Star Firms, Information Externalities, and Predictability*

Vidhi Chhaochharia, *University of Miami*

Alok Kumar, *University of Miami*

Mehrshad Motahari, *City, University of London*

Ville Rantala, *University of Miami*

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Abstract: We study information externalities generated by industry-specific "star firms." Changes in stars' relative earnings growth predict future earnings growth, consensus earnings surprises, and job postings of same-industry nonstar firms. We also find that stars' earnings performance changes predict GDP and employment growth at the industry level, and earnings predictability is stronger in less competitive industries. These information externalities are not fully reflected in stock prices, which generates predictability in returns. A Long-Short industry portfolio strategy based on earnings growth of star firms earns an annualized six-factor alpha of 8.64%. These findings provide valuation-based evidence of economic importance of star firms.

Keywords: Star firms, sell-side equity analysts, earnings predictability, return predictability, information spillover.

JEL Codes: G12, G14, G24.

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* Please address all correspondence to Vidhi Chhaochharia, vidhi@miami.edu; Alok Kumar, akumar@miami.edu; Mehrshad Motahari, Mehrshad.Motahari@city.ac.uk; and Ville Rantala, vrantala@bus.miami.edu. We thank Juan Sotes-Paladino, Rosy Xu, seminar participants at University of Cambridge, and conference participants at the Santiago Finance Workshop for useful comments and helpful suggestions. We are responsible for all remaining errors and omissions.

1. Introduction

Very large and dominant 'superstar' firms have a significant and sometimes disproportionate impact on various macroeconomic outcomes. For example, these firms dominate exports, foreign direct investment, and research and development, which in turn, has generated a sharp increase in their profits and an increased industry concentration in the U.S. (Autor et. al., 2017, Grullon et al., 2019; De Loecker et. al., 2020).[1] The recent growth in artificial intelligence related technologies has further emphasized the importance of superstar firms (Babina et al., 2024). These firms also play a significant role in aggregate macroeconomic fluctuations (Gabaix 2011; Jannati, Korniotis, and Kumar 2020).

The rise and dominance of star firms can be attributed to several economic factors, including economies of scale, increasing importance of proprietary information technology (Bessen, 2020), accumulation of intangible digital capital (Tambe et al., 2020), easier access to human capital (Choi, Lou, and Mukherjee, 2017), and weakening anti-trust enforcement (Döttling, Gutiérrez, and Philippon, 2017). As large firms attain superstar status, they can use their market power to create barriers to entry. Because star firms influence the broader economy and the industries around them, changes in star firms' operational and earnings performance are likely to affect the future earnings and performance of other related firms. Further, if market participants such as sell-side equity analysts do not fully account for this dynamic, it can create predictable patterns in related firms' earnings surprises and returns.

In this paper, we extend and complement the extant literature on star firms to investigate the financial and economic information externalities of star firms within industries. We analyze

[1] Autor et al. (2017), Autor et al. (2020), and Barkai (2020) provide evidence that the rise of superstar firms has contributed to a decline in the share of GDP going to labor. Further, Gutiérrez and Philippon (2019) show that, as industries become more concentrated, large profitable firms tend to invest less, which creates investment gaps.

whether performance shifts of star firms can predict future earnings growth and stock returns of connected nonstar firms and contribute to future GDP and employment growth at the industry level. We also investigate whether sell-side analysts fully incorporate star firms' information externalities into earnings forecasts. Our results provide valuation-based evidence on how star firms influence other connected firms around them.

We use the definition of industry star firms developed in Gutiérrez and Philippon (2019). They define industry stars for 60 different Bureau of Economic Analysis (BEA) industries. By construction, the industry stars also include the largest economy-wide stars. The industry-level star firm definition has several advantages for our study. In particular, star firms identified by their classification are not concentrated in any particular industry, which ensures that our results are not driven by some industry-specific phenomena. Further, sell-side security analysts typically specialize in specific industries, which means that same analysts often issue forecasts on star and nonstar firms within an industry. Last, the number of star firms and industries remains constant over time, which further helps in the interpretation of empirical results.

Star firms are typically large but not all large firms are star firms. Based on descriptive statistics, Gutiérrez and Philippon (2019) industry star firms differ from large nonstar firms along several characteristics associated with superstar firms in the previous literature. We define large nonstars as firms that are within the top 30% of market capitalization within their industry and find that stars are more profitable, have higher R&D and capital expenditure, and are more innovative based on the number of patents.[2]

We start our empirical analysis by documenting that changes in star firms' relative earnings performance predict the earning growth of same-industry nonstar firms. To measure the relative

[2] We follow the definition of Hou (2007) who defines large firms in an industry as those that are in the top 30% based on their market capitalization.

earnings performance of star and nonstar firms, we create a measure called *ΔEGP Difference* that captures the relative earnings growth difference between star and nonstar firms within the same industry. Specifically, it captures the change in the difference between star and nonstar firms' average earnings growth between quarters *t-1* and *t-2*. *Earnings Growth (EGP)* in quarter *t* is defined as earnings per share in quarter *t* minus earnings in quarter *t-4*, scaled by the share price. *ΔEGP Difference* is high (low) when star firms' earnings growth relative to nonstar firms' earnings growth is higher (lower) in the current quarter than in the previous quarter. Intuitively, it obtains high values when star firms' earnings growth increases relative to nonstar firms across quarters.

The conjecture that the *ΔEGP Difference* measure captures information about current and future firm performance is supported by the results of He and Narayanamoorthy (2020) who find that earnings growth acceleration, defined as quarter-over-quarter change in earnings growth, has explanatory power for future excess returns.[3] Their earnings growth measure is identical to ours and another interpretation for the *ΔEGP Difference* variable is that it captures the difference in earnings acceleration between star and nonstar firms. Earnings acceleration-based trading has been viewed as a viable trading strategy in the popular press (He and Narayanamoorthy 2020).

We estimate quarterly industry-level panel regressions where we explain the average earnings growth of nonstar and star firms using *ΔEGP Difference*. The regressions control for lagged values of the dependent variable and include year-quarter and industry fixed effects. We find that one-quarter lagged *ΔEGP Difference* predicts the average earnings growth of nonstar firms. In nonstar firm regressions, the coefficients on *ΔEGP Difference* are between 0.10 and 0.019 with *t*-values

[3] He and Narayanamoorthy (2020) show that earnings growth acceleration can predict excess returns because investors are focused on earnings change compared to the same quarter in the previous year and tend to ignore the information content of growth acceleration relative to the previous quarter.

between 3.9 and 5.1. These coefficient estimates imply that a one standard deviation increase in *ΔEGP Difference* leads to a 0.1 to 0.2 standard deviation increase in the dependent variable.

In contrast, the same coefficients in regressions explaining star firms' average earnings growth are negative and statistically insignificant. The difference between the estimates for star firms and nonstar firms indicates that changes in star firms' relative earnings performance can predict nonstar firms' earnings growth, but they are unable to predict star firms' future earnings growth.

We also find evidence that star firms' performance shifts captured by *ΔEGP Difference* can predict other economic outcomes at the industry level, indicating that star firms' information externalities extend to non-financial outcome variables. We first test whether *ΔEGP Difference* can predict changes in nonstar firms' quarterly job postings. Job postings is an interesting variable to analyze because it is a timely measure of firms' growth and growth prospects. Using industry-level panel regressions that are similar to our previous specifications explaining earnings growth, we find that a one standard deviation increase in lagged *ΔEGP Difference* is associated with a 34% percent increase in the number of quarterly job postings by same-industry nonstar firms.

Furthermore, in industry-level panel regressions predicting quarterly year-over-year real GDP growth and employment growth, we find that a one standard deviation increase in lagged *ΔEGP Difference* is associated with a 0.5% to 0.6% higher industry-level GDP growth and 0.1 to 0.2% higher employment growth, respectively. These effects are statistically significant at the 10% level or higher. Notably, the industry GDP and employment growth figures also include the effect of non-listed firms.

In the next set of tests, we examine whether security analysts use the information in star firms' relative earnings growth to update their earnings forecasts. Our conjecture is that sell-side equity analysts may not be completely aware of the information externalities of star firms. As a result, they would not fully account for the information content in star firms' earnings and, consequently, the *ΔEGP Difference* variable would predict the consensus earnings surprises of nonstar firms.

To test this conjecture, we regress nonstar firms' average quarterly consensus forecast-based earnings surprise at the industry level on lagged *ΔEGP Difference.* The regressions include the same control variables as our previous earnings growth regressions, and we additionally estimate specifications that control for lagged consensus-based earnings surprises. Consistent with our conjecture, we find that the coefficient on *ΔEGP Difference* is positive and statistically significant (coefficient estimate = 0.015, *t*-value = 2.5), indicating that analysts underreact to the information content in star firms' earnings surprises. Based on the coefficient estimates, a one standard deviation change in *ΔEGP Difference* corresponds to a 0.1 standard deviation increase in the dependent variable.

Consistent with the earnings surprise results, we also find that the *ΔEGP Difference* can predict nonstar firms' abnormal returns around earnings announcements. The *ΔEGP Difference* coefficient estimates in regressions explaining nonstars' cumulative abnormal returns over the [0, 2] day window are positive and statistically significant with a coefficient value of 0.07. In contrast, the coefficient estimates in star firm regressions are negative and statistically insignificant.

Next, we analyze potential economic channels that contribute to star firms' information externalities. Dominant firms can influence other firms through their market power, and a natural prediction is that their effect is more pronounced in less competitive industries. We find empirical support for this conjecture when we estimate our earnings predictability and earnings surprise predictability regressions separately for industries whose Lerner index is above and below median.[4] A high value for the Lerner index indicates a higher price markup above marginal costs

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[4] Lerner index is a widely used measure of market power and competitiveness. See for example, Nickell (1996) and Aghion et al. (2005).

and thus a less competitive industry. In regressions explaining unexpected earnings, the high-Lerner index *ΔEGP Difference* coefficient is 60% higher than the low-Lerner index coefficient. The difference is even more amplified in regressions explaining consensus earnings surprises, where the high-Lerner coefficient is 3.5 times as high as the low-Lerner coefficient.

In the last set of tests, we demonstrate that our core findings have asset pricing implications. Specifically, using a Long-Short industry portfolio strategy, we analyze whether star firms' earnings performance can predict the monthly cross-sectional stock returns of nonstar firms. To have a higher-frequency measure of earnings performance shifts, we calculate *ΔEGP Difference* every month based on earnings announcements in months *t-1* to *t-3* and denote this as *ΔEGP Difference Monthly*. We create monthly market value-weighted quintile portfolios of industries with the highest and lowest lagged values of *ΔEGP Difference Monthly.* Our Long portfolio invests in the eleven highest-ranked industry portfolios and the Short portfolio invests in the eleven lowest-ranked industry portfolios. These correspond to the top and bottom quintile within the 55 industries for which we have sufficient observations.

Consistent with our previous results, we find that star firms' relative earnings performance contains information that is not fully incorporated into market prices and can predict future stock returns. The Long-Short portfolio earns an average monthly six-factor alpha of 0.72%, which is statistically significant with a *t*-statistic of 2.35. In line with these results, we also find that there is a general lead-lag relation between star firms' and nonstar firms' stock returns. We form market value-weighted quintile portfolios of nonstar firms in industries with the highest and lowest lagged average stock return of star firms in the previous month. A Long-Short investment strategy based on these portfolios earns a monthly six-factor alpha of 0.46% with a *t*-statistic of 2.41.

Finally, we confirm that star firms have unique information externalities that are not shared by other large firms. We replicate our main analyses after replacing industry star firms with the four next largest firms in each industry and test whether they have similar predictive power on other same-industry nonstar firms. The results indicate that *ΔEGP Difference* calculated based on these "substitute" stars can still statistically significantly predict nonstars' earnings growth, albeit with a coefficient magnitude that is only half of the actual star coefficient. However, the substitute stars cannot statistically significantly predict any outcomes that involve analyst forecasts or stock returns. All coefficients in regressions predicting nonstar firms' earnings surprises, earnings announcement returns, and abnormal stock returns are statistically insignificant. These placebo tests show that the star firm effect we capture is not a general large firm effect.

Together, these results contribute to several strands of accounting, economics, and finance literature. The stock return and earnings surprise findings provide novel valuation-based evidence that star firms have information externalities and influence the performance of other connected firms. Our results are stronger in less competitive industries, which suggests that market power is an important source of star firms' influence.

The effects on industry level GDP and employment growth indicate that star firms have performance spillover effects that extend to non-financial outcomes. These results link to previous literature using accounting variables to predict aggregate macroeconomic outcomes, such as GDP, employment, and price indices.[5] We show that a leading indicator based on a small group of star firms can predict growth and economic activity at the industry level.

[5] Konchitchki and Patatoukas (2014) demonstrate that aggregate accounting earnings growth serves as a leading indicator of future GDP growth, particularly for the one-quarter-ahead forecast horizon. Their findings highlight the predictive power of accounting information in anticipating economic activity. Building upon this research, Gallo et al. (2016) discover that the Federal Reserve responds to aggregate accounting earnings growth, suggesting that accounting data influences monetary policy decisions. Similarly, Shivakumar and Urcan (2017) show that aggregate earnings growth predicts future investment and price index forecast errors, further emphasizing the importance of accounting variables in forecasting macroeconomic outcomes. In addition to earnings growth, other accounting

The results with *ΔEGP Difference* variable extend the earnings acceleration results of He and Narayanamoorthy (2020) by demonstrating that informative star firms' relative earnings acceleration can predict *other* firms' future earnings and stock returns. Earnings growth acceleration is less salient than year-over-year earnings growth, which can result in underreaction among security analysts and market participants.

Finally, our return results also add to the literature on lead-lag effects in stock returns.[6] We identify a new lead-lag pattern where star firms' earnings and stock return performance can predict the returns and earnings surprises of other connected firms. In related work, Hou (2007) finds that the returns of the largest firms in an industry lead the returns of the smallest firms in an industry.[7] We discover a similar lead-lag pattern, but our "lag" sample is not limited to small firms and only some of the large firms are classified as star firms in the "lead" sample. The finding that our results are stronger in less competitive industries indicates that market underreaction to industry dynamics can contribute to star firms' predictive power.

2. Data Sources and Variables

2.1 Data Sources

We use stock price and stock return data from the Center for Research on Securities Prices (CRSP) database, financial information from Compustat, and analysts' quarterly earnings forecasts and associated earnings information from the Institutional Broker Estimates System (I/B/E/S) detail history file. The earnings per share (EPS) values are from I/B/E/S (Item Actual), and they are adjusted for stock splits using item CFACPR in CRSP. Our sample includes common stocks

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variables have been shown to provide valuable insights into the state of the economy. For instance, Hirshleifer et al. (2009) find that accruals can indicate a temporary increase in earnings followed by an economic slowdown.

[6] Lead-lag patterns where one group of stocks leads the returns of another group of stocks have been documented for example in Moskowitz and Grinblatt (1999) Cohen and Frazzini (2008), Menzly and Ozbas (2010), Cohen and Lou (2012), Parsons et al. (2020), Ali and Hirshleifer (2020) and Huang et al. (2022).

[7] Lo and MacKinlay (1990) demonstrate that the returns of large firms lead those of smaller firms in general.

with share code 10 or 11. We adjust the CRSP returns for delisting following the procedure of Shumway (1997). In analyses that involve earnings announcement dates, we limit the sample to post-1993 observations due to known data errors in the early years covered by I/B/E/S. The sample period for analyses that only use stock return data is 1984 to 2020.

We apply multiple filters to address data errors and potential concerns about data quality. We require the date on which an analyst forecast becomes effective (ACTDATS) to be on or after the analyst forecast announcement date (ANNDATS), and the forecast review date (REVDATS) should be after the forecast announcement date (ANNDATS). We further require at least two analysts covering a stock each quarter and at least two firms covered by sample analysts. Last, we exclude firms with prices below $1 to ensure that our results are not driven by illiquid firms.

In our job posting analyses, we use job posting data from LinkUp. LinkUp is a data vendor that collects job postings information directly from company websites and covers a near universe of 160 million job ads. Campello, Kankanhalli, and Muthukrishnan (2020) show that LinkUp job postings data are representative of corporate hiring activities in the U.S. Specifically, they show that job postings are correlated with job gains, employee payroll, and total private sector hires in the Bureau of Labor Statistics Job Openings and Labor Turnover Survey (JOLTS).

The LinkUp job postings data includes the title, job description, company information, geographic location, creation date, and O*NET job classification code. The original LinkUp dataset covers 163,171,800 job postings from August 2007 to May 2022. After excluding job postings of private firms and those with missing information, our final sample consists of 671,084 observations, including 3,515 firms from 2008 to 2020. We aggregate the job postings at the industry level to create industry level job postings variables for star and nonstar firms, respectively.

We utilize quarterly industry-level real GDP data from the Bureau of Economic Analysis (BEA), spanning from 2005 to 2020. Additionally, we source industry-level employment data from the Bureau of Labor Statistics (BLS), covering the period from 1992 to 2020. We use the North American Industry Classification System (NAICS) industry codes to merge BEA and BLS datasets with our sample. In instances where industry-level real GDP or employment data are unavailable for our specific industry definitions, we aggregate the quarterly figures for sub-industries to align them with our industry classifications.

2.2 Defining Star Firms

To identify dominant star firms at the industry level, we use the industry star definition of Gutiérrez and Phillipon (2019). They define star firms as top four firms by the market value of equity within each BEA industry.[8] BEA follows the NAICS for grouping firms into industries. We use NAICS codes from Compustat to match firms with their corresponding BEA industry classification.

Following Gutiérrez and Phillipon (2019), we rank all firms within an industry by their market capitalization at the end of December each year and specify the top four as star firms for the following year. In cases of missing CRSP market capitalization data, we use Compustat to calculate the values. If both sources are unavailable, we fill in the missing market capitalization ranks with firms' net sales (Compustat SALE) ranks within each industry.[9]

Appendix Table A.2 presents the percentage of market capitalization of star and nonstar firms within the 60 BEA industry groups. We exclude five industry groups due to insufficient observations because we require at least five nonstar firms in the industry each month. These five

[8] Top four firms approximately correspond to the largest 5th percentile of firms based on the average number of firms across all industries.
[9] Our results are similar when we do not fill in missing CRSP market capitalization values using other sources.

industries are presented in Appendix Table A.2 with zero observations. On average, star firms occupy from 30% to 90% of total market capitalization of an industry. Most industries have at least 4 star firms on average and the average number of nonstar firms ranges from 5 to 517.

2.3 Star Firms versus Large Firms

Summary statistics indicate that the Gutiérrez and Philippon (2019) star firms differ from other large firms in their profitability, investment activities, and innovativeness. Table 2 compares the characteristics of star firms and nonstar large firms. We define "large firms" following the definition of Hou (2007), who classifies them as those belonging to the 30% of market capitalization in each industry.

Star firms are more profitable based on their Return on Assets (ROA) and Return on Equity (ROE). The median ROA of star firms is 6%, which is 50% higher than large nonstars' median ROA of 3% (means are 12% and 6%, respectively). They also have lower cost of goods sold and non-production expenses relative to sales, which is consistent with economies of scale. We find that star firms are more innovative and research-oriented than typical large firms, as measured by the amount of capital and R&D expenditure and the number of patents. Star firms file an average of 92.35 patents per year, as compared to 15.30 patents by large nonstar firms. Panel B shows that there is also a statistically significant difference in means of all these characteristics when we compare star firms with large nonstar firms that are within the same industry.

2.4 Measuring Relative Earnings Performance and Earnings Surprises

To measure relative earnings performance, we define a variable denoted as $\Delta EGP\ Difference_{j,t}$, which captures changes in the earnings growth differences between star and nonstar firms in the same industry in each quarter t. It is defined as follows:

$$\Delta EGP\ Difference_{j,t} = \left(\overline{EGP}_{star_{j,\ t}} - \overline{EGP}_{nonstar_{j,\ t}}\right) - \left(\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-1}}\right) \tag{1}$$

where $\overline{EGP}_{star\,j,t}$ and $\overline{EGP}_{nonstar\,j,t}$ refer to the equal-weighted average earnings growth *(EGP)* of star firms and nonstar firms in industry *j* in quarter *t*, respectively. *EGP* is a measure of earnings growth for each firm *i* and, following previous related studies, we define it as the earnings per share (*EPS*) in quarter *t* minus *EPS* in quarter *t–4*, scaled by share price ten days before the earnings announcement date. Specifically,

$$EGP_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{Price_{i,t}} \tag{2}$$

We define *ΔEGP Difference* for industry-quarter observations where the industry has at least five nonstar firms in addition to star firms. This measure is based on a *change* in the difference between star and nonstar firms' earnings growth and, intuitively, it obtains high values when star firms' earnings growth across quarters increases relative to same-industry nonstar firms. Measuring the change in earnings growth difference between quarters ensures that we are not capturing differences in long-term trends between stars and nonstars. However, for robustness, we also provide results that are simply based on the difference between stars' and nonstars' $EGP_{i,t}$.

Our measure is motivated by the results of He and Narayanamoorthy (2020) who find that earnings growth acceleration defined as quarter-over-quarter change in earnings growth ($EGP_{I,t}$) can predict companies' future excess returns and earnings growth. They argue that this earnings acceleration anomaly is attributable to the market missing, at least partially, the implications of earnings acceleration for earnings growth two and three quarters in the future. Our *ΔEGP Difference Monthly*$_{j,t-1}$ can also interpreted as the difference between star firms' and nonstar firms' earnings growth acceleration over the previous quarter according to their measure.[10]

[10] *ΔEGP Difference*$_{j,t}$ can also be expressed as $\left(\overline{EGP}_{star_{j,\,t}} - \overline{EGP}_{star_{j,\,t-1}}\right) - \left(\overline{EGP}_{nonstar_{j,\,t}} - \overline{EGP}_{nonstar_{j,\,t-1}}\right)$ which is the same as star firms' earnings growth acceleration minus nonstars' earnings growth acceleration according to the He and Narayanamoorthy (2020) definition.

For asset pricing tests, we create a monthly measure of relative earnings performance called $\Delta EGP\ Difference\ Monthly_{j,t-1}$ for our return prediction tests.[11] This is similar to the quarterly $\Delta EGP\ Difference_{j,t}$ measure, except that it is constructed monthly by taking earnings announcement dates into account (I/B/E/S ANNDATS or Compustat RDQ, whichever is earlier if they disagree). This higher frequency allows us to predict returns using the most recent earnings information available to market participants. For a firm to be included in the $\Delta EGP\ Difference\ Monthly_{j,t}$ calculation each month, it needs to have non-missing *EGP* observations at least during the past two quarters.

Last, we construct measures of analyst earnings surprise for star and nonstar firms. We compute each firm's analyst earnings surprise ($ES_{i,t}$) as follows:

$$ES_{i,\,t} = \frac{EPS_{i,t} - \ Consensus\ Forecast_{i,t}}{Price_{i,t}}, \tag{3}$$

where $EPS_{i,t}$, $Conssensus\ Forecast_{i,t}$, and $Price_{i,t}$ are firm *i*'s actual *EPS*, analysts' median forecast, and share price ten days before the earnings announcement date, respectively. We take the average earnings surprise of star and nonstar firms in each industry *j* and quarter *t* to achieve industry-level measures of earnings surprise for star and nonstar firms, i.e., $\overline{ES}_{star_{j,\,t}}$ and $\overline{ES}_{nonstar_{j,\,t}}$, respectively.

Panel A of Table 1 presents summary statistics for all our earnings measures described above. The earnings performance variables $\Delta EGP\ Difference_{j,t}$ and $\Delta EGP\ Difference\ Monthly_{j,t}$ have almost identical distributions with means and medians close to zero. Specifically, the mean of $\Delta EGP\ Difference_{j,t}$ is 0.017 and has a median of 0.006. Also, according to $\overline{EGP}_{star/nonstar_{j,\,t}}$ and $\overline{ES}_{star/nonstar_{j,\,t}}$, nonstar firms have lower mean and median average *EGP* and *ES* values and greater standard deviations as compared to star firms.

[11] We use quarterly *ΔEGP Difference* in analyses where the dependent variable is based on earnings announcements to ensure that our dependent and independent variables consist of earnings that are announced in different quarters.

3. Star Firms and Industry Spillover Effects

We start our analysis by testing whether shifts in star firms' relative earnings performance as measured by *ΔEGP Difference* can predict the earnings growth of other related firms. We then extend the analysis to industry spillover effects in employment and GDP growth.

3.1 Predicting Earnings Growth

We estimate quarterly panel regressions where the dependent variable is either the average earnings growth of nonstar firms or star firms within industry j during quarter t. The key independent variable is $\Delta EGP\ Difference_{j,t-1}$. These regressions control for lagged values of the dependent variable (i.e., $\overline{EGP}_{j,t-1}$, $\overline{EGP}_{j,t-2}$, and $\overline{EGP}_{j,t-3}$) and include year-quarter and industry fixed effects.

The fixed effects control for all common industry- and time-specific factors that potentially affect the earnings growth of star and nonstar firms. When these fixed effects are included, we are effectively comparing the earnings growth of star and nonstar firms within a certain industry and year-quarter. We cluster standard errors by year-quarter and industry.

Table 3 reports the earnings growth predictability regression estimates. In columns (1)-(3), we report the panel regression results for nonstar firms and columns (4)-(6) report the results for star firms. Our conjecture is that $\Delta EGP\ Difference_{j,t-1}$ would predict earnings growth of nonstar firms, as star firms are likely to contain useful information about nonstar firms.

The estimates in Columns (1)-(3) of Table 3 confirm our conjecture. The change in star firms' relative earnings performance captured by $\Delta EGP\ Difference_{j,t-1}$ can predict nonstar firms' earnings growth in the same industry and quarter, after controlling for lagged earnings growth of nonstar firms. The coefficients on *ΔEGP Difference* are between 0.100 and 0.190 with *t*-statistics between 3.89 and 5.07, respectively. In terms of economic magnitudes, these coefficient estimates imply that one standard deviation increase in $\Delta EGP\ Difference_{j,t-1}$ is associated with a 0.1-0.2 standard deviation increase in the earnings growth of nonstar firms.

To rule out the possibility that $\Delta EGP\ Difference_{j,t-1}$ captures general industry information that affects stars and nonstars equally, in Columns (4)-(6), we re-estimate the earnings regressions so that we form the dependent variable based on star firms instead of nonstar firms. We find that $\Delta EGP\ Difference_{j,t-1}$ is unable to predict the earnings growth of star firms. Specifically, the coefficients on $\Delta EGP\ Difference_{j,t-1}$ are in the range of -0.059 to -0.063, and they are statistically and economically insignificant. These results show that information in earnings growth of star firms, rather than industry and time trends, predicts the earnings growth of nonstar firms.

For robustness, we repeat our test using an alternative measures of relative earnings performance. First, we define relative earnings performance by using the quarterly difference in earnings growth, without any detrending. Instead of using $\Delta EGP\ Difference_{j,t-1}$ (see equation (1)), we use the lagged difference $\left(\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-1}}\right)$. The regression estimates are reported in Appendix Table A.3, Panel A. We find that our results remain qualitatively similar.

For additional robustness, we use a third relative earnings performance measure. Specifically, we define star firms' relative earnings performance using year-over-year percentage growth in firm-level earnings based on split-adjusted *EPS*. The new relative earnings performance variable at t is defined as $\left(\overline{EGPRCT}_{star_{j,\ t}} - \overline{EGPRCT}_{nonstar_{j,\ t}}\right) - \left(\overline{EGPRCT}_{star_{j,\ t-1}} - \overline{EGPRCT}_{nonstar_{j,\ t-1}}\right)$, where *EGPRCT* is the percentage growth in *EPS* relative to the same quarter in the previous year. The results reported in Panel B of Appendix Table A.3 show that the percentage growth variable is positive and statistically significant at the 10% level. This lower statistical significance is not surprising since we can only define the percentage growth in earnings for firms with positive earnings per share, which limits the sample size.

3.2 Predicting Job Postings

Thus far our results suggest that star firms' relative earnings performance predicts the earnings growth of same-industry nonstar firms. Next, we examine whether *ΔEGP Difference* can predict nonstar firms' job postings, which is another firm outcome that is associated with growth and growth expectations. Job postings are a timely measure of firm-level demand for labor and human capital that reflects the growth of companies' operations. Star firms' performance shifts may influence hiring activities among connected nonstar firms through profitability spillovers and local multiplier effects (e.g., Moretti, 2010).

To test this conjecture, we estimate quarterly industry-level panel regressions where we explain the average number of job postings for nonstar and star firms with *ΔEGP Difference*. Like our previous earnings regressions, these regressions control for lagged values of earnings growth and they include year-quarter fixed effects and industry fixed effects. We also estimate specifications where we control for the lagged value of average job postings.

The job postings regression estimates are reported in Table 4. The results in Columns (1) and (2) indicate that one-quarter lagged *ΔEGP Difference* statistically significantly predicts the number of job postings of nonstar firms. The coefficient estimate with the standard control variables is 24.32 (*t*-statistic = 2.33) and 25.32 (*t*-statistic = 2.22) when we additionally control for lagged value of the dependent variable. These coefficient values imply that a one standard deviation increase in *ΔEGP Difference* is associated with a 34% to 36% increase in the number of job postings for nonstar firms.

In contrast, Columns (3) and (4) report that the same coefficients in regressions explaining star firms' average job postings are statistically insignificant and negative. The difference between the estimates for star firms and nonstar firms indicates that star firms' relative earnings performance can predict nonstar firms' earnings growth and job postings, but they are unable to predict star firms' job postings. These job posting results provide further evidence of growth spillover effects from star firms to nonstar firms.

3.3 Predicting Industry-Level GDP and Employment Growth

Building on the spillover effects in earnings growth and job postings, we hypothesize that *ΔEGP Difference* also contains information relevant for predicting broader industry-level economic fundamentals. We study its ability to predict quarterly real GDP and employment growth. These analyses differ from the previous regressions because it is not possible to separate star firms' and nonstar firms' contribution to industry-level employment and GDP growth, and the industry statistics also include non-listed firms. Furthermore, the time series for real GDP growth is shorter due to limited availability of industry-level data and only starts in 2006.

Table 5 presents results from regressions explaining quarterly year-over-year growth rates of real GDP (Panel A) and employment (Panel B) at the industry level. In Panel A, the results indicate that $\Delta EGP\ Difference_{j,t-1}$ is positively and statistically significantly associated with higher future real GDP growth across all models. The coefficients for $\Delta EGP\ Difference_{j,t-1}$ range from 0.345 to 0.442, with *t*-statistics indicating statistical significance at the 10% level or higher in all models. These results remain robust after controlling for lagged average industry earnings growth ($\overline{EGP}_{j,t-1}$), lagged quarterly GDP growth ($GDP\ Qtr\ Growth_{j,t-1}$), lagged values of the dependent variable from the previous quarter ($GDP\ YoY\ Growth_{j,t-1}$), and the same quarter of the previous year ($GDP\ YoY\ Growth_{j,t-4}$). Economically, a one standard deviation increase in $\Delta EGP\ Difference_{j,t-1}$ is associated with a 0.5% to 0.6% increase in industry-level real GDP growth. This response is comparatively even higher than the effect of a one standard deviation change on future earnings growth in the regressions of Table 3.

Panel B focuses on the employment growth rate as the dependent variable. Similar to Panel A, the regressions include control variables for lagged values of employment growth and industry earnings growth. *ΔEGP* $Difference_{j,t-1}$ is again positively associated with higher employment growth, indicating that industries with a higher relative earnings growth of star firms tend to see higher employment growth in the next quarter. The coefficients for *ΔEGP* $Difference_{j,t-1}$ range from 0.079 to 0.135, corresponding to a 0.1% to 0.2% increase in employment growth per standard deviation increase in *ΔEGP* $Difference_{j,t-1}$. The results are statistically significant at the 10% level or higher.

Altogether, these findings underscore the broader economic influence of star firms beyond their immediate firm-specific performance and output. The results show that star firms' predictive ability also extends to performance in non-financial outcomes.

4. Star Firms and Earnings Surprises

Our earnings growth regression estimates indicate that star firms contain information relevant to predicting nonstar firms' future growth. A natural question to ask is whether market participants recognize this. In this Section, we investigate whether sell-side analysts incorporate star firm earnings information when making forecasts on nonstar firms. We also analyze how so-called superstar firms and industry competitiveness influence earnings predictability.

4.1 Earnings Surprise Predictability

In the earnings surprise analysis, we use *ΔEGP* $Difference_{j,t-1}$ to predict the average quarterly earnings surprise of either star or nonstar firms within industry *j*. Our regression specifications are similar to the earnings growth regressions reported in Table 6. We separately regress year-quarter earnings surprise for industry-level star and nonstar firms on *ΔEGP* $Difference_{j,t-1}$. We include lagged earnings surprises as control variables and include industry as well as year-quarter fixed effects.

In Columns (1)-(3) of Table 6, we regress the average earnings surprise of nonstar firms (i.e., $\overline{ES}_{nonstar\,j,t}$) on *ΔEGP Difference*$_{j,t-1}$. We find that the *ΔEGP Difference*$_{j,t-1}$ significantly predicts the earnings surprise of nonstar firms. Specifically, the coefficient on *ΔEGP Difference* is positive and statistically significant with a coefficient value of 0.015 and *t*-statistic of 2.5. These results suggest that analysts underreact to the information in star firms' earnings surprises. In economic terms, one standard deviation change in *ΔEGP Difference* corresponds to an increase in earnings surprise of nonstar firms that is 10% of the standard deviation of this measure.

In Columns (4)-(6), we regress average consensus earnings surprise of star firms within the same industry (i.e., $\overline{ES}_{star_{j,\,t}}$) on *ΔEGP Difference*$_{j,t-1.}$ The coefficients on *ΔEGP Difference* are negative and insignificant, and consistent with our previous earnings predictability results.

We also test whether star firms' predictive ability extends beyond small firms. We classify the top 30% of firms based on market capitalization as large firms, the middle 40% as medium-sized firms, and the bottom 30% as small firms. Hou (2007) uses a similar categorization in a study on lead-lag effects in stock returns. Appendix Table A.4 repeats the earnings growth and earnings surprise predictability regressions of Tables 3 and 4 using two subsamples where we either exclude small nonstar firms or only include medium-sized nonstar firms. The *ΔEGP Difference*$_{j,t-1}$ coefficients remain positive and statistically significant in these subsamples, indicating that stars' predictive ability is not limited to small firms. This also differentiates our findings from previously documented lead-lag patterns in stock returns where large firms' performance can exclusively predict the future performance of small firms (for example, Lo and MacKinlay 1990; Hou 2007).

4.2 Influence of Superstar Firms

If star firms' earnings contain material information about peer nonstar firms' future earnings, a natural question to ask is whether star firms have varying levels of informational importance. In particular, dominant star firms or *superstars* should have stronger influence on nonstar firms. We define superstar firms as star firms that have a more dominant presence in their corresponding industries. We first sort all star firms across all industries by their ratio of market capitalization to total industry market capitalization at the end of each calendar year. We then classify stars with above-median market capitalization ratios as superstars and the rest of star firms as regular stars for the following calendar year.

In Table A.5 we repeat our earnings growth (see Table 3) and earnings surprise (see Table 6) regressions separately for superstars and regular stars as defined above. Specifically, we re-construct *ΔEGP Difference* measures to include only superstars or regular stars, keeping the specifications otherwise unchanged. The results in Columns (1) and (2) of Table 4 show that both superstars and regular stars have statistically significant *ΔEGP Difference* coefficient estimates. Earnings growth of both types of star firms can predict the earnings growth of nonstar firms. However, the effect of superstar firms' earnings performance has a 26% stronger effect, compared to that of regular stars.

In Columns (3) and (4) of Table A.5, we find similar results when predicting the earnings surprise of nonstar firms. Superstars' *ΔEGP Difference* coefficient of 0.028 is almost three times larger than the coefficient for regular stars (estimate = 0.010). This evidence indicates that even though superstars' earnings contain more information relative to other stars', analysts are less effective in incorporating superstar firms' earnings information into their earnings forecasts.

Taken together, these results suggest that there is significant heterogeneity in the influence of star firms. As expected, a subset of star firms that are larger relative to the size of nonstar firms in their industry dominate and contain considerably more information than regular star firms.

4.3 Market Power, Earnings Predictability, and Analyst Underreaction

We then analyze whether star firms are more influential in less competitive industries. We measure industry competitiveness using Lerner index, which is defined as the sum of operating income before depreciation (Compustat item OIBDP) less depreciation (item DP) for all firms in an industry divided by the sum of total sales (item SALE) across the same firms. The higher the value of the index, the less competitive an industry is. Each year, we classify industries into high Lerner and low Lerner industries based on their previous year's Lerner index values. The high Lerner industries have above median Lerner index values and the low Lerner industries have below median index values.

Table 7 estimates our previous earnings growth predictability and earnings surprise predictability regressions separately for high Lerner and low Lerner industries. The results are consistently more economically and statistically significant for high Lerner index industries. In regressions explaining unexpected earnings, the high-Lerner index *ΔEGP Difference* coefficient (0.26, *t*-value 5.65) is 60% higher than the low-Lerner Index coefficient (0.16, *t*-value 3.26). The difference is even more amplified in regressions explaining consensus earnings surprises, where the high-Lerner coeffient (0.028, *t*-value 1.99) is 3.5 times as high as the low-Lerner coefficient (0.008, *t*-value 1.83). These results suggest that market power contributes to star firms' information externalities and spillover effects.

4.4 Predicting Market Reaction

If analysts underreact to shifts in star firms' relative earnings performance, it is likely that market does not fully incorporate the information contained in the earnings of star firms into prices. Consequently, star firms' relative earnings performance could predict the short-term returns of nonstar firms. To test this conjecture, we regress cumulative abnormal returns of nonstar firms around earnings announcements, aggregated at the industry level, on our key $\Delta EGP\ Difference_{j,t-1}$ measure. Some specifications include the average earnings announcement returns for star and nonstar firms during the previous quarter as additional control variables. All regressions include year-quarter and industry fixed effects, which control for all common industry- and time-specific factors that potentially affect the earnings surprises for star and nonstar firms. Like before we cluster standard errors by year-quarter and industry.

Table 8 reports the market reaction regression results. We find that $\Delta EGP\ Difference_{j,t-1}$ positively predicts cumulative abnormal returns of nonstar firms in a [0, 2] window around earnings announcements. Specifically, as reported in Column (1), one unit increase in $\Delta EGP\ Difference_{j,t-1}$ is associated with a 6.8% higher return for nonstar firms around earnings announcements. This effect is statistically significant at the 5% level. In Columns (2) and (3), we control for lagged announcement returns for nonstar and star firms as additional control variables. Star firms' earnings performance still predicts nonstar firm returns. As a placebo test, we estimate the same regression on star firm returns and do not find any significant effect (see Columns (4)-(6)).

Together, these results indicate that star firms' relative earnings performance positively predicts nonstar firm returns, suggesting that star firms have relevant information about nonstar firms that is not already incorporated into prices.

4.5 Mixed Information Signals and Analyst Underreaction

Our results so far suggest that star firms contain information about nonstar firms and analysts underreact to such information. A natural follow-up hypothesis is that analysts are more likely to underreact in situations where the information signals on star firms are confusing or less salient. To test this conjecture, we define one such instance where star firms' relative earnings performance shift has a different sign than the sign of abnormal earnings announcement return of star firms. The different signs on $\Delta EGP\ Difference_{j,t-1}$ and the earnings announcement return might confuse analysts who may fail to fully account for this information in their forecasts.

Using a similar regression structure as in Table 8, we interact $\Delta EGP\ Difference_{j,t-1}$ with an indicator variable that takes a value one if both the sign of the average CAR for star firms and the difference between lagged CAR of star firms and nonstar firms have the opposite sign compared to that of $\Delta EGP\ Difference_{j,t-1}$.[12] Otherwise, the indicator takes the value of zero. The regressions control for lagged earnings surprises for star and nonstar firms.

The results are reported in Appendix Table A.6. We find that analysts are more likely to underreact to information on star firms' earnings performance when signals across star and nonstar firms are mixed. As reported in Column (1), the coefficient on the interaction term is 0.019 and it is statistically significant. In Column (2), we additionally control for earnings surprise and find a similar effect.

[12] When $\Delta EGPDifference_{t-1}$ is positive, the indicator is equal to one if the average star CAR has a negative sign, and it is more negative than the nonstar average CAR. Conversely, when $\Delta EGPDifference_{t-1}$ is negative, the indicator is equal to one if the average star CAR has a positive sign and is more positive than the average nonstar CAR. As previously, CARs are measured over a [0, 2] day window.

5. Star Firms and Stock Returns

Our previous findings indicate that changes in star firms' relative earnings performance can predict nonstars' earnings announcement returns. To further examine the influence of star firms on financial market outcomes, we examine the potential asset pricing implications of the observed link between star and nonstar firms. We develop a trading strategy to exploit the cross-sectional differences in the effect of star firms' earnings performance shifts. We also investigate potential lead-lag relations between the returns of star and nonstar firms.

5.1 Earnings Performance Shifts and Stock Returns

We start by creating market-value weighted quintile portfolios of nonstar firms in industries with the highest and lowest lagged values of *ΔEGP Difference.* Each month, we form quintiles by sorting all industries using the Δ*EGP* difference between star and nonstar firms within their corresponding industries measured at the end of the previous month (i.e., *ΔEGP Difference* $Monthly_{j,t-1}$). The portfolios are updated monthly. *ΔEGP Difference Monthly* is calculated based on earnings announcements during months *t-1* and *t-3*.

We create a value-weighted Long portfolio that invests in nonstar portfolios of the eleven highest-ranked industries and a value-weighted Short portfolio that invests in nonstar portfolios of the eleven lowest-ranked industries. These portfolios correspond to the top and bottom quintile within the 55 industries for which we have sufficient observations. The industry nonstar portfolios' weight in the value-weighted quintiles is based on the sum of market capitalizations of all nonstar firms in that industry at the beginning of the month. We then define a Long-Short portfolio strategy where we Long the quintile of firms with the highest lagged *ΔEGP Difference Monthly* values and Short industries with the lowest *ΔEGP Difference Monthly* values. The mean return of the lowest and highest quintile portfolios are 0.698% and 1.292% (see Appendix Table A.7), respectively.

We compute the monthly value-weighted returns of each quintile as well as the Q5-Q1 Long-Short portfolio and regress the excess portfolio returns on the Fama and French (2015) five factors plus the momentum factor. Table 9 reports the portfolio alphas and factor beta estimates. The beta estimates indicate that Q5 firms, which are in industries with larger positive star firm earnings performance shifts, are typically profitable firms. In contrast, firms facing low or negative shifts in peer star firms' earnings, included in Q1 portfolios, are typically value stocks. Both extreme quintiles have positive loading on size and negative loadings on momentum.

The Q1 and Q5 portfolios generate monthly alphas of -0.384% and 0.341%, respectively. The other quintile portfolios do not produce significant alphas, suggesting that almost all of the return predictability comes from firms with extreme star firm earnings performance shifts. The Long-Short portfolio results based on Q5-Q1 indicate that high *ΔEGP Difference Monthly* firms outperform the low *ΔEGP Difference Monthly* firms by 0.725% per month (*t*-statistic = 2.35) on a risk-adjusted basis.

5.2 Lead-Lag Relation in Stock Returns

So far, our results indicate that star firms' relative earnings growth acceleration predicts the earnings growth of nonstar firms and this information is not fully incorporated in stock prices. We now directly examine the relation between the returns of star and nonstar firms. Based on the findings in the comovement literature (e.g., Hou 2007; Hameed et al., 2015), we posit that underreaction related to information spillover between connected firms may generate predictable lead-lag relation in stock returns.

To test the lead-lag relation between star and nonstar returns, each month, we sort nonstar firms by the value-weighted average return of same-industry star firms in the previous month. We then calculate the value-weighted average monthly returns of the quintile portfolios and adjust for risk using the six-factor model described in the previous subsection.

Table 10, Panel A reports the portfolio abnormal returns and the factor betas. The average monthly abnormal return spread between the top and bottom quintile portfolios (Q5-Q1) is 0.465% (*t*-statistic = 2.41), suggesting that nonstar firms in industries with the best lagged star firm performance outperform those in industries with the worst lagged star performance by 46 basis points per month. The regression alphas show a significant lead-lag relation between the returns of stars and nonstars, particularly in industries with extremely high (Q5) and low (Q1) past star firm returns. Specifically, Q5 and Q1 quintiles generate monthly alphas of 0.239% (*t*-statistic = 2.02) and -0.226% (*t*-statistic = -1.77), respectively.

In Panel B, we do a placebo test to check whether nonstar firm returns predict star firm returns. In this case, we form star firm quintiles by sorting on lagged value-weighted nonstar firm returns. We find an insignificant Long-Short portfolio alpha, suggesting that nonstar firm returns do not contain useful information about future performance of star firms. This one-way lead-lag return comovement between star and nonstar firms is in line with our earlier finding that only star firms' earnings performance changes contain relevant information about nonstar firms' future performance.

6. Is the Star Firm Effect Merely a Large Firm Effect?

In the last set of tests, we examine whether other large firms share the same information externalities as star firms. We repeat our main analyses where we assign the next four largest firms in each industry as "star substitutes". This means that we effectively replace the stars with the same number of other large firms. As before, the regressions include industry-quarter observations with at least five nonstar firms.

Appendix Table A.8 reports results from regressions where we explain nonstar firms' earnings growth, earnings surprises, and earnings announcement returns with *ΔEGP* $Difference_{j,t-1}$ calculated using these star substitutes and Appendix Table A.9 reports six-factor alphas from nonstar firm portfolios formed based on the corresponding *ΔEGP Difference* $Monthly_{j,t-1.}$ The regressions in these Appendix tables are identical to the specifications in Tables 3, 4, 6, and 9. The substitute *ΔEGP* $Difference_{j,t-1}$ is based on the relative earnings growth difference between the substitute star firms and the remaining nonstar firms.

Panel A of Appendix Table A.8 shows that star substitutes can predict nonstars' earnings growth, but the coefficient magnitudes are 30-50% of the corresponding coefficients for actual stars. However, the substitute stars do not have predictive ability in any of the analyses that involve analyst forecasts or stock returns. The substitute star *ΔEGP* $Difference_{j,t-1}$ coefficients are statistically insignificant in regressions explaining nonstar firms' earnings surprises (Appendix Table A.8, Panel B) and earnings announcement returns (Appendix Table A.8, Panel C), and the Long-Short alpha in the portfolio test based on *ΔEGP Difference* $Monthly_{j,t-1}$ is also statistically insignificant. (Appendix Table A.9). Together, these placebo tests confirm that the effects we identify are specific to star firms and are not merely general large firm effects.

7. Summary and Conclusions

This study examines whether very large and dominant "star" firms generate information externalities that are useful for predicting the future performance of other connected firms and the broader industry around them. Star firms are known to have a large and sometimes disproportionate impact on various macroeconomic outcomes, and they can influence other firms through various spillover and multiplier effects. Our key conjecture is that changes in star firms' performance influence the future earnings and growth of other related firms. Further, market participants such as sell-side equity analysts may not fully incorporate useful information related to star firms into their earnings forecasts of related firms. Consequently, financial information externalities of industry star firms would generate predictable patterns in firm-level earnings and returns of nonstar firms.

We test these conjectures using the definition of industry star firms developed in Gutiérrez and Philippon (2019). Consistent with our conjectures, we find that changes in star firms' relative earnings performance contain incremental information, as they predict the earnings growth, earnings surprises, and labor market activities (i.e., job postings) of other nonstar firms in the same industry. At the industry level, star firms' earnings performance shifts serve as a leading indicator that can predict future GDP and employment growth. The evidence of earnings predictability is stronger in less competitive industries, which suggests that market power is an important source of star firms' influence.

Interestingly, these information externalities are not immediately incorporated in stock prices. A Long-Short trading strategy based on changes in industry stars' relative earnings performance earns an annualized risk-adjusted return of over 8%. Together, these findings provide valuation-based evidence of economic importance of star firms. More broadly, these results highlight the influence and importance of very large firms in financial markets.

In future work, it may be interesting to examine how star firms' performance shifts propagate across firm networks and industries. It can also be useful to examine the heterogeneity in the impact of star firms. For instance, local star firms, or star firms with star corporate managers, might be more influential. Similarly, the influence of star firms might vary based on their position in firm networks.

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Table 1
Summary Statistics

This table presents summary statistics for our main variables. Panel A reports statistics on variables that are measured at the industry level and Panel B reports on variables that are measured at the firm level. The sample period is 1994 to 2020 for all variables except the job posting variables ($\overline{JPG}_{star_{j,t}}$ and $\overline{JPG}_{nonstar_{j,t}}$), which are available from 2008 to 2020, and asset pricing variables (*MIS* variables and all firm-month variables), which are reported for the 1984 to 2020 period. Patent citation statistics are only reported for firms that have patents. Definitions of all variables are presented in Appendix Table A.1. We use the definition of industry star firms developed in Gutiérrez and Philippon (2019).

Variable	Mean	Std. Dev.	25th Pctl.	Median	75th Pctl.	N
Panel A: Industry-Level Variables						
Statistics based on industry-quarter observations:						
ΔEGP Difference$_{j,t}$ (× 100)	0.017	1.409	-0.382	0.006	0.413	4,478
$\overline{EGP}_{star_{j,t}}$ (× 100)	-0.032	1.179	-0.080	0.121	0.292	4,616
$\overline{EGP}_{nonstar_{j,t}}$ (× 100)	-0.259	1.469	-0.460	0.011	0.315	4,710
$\overline{ES}_{star_{j,t}}$ (× 100)	0.042	0.278	-0.008	0.046	0.120	4,764
$\overline{ES}_{nonstar_{j,t}}$ (× 100)	-0.016	0.296	-0.113	0.013	0.117	4,793
GDP YoY Growth$_{j,t}$	0.0112	0.0846	-0.0139	0.0185	0.0473	2,601
EMPL YoY Growth$_{j,t}$	0.0050	0.0636	-0.0152	0.0112	0.0297	4,728
$\overline{JPG}_{star_{j,t}}$	8.665	334.795	-0.246	0.002	0.329	1,975
$\overline{JPG}_{nonstar_{j,t}}$	0.789	8.377	-0.220	0.023	0.323	1,995
Star Firms' Announcement Return (× 100)	0.054	3.809	-1.868	0.055	2.002	4,764
Nonstar Firms' Announcement Return (× 100)	0.011	2.690	-1.280	0.029	1.333	4,793
Statistics based on industry-month observations:						
ΔEGP Difference Monthly$_{j,t}$ (× 100)	0.008	1.409	-0.380	0.006	0.388	12,537
Panel B: Firm-Level Variables						
Statistics based on firm-year observations:						
ROA$_{i,t}$	-0.017	1.219	-0.017	0.020	0.062	176,144
ROE$_{i,t}$	-0.451	79.894	-0.045	0.072	0.136	176,145
COGS/Sales$_{i,t}$	3.232	128.567	0.451	0.636	0.783	176,126
SG&A/Sales$_{i,t}$	0.825	23.334	0.148	0.252	0.399	145,142
CAPEX + R&D Share$_{i,t}$	0.020	0.083	0.000	0.001	0.005	86,604
Citations of Patents Filed Annually$_{i,t}$	599.803	3390.776	11.000	52.000	229.000	40,262
Number of Patents Filed Annually$_{i,t}$	8.125	95.033	0.000	0.000	0.000	184,912
Citations of Patents Issued Annually$_{i,t}$	616.714	3198.698	16.000	65.000	263.000	41,489
Number of Patents Issued Annually$_{i,t}$	7.784	92.100	0.000	0.000	0.000	184,912
Statistics based on firm-month observations:						
Size$_{i,t}$	2.369	9.009	0.046	0.195	0.980	1,729,210
B/M$_{i,t}$	0.721	0.668	0.302	0.556	0.916	1,729,210
Momentum$_{i,t}$	0.152	0.603	-0.192	0.065	0.345	1,682,419
Reversal$_{i,t}$	0.012	0.146	-0.062	0.002	0.072	1,728,935
Profitability$_{i,t}$	-0.008	0.178	-0.003	0.026	0.067	1,727,450
Investment$_{i,t}$	0.223	0.651	-0.011	0.077	0.222	1,675,128

Table 2
Star Firm Characteristics

This table presents summary statistics comparing all firms, star firms and large nonstar firms. Panel A reports means and medians of firm characteristics for all firms, star firms, and large nonstar firms, respectively. Panel B reports industry-level means for star firms and large same-industry firms. In panel A, the statistics are based on annual firm observations and in Panel B they are based on annual industry-level means. Star firms are industry star firms defined as in Gutiérrez and Philippon (2019). Large nonstar firms are nonstar firms in the top 30% of market capitalization in each industry. Number of patents and citation count data is obtained from Kogan et al. (2017). Exact variable definitions are reported in Appendix Table A.1. Patents filed and issued are the number of patents filed/issued during a calendar year. The final columns in Panel A provides *p*-values from the Satterthwaite *t*-test and the Kruskal-Wallis median test, assessing the statistical significance of the differences between star and large firms' characteristics. The final column in Panel B provides *p*-values from a pairwise *t*-test comparing industry-level star firm mean values to corresponding same-industry large nonstar firm means. The sample spans the period from 1984 to 2020.

Panel A: Star Firms Compared to All Firms and All Large Nonstar Firms

Variable	All Firms		Star Firms		Large Nonstar Firms		Star vs. Large *p*-value	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Performance and profitability measures								
ROA	-0.02	0.02	0.12	0.06	0.06	0.04	0.12	0.00
ROE	-0.45	0.07	0.23	0.14	0.09	0.11	0.02	0.00
COGS/Sales	3.23	0.64	0.78	0.66	1.76	0.60	0.17	0.00
SG&A/Sales	0.83	0.25	0.20	0.16	0.45	0.23	0.00	0.00
Investments and innovativeness								
(Capital Exp + R&D)/Income	0.02	0.00	0.22	0.14	0.02	0.00	0.00	0.00
Citations of patents filed (past year)	599.80	52.00	2855.15	234.00	708.96	114.00	0.00	0.00
Citations of patents filed (cumulative)	7864.82	305.00	50963.53	2075.50	11925.46	992.00	0.00	0.00
Number of patents filed (past year)	8.13	0.00	92.35	0.00	15.30	0.00	0.00	0.00
Number of patents filed (cumulative)	185.91	0.00	2038.03	16.00	380.33	1.00	0.00	0.00

Panel B: Star Firms Compared to Large Same-Industry Nonstar Firms			
Variable	Star Firm Industry Mean	Large Same-Industry Nonstar Mean	Star vs. Large *p*-value
Performance and profitability measures			
ROA	0.12	0.09	0.00
ROE	0.24	0.12	0.00
COGS/Sales	0.62	0.98	0.00
SG&A/Sales	0.21	0.33	0.00
Investments and innovativeness			
(Capital Exp + R&D)/Income	0.28	0.10	0.00
Citations of patents filed (past year)	2482.8	286.17	0.00
Citations of patents filed (cumulative)	45329	4683.7	0.00
Number of patents filed (past year)	101.96	7.91	0.00
Number of patents filed (cumulative)	2222.9	236.11	0.00

Table 3
Predicting Star and Nonstar Firms' Earnings Growth

This table reports regression results explaining star and nonstar firms' earnings growth (*EGP*) at the industry level ($\overline{EGP}_{star/nonstar_{j,t}}$). Columns (1) to (3) and (4) to (6) use the *ΔEGP Difference*$_{j,t-1}$ to explain nonstar and star firms' earnings growth respectively. *EGP* is defined as the earnings per share (*EPS*) in quarter *t* minus *EPS* in quarter *t*–4, scaled by share price ten days before the earnings announcement date. The main explanatory variable *ΔEGP Difference*$_{j,t-1}$ is calculated as ($\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-1}}$)–($\overline{EGP}_{star_{j,\ t-2}} - \overline{EGP}_{nonstar_{j,\ t-2}}$). $\overline{EGP}_{star_{j,\ t}}$ and $\overline{EGP}_{nonstar_{j,\ t}}$ refer to the equal-weighted average earnings growth *(EGP)* of star firms and nonstar firms in industry *j* in quarter *t*, respectively. Other explanatory variables include three lagged values of $\overline{EGP}_{star/nonstar_{j,t}}$. Detailed variable definitions are presented in Appendix Table A.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are dual-clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Nonstar Firms (g = nonstar)			**Star-Firms** (g = star)		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEGP Difference$_{j,\ t-1}$	0.100***	0.190***	0.187***	-0.027	-0.033	-0.024
	(3.897)	(5.074)	(4.971)	(-0.849)	(-1.128)	(-0.866)
$\overline{\mathrm{EGP}}_{g_{j,t-1}}$	0.582***	0.703***	0.698***	0.585***	0.597***	0.589***
	(13.586)	(15.000)	(15.546)	(14.189)	(8.362)	(8.908)
$\overline{\mathrm{EGP}}_{g_{j,t-2}}$		-0.163***	-0.137***		-0.021	0.031
		(-4.682)	(-3.391)		(-0.253)	(0.399)
$\overline{\mathrm{EGP}}_{g_{j,t-3}}$			-0.050			-0.087**
			(-1.092)			(-2.231)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,469	4,469	4,438	4,447	4,447	4,418
R^2	0.406	0.414	0.415	0.386	0.386	0.391

Table 4
Predicting Job Postings of Star and Nonstar Firms

This table reports regression results explaining growth in nonstar (columns (1)-(2)) and star (columns (3)-(4)) firms' average number of quarterly job postings at the industry level ($\overline{JPG}_{star/nonstar_{j,\ t}}$). This is defined as $(\overline{JP}_{star/nonstar_{j,\ t}} - \overline{JP}_{star/nonstar_{j,\ t-1}})/\overline{JP}_{star/nonstar_{j,\ t-1}}$, where $\overline{JP}_{star/nonstar_{j,\ t}}$ is the average number of job postings by star/nonstar firms in industry *j* in quarter *t*. The main explanatory variable $\Delta EGP\ Difference_{j,t-1}$ is calculated as $(\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-1}}) - (\overline{EGP}_{star_{j,\ t-2}} - \overline{EGP}_{nonstar_{j,\ t-2}})$. $\overline{EGP}_{star_{j,\ t}}$ and $\overline{EGP}_{nonstar_{j,\ t}}$ refer to the equal-weighted average earnings growth *(EGP)* of star firms and nonstar firms in industry *j* in quarter *t*, respectively. The control variables include lagged values of $\overline{EGP}_{star/nonstar_{j,\ t}}$ and $\overline{JPG}_{star/nonstar_{j,\ t}}$ (in columns (2) and (4)). Detailed variable definitions are presented in Appendix Table A.1. The sample period is from 2008 to 2020. Regressions include industry and year-quarter fixed effects. Standard errors are clustered at the industry level. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Nonstar Firms (g=nonstar)		**Star-Firms** (g=star)	
	(1)	(2)	(3)	(4)
ΔEGP Difference$_{j,\ t-1}$	24.322**	25.234**	-323.897	16.354
	(2.339)	(2.225)	(-0.921)	(0.926)
$\overline{\text{EGP}}_{g_{j,t-1}}$	1.156	1.330	-400.879	-25.915
	(0.131)	(0.090)	(-1.037)	(-0.464)
$\overline{\text{EGP}}_{g_{j,t-2}}$	-46.908	-54.610	595.721	-20.766
	(-1.499)	(-1.594)	(0.963)	(-0.892)
$\overline{\text{EGP}}_{g_{j,t-3}}$	-30.347	-29.464	307.975	42.974
	(-1.138)	(-0.959)	(0.990)	(1.234)
$\overline{\text{JPG}}_{g_{j,t-1}}$		-0.096		0.000
		(-1.467)		(-0.860)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1,954	1,923	1,943	1,897
R^2	0.127	0.143	0.049	0.070

Table 5
Predicting Industry-Level GDP and Employment Growth

This table reports regression results explaining industry-level quarterly real GDP growth (*GDP YoY Growth*$_{j,t}$) in Panel A and employment growth (*EMPL YoY Growth*$_{j,t}$) in Panel B. The dependent variables measure year-over-year growth relative to the same quarter in the previous year. The main explanatory variable *ΔEGP Difference*$_{j,t-1}$ is calculated as $(\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-1}}) - (\overline{EGP}_{star_{j,\ t-2}} - \overline{EGP}_{nonstar_{j,\ t-2}})$. $\overline{EGP}_{j,t}$, $\overline{EGP}_{star_{j,\ t}}$ and $\overline{EGP}_{nonstar_{j,\ t}}$ refer to the equal-weighted average earnings growth *(EGP)* of all firms in industry *j* in quarter *t*, respectively. *EGP* is defined as the earnings per share (*EPS*) in quarter *t* minus *EPS* in quarter *t–4*, scaled by share price ten days before the earnings announcement date. Other explanatory variables include three lagged values of $\overline{EGP}_{j,t}$, lagged quarterly growth (*GDP/EMPL Qtr Growth*$_{j,t-1}$), and lagged values of the dependent variable from the previous quarter (*GDP/EMPL YoY Growth*$_{j,t-1}$), and the same quarter of the previous year (*GDP/EMPL YoY Growth*$_{j,t-4}$). Detailed variable definitions are presented in Appendix Table A.1. The sample period in Panel A is from 2006 to 2020 and in Panel B is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are dual-clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

Panel A: Real GDP Growth

	(1)	(2)	(3)	(4)	(5)	(6)
ΔEGP Difference$_{j,\ t-1}$	0.382***	0.401**	0.402**	0.442**	0.428**	0.345*
	(3.262)	(2.322)	(2.346)	(2.361)	(2.272)	(1.827)
$\overline{\text{EGP}}_{j,t-1}$	2.140***	2.204**	2.203**	2.238**	1.160**	0.797*
	(2.809)	(2.625)	(2.608)	(2.679)	(2.087)	(1.762)
$\overline{\text{EGP}}_{j,t-2}$		-0.097	-0.099	-0.193	-0.378	-0.680
		(-0.241)	(-0.231)	(-0.413)	(-0.943)	(-1.619)
$\overline{\text{EGP}}_{j,t-3}$			0.002	0.211	0.587**	0.249
			(0.008)	(0.709)	(2.062)	(1.064)
GDP YoY Growth$_{j,t-4}$				-0.174***	-0.106***	-0.228***
				(-3.547)	(-2.795)	(-9.999)
GDP Qtr Growth$_{j,t-1}$					1.081***	0.341*
					(5.182)	(1.801)
GDP YoY Growth$_{j,t-1}$						0.698***
						(19.814)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,490	2,490	2,489	2,323	2,323	2,323
R^2	0.429	0.429	0.429	0.452	0.637	0.800

Panel B: Employment Growth						
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEGP Difference$_{j,\,t-1}$	0.135***	0.085**	0.079**	0.088**	0.091***	0.102*
	(3.345)	(2.597)	(2.261)	(2.392)	(2.682)	(1.758)
$\overline{\mathrm{EGP}}_{j,t-1}$	0.948**	0.760*	0.791*	0.817**	0.722**	0.507**
	(2.193)	(1.935)	(2.007)	(2.047)	(2.093)	(2.464)
$\overline{\mathrm{EGP}}_{j,t-2}$		0.289*	0.071	0.073	0.007	-0.247
		(1.813)	(0.450)	(0.473)	(0.049)	(-1.493)
$\overline{\mathrm{EGP}}_{j,t-3}$			0.324**	0.255**	0.280***	0.109
			(2.656)	(2.235)	(2.693)	(1.476)
EMPL YoY Growth$_{j,t-4}$				0.168**	0.160**	-0.108*
				(2.426)	(2.454)	(-1.788)
EMPL Qtr Growth$_{j,t-1}$					0.397**	0.021
					(2.506)	(0.317)
EMPL YoY Growth$_{j,t-1}$						0.750***
						(10.803)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,422	4,422	4,420	4,420	4,420	4,420
R^2	0.510	0.511	0.512	0.524	0.567	0.789

Table 6
Predicting Earnings Surprises of Star and Nonstar Firms

This table reports regression results explaining nonstar (Columns (1) –(3)) and star (Columns (4)–(6)) firms' average earnings surprise (*ES*) at the industry level ($\overline{ES}_{star/nonstar_{j,\,t}}$). *ES* is the difference between actual earnings per share and analysts' consensus forecast, scaled by share price ten days before the earnings announcement. The main explanatory variable $\Delta EGP\ Difference_{j,t\text{-}1}$ is calculated as ($\overline{EGP}_{star_{j,\,t\text{-}1}}$– $\overline{EGP}_{nonstar_{j,\,t\text{-}1}}$)–($\overline{EGP}_{star_{j,\,t\text{-}2}}$ – $\overline{EGP}_{nonstar_{j,\,t\text{-}2}}$) $\overline{EGP}_{star_{j,\,t}}$ and $\overline{EGP}_{nonstar_{j,\,t}}$ refer to the equal-weighted average earnings growth *(EGP)* of star firms and nonstar firms in industry *j* in quarter *t*, respectively. The control variables include lagged values of $\overline{EGP}_{nonstar_{j,\,t}}$ and $\overline{ES}_{nonstar_{j,\,t}}$ (in columns (1) and (2)) or $\overline{EGP}_{star_{j,\,t}}$ and $\overline{ES}_{star_{j,\,t}}$ (in columns (3) and (4)). Detailed variable definitions are presented in Appendix Table A.1. The sample period is from 1994 to 2020. regressions include industry and year-quarter fixed effects. Standard errors are dual-clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Nonstar Firms (g=nonstar)		**Star-Firms** (g=star)	
	(1)	(2)	(3)	(4)
ΔEGP Difference$_{j,\,t-1}$	0.015**	0.015**	-0.004	-0.004
	(2.478)	(2.549)	(-0.738)	(-0.781)
$\overline{EGP}_{g_{j,t-1}}$	0.033***	0.019**	0.032**	0.014**
	(3.866)	(2.359)	(2.645)	(2.370)
$\overline{EGP}_{g_{j,t-2}}$	-0.021**	-0.017*	0.003	0.007
	(-2.256)	(-1.749)	(0.128)	(0.310)
$\overline{EGP}_{g_{j,t-3}}$	0.015**	0.015**	-0.007	-0.006
	(2.545)	(2.529)	(-1.017)	(-0.706)
$\overline{ES}_{g_{j,t-1}}$		0.162***		0.183***
		(3.308)		(2.951)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	4,447	4,447	4,441	4,441
R^2	0.162	0.182	0.109	0.134

Table 7
Predicting Unexpected Earnings and Earnings Surprises of High and Low Lerner Index Industries

This table reports results from regressions explaining nonstar firms' earnings growth (*EGP*) and earnings surprises (ES) at the industry level for subsamples of industries with high and low Lerner Index values. Each year, we use the median industry Lerner Index from the previous year to split industries into High Lerner (above median) and Low Lerner (below median) industries. Industry-level Lerner Index is defined as the sum of operating income before depreciation (Compustat item OIBDP) less depreciation (item DP) for all firms in an industry divided by the sum of total sales (item SALE) across the same firms. Earnings surprise is the difference between actual earnings per share and analysts' consensus forecast, scaled by share price ten days before the earnings announcement. The main explanatory variable $\Delta EGP\ Difference_{j,t-1}$ is calculated as $(\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-1}}) - (\overline{EGP}_{star_{j,\ t-2}} - \overline{EGP}_{nonstar_{j,\ t-2}})$. Other explanatory variables include three lagged values of the dependent variable. Detailed variable definitions are presented in Appendix Table A.1. The sample period is from 1994 to 2020. We exclude the banking and utilities industries and include industry-quarter observations with at least five nonstar firms. The regressions include industry and year-quarter fixed effects. Standard errors are clustered at the industry level. Standard errors are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Earnings Growth (EGP)		Earnings Surprise (ES)	
	High Lerner	Low Lerner	High Lerner	Low Lerner
	(1)	(2)	(3)	(4)
ΔEGP Difference$_{j,\ t-1}$	0.255***	0.160***	0.028*	0.008*
	(5.65)	(3.26)	(1.99)	(1.83)
$\overline{EGP}_{nonstar_{j,t-1}}$	0.763***	0.658***	0.039**	0.009
	(11.75)	(11.33)	(2.03)	(1.45)
$\overline{EGP}_{nonstar_{j,t-2}}$	-0.252***	-0.086	-0.032*	-0.009
	(-4.13)	(-1.34)	(-1.75)	(-1.14)
$\overline{EGP}_{nonstar_{j,t-3}}$	-0.005	-0.088	0.010	0.016***
	(-0.10)	(-1.27)	(0.73)	(2.85)
$\overline{ES}_{nonstar_{j,t-1}}$			0.066	0.224***
			(1.14)	(3.32)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2,120	2,104	2,125	2,108
R^2	0.447	0.420	0.190	0.230

Table 8
Predicting Earnings Announcement Returns of Star and Nonstar Firms

This table reports regression results explaining star firms' and nonstar firms' earnings announcement returns. Earnings announcement returns are market-adjusted cumulative abnormal returns within the [0, 2] window around announcement date. The main explanatory variable *ΔEGP Difference*$_{j,t-1}$ is defined as in Section 2.3. The control variables include stars' and nonstars' average announcement returns in the previous quarter. Detailed variable definitions are presented in Appendix Table A.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are dual-clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Nonstar Firms			**Star Firms**		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEGP Difference$_{j,t-1}$	0.068**	0.070**	0.070**	-0.063	-0.063	-0.059
	(2.38)	(2.40)	(2.41)	(-1.32)	(-1.32)	(-1.27)
Nonstars' Avg Announcement Return$_{j,t-1}$		0.017	0.018		0.000	0.010
		(0.57)	(0.59)		(0.01)	(0.35)
Stars' Avg Announcement Return$_{j,t-1}$			-0.005			-0.072***
			(-0.38)			(-3.74)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,478	4,478	4,478	4,471	4,471	4,471
R^2	0.080	0.081	0.081	0.048	0.048	0.052

Table 9
Performance Estimates for Star Earnings Performance-Based Portfolios

This table reports the factor model estimates for nonstar firm quintile portfolios formed based on lagged values of *ΔEGP Difference Monthly.* Every month *t*, we sort equal-weighted industry portfolios of nonstar firms based on *ΔEGP Difference Monthly*$_{j,t-1}$ calculated as $(\overline{EGP}_{m_{star_{j,\,t-1}}} - \overline{EGP}_{m_{nonstar_{j,\,t-1}}}) - (\overline{EGP}_{m_{star_{j,\,t-4}}} - \overline{EGP}_{m_{nonstar_{j,\,t-4}}})$ and form quintile portfolios. We then compute the value-weighted quintile returns using the sum of market capitalizations of all nonstar firms in each industry as the industry portfolio weight. $\overline{EGP}_{m_{star_{j,\,t}}}$ ($\overline{EGP}_{m_{nonstar_{j,\,t}}}$) is star firms' (nonstar firms') average earnings growth (*EGP*) at the industry level announced during months *t*, *t-1*, *or t-2*. The portfolios are updated monthly. We regress the monthly excess returns of quintile portfolios on six risk factors consisting of the factors in the Fama and French (2015) five-factor model plus momentum (*MOM*). The sample period is from 1994 to 2020. *t*-statistics in parentheses are computed based on standard errors with Newey-West correction with three lags. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Alpha	0.725**	-0.384*	0.148	-0.010	-0.129	0.341
	(2.350)	(-1.890)	(0.780)	(-0.070)	(-0.800)	(1.440)
RMRF	-0.081	1.172***	1.119***	1.106***	1.109***	1.091***
	(-0.610)	(20.730)	(20.090)	(24.760)	(26.230)	(9.450)
SMB	-0.148	0.621***	0.424***	0.314***	0.426***	0.474***
	(-1.210)	(8.100)	(4.780)	(3.700)	(6.120)	(4.500)
HML	-0.100	0.248**	0.036	0.124	0.129	0.148
	(-0.460)	(2.190)	(0.410)	(1.510)	(1.260)	(0.940)
CMA	-0.241	0.014	0.220	-0.041	-0.056	-0.227
	(-0.940)	(0.090)	(1.580)	(-0.340)	(-0.420)	(-1.070)
RMW	0.327	0.083	0.068	0.110	-0.124	0.411**
	(1.520)	(0.770)	(0.550)	(0.870)	(-1.310)	(2.280)
Mom	-0.285***	-0.220***	-0.213***	-0.085	-0.206***	-0.505***
	(-3.110)	(-4.970)	(-3.550)	(-1.430)	(-3.970)	(-6.050)
N	324	324	324	324	324	324
Adj R^2	0.081	0.778	0.794	0.814	0.826	0.695

Table 10
Performance Estimates for Lead-Lag Return Portfolios

This table reports the factor model estimates for quintile portfolios formed based on lagged returns of same-industry star firms and nonstar firms. In Panel A, we rank industries based on the lagged value-weighted average returns of their star firms and form the quintile portfolios of nonstar firms. In Panel B, we rank industries based on the lagged value-weighted average returns of their nonstar firms and form the quintile portfolios of star firms. We regress the monthly excess returns of quintile portfolios on various risk factors using a six-factor model containing the Fama and French (2015) five-factor model plus momentum (*MOM*). The sample period is from 1984 to 2020. *t*-statistics in parentheses are computed based on standard errors with Newey-West correction with three lags. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

Panel A: Nonstar firm portfolios						
	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Alpha	0.465**	-0.226*	0.031	-0.086	-0.005	0.239**
	(2.410)	(-1.770)	(0.290)	(-0.670)	(-0.040)	(2.020)
RMRF	-0.139***	1.104***	1.022***	1.043***	1.004***	0.965***
	(-2.860)	(29.780)	(28.820)	(26.270)	(26.820)	(34.620)
SMB	-0.011	0.311***	0.321***	0.171***	0.096	0.299***
	(-0.130)	(6.160)	(5.790)	(2.820)	(1.580)	(5.610)
HML	-0.047	0.066	0.035	0.071	0.011	0.019
	(-0.390)	(0.780)	(0.370)	(0.860)	(0.190)	(0.250)
CMA	-0.108	0.024	-0.081	0.016	-0.020	-0.084
	(-0.530)	(0.230)	(-0.750)	(0.130)	(-0.210)	(-0.670)
RMW	-0.224*	-0.043	0.048	0.017	0.024	-0.267***
	(-1.790)	(-0.630)	(0.730)	(0.200)	(0.370)	(-2.900)
Mom	0.095	-0.030	-0.057	0.018	-0.053	0.064
	(1.070)	(-0.560)	(-1.490)	(0.270)	(-1.180)	(1.440)
N	444	444	444	444	444	444
Adj R^2	0.035	0.825	0.821	0.797	0.815	0.796
Panel B: Star firm portfolios						
	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Alpha	0.286	-0.308**	0.024	0.009	-0.009	-0.021
	(1.310)	(-2.070)	(0.200)	(0.080)	(-0.060)	(-0.150)
RMRF	-0.123**	1.060***	1.042***	0.994***	1.015***	0.937***
	(-2.070)	(23.860)	(32.170)	(31.540)	(28.570)	(28.240)
SMB	0.022	-0.083	-0.303***	-0.194***	-0.126**	-0.061
	(0.210)	(-1.180)	(-5.550)	(-4.650)	(-2.360)	(-1.160)
HML	-0.050	0.081	0.136*	0.022	-0.227***	0.031
	(-0.340)	(0.770)	(1.870)	(0.390)	(-3.820)	(0.400)
CMA	-0.048	0.039	-0.083	0.055	0.157	-0.009
	(-0.210)	(0.310)	(-0.990)	(0.460)	(1.590)	(-0.060)
RMW	0.018	0.162**	0.041	0.121*	0.170**	0.180**
	(0.120)	(1.970)	(0.380)	(1.900)	(2.050)	(2.130)
Mom	0.101	-0.112*	0.018	-0.029	0.002	-0.012
	(0.980)	(-1.740)	(0.290)	(-0.740)	(0.030)	(-0.240)
N	444	444	444	444	444	444
Adj R^2	0.016	0.736	0.782	0.814	0.780	0.674

Appendix

Table A.1
Variable Definitions

This table describes our variables and data sources.

Variable Name	Source	Description
Announcement Return	CRSP	The earnings announcement event study market adjusted cumulative abnormal returns over a [0, 2] window.
B/M	CRSP and Compustat	The ratio of the book value to the market capitalization of the firm.
Capital Exp + R&D Share	Compustat	The firm sum of capital expenditures (Compustat CAPX) and research and development expense (Compustat XRD) divided by the total industry (based on BEA industry classifications).
COGS/Sales	Compustat	Cost of goods sold (Compustat COGS) divided by sales (Compustat SALE).
Citations of patents filed	Kogan et al. (2017)	This is the number of citations of patents filed during a calendar year. The data is from the Kogan et al. (2017) depository available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
Citations of patents issued	Kogan et al. (2017)	This is the number of citations of patents issued during a calendar year. The data is from the Kogan et al. (2017) depository available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
$\overline{\mathrm{EG}}_{\mathrm{star}}$	I/B/E/S and Compustat	The equal-weighted average EPS growth *(EG)* of star firms in the industry.
$\overline{\mathrm{EG}}_{\mathrm{nonstar}}$	I/B/E/S and Compustat	The equal-weighted average EPS growth *(EG)* of nonstar firms in the industry.
EGP	Compustat	This is calculated as earnings per share (*EPS*) in quarter t minus *EPS* in quarter *t – 4* scaled by share price.
$\overline{\mathrm{EGP}}$	Compustat	The equal-weighted average earnings growth *(EGP)* in the industry.

Variable Name	Source	Description
$\overline{\text{EGP}}_{\text{star}}$	I/B/E/S and Compustat	The equal-weighted average earnings growth *(EGP)* of star firms in the industry.
$\overline{\text{EGP}}_{\text{nonstar}}$	I/B/E/S and Compustat	The equal-weighted average earnings growth *(EGP)* of nonstar firms in the industry.
EGPRCT	I/B/E/S and Compustat	Percentage growth in earnings per share (*EPS*) of firm *j* in quarter *t* relative to the same quarter in the previous year. Only defined for firms with positive earnings per share.
EMPL Qtr Growth	Bureau of Labor Statistics	Industry-level end-of-quarter total employment for quarter *t* minus the value from quarter *t–1* divided by the value in quarter *t–1*.
EMPL YoY Growth	Bureau of Labor Statistics	Industry-level end-of-quarter total employment for quarter *t* minus the value from quarter *t–4* divided by the value in quarter *t–4*.
GDP Qtr Growth	Bureau of Economic Analysis	Industry-level real GDP for quarter *t* minus the value from quarter *t–1* divided by the value in quarter *t–1*.
GDP YoY Growth	Bureau of Economic Analysis	Industry-level real GDP for quarter *t* minus the value from quarter *t–4* divided by the value in quarter *t–4*.
Investment	Compustat	The change in total assets (Compustat AT) divided by the previous fiscal year's total assets (Fama and French, 2015).
$\overline{\text{JPG}}_{\text{star}}$	LinkUp	Percentage growth in star firms' job postings defined as $((\overline{JP}_{star\,j,t} - \overline{JP}_{star\,j,t-1})/\overline{JP}_{star\,j,t-1}$, where $\overline{JP}_{star\,j,t}$ is the average number of job postings by star firms in industry *j* in quarter *t*.
$\overline{\text{JPG}}_{\text{nonstar}}$	LinkUp	Percentage growth in nonstar firms' job postings defined as $((\overline{JP}_{nonstar\,j,t} - \overline{JP}_{nonstar\,j,t-1})/\overline{JP}_{nonstar\,j,t-1}$, where $\overline{JP}_{nonstar\,j,t}$ is the average number of job postings by nonstar firms in industry *j* in quarter *t*.
Lerner Index	Compustat	Following Grullon et al. (2019), this is defined as operating income before depreciation (Compustat OIBDP) minus depreciation (Compustat DP) scaled by total sales (Compustat SALE).

Variable Name	Source	Description
Momentum	CRSP	The prior year's monthly compounded buy-and-hold return skipping the last month.
Number of patents filed	Kogan et al. (2017)	This is the number of patents filed during a calendar year. The data is from the Kogan et al. (2017) depository available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
Number of patents issued	Kogan et al. (2017)	This is the number of patents issued during a calendar year. The data is from the Kogan et al. (2017) depository available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
Profitability	Compustat	Income before extraordinary items (Compustat IB) divided by total assets (Compustat AT).
Reversal	CRSP	Buy-and-hold return over the previous month.
ROA	Compustat	Income before extraordinary items (Compustat IB) divided by total assets (Compustat AT).
ROE	Compustat	Income before extraordinary items (Compustat IB) divided by book equity.
SG&A/Sales	Compustat	Selling, general, and administrative expenses (Compustat XSGA) divided by sales (Compustat SALE).
Size	CRSP	Price times shares outstanding (in billion USD).
ΔEGPRCT Difference	I/B/E/S and Compustat	$\Delta EGPRCT\ Difference_{j,t}$ is calculated as follows: $\Delta EGPRCT\ Difference_{j,t} = \left(\overline{EGPRCT}_{star\ j,t} - \overline{EGPRCT}_{nonstar\ j,t}\right) - \left(\overline{EGPRCT}_{star\ j,t-1} - \overline{EGPRCT}_{nonstar\ j,t-1}\right)$, where $\overline{EGPRCT}_{star\ j,t}$ and $\overline{EGPRCT}_{nonstar\ j,t}$ are *EGPRCT*s of quarter *t* averaged across all star and nonstar firms in each industry, respectively.
ΔEGP Difference	I/B/E/S and Compustat	*ΔEGP Difference* $_{j,\,t}$ is calculated as follows: $\Delta EGP\ Difference_{j,t} = \left(\overline{EGP}_{star\ j,t} - \overline{EGP}_{nonstar\ j,t}\right) - \left(\overline{EGP}_{star\ j,t-1} - \overline{EGP}_{nonstar\ j,t-1}\right)$, where $\overline{UE}_{star\ j,t}$ and $\overline{UE}_{nonstar\ j,t}$ are *EGP*s of quarter *t* averaged across all star and nonstar firms in each industry, respectively.

Variable Name	Source	Description
ΔEGP Difference Monthly	I/B/E/S and Compustat	*ΔEGP Difference Monthly $_{j,t}$ is calculated as follows:* $\Delta EGP\ Difference\ Monthly_{j,t} = \left(\overline{EGP}_{m_{star\ j,t}} - \overline{EGP}_{m_{nonstar\ j,t}}\right) - \left(\overline{EGP}_{m_{star\ j,t-3}} - \overline{EGP}_{m_{nonstar\ j,t-3}}\right),$ where $\overline{EGP}_{m_{star\ j,t}}$ ($\overline{EGP}_{m_{nonstar\ j,t}}$) is star firms' (nonstar firms') average *EGP* at the industry level announced during months *t*, *t-1*, *or t-2*. *EGP* is defined in the same way as in *ΔEGP Difference.*

Table A.2
Industry Distribution of Star and Nonstar Firms

The table presents BEA industry distributions of star and nonstar firms.

#	Industry name	Average number of star firms	Average % market cap of star firms	Average number of nonstar firms	Average % market cap of nonstar firms
1	Accommodation	4	0.669	23	0.331
2	Food services and drinking places	4	0.709	61	0.291
3	Administrative and support services	4	0.51	64	0.49
4	Farms	4	0.856	9	0.144
5	Forestry, fishing, and related activities	0	0	0	0
6	Performing arts, spectator sports, museums, and related activities	3	0.789	6	0.211
7	Amusements, gambling, and recreation industries	3	0.657	16	0.343
8	Federal Reserve banks, credit intermediation, and related activities	4	0.327	517	0.673
9	Computer systems design and related services	4	0.505	81	0.495
10	Construction	4	0.402	54	0.598
11	Computer and electronic products	4	0.362	461	0.647
12	Electrical equipment, appliances, and components	4	0.496	56	0.517
13	Fabricated metal products	4	0.524	63	0.49
14	Furniture and related products	4	0.572	21	0.428
15	Machinery	4	0.303	233	0.705
16	Miscellaneous manufacturing	4	0.658	35	0.342
17	Nonmetallic mineral products	4	0.601	18	0.399
18	Primary metals	4	0.472	41	0.528
19	Motor vehicles, bodies and trailers, and parts	4	0.484	95	0.516
20	Wood products	3	0.715	16	0.285
21	Educational services	4	0.74	13	0.26
22	Funds, trusts, and other financial vehicles	0	0	0	0
23	Ambulatory health care services	4	0.542	54	0.458
24	Hospitals and nursing and residential care facilities	4	0.661	23	0.339
25	Social assistance	3	0.453	5	0.547
26	Data processing, internet publishing, and other information services	4	0.733	89	0.267
27	Motion picture and sound recording industries	4	0.908	20	0.092
28	Publishing industries, except internet (includes software)	4	0.589	153	0.411
29	Broadcasting and telecommunications	4	0.478	113	0.522
30	Insurance carriers and related activities	4	0.346	131	0.654
31	Legal services	0	0	0	0
32	Mining, except oil and gas	4	0.632	25	0.368
33	Oil and gas extraction	4	0.397	95	0.603
34	Support activities for mining	3	0.598	25	0.402
35	Miscellaneous professional, scientific, and technical services	4	0.406	85	0.594
36	Apparel and leather and allied products	4	0.582	52	0.418

#	Industry name	Average number of star firms	Average % market cap of star firms	Average number of nonstar firms	Average % market cap of nonstar firms
37	Chemical products	4	0.359	317	0.65
38	Food and beverage and tobacco products	4	0.535	86	0.479
39	Paper products	4	0.689	31	0.311
40	Petroleum and coal products	4	0.864	17	0.136
41	Plastics and rubber products	4	0.575	37	0.425
42	Printing and related support activities	4	0.655	20	0.345
43	Textile mills and textile product mills	4	0.651	23	0.349
44	Other	4	0.979	35	0.021
45	Other services, except government	4	0.78	15	0.22
46	Real estate	2	0.368	41	0.772
47	Rental and leasing services and lessors of intangible assets	3	0.529	42	0.471
48	Retail trade	4	0.427	203	0.573
49	Securities, commodity contracts, and investments	4	0.458	72	0.542
50	Warehousing and storage	0	0	0	0
51	Air transportation	4	0.7	19	0.3
52	Transit and ground passenger transportation	0	0	0	0
53	Other transportation and support activities	4	0.875	11	0.125
54	Pipeline transportation	4	0.816	7	0.184
55	Rail transportation	4	0.812	9	0.188
56	Truck transportation	4	0.576	21	0.424
57	Water transportation	2	0.6	6	0.4
58	Utilities	4	0.206	129	0.794
59	Waste management and remediation services	4	0.902	19	0.098
60	Wholesale trade	4	0.343	140	0.657

Table A.3
Predicting Earnings Growth using Alternative Measures

This table reports the results of model specifications (1) to (3) of Table 3 with alternative forms of the main explanatory variable. In Panel A, the main explanatory variable is *EGP Difference* $_{j,\ t-1}$ calculated as the lagged difference ($\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-1}}$). $\overline{EGP}_{star_{j,\ t}}$ and $\overline{EGP}_{nonstar_{j,\ t}}$ refer to the equal-weighted average earnings growth *(EGP)* of star firms and nonstar firms in industry *j* in quarter *t*, respectively. The main explanatory in Panel B is *ΔEGPRCT Difference*$_{j,t-1}$ defined as ($\overline{EGPRCT}_{star_{j,\ t}} - \overline{EGPRCT}_{nonstar_{j,\ t}}$) − ($\overline{EGPRCT}_{star_{j,\ t-1}} - \overline{EGPRCT}_{nonstar_{j,\ t-1}}$). *EGPRCT* $_{j,\ t-1}$ is the percentage growth in earnings per share (*EPS*) of firm *j* in quarter *t* relative to the same quarter in the previous year. It is defined only for firms with positive *EPS* The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are dual-clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients and ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

Panel A: Earnings performance measured using difference in earnings growth			
	(1)	(2)	(3)
EGPRCT Difference$_{j,\ t-1}$	0.150***	0.157***	0.162***
	(3.066)	(3.247)	(3.429)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-1}}$	0.654***	0.665***	0.665***
	(15.107)	(-14.448)	(-14.695)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-2}}$		-0.020	0.009
		(-0.664)	(-0.341)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-3}}$			-0.061
			(-1.340)
Year-Quarter FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	4,526	4,496	4,464
R^2	0.409	0.409	0.41

Panel B: Earnings performance measured using earnings growth			
	(1)	(2)	(3)
ΔEGPRCT Difference$_{j,\ t-1}$	0.001*	0.001*	0.001*
	(1.694)	(1.926)	(1.933)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-1}}$	0.591***	0.620***	0.618***
	(14.233)	(12.682)	(13.099)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-2}}$		-0.050	-0.010
		(-1.652)	(-0.349)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-3}}$			-0.069
			(-1.672)
Year-Quarter FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	4,317	4,317	4,292
R^2	0.430	0.431	0.435

Table A.4
Star Firms' Predictive Ability Outside Small Firms

This table reports results from regressions analyzing star firms' ability to predict nonstar firms' earnings growth and earnings surprises in two subsamples that do not include small firms. We classify the top 30% of firms based on market capitalization as large firms, the middle 40% as medium-sized firms, and the bottom 30% as small firms. One subsample excludes small nonstar firms and the other subsample only consists of medium-sized firms. Panel A reports the results of model specifications (1) to (3) of Table 3 that predict nonstar firms' earnings growth and Panel B reports the results of model specifications (1) to (2) of Table 6 that predict consensus earnings surprises. Details of the specifications and control variables are reported in Tables 3 and 4.

Panel A: Regressions Explaining Nonstar Firms' Average Earnings Growth

Sample:	Excluding Small Nonstar Firms			Only Mid-Sized Nonstar Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEGP Difference$_{j,\,t-1}$	0.115***	0.182***	0.178***	0.124***	0.179***	0.174***
	(3.09)	(4.24)	(4.18)	(3.65)	(3.76)	(3.72)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-1}}$	0.582***	0.673***	0.670***	0.565***	0.634***	0.634***
	(14.83)	(12.97)	(13.07)	(14.67)	(11.99)	(12.12)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-2}}$		-0.124**	-0.077		-0.094*	-0.062
		(-2.39)	(-1.39)		(-1.86)	(-1.20)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-3}}$			-0.086***			-0.065**
			(-3.05)			(-2.26)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,385	4,385	4,333	4,345	4,345	4,281
R^2	0.388	0.393	0.402	0.369	0.372	0.379

Panel B: Regressions Explaining Nonstar Firms' Average Consensus Earnings Surprises

Sample:	Excluding Small Nonstar Firms		Only Mid-Sized Nonstar Firms	
	(1)	(2)	(3)	(4)
ΔEGP Difference$_{j,\,t-1}$	0.015**	0.015**	0.015**	0.015**
	(2.24)	(2.31)	(2.15)	(2.19)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-1}}$	0.033***	0.016**	0.036***	0.021***
	(3.59)	(2.19)	(3.89)	(2.83)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-2}}$	-0.015*	-0.010	-0.012	-0.008
	(-1.74)	(-1.08)	(-1.23)	(-0.82)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-3}}$	0.012*	0.011*	0.009*	0.008
	(2.00)	(1.87)	(1.78)	(1.65)
$\overline{\text{ES}}_{\text{nonstar}_{j,t-1}}$		0.184***		0.150***
		(4.45)		(3.74)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	4,350	4,350	4,308	4,308
R-squared	0.132	0.159	0.125	0.143

Table A.5
Predicting Earnings Growth and Earnings Surprises of Nonstar Firms Using Star Firm Subcategories

This table reports results from regressions explaining nonstar firms' average quarterly earnings growth ($\overline{EGP}_{nonstar_{j,\ t}}$) and earnings surprises ($\overline{ES}_{nonstar_{j,\ t}}$) at the industry level. Earnings surprise *ES* is the difference between actual earnings per share and analysts' consensus forecast, scaled by share price ten days before the earnings announcement. Superstars are star firms whose ratio of firm market capitalization to total industry market capitalization is above the cross-sectional median of this ratio across star firms of all industries. The below-median star firms are identified as regular stars. *ES* is the difference between actual earnings per share and analysts' consensus forecast, scaled by share price ten days before the earnings announcement. The main explanatory variable $\Delta EGP\ Difference_{j,t-1}$ is defined as in Section 2.3 We form $\Delta EGP\ Difference_{j,t-1}$ separately based on super stars and regular stars in the respective regressions. The control variables include lagged values of $\overline{EGP}_{nonstar_{j,\ t}}$ and $\overline{ES}_{nonstar_{j,\ t}}$. Detailed variable definitions are presented in Appendix Table A.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are clustered at the industry level. *t*-statistics are dual-clustered by year-quarter and industry. . ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Earnings Growth (EGP)		**Earnings Surprise (ES)**	
	Super star	Regular star	Super star	Regular star
	(1)	(2)	(3)	(4)
ΔEGP Difference$_{j,\ t-1}$	0.223***	0.177***	0.028**	0.010*
	(4.44)	(3.63)	(2.33)	(1.71)
$\overline{EGP}_{nonstar_{j,t-1}}$	0.694***	0.711***	0.032***	0.008
	(12.48)	(11.38)	(2.76)	(1.18)
$\overline{EGP}_{nonstar_{j,t-2}}$	-0.167***	-0.097	-0.032**	-0.002
	(-3.30)	(-1.56)	(-2.69)	(-0.33)
$\overline{EGP}_{nonstar_{j,t-3}}$	-0.011	-0.115***	0.010	0.018***
	(-0.19)	(-3.05)	(1.41)	(3.16)
$\overline{ES}_{nonstar_{j,t-1}}$			0.080	0.297***
			(1.45)	(5.07)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1,774	2,671	1,779	2,675
R^2	0.395	0.507	0.191	0.295

Table A.6
Earnings Surprise Regression Estimates: Mixed Signals

This table reports regression results explaining nonstar firms' earnings surprise at the industry level ($\overline{ES}_{nonstar\,j,t}$) when signals are mixed. Earnings announcement returns are market-adjusted cumulative abnormal returns within the [0, 2] window around announcement date. The Opposite Sign Announcement Return indicator is a dummy variable that takes a value one when star firms' lagged average announcement has opposite sign compared to *ΔEGP Difference*$_{j,t-1}$ and is also lower (higher) than nonstars' announcement returns when the *ΔEGP Difference*$_{j,t-1}$ sign is positive (negative). *ΔEGP Difference*$_{j,t-1}$ is defined as in Section 2.3. The control variables include lagged values of $\overline{EGP}_{nonstar_{j,\,t}}$ and $\overline{ES}_{nonstar_{j,\,t}}$. Detailed variable definitions are presented in Appendix Table A.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are clustered by year-quarter, industry, and opposite sign announcement return indicator. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
ΔEGP Difference$_{j,\,t-1}$ × Opposite Sign Announcement Return$_{j,\,t-1}$	0.019**	0.017**		
	(2.264)	(2.261)		
ΔEGP Difference$_{j,\,t-1}$	0.009**	0.010**	0.015**	0.015**
	(2.565)	(2.534)	(2.992)	(2.486)
Opposite Sign Announcement Return$_{j,\,t-1}$	0.000	0.000	0.000	0.000
	(0.697)	(0.581)	(0.727)	(0.608)
$\overline{EGP}_{nonstar_{j,t-1}}$	0.035***	0.021*	0.034***	0.021*
	(2.967)	(1.867)	(2.653)	(1.614)
$\overline{EGP}_{nonstar_{j,t-2}}$	-0.025***	-0.020***	-0.022***	-0.018***
	(-6.040)	(-5.922)	(-7.574)	(-7.281)
$\overline{EGP}_{nonstar_{j,t-3}}$	0.017***	0.017***	0.016***	0.016***
	(2.845)	(3.061)	(2.879)	(3.010)
$\overline{ES}_{nonstar_{j,t-1}}$		0.159***		0.160***
		(5.256)		(5.088)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	4,438	4,438	4,438	4,438
R^2	0.162	0.182	0.164	0.183

Table A.7
Raw Returns of Earnings Performance-Based Portfolios

This table reports the raw value-weighted monthly returns for nonstar firm quintile portfolios based on lagged values of *ΔEGP Difference Monthly.* Every month *t*, we sort equal-weighted industry portfolios of nonstar firms based on *ΔEGP Difference* $Monthly_{j,t-1}$ calculated as *ΔEGP Difference* $Monthly_{t-1}$ = $(\overline{EGP}_{m_{star_{j,\,t-1}}} - \overline{EGP}_{m_{nonstar_{j,\,t-1}}}) - (\overline{EGP}_{m_{star_{j,\,t-4}}} - \overline{EGP}_{m_{nonstar_{j,\,t-4}}})$, and form quintiles. We then compute the value-weighted quintile returns using the sum of market capitalizations of all nonstar firms in each industry as the industry weight. $\overline{EGP}_{m_{star_{j,\,t}}}$ $(\overline{EGP}_{m_{nonstar_{j,\,t}}})$ is star firms' (nonstar firms') average *EGP* at the industry level announced during months *t*, *t-1*, *or t-2*. The quintile portfolios are updated monthly. We include industry-months with at least five nonstar firms. The sample period is from 1994 to 2020. *t*-statistