c,y} \\ & + \beta_2 \mathbb{1}_r\Big(r = Rank_{c,y}\Big) \times \mathbb{1}_\tau\Big(\tau = Event\_Time_{t,y}\Big) \\ & + \beta_3 Post\_Award_{t,y} \times Industry\_Rank_{c,y} \\ & + \beta_4 Post\_Award_{t,y} \times Log(\#\ Employees_{c,y}) \\ & + \beta_5 Post\_Award_{t,y} \times Log(Revenue_{c,y}) \\ & + \alpha_{c,y} + \alpha_{t,i,y} + \epsilon_{c,t,y} \end{aligned} \tag{2}$$

where *Log(Outcome)* is the natural logarithm of the outcome of interest (e.g., equity capital access) of company c, in ranking cohort y, at time t; *Post_Award* is an indicator that takes the value of one for time periods after the ranking year ($t > y$) (and zero otherwise); *Top_Industry* is an indicator that takes the value of one if company c achieved the highest rank in its industry in a ranking year y (and zero otherwise); $\mathbb{1}_r\Big(r = Rank_{c,y}\Big)$ is an indicator that takes the value of one for the actual rank r of company c in a given ranking year y (and zero otherwise); $\mathbb{1}_\tau\Big(\tau = Event\_Time_{t,y}\Big)$ an indicator that takes the value of one for a given difference between the time period t and the ranking year y (i.e., event time $\tau = t - y$); *Log(# Employees)* is the natural logarithm of the number of employees plus one of company c at the time of the ranking year y; *Log(Revenue)* is the natural logarithm of revenue plus one of company c at the time of the ranking year y; $\alpha_{c,y}$ is a fixed effect for company c and ranking cohort/year y; and $\alpha_{t,i,y}$ is a fixed effect for industry i and ranking cohort y at time t. As before, we cluster standard errors by company c.

The coefficient of interest in the above equation is β_1 which captures differential changes experienced by treated companies (i.e., those with industry recognition) relative to control companies (i.e., those without industry recognition) around the ranking release.[5] The other coefficients in the equation capture the association between our outcomes of interest and the control variables. The main control in this design is the interacted rank and event-time fixed effect ($Rank \times Event\_Time = \mathbb{1}_r \times \mathbb{1}_\tau$). This fixed effect flexibly controls for the company's rank and related growth over time (relative to the ranking year).[6] By including this effect, we, for example, compare the changes experienced by GoGuardian, the fastest-growing education company in 2018 with overall rank 66, around the 2018 ranking release with the changes experienced by other companies ranked 66^{th} in any of the other ranking releases between 2009 and 2018 (e.g., the sixth fastest-growing advertising company Gimbal in 2017). By additionally including industry-cohort-time fixed effects, we account for differences between industries (e.g., the education industry growing slower than the advertising industry) and any changes in those industries over time (e.g., the education industry growing more strongly in 2018 than in other years). To further account for differences across companies in the same industry, we focus on within-company changes around a given ranking release through company-cohort fixed effects.

As in our first design, we again control for differential trends of companies of different size around the ranking year by including interactions of the post-ranking indicator with companies' number of employees and revenue. In addition, we control for the possibility that companies with different industry ranks may grow differently after the ranking release. We do so by including the interaction between the post-ranking indicator and (polynominals of) companies' industry rank as a control. We include this control in the top-industry specification given that we expect the top-industry recognition to have a discontinuous attention impact on its recipients. In the top-500 design, by contrast, we expect that the inclusion in the top 500 list may not solely (or even primarily) lead to a discontinuous shift in attention

[5]In some specifications, we also include indicators for the second and third fastest-growing companies in a given industry (interacted with the post-ranking indicator) to compare and contrast the top-industry companies with the ones just below the top-industry rank.

[6]In an alternative specifications, we use a coarsened growth variable (coarsened into 1,000 groups) instead of *Rank*

for all top 500 companies. It can also plausibly affect companies by increasing the sensitivity between companies' rank and their future outcomes (e.g., growth), as a result of greater attention paid to the ranks of top 500 companies. Accordingly, in the top-500 design, we abstain from controlling this effect away, whereas we want to account for any such possibly confounding changes in the top-industry design.

3.2 Company Data

We obtain data on private U.S. companies included in the most expansive (*Inc. 5000*) ranking of the fastest-growing companies from *Inc.* magazine's annual rankings for years 2009 to 2018 directly from the publisher. The data contain information on companies' ranks, names, industry, location, website address, three-year revenue growth, revenues, and number of employees.[7] Across the 10 annual rankings, companies can re-apply and re-appear several times. To account for this feature, we create a unique company identifier. The identifier is primarily based on company's (standardized) website address, a data item that is relatively stable across years. We refine our identifier by incorporating additional information (e.g., standardized company names or location information) and manually verifying matches. In this process, we remove 662 company-ranking-year observations (less than 1.5% of our sample) for which we obtained multiple potential company matches (Panel A of Table 1).The resulting baseline award sample comprises 21,774 private U.S. companies and a total of 49,245 company-ranking-year observations. The average *Inc. 5000* company, accordingly, is included in the top 5000 list slightly more than twice over our 10-year sample period.

We collect data on our sample companies' information disclosure on their websites from Archive.org's *Wayback machine* (e.g., Boulland et al., 2019; Hoberg et al., 2022). Using companies' standardized website address (e.g., invoicecloud.net), we obtain historical copies of companies' website content for a window of five years around the ranking year for each

[7] The *Inc.* ranking features 5000 companies starting in 2007. However, we discard 2007 and 2008 as not all companies have available website data. We often rely on companies' websites as a unique identifier when matching the award data to other data sets.

company-ranking-year combination.[8] InvoiceCloud, for example, was included in the rankings of 2015 and 2018. We accordingly download copies of invoicecloud.net's website content for years 2013 to 2017 and 2016 to 2020. We are unable to obtain historical website copies around the ranking year from Archive.org for only 2,097 company-ranking-year observations (less than 5% of our baseline sample), leading to a website sample of 47,148 company-ranking-year (or 20,967 company) observations. We then measure companies' award disclosure calculating the frequency of mentions of the *Inc.* ranking and awards on companies' websites (counting the keywords "Inc. 500(0)", "Inc. 500", or "Inc. 5000", depending on the outcome variable). Examples for such company disclosures are contained in Appendix B.

We further collect data on our sample companies' financing and business success from Pitchbook, one of the most comprehensive sources for financial data on private companies in the U.S. (Retterath and Braun, 2020). We merge Pitchbook's data with our sample of ranked companies via Pitchbook's matching algorithm, using information on companies' name, location, and website address (requiring a minimum matching score of 15). The data contain information on companies' total funding raised and equity funding growth which we use to measure companies' financing activities in a given quarter. The data also contain information on exits (e.g., public offerings or mergers and acquisitions) and survival (e.g., bankruptcy). We use this information, in combination with information on companies' activity status from Bureau van Dijk's *Orbis* data and Archive.org's *Wayback machine*, to measure companies' business success. For companies without information on financing transactions, successful exits, or failure, we assume that they have not failed yet, but have also not obtained notable amounts of external financing. As a result, the sample for our capital-access and business-success tests corresponds to our baseline sample of companies included in the *Inc. 5000* rankings.

Lastly, we obtain data on companies' job postings from Burning Glass Technology (BGT). BGT scrapes and records the full text of companies' online job postings (e.g., Forsythe et al.,

[8] For each landing page, we crawl the full-texts of up to 20 links per landing page.

2020; Azar et al., 2020; Hershbein and Kahn, 2018; Modestino et al., 2020). The job-posting data allow us to measure companies' labor demand (e.g., Hershbein and Kahn, 2018). They also provide us with another disclosure channel for companies to advertise their awards (other than through their websites). BGT's job-posting data are available from 2010 onward. As we require a two-year period before companies' first ranking, the sample for our labor-demand tests exclude the two first ranking years (2009 and 2010).[9] Our labor-demand sample thus contains 18,382 companies (39,515 company-ranking-year) observations.

In Table 1, we report the descriptive statistics for the various samples and variables. In Panel A, we provide details on the sample selection and corresponding sample sizes. In Panel B, we report descriptive statistics for the variables obtained from the *Inc.* magazine data. The average (median) company in our sample has revenue of \$49m (\$4.87m) and 256 (50) employees in the year before the award ranking. In line with the rankings targeting fast-growing companies, our sample companies boast relatively high growth rates. The average (median) three-year revenue-growth rate is 4.24 (1.32), which corresponds to an annual growth of 73.7% (32.4%). Given that the rankings sort companies by growth, *Inc. 500* companies have a substantially higher growth rate than companies outside of the top 500. The average (median) three-year growth rate is 26.3 (15.2), which corresponds to an annual growth of 301% (253%). This difference in growth rates necessitates the use of narrow bandwidths and/or rank (or growth) controls, as described in section 3.1. The *Inc. 500* companies also differ in terms of size from those companies outside of the top 500. Notably, the top 500 companies are relatively smaller. Their average revenue is only \$26.35m. This size difference reflects that it is easier to achieve higher growth rates for companies starting from a low size (i.e., denominator), such as small, early-stage companies. Consistent with a selection on small, high-growth companies, we observe, in Panel C, that our sample companies are clustered in tech-oriented industries (e.g., IT Services) and are

[9] For the first award year 2011, we only have 18 months of pre-period data. Additionally, our BGT data ends in December 2019. Thus, we only have 18 months of post-period data for the 2018 award issue. By including fixed effects nested within ranking-year (e.g., $Industry \times Award\_Year \times Website\_Year$ fixed effects in Table 3), however, our designs flexibly account for those different time horizons.

located in states known for their startup scene (e.g., California).

4 Results

4.1 Award Disclosure

We first examine whether companies publicly advertise their *Inc.* award ranking. As a prominent advertising and communication channel for private companies, we focus on disclosures of award-related news and mentions on corporate websites (e.g., Boulland et al., 2019). We report the main descriptive statistics for this website sample in Panel B of Table 1. On average, we were able to gather 4.43 website copies per company and we have the full set of five website copies for 71.5% of all companies. A company mentions the *Inc. 500(0)* (*Inc. 500*) award on average 3.7 (1) times on their website in a given year. However, this distribution is somewhat skewed as the award is only mentioned by 22.8% of all observations at least once.[10] Finally, *Inc. 500* companies are more likely to mention the *Inc. 500* award compared to companies from the full sample (average of 1.68 versus 1).

In Panel A of Table 3, we report the results from comparing companies that are just inside the top 500 list with those that are just outside of it.[11] In the first four columns, we restrict our regression sample to companies ranked between 1 and 1,000. In column 1, we examine the impact of companies' top-500 status on a broad measure of award mentions, capturing the frequency of any *Inc.* related words. We find that top-500 companies exhibit significantly more frequent mentions of their awards on their websites after the ranking release than companies outside the top 500 (i.e., those in the top 5000). The coefficient magnitude suggests that top-500 companies increase their disclosure by 30% relative to the

[10] The sample contains two years of pre-award data. Additionally, due to capacity constraints, we only crawl up to 20 links per landing page. Thus, we might miss the relevant page if a company only discloses the award on a less salient webpage below the main domain.

[11] Throughout this analysis, we consider websites released during the announcement year either as part of the pre- (before August) or the post-period (beginning in August). Therefore, we treat the two parts of the announcement year separately for the $\alpha_{i,t,y}$ fixed effect. Otherwise, this fixed effect would not subsume *Post_Award*; however, we obtain very similar results without making adjustment

pre-ranking period and non-top-500 companies.

In the remaining columns in Panel A, we vary the measurement of the disclosure outcome and the bandwidth around the top-500 cutoff. In column 2, we use an indicator for award mentions, instead of the frequency of award mentions. This extensive-margin test shows results consistent with our earlier intensive margin results: Companies that make the *Inc. 500* list are 10 percentage points more likely to disclose the award (relative to an unconditional mean of 23%). In column 3, we narrow the award mentions down to terms specific to the *Inc. 500* award. We find that top-500 companies are substantially more likely to mention their specific award. The coefficient magnitude is substantially larger for this narrow measure compared to estimate in column 1, where we use a broad award measure (which also includes top-5000 mentions). This pattern highlights that both top-500 and top-5000 companies tend to disclose their awards. But top-500 companies disclose it more frequently. In column 4, we again use a narrow award definition, but this time we use terms specific to the *Inc. 5000* award. This narrow definition allows us to run a placebo test. We find that top-500 companies are not more likely to disclose *Inc. 5000* awards. If anything, they are slightly less likely compared to the control group, consistent with companies falling just out of the top 500 advertising their top-5000 award. These results are robust to restricting our sample to companies closer to the top-500 cutoff. Columns 5 and 6, for example, replicate our estimate for the broad award measure (column 1) for companies ranked 300 to 700 and 400 to 600, respectively.

In Panel B of Table 3, we examine the dynamics of disclosure effect of the top-500 award. In column 1, we find that the disclosure effect manifest significantly after the ranking release and reaches its peak in the year after the award announcement. However, these companies also mention the award somewhat more frequently two years before the award announcement. This pattern likely reflects that companies can appear in the rankings in multiple years (e.g., first making it into the top 5000 before finally making the top 500). Consistent with this explanation, we observe that this effect vanishes when using the narrow top-500 disclosure outcome (column 3) and also reduces when using narrower bandwidths (columns 5 and 6). The results in column 4, with top-5000 award mentions showing the opposite pattern, lend further support to this explanation.

In Table 4, we repeat our disclosure analysis for the top-industry award. In column 1, we find a large and significant effect of receiving a top-industry award on companies' award disclosures on their websites. This effect is robust to including additional (flexible) controls for companies' growth and ranks (columns 2 and 3). It is also substantially larger than the effect of ranking second or third in a given industry (column 4). Lastly, the disclosure effect is again robust to using a narrower sample (e.g., companies ranked 1 to 1,000 in column 5; and companies ranked 1 to 500 in column 6).

Collectively, our disclosure results suggest that companies actively advertise their awards on their corporate websites. This finding suggests that companies perceive the awards as noteworthy and potentially helpful in attracting attention. Interestingly, and consistent with our expectation, companies appear to view top-500 awards as more noteworthy than top-5000 awards, and top-industry awards as even more noteworthy than top-500 awards. They advertise those awards on their websites, but also in their job postings, as we show graphically in Figure 1. Besides the direct award mentions, companies also mention terms related to financial performance (e.g., "revenue" and "growth") more frequently on their websites and in their job postings (but not other financial terms, as we find in untabulated tests). Overall, our disclosure results are consistent with companies viewing the *Inc.* awards as relevant for various stakeholders, including investors and customers checking companies' websites and prospective employees reading companies' job postings. In the next sections, we explore whether companies indeed gain attention and benefit from receiving the awards and disclosing them.

4.2 Capital Access

We next examine whether company awards help attracting attention in capital markets. They may prove particularly useful for venture and private equity investors in screening potential investment targets and assessing the viability of early-stage companies' business models. In Panel B of Table 2, we report the descriptive statistics for the financing sample and outcomes. In any given quarter, companies have a 0.9% likelihood of receiving any type of new funding. Conditional on having a funding round, companies in our sample receive on average $88.9m (median $15m), which is a sizable amount for companies in our sample. Equity growth capital (mainly via venture capital or private equity) constitutes a relevant portion of this amount. The frequency rate for this type of funding is 0.5% in any given quarter with an average deal size of $25.7m (median $9.49m). Additionally, companies in the top 500 tend to have more frequent but smaller financing rounds.

In Panel A of Table 5, we report the results from comparing companies that are just inside the top 500 list with those that are just outside of it. In the first three columns, we use the natural logarithm of total funding (plus one) as the outcome variable and successively narrower bandwidths around rank 500. Across all three columns, we find a significant and positive effect of the top-500 award on companies' total financing amount after the ranking release. The coefficient magnitude in column 3, for example, suggests that placing in the top 500 (rank 401 to 500) increases the amount of financing by 2.1% relative to companies outside of the top 500 (rank 501 to 600). In the last two columns, we additionally explore the top-500 award effect on equity-growth funding. We again find consistently positive coefficients, albeit at weaker significance in the narrowest sample.

In Panel B of Table 5, we repeat the financing analysis for the top-industry award. In column 1, we find a large, positive, and significant effect of the top-industry award on companies' funding. The coefficient magnitude suggests that top-industry companies obtain 4.7% more financing within the two years following the ranking release relative to similar control companies with an identical overall rank. This effect is substantially larger than the top-500 effect, documented in Panel A. It is robust to using more flexible controls (column 2), controlling for second and third ranked companies (column 3), and alternative funding measures (i.e., equity growth; columns 4 and 5).

Collectively, these results suggest that companies gain investors' attention as a result of the ranking releases and disclosures. The increased attention appears to benefit companies' access to (equity) capital notably. In line with our prior disclosure results, this benefit is greatest for companies receiving a top-industry award. The capital-market benefits of the awards likely help companies grow their business (e.g., financing the growth of their labor force).

4.3 Labor Demand

Besides companies' capital access, we examine whether company awards increase companies' demand for labor, and possibly improve companies' access to skilled labor. Skilled labor is a key input for early-stage companies to grow their business and attract new talent is particularly important for growing companies. We proxy for labor demand by the number of a company's online job postings in a given quarter. In Panel C of Table 1, we show descriptive statistics for the labor-demand sample and outcomes. On average, companies post 9.92 new jobs per quarter. Although the the distribution is skewed (median of 0), we observe at least one job posting per company-quarter for 34% of all observations. For our analyses, we use both the natural logarithm (plus one) as well as a dichotomized variable (coded as one if a company posted a job and zero otherwise) of the number of job postings.

In Panel A of Table 6, we report the results from comparing companies that are just inside the top 500 list with those that are just outside of it. In the first three columns, we focus on the number of job postings and in the last two columns on whether a company posted any job during a given quarter. For the specifications with broader bandwidths (column 1, 2 and 4), we consistently find a positive effect of the inclusion in the *Inc. 500* on subsequent hiring. The coefficient in column 1, for example, suggests that hiring increases by 7.4% relative to the quarters before winning the award. Also the 1.9 percentage point increase in column 4 represents an economically meaningful change, amounting to a 5.5% increase relative to the unconditional mean (34%). However, we obtain insignificant results for the narrowest bandwidth ([400;600]) in column 3 and 5.[12]

In Panel B of Table 6, we repeat the labor analysis for the top-industry award. In our preferred specification with rank fixed effects, we find an increase in the number of job postings by 19.1% (column 2) for top-industry companies in the quarters following the award announcement. Notably, this effect only materializes for the highest ranked company, but not for the second or third highest ranked company withing a given industry (column 3). The positive labor-demand effect also holds for a narrower sample (column 4) or with a binary coding of our outcome variable (column 5). Thus, compared to the top-500 award, we find a stronger effect of the top-industry award on companies' hiring.

Taken together, these results suggest that companies with awards—especially the top-industry award—not only receive more financing, but also (try to) grow their business through hiring more employees. As a result, we expect that award-winning companies exhibit greater business success in the future thanks to a better access to capital and labor markets.

4.4 Business Success

We lastly examine whether company awards ultimately translate into greater future business success. We determine business success by identifying whether a company had a successful exit and/or is more likely to survive. To approximate a successful exit, we use information on all completed security offerings or M&A transactions with non-missing deal sizes as reported in Pitchbook. We follow Kerr et al. (2014) and require that a company completed such a deal with a total deal size of at least $5m. In Panel C of Table 2, we find

[12] The weaker response compared to the capital access result (4.2) could be driven by a noisier outcome variable. Specifically, we need to rely on a fuzzy name matching between our award and job posting data (e.g., unable to match via company websites etc.) and only observe a subset of all actual employment changes (online job postings). Therefore, we likely underestimate the award effect on companies' subsequent hiring.

that about 8.7% of all companies in our sample had such a successful exit until 2021. Their average exit amount is \$483m (median of \$140m); substantially more than the average deal size for our entire sample (\$41m). To measure companies' survival, we combine information from various data sources to determine whether a company became inactive until 2021 (see Section 3.2). About 11.4% of all companies in our sample failed (Panel C of Table 2). Our measures of business success capture future success. Accordingly, we only have one outcome per company and ranking cohort. Thus, unlike in prior analyses, we cannot additionally exploit the time-series dimension, using a difference-in-differences specification. Still, we generally follow the basic idea behind our main research designs, comparing companies just above the award ranks with those just below while controlling for companies' actual ranks (or coarse growth) across cohorts.

In Panel A of Table 7, we report the results from our top-500 analysis. We do find significant positive effects in the broader top-500 specifications (columns 1 and 4), suggesting that company awards lead to companies' success. However, the results become insignificant for narrower bandwidths (see columns 2 and 3) or with our alternative outcome variable (column 5). This mixed result is not unexpected given the more limited salience of the award and somewhat weaker results documented for our previous outcomes in the capital market (Section 4.2) and labor market (Section 4.3).

In Panel B of Table 7, we turn our focus on the top-industry award analysis. We find that top-industry award winners have a 6.4 or 6.5 percentage points higher likelihood of successfully exiting relative to other companies with the same coarse growth (column 1) or actual rank (column 2). This economically significant increase along the extensive margin also largely explains why the average dollar value of companies' exits increases by almost 40% (column 4). Finally, in the last column, we find less frequent (6.9 percentage points) failures for companies winning the top-industry awards. Compared to Panel A, this result suggests that especially salient awards such as top-industry awards have a sizable and lasting effect.

5 Conclusion

The millions of private companies in the U.S. are the backbone of the economy and a key driver of economic growth. Given the large number of private companies, however, early-stage companies with new business ideas can struggle to stand out from the crowd and gain market participants' attention, hampering their growth and ultimate business success. In this paper, we study whether fast-growing companies can attract market participants' attention through participation in and disclosure of private company rankings.

Rankings of fast-growing private companies are frequently curated and published by business newspapers and consultancies (e.g., *Inc.* magazine, the Financial Times, and Deloitte). The rankings typically require companies to submit financial information (e.g., tax returns or financial statements) to the ranking organization. Ranking organizations then harmonize the information, benchmark the companies along a pre-defined dimension (e.g., revenue growth), and select the top-performing companies for recognition.

Using two salient recognitions annually awarded by *Inc.* magazine—the inclusion in the list of the "*500 fastest-growing companies*" and the designation as the "*fastest-growing company in the industry*"—, we find evidence that companies actively advertise their awards on their corporate websites and in their job postings. As a result of companies' awards and advertising, we find evidence that companies gain easier access to external capital (e.g., equity funding growth), exhibit more demand for labor (e.g., job postings), and experience greater business success (e.g., more successful exits and longer survival).

Collectively, our evidence suggests that private company rankings and awards serve an important function: They help early-stage companies attract attention of capital providers, skilled labor, and business partners. Compared to alternative mechanisms (e.g., voluntary disclosure of financial statements), rankings and awards appear particularly well suited for private companies seeking to gain attention because they reduce market participants' information costs (e.g., by harmonizing, benchmarking, and filtering company data) while limiting companies' loss of sensitive information (e.g., by coarsening the disclosed information).

References

Appel, I., T. Gormley, and D. Keim, 2016, Passive investors, not passive owners, *Journal of Financial Economics* 121, 111–141.

Azar, J., I. Marinescu, M. Steinbaum, and B. Taska, 2020, Concentration in U.S. labor markets: Evidence from online vacancy data, *Labour Economics* 66, 101886.

Barber, T., B.and Odean, 2007, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Bernard, D., 2016, Is the risk of product market predation a cost of disclosure?, *Journal of Accounting and Economics* 62, 305–325.

Blankespoor, E., E. deHaan, and I. Marinovic, 2020, Disclosure processing costs, investors' information choice, and equity market outcomes: A review, *Journal of Accounting and Economics* 70, 101344.

Boulland, R., T. Bourveau, and M. Breuer, 2019, Corporate websites: A new measure of voluntary disclosure, *Working Paper (Available at: Link)* .

Breuer, M., C. Leuz, and S. Vanhaverbeke, 2022, Reporting regulation and corporate innovation, *NBER Working Paper (Available at: Link)* .

Cao, R., 2021, Information frictions in new venture finance: Evidence from Product Hunt rankings, *Working Paper (Available at: Link)* .

Christensen, H., E. Floyd, L. Liu, and M. Maffett, 2017, The real effects of mandated information on social responsibility in financial reports: Evidence from mine-safety records, *Journal of Accounting and Economics* 64, 284 – 304.

Crenshaw, C., 2021, Mind the (data) gaps, *Keynote Address at the 8th Annual Conference on Financial Market Regulation (CFMR) (Available at: Link)* .

Da, Z., J. Engelberg, and P. Gao, 2011, In search of attention, *The Journal of Finance* 66, 1461–1499.

Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda, 2014, The role of entrepreneurship in U.S. job creation and economic dynamism, *Journal of Economic Perspectives* 28, 3–24.

DellaVigna, S., and J. Pollet, 2009, Investor inattention and friday earnings announcements, *Journal of Finance* 64, 709–749.

Den Haan, W., L. Freund, and P. Rendahl, 2021, Volatile hiring: Uncertainty in search and matching models, *Journal of Monetary Economics* 123, 1–18.

Dessaint, O., and F. Derrien, 2018, The effects of investment bank rankings: Evidence from M&A league tables, *Review of Finance* 22, 1375–1411.

Edmans, A., 2011, Does the stock market fully value intangibles? Employee satisfaction and equity prices, *Journal of Financial Economics* 101, 621–640.

Ewens, M., and J. Farre-Mensa, 2022, Private or public equity? The evolving entrepreneurial finance landscape, *Annual Review of Financial Economics* 14, forthcoming.

Fishman, M., and K. Hagerty, 1989, Disclosure decisions by firms and the competition for price efficiency, *Journal of Finance* 44, 633–646.

Focke, F., Maug. E., and A. Niessen-Ruenzi, 2017, The impact of firm prestige on executive compensation, *Journal of Financial Economics* 123, 313–336.

Forsythe, E., , L. Kahn, F. Lange, and D. Wiczer, 2020, Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims, *Journal of Public Economics* 189, 104238.

Foster, L., J. Haltiwanger, and C. Syverson, 2016, The slow growth of new plants: Learning about demand?, *Economica* 83, 91–129.

Grossman, S., 1981, The informational role of warranties and private disclosure about product quality, *Journal of Law and Economics* 24, 461–483.

Haltiwanger, J., 2022, Entrepreneurship in the twenty-first century, *Small Business Economics* 58, 27–40.

Haltiwanger, J., R. Jarmin, and J. Miranda, 2013, Who creates jobs? Small versus large versus young, *Review of Economics and Statistics* 95, 347–361.

Hartzmark, S., 2015, The worst, the best, ignoring all the rest: The rank effect and trading behavior, *Review of Financial Studies* 28, 1024–1059.

Hartzmark, S., and A. Sussman, 2019, Do investors value sustainability? A natural experiment examining ranking and fund flows, *Journal of Finance* 74, 2789–2837.

Hershbein, B., and L. Kahn, 2018, Do recessions accelerate routine-biased technological change? evidence from vacancy postings, *American Economic Review* 108, 1737–72.

Hoberg, G., C. Knoblock, G. Phillips, J. Pujara, L. Raschid, and J. Qiu, 2022, Filling the private firm void: Using representation learning to identify competitor relationships between businesses, *Working Paper (Available at: Conference website)* .

Howell, S., 2017, Financing innovation: Evidence from R&D grants, *American Economic Review* 107, 1136–64.

Howell, S., 2020, Reducing information frictions in venture capital: The role of new venture competitions, *Journal of Financial Economics* 136, 676–694.

Howell, S., M. Niessner, and D. Yermack, 2020, Initial coin offerings: Financing growth with cryptocurrency token sales, *Review of Financial Studies* 33, 3925–3974.

Kaniel, R., and R. Parham, 2017, WSJ category kings – The impact of media attention on consumer and mutual fund investment decisions, *Journal of Financial Economics* 123, 337–356.

Kerr, W., J. Lerner, and A. Schoar, 2014, The consequences of entrepreneurial finance: Evidence from angel financings, *Review of Financial Studies* 27, 20–55.

Kim, S., and S. Kim, 2020, Fragmented securities regulation: Neglected insider trading in stand-alone banks, *Working Paper (Available at: Link)* .

Kobe, K., and R. Schwinn, 2018, Small business GDP 1998–2014, *Produced for the U.S. Small Business Administration, Office of Advocacy (Available at Link)* .

Merton, R., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483–510.

Milgrom, P., 1981, Good news and bad news: Representation theorems and applications, *Bell Journal of Economics* 12, 380–391.

Minnis, M., 2011, The value of financial statement verification in debt financing: Evidence from private us firms, *Journal of Accounting Research* 49, 457–506.

Minnis, M., and N. Shroff, 2017, Why regulate private firm disclosure and auditing?, *Accounting and Business Research* 47, 473–502.

Modestino, A., D. Shoag, and J. Ballance, 2020, Upskilling: Do employers demand greater skill when workers are plentiful?, *Review of Economics and Statistics* 102, 793–805.

Retterath, A., and R. Braun, 2020, Benchmarking venture capital databases, *Working Paper (Available at: link)* .

Ross, S., 1979, Disclosure regulation in financial markets: Implications of modern finance theory and signaling theory, in F. R. Edwards, ed., *Issues in Financial Regulation* (McGRaw-Hill).

U.S. Small Business Administration, 2021, Small business profile, *White Paper (Available at link)* .

Figure 1: Disclosure Effects of Award Ranking

The figure shows the disclosure behavior of Inc. 500/Inc. 5000 award companies in job postings around the Inc. 500 threshold. We plot out the number of times a company mentions the *Inc.* award in a given quarter in job postings around the award date. To construct this variable, we rely on the job-posting sample (as defined in Table 2) and count the number of mentions of "Inc. 500(0)" in the full texts of the companies' quarterly job postings. The omitted quarter ("Quarter −1") is the quarter before the the award announcement. The 3^{rd} quarter of the award year ("Quarter 0") indicates the quarter of the award announcement (i.e., July to September as awards are typically announced during August or September of a given year).

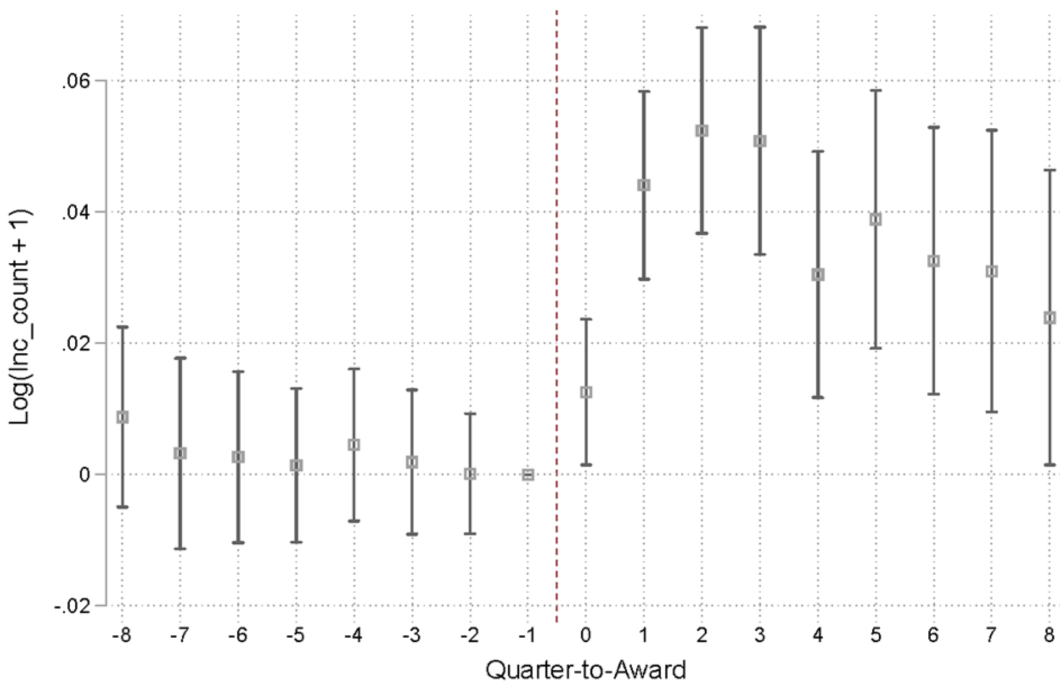

Table 1: Sample Selection and Descriptive Statistics for Award Data

The table presents details on the sample selection (Panel A), descriptive statistics for the variables based on the award data (Panel B) as well as information on the industry and geographical distribution of Inc. 500/Inc. 5000 companies (Panel C). As displayed in Panel A of Table 1, a company c can obtain the Inc. award in multiple years t. In Panel B, *Rank* is the company's rank in the Inc. 500/Inc. 5000 award ranking in year t. Revenue is the company's revenue (in 1,000s) in year *t-1*. *# Employees* is the number of employees in year *t-1*. *3-Year Growth* is the company's revenue growth between *t-4* and *t-1*. *Industry_Rank* is the company's *Rank* after sorting within industry in award year t. Inc. 500 Sub Sample is the sub-sample that only includes companies with a ranking better than 500. In Panel C, we show the top and bottom 5 industries (out of 27 industries in total).

Panel A: Sample Selection Procedure

Data Requirements	*Number of Obs.*	*Thereof Inc. 500 Obs.*
Member of the Inc. 500/Inc. 5000 between 2009 and 2018	49,907	5,003
Minus companies that cannot be uniquely identified	-662	-25
Minus companies with unavailable website copies two years around award date	-2,097	-165
Total Website Sample (max):	47,148	4,813
Thereof: Unique Companies	20,978	3,840
Member of the Inc. 500/Inc. 5000 between 2009 and 2018	49,907	5,003
Minus companies that cannot be uniquely identified	-662	-25
Total Financing Sample (max):	49,245	4,978
Thereof: Unique Companies	21,774	3,966
Member of the Inc. 500/Inc. 5000 between 2011 and 2018	40,002	4,000
Minus companies that cannot be uniquely identified	-487	-18
Total Job Posting Sample (max):	39,515	3,982
Thereof: Unique Companies	18,382	3,199

Panel B: Descriptive Statistics on Inc.500/Inc. 5000 Companies from 2009 to 2018

(N up to 49,245)	Mean	Std. Dev.	P1	P25	Median	P75	P99
Full Sample:							
$\text{Rank}_{c,t}$	2,491	1,442	50	1,242	2,489	3,740	4,945
$\text{Revenue}_{c,t-1}$	49,407	348,892	2,049	4,865	10,398	27,365	638,820
# $\text{Employees}_{c,t-1}$	256	2,398	4	24	50	128	3,200
3-Year $\text{Growth}_{c,t-1}$	4.3	16.6	0.1	0.7	1.3	3	50
$\text{Industry\_Rank}_{c,t}$	162	144	2	51	120	229	618
Inc. 500 Sub-Sample:							
$\text{Rank}_{c,t}$	250	144	5	125	250	375	495
$\text{Revenue}_{c,t-1}$	26,350	102,598	2,037	4,245	8,333	19,442	312,304
# $\text{Employees}_{c,t-1}$	101	321	3	18	37	86	934
3-Year $\text{Growth}_{c,t-1}$	26.3	46.6	5.8	10.5	15.2	26.3	177
$\text{Industry\_Rank}_{c,t}$	17.1	13.6	1	6	14	2 6	56

Panel C: Industry and Geographical Distribution

Top 5 Industries		*Bottom 5 Industries*	
Advertising & Marketing	10.81%	Environmental Services	0.38%
IT Services	9.51%	Computer Hardware	0.60%
Software	8.18%	Engineering	0.72%
Health	8.12%	Travel & Hospitality	0.80%
Government Services	7.96%	Insurance	1.16%
Top 5 States:		*Bottom 5 States:*	
CA	13.62%	AK	0.03%
TX	8.00%	PR	0.03%
NY	6.60%	WY	0.03%
FL	6.17%	SD	0.09%
VA	5.80%	HI	0.11%

Table 2: Descriptive Statistics for Companies' Websites Disclosures, Job Postings and Financing Data

The table presents descriptive statistics on the website sample from 2009 to 2018 (Panel A), as used in Table 3 and Table 4, the financing sample from 2009 to 2018 (Panel B) as used in Table 5 and Table 7 and the job posting sample from 2011 to 2018 (Panel C), as used in Table 6. For Panel A, we obtain historical copies of companies websites using Archive.org's Wayback machine. We obtain one historical website copy per year in a five-year window around the award date (i.e., up to five website-years as displayed in the variable *Website_Years*) and crawl the full-texts of up to 20 links per landing page. Using the full-texts of these webpages, we construct *# Inc* (*# Inc_500*, *# Inc_5000*), which is the number of times "Inc. 500(0)" ("Inc. 500", "Inc. 5000") is mentioned on a company's webpage in year y for a company c that won the award in year t. In Panel B, we match Inc. 500/Inc. 5000 companies to Pitchbook using location, website, and company name via Pitchbook's matching algorithm (requiring a matching score of at least 15). *$ Funding* is the total funding (in millions) received in quarter-year q by of a company c that won the award in year t (including all deals except for Debt – PPP, Secondary Transaction, Share Repurchase, Bankruptcy or Out of Business). *$ Equity Growth* is the total equity-growth related funding (in millions) received in quarter-year q by a company c that won the award in year t (including all deals that are classified as Accelerator/Incubator, Angel, Corporate, Early Stage VC, Later Stage VC, PE Growth/Expansion, Seed Round, Mezzanine, Convertible Debt or Equity Crowdfunding). *$ Success Exit* is the total amount received (in millions) by company c in a security offering or an M&A transaction (including deal types Buyout/LBO, IPO, Merger/Acquisition, PIPE or SPO). When transforming the variable into an indicator *D(Success Exit)* in Table 7, we follow Kerr et al. (2014) and code all exits with a deal size of at least US$5 million as '1' (and '0' otherwise). *D(Failure)* is an indicator that takes the value of one if the company did not have a successful exit and is inactive based on one of the following three conditions: (i) no longer has an active website (proxied by no longer having a copy in the Wayback machine between 2019 to 2021), (ii) went out of business according to Pitchbook (Bankruptcy or Out of Business), or (iii) is flagged as inactive in BvD's Orbis database. In Panel C, we match Inc. 500/Inc. 5000 companies to job postings from Burning Glass Technologies using the company's (standardized) company name in a stringent fuzzy match. We retain all job postings that appear in five-year window around the award announcement (i.e., eight quarters before and eight quarters after Q3 of award year t). *Num_Postings* is the number of job postings in quarter-year q for a company c that won the award in year t.

Panel A: Historical Copies of Websites of Inc.500/Inc. 5000 Companies (Website Sample)

(N up to 215,250)	Non-Zero %	Mean	Std. Dev.	P1	P25	Median	P75	P99
Full Sample:								
Website_Years$_{c,t}$	100%	4.4	1.1	1	4	5	5	5
# Inc$_{c,t,y}$	22.8%	3.7	14	0	0	0	0	59
# Inc 500$_{c,t,y}$	8.0%	1	6.47	0	0	0	0	28
# Inc 5000$_{c,t,y}$	17.9%	2.7	11.9	0	0	0	0	50
Inc. 500 Sub-Sample:								
Website_Years$_{c,t}$	100%	4.4	1	1	4	5	5	5
# Inc$_{c,t,y}$	23.9%	2.8	12.4	0	0	0	0	50
# Inc 500$_{c,t,y}$	19.1%	1.7	8.7	0	0	0	0	41
# Inc 5000$_{c,t,y}$	9.9%	4.5	16	0	0	0	0	71

Panel B: Financing Data of Inc. 500/Inc. 5000 Companies (Financing Sample)

(N up to 837,165)	Non-Zero %	Mean	Std. Dev.	P1	P25	Median	P75	P99
Full Sample:								
\$ $\text{Funding}_{c,t,q}$	0.9%	1.1	37.5	0	0	0	0	3.2
\$ $\text{Equity Growth}_{c,t,q}$	0.5%	0.18	7.4	0	0	0	0	0
\$ Success Exit_{c}	8.7%	41.8	381	0	0	0	0	958
$\text{D(Failure}_{c})$	11.4%	0.1	0.3	0	0	0	0	1
Inc. 500 Sub-Sample:								
\$ $\text{Funding}_{c,t,q}$	2.0%	1.6	61.7	0	0	0	0	20.6
\$ $\text{Equity Growth}_{c,t,q}$	1.6%	0.6	11	0	0	0	0	12
\$ Success Exit_{c}	11.3%	51.1	370	0	0	0	0	1,100
$\text{D(Failure}_{c})$	13.6%	0.1	0.3	0	0	0	0	1

Panel C: Job Postings of Inc.500/Inc. 5000 Companies (Job Posting Sample)

(N up to 647,018)	Non-Zero %	Mean	Std. Dev.	P1	P25	Median	P75	P99
Full Sample:								
$\text{Num\_Postings}_{c,t,q}$	34.0%	9.9	133	0	0	0	2	162
Inc. 500 Sub-Sample:								
$\text{Num\_Postings}_{c,t,q}$	30.3%	10	273	0	0	0	1	108

Table 3: Difference-in-Differences Design Analysis of Yearly Website Disclosures

This table analyzes Inc. 500/Inc. 5000 members' historical website disclosures in a five-year window around the award date (up to 43,295 company-website-years). In Panel A, we implement a DiD design. *Post_Award* is an indicator that takes the value of one for companies' website copies that were published after the award announcement and zero otherwise. *Inc_500_M* is an indicator that takes the value of one if a company has a Rank <= 500 and zero otherwise. The outcome variables capture the number of times that the Inc. award is mentioned on a company's webpage in a given company-year (as defined in Panel A of Table 2); we use the natural logarithm (plus one) or a binary coding for the outcome variables. We include *Company×Award_Year* (as a company can win awards in multiple years) and *Industry×Award_Year×Website_Year* fixed effects, which subsume the main effects for *Inc_500_M* and *Post_Award*. Panel B replaces *Post_Award* by yearly indicators (*Year_To_Award*) that mark the year relative to the date of the award year (i.e., calculated as website copy year y minus company award year t). The omitted category is *Year_To_Award* ($t = -1$). $t = 0$ should be mostly considered as part of the post-period as 89.02% of the website copies in our sample were released in or after August of the announcement year (awards are announced in August of a given year). For the remaining variable definitions see the notes of Table 2. T-statistics are based on robust standard errors clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Difference-in-Differences Design

	(1) Log(# Inc)	(2) # Inc > 0	(3) Log(# Inc 500)	(4) Log(# Inc 5000)	(5) Log(# Inc)	(6) Log(# Inc)
Sample Restriction (Ranks)	[1; 1,000]	[1; 1,000]	[1; 1,000]	[1; 1,000]	[300; 700]	[400; 600]
Test Variables						
Post_Award × Inc_500_M	0.263***	0.101***	0.405***	-0.082***	0.201***	0.281***
	(11.04)	(11.34)	(22.77)	(-4.43)	(5.33)	(4.93)
Controls						
Post_Award × Log(# Employees)	-0.034**	-0.004	-0.030***	-0.014	-0.026	-0.038
	(-2.39)	(-0.81)	(-2.63)	(-1.32)	(-1.23)	(-1.23)
Post_Award × Log(Revenue)	-0.095***	-0.043***	-0.039***	-0.065***	-0.123***	-0.113***
	(-6.21)	(-7.89)	(-3.24)	(-5.67)	(-5.37)	(-3.54)
Fixed Effects						
Company×Award_Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year×Website_Year	Yes	Yes	Yes	Yes	Yes	
N	43,256	43,256	43,256	43,256	17,212	8,410
# Companies	6,629	6,629	6,629	6,629	3,240	1,715
Adjusted R^2	0.448	0.427	0.466	0.381	0.433	0.430

Panel B: Dynamics of Disclosure Effect

	(1) Log(# Inc)	(2) # Inc > 0	(3) Log(# Inc 500)	(4) Log(# Inc 5000)	(5) Log(# Inc)	(6) Log(# Inc)
Sample Restriction (Ranks)	[1; 1,000]	[1; 1,000]	[1; 1,000]	[1; 1,000]	[300; 700]	[400; 600]
Test Variables						
Year_To_Award ($t = -2$) × Inc_500_M	0.065***	0.023***	0.007	0.054***	0.039	0.036
	(3.38)	(3.09)	(0.50)	(3.63)	(1.17)	(0.74)
Year_To_Award ($t = 0$) × Inc_500_M	0.254***	0.099***	0.364***	-0.055***	0.196***	0.258***
	(10.01)	(10.31)	(19.12)	(-2.72)	(4.62)	(3.98)
Year_To_Award ($t = 1$) × Inc_500_M	0.325***	0.117***	0.438***	-0.048**	0.263***	0.358***
	(11.28)	(10.67)	(20.40)	(-2.09)	(5.75)	(5.13)
Year_To_Award ($t = 2$) × Inc_500_M	0.267***	0.101***	0.381***	-0.067***	0.189***	0.268***
	(8.90)	(8.68)	(17.05)	(-2.83)	(3.82)	(3.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Company×Award_Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year×Website_Year	Yes	Yes	Yes	Yes	Yes	
N	43,256	43,256	43,256	43,256	17,212	8,410
# Companies	6,629	6,629	6,629	6,629	3,240	1,715
Adjusted R^2	0.448	0.426	0.465	0.381	0.433	0.430

Table 4: Within-Industry Analysis of Yearly Website Disclosures

This table analyzes the historical website disclosures of top industry companies in a five-year window around the award date (up to 213,352 company-website-years). *Top_Industry #1* is an indicator that takes the value of one if a company has the highest ranking within their industry in a given award year (27 industries in total) and zero otherwise. Other *Top_Industry* variables are constructed following the same method. For the remaining variable definitions, see the notes of Table 2 and Table 3. Besides the same fixed effects as in Table 3, we additionally include *Coarse_Growth* x *Event_Time* (coarsening 3-Year Growth into 1,000 groups) or *Rank* x *Event_Time* fixed effects (controlling for the firm's actual ranking). *Event_Time* is the difference between *Award_Year* and the *Website_Year* (i.e., ranges from -2 to 2). T-statistics are based on robust standard errors clustered by company. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	(1) Log(# Inc)	(2) Log(# Inc)	(3) Log(# Inc)	(4) Log(# Inc)	(5) Log(# Inc)	(6) Log(# Inc)
Sample Restriction (Ranks)	[1; 5,000]	[1; 5,000]	[1; 5,000]	[1; 5,000]	[1; 1,000]	[1; 500]
Test Variables						
Post_Award × Top_Industry #1	0.474***	0.227**	0.229**	0.268**	0.276***	0.231**
	(5.64)	(2.23)	(2.28)	(2.50)	(2.74)	(2.19)
Post_Award × Top_Industry #2				0.079		
				(0.86)		
Post_Award × Top_Industry #3				0.105		
				(1.12)		
Controls						
Post_Award × Industry_Rank	-0.003***	-0.001***	-0.001**	-0.001**	-0.005	-0.008
	(-13.18)	(-2.79)	(-2.30)	(-2.46)	(-1.16)	(-0.75)
Post_Award × Industry_Rank^2	0.000***	0.000**	0.000	0.000	0.000	0.000
	(9.15)	(2.10)	(1.50)	(1.63)	(0.48)	(0.49)
Post_Award × Log(# Employees)	-0.008	-0.005	-0.002	-0.002	-0.023	-0.034*
	(-1.38)	(-0.86)	(-0.29)	(-0.28)	(-1.61)	(-1.65)
Post_Award × Log(Revenue)	-0.081***	-0.082***	-0.083***	-0.083***	-0.111***	-0.101***
	(-13.33)	(-13.36)	(-13.34)	(-13.34)	(-7.09)	(-4.65)
Fixed Effects						
Company×Award_Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year×Website_Year	Yes	Yes	Yes	Yes	Yes	Yes
Coarse_Growth×Event_Time	No	Yes	No	No	No	No
Rank×Event_Time	No	No	Yes	Yes	Yes	Yes
N	213,352	213,352	213,352	213,352	43,196	21,712
# Companies	20,657	20,657	20,657	20,657	6,627	3,794
Adjusted R^2	0.504	0.502	0.489	0.504	0.429	0.420

Table 5: Change in Companies' Financing Around the Award Date

This table analyzes the impact of the company award on companies' financing in a five-year window around the award (up to 168,487 company-quarter observations in Panel A and up to 832,184 company-quarter observations in Panel B). The outcome variables capture the $ amount that companies received in *Funding* or *Equity Growth* capital in a given company-quarter (as defined in Panel B of Table 2); we use the natural logarithm (plus one). *Event_Time* is the difference between the third quarter of the *Award_Year* and a given financing *Quarter* (i.e., ranges from -8 to 8). For the remaining variable definitions see the notes of Table 2 to Table 4. T-statistics are based on robust standard errors clustered by company. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Difference-in-Differences Design around Inc. 500 Award

	(1) Log($ Funding)	(2) Log($ Funding)	(3) Log($ Funding)	(4) Log($ Equity Growth)	(5) Log($ Equity Growth)
Sample Restriction (Ranks)	[1; 1,000]	[300; 700]	[400; 600]	[1; 1,000]	[400; 600]
Test Variables					
Post_Award × Inc_500_M	0.010**	0.010*	0.021**	0.003	0.013*
	(2.40)	(1.67)	(2.41)	(0.83)	(1.84)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Company×Award_Year	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year×Quarter	Yes	Yes	Yes	Yes	Yes
N	168,487	67,218	33,201	168,487	33,201
# Companies	6,944	3,392	1,808	6,944	1,808
Adjusted R^2	0.0788	0.0772	0.0775	0.0759	0.0712

Panel B: Discontinuity around Top Industry Award

	(1) Log($ Funding)	(2) Log($ Funding)	(3) Log($ Funding)	(4) Log($ Equity Growth)	(5) Log($ Equity Growth)
Sample Restriction (Ranks)	[1; 5,000]	[1; 5,000]	[1; 1,000]	[1; 5,000]	[1; 1000]
Test Variables					
Post_Award × Top_Industry #1	0.046**	0.056***	0.063***	0.050***	0.047***
	(2.57)	(3.06)	(2.86)	(3.49)	(3.27)
Post_Award × Top_Industry #2			0.011		
			(0.60)		
Post_Award × Top_Industry #3			0.019		
			(1.02)		
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Company×Award_Year	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year×Quarter	Yes	Yes	Yes	Yes	Yes
Coarse_Growth×Event_Time	Yes	No	No	No	No
Rank×Event_Time	No	Yes	Yes	Yes	Yes
N	832,184	832,184	168,283	832,184	168,283
# Companies	21,727	21,727	6,942	21,727	6,942
Adjusted R^2	0.0715	0.0661	0.0722	0.0588	0.0700

Table 6: Change in Companies' Employment Growth around the Award Date

This table analyzes the impact of the company award on companies' quarterly job postings in a five-year window around the award date (up to 130,003 firm-quarter observations in Panel A and up to 642,676 company-quarter observations in Panel B). The outcome variables capture the number of job postings in a given company-quarter and are defined in Panel C of Table 2; we use the natural logarithm (plus one) or a binary coding for the outcome variables. *Event_Time* is the difference between the third quarter of the *Award_Year* and a given job posting *Quarter* (i.e., ranges from -8 to 8). For the remaining variable definitions see the notes of Table 2 to Table 4. T-statistics are based on robust standard errors clustered by company. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Difference-in-Differences Design around Inc. 500 Award

	(1) Log(# Job Postings)	(2) Log(# Job Postings)	(3) Log(# Job Postings)	(4) D(# Job Postings)	(5) D(# Job Postings)
Sample Restriction (Ranks)	[1; 1,000]	[300; 700]	[400; 600]	[1; 1,000]	[400; 600]
Test Variables					
Post_Award × Inc_500_M	0.072***	0.056**	-0.013	0.019***	-0.016
	(4.28)	(2.30)	(-0.38)	(2.96)	(-1.09)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Company×Award_Year	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year×Quarter	Yes	Yes	Yes	Yes	Yes
N	130,003	51,827	25,542	130,003	25,542
# Companies	5,654	2,719	1,445	5,654	1,445
Adjusted R^2	0.662	0 .671	0.681	0.481	0.493

Panel B: Discontinuity around Top Industry Award

	(1) Log(# Job Postings)	(2) Log(# Job Postings)	(3) Log(# Job Postings)	(4) Log(# Job Postings)	(5) D(# Job Postings)
Sample Restriction (Ranks)	[1; 5,000]	[1; 5,000]	[1; 5,000]	[1; 1,000]	[1; 5,000]
Test Variables					
Post_Award × Top_Industry #1	0.180**	0.174**	0.171**	0.188**	0.063**
	(2.41)	(2.24)	(2.09)	(2.50)	(2.12)
Post_Award × Top_Industry #2			-0.023		
			(-0.39)		
Post_Award × Top_Industry #3			0.021		
			(0.33)		
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Company×Award_Year	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year×Quarter	Yes	Yes	Yes	Yes	Yes
Coarse_Growth×Event_Time	Yes	No	No	No	No
Rank×Event_Time	No	Yes	Yes	Yes	Yes
N	642,676	642,676	642,676	129,706	642,676
# Companies	18,337	18,337	18,337	5,649	18,337
Adjusted R^2	0.723	0.722	0.722	0.661	0.505

Table 7: Top Industry Companies' Successful Exit and Survival

This table analyzes the impact of the company award on a company's successful exit or failure in a cross-sectional regression (up to 9,991 observations from 6,944 firms in Panel A and up to 48,952 observations from 21,727 firms in Panel B; a firm can appear multiple times in the data as a firm can win awards in multiple years). The outcome variables capture whether a company had a successful exit or failure and are defined in Panel B of Table 2; we use a binary coding for the outcome variables or the natural logarithm (plus one). For the remaining variable definitions see the notes of Table 2 to Table 4. T-statistics are based on robust standard errors clustered by company. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Difference-in-Differences Design around Inc. 500 Award

	(1) D(Success Exit)	(2) D(Success Exit)	(3) D(Success Exit)	(4) Log($ Success Exit)	(5) D(Failure)
Sample Restriction (Ranks)	[1; 1,000]	[300; 700]	[400; 600]	[1; 1,000]	[1; 1,000]
Test Variables					
Post_Award × Inc_500_M	0.018***	-0.001	0.001	0.122***	0.005
	(3.00)	(-0.10)	(0.05)	(3.78)	(1.05)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Company×Award_Year	Yes	Yes	Yes	Yes	Yes
Industry×Award_Year	Yes	Yes	Yes	Yes	Yes
N	9,911	3,954	1,953	9,911	9,911
# Companies	6,944	3,392	1,808	6,944	6,944
Adjusted R^2	0.105	0.098	0.135	0.127	0.014

Panel B: Discontinuity around Top Industry Award

	(1) D(Success Exit)	(2) D(Success Exit)	(3) D(Success Exit)	(4) Log($ Success Exit)	(5) D(Failure)
Sample Restriction (Ranks)	[1; 5,000]	[1; 5,000]	[1; 5,000]	[1; 5,000]	[1; 5,000]
Test Variables					
Top_Industry #1	0.064**	0.065*	0.077**	0.332*	-0.069**
	(1.99)	(1.93)	(2.11)	(1.83)	(-2.49)
Top_Industry #2			0.036		
			(1.27)		
Top_Industry #3			-0.000		
			(-0.00)		
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Industry×Award_Year	Yes	Yes	Yes	Yes	Yes
Coarse_Growth	Yes	No	No	No	No
Rank	No	Yes	Yes	Yes	Yes
N	48,952	48,952	48,952	48,952	48,953
# Companies	21,727	21,727	21,727	21,727	21727
Adjusted R^2	0.104	0.101	0.101	0.126	0.0113

Appendix

A Excerpts from the 2018 Award Ranking

This appendix contains excerpts from the 2018 Inc. 500/Inc. 5000 award to illustrate the selection process (Panel A), the cover of the magazine (Panel B) and how the ranking is presented within the magazine (Panel C).

Panel A: How the 2018 Inc. 5000 Companies Were Selected

Companies on the 2018 *Inc.* 5000 are ranked according to percentage revenue growth from 2014 to 2017. To qualify, companies must have been founded and generating revenue by March 31, 2014. They must be U.S.-based, privately held, for-profit, and independent–not subsidiaries or divisions of other companies–as of December 31, 2017. (Since then, some on the list have gone public or been acquired.) The minimum revenue required for 2014 is $100,000; the minimum for 2017 is $2 million. As always, Inc. reserves the right to decline applicants for subjective reasons. Note: Growth rates used to determine company rankings were calculated to two decimal places. In the case of ties, the companies with more revenue were placed higher. (Source: Inc.com)

Panel B: September Issue of Inc. Magazine 2018

Panel C: 2018 Ranking in September Issue, "Advertising + Marketing"-industry

ADVERTISING + MARKETING

Includes traditional advertising agencies and public relations firms, as well as SEO specialists, data-analysis experts, and developers of online marketing platforms.

Number of companies **50** → Total revenue **$946.2M** → Median revenue **$6.7M** → Median growth rate **1,998.2%** → Total employment **2,385**

Company	Rank	Three-year growth	2017 revenue	Number of employees
INOVA US 2008 KEY BISCAYNE, FLA. CEO: Fernando Mercenari, *inovaus.com* Provides direct response marketing of products advertised on television.	14	13,135.2%	$39.4M	25
LO70S 2013 HENDERSON, NEV. CEO: Jim Battista, *lo70s.com* Provides full-service, programmatic advertising specializing in media monetization.	26	9,153.8%	$30.3M	9
FUNDED TODAY 2014 SOUTH OGDEN, UTAH CEOS: Zach Smith and Thomas Alvord, *funded.today* Consults for entrepreneurs looking to increase pledges to their crowdfunding campaigns.	27	8,797.7%	$11.7M	55
FOX DEALER 2013 PASADENA, CALIF. CEO: GianCarlo Asong, *foxdealer.com* Operates an automotive digital agency specializing in custom websites and design.	41	6,423.9%	$18.7M	35
DIGITAL HYVE 2014 SYRACUSE, N.Y. CEOS: Jeff Knauss and Jake Tanner, *digitalhyve.com* Operates a digital marketing agency that connects brands to targeted audiences.	52	5,064.4%	$5.2M	24
INFUSEMEDIA 2012 NEWTON, MASS. CEO: Alexander Kesler, *infusemedia.com* Generates leads for B2B companies by promoting content.	54	4,889.3%	$5.3M	250
PROJECT X 2010 NEW YORK CITY CEO: John Laramie, *pjxmedia.com* Provides media-buying services for out-of-home ads such as billboards.	65	4,411%	$51.9M	26
MONKEDIA 2014 IRVING, TEXAS CEO: Noah Curran, *monkedia.com* Helps businesses increase online traffic, sales, and engagement, and develops their social presence.	67	4,394.9%	$12M	30
ADCELLERANT 2013 DENVER CEOS: Brock Berry and Caitlin Logue, *adcellerant.com* Provides digital advertising and related services to businesses.	83	3,945%	$8.9M	28
IMPACT MAILERS 2013 MARIETTA, GA. CEO: Jeff Shapiro, *impactmailers.com* Designs high-gloss plastic-laminate advertising postcards.	92	3,764.7%	$4.6M	7
SWARM 2014 MIAMI CEOS: Tony Albelo and Javi Zayas, *swarminc.com* Partners with brands to create special events, such as beer and food festivals, art walks, and holiday celebrations.	98	3,681.3%	$11.3M	35
ADSUGAR 1999 MARTINSVILLE, N.J. CEO: Amit Raut, *adsugar.com* Specializes in performance-based digital marketing for clients.	100	3,636.4%	$20M	15
THE MEDIA MANAGER 2014 ROCHESTER, MINN. CEO: Brian Bos, *themediamgr.com* Specializes in direct-response media buying and campaign strategy.	103	3,562.5%	$7.1M	5

RANK **THREE-YEAR GROWTH** **2017 REVENUE** **NUMBER OF EMPLOYEES** ●*Past honoree* ●●*Two-time past honoree* ●●●*Three-time past honoree*

B Examples for Company Disclosures

This appendix contains two examples for mentions of the award on companies' webpages. In Panel A, the Inc. 500 award is mentioned in the "About Us"-section and in the footer of the webpage. In Panel B, the company released a specific blog post on their webpage.

Panel A: Excerpt of "About Us"-Section by Garrett Companies

We use our successes to better our team, communities in which we work, and the lives of those that choose to call our campuses home.

The Garrett Companies is the #1 fastest growing privately held real estate company in the USA (Inc.500, 2018). The Company is repeatedly ranked as a Best Place to Work in both the State of Indiana (Indiana Chamber of Commerce) as well as Nationwide (Outside Magazine, Inc. Magazine). Most recently The Garrett Companies was 100% Certified as a Great Place to Work.

If you are looking for a change in career and want to use your talents while being challenged to grow – give us a shout.

NEWS BLOG CAREERS EMPLOYEES

THE GARRETT COMPANIES Inc. 500 #1 #1 #1 GARRETT CONSTRUCTION

Copyright ©2019 - The Garrett Companies LLC. All rights reserved.

Panel B: Excerpt of Blog Post by Crimecheck

Crimcheck Breaks Into the Inc 500 List (Rank #428)

Imagine climbing up over 4,000 places on one the most coveted lists of US companies in order to be placed as one of among the top 500. Crimcheck has accomplished this on the Inc. 5000 list over the course of just one year.

In 2017, our rank on the Inc. 5000 list was #4512. **In 2018, our rank shot up to #428**. Essentially, we climbed up an incredible 4,084 places in just 12 months. Wow! **To make matters even sweeter, being #428 places us in the celebrated Inc. 500**.

Click here to see our listing.

Impressive Numbers

The figures which enabled Crimcheck to break into the Inc 500 are impressive by any standard. The company posted a 3-year revenue growth of 1,166%. Basically, this means that the company's revenue grew by an average of 388.67% per annum over the period from 2015 to 2017.

These are numbers that any company would be proud of. For a company in the background-screening business, these numbers are almost unbelievable. However, given the rigorous process Inc. uses for screening companies, one has no choice but to believe these almost insane figures.

More Accolades

Crimcheck's impressive figures did more than just get us into the top 500 US companies of 2018. The company also scored top ranks at both state and city level. At the state level, Crimcheck was ranked 6th among the top companies in Ohio. When it came to the city level, Crimcheck was ranked the number one (#1) top company in Cleveland, Ohio. This basically means that we recorded the fastest-revenue growth in Cleveland, OH area over the past three years.

What's the Big Deal?

Getting into the Inc 500 is the premier goal for most eligible companies in the US. This is because of what the list has grown to represent since 1982. Back then, the list was simply a rank of the best-performing companies in terms of revenue growth. However, nowadays the situation is quite different.

Today, the Inc. 500 celebrates entrepreneurial ingenuity, vision, and business innovation. More than just an editorial award, the list showcases the ultimate embodiments of American enterprise. The top-ranked company in 2018, for instance, is a 5-year-old company (founded in 2013) which grew by jaw-dropping 75,661%

Now, Crimcheck's 1,166% growth may seem paltry compared to the #1 ranked company (which is called SwanLeap, BTW). However, this is a great achievement for two major reasons:

For starters, this the first time that a background-checks company is breaking into the Inc. 500. No background check company has ever even gotten close to the Inc. 500. Basically, just like we have been blazing trails through innovative service-delivery in the background-checks industry, it seems we're setting the pace yet again.

Secondly, the sheer competitiveness of the last three years makes our achievement all the more special. The period from 2015 to 2017 was fiercely competitive in the background checks industry. This is because – as job

...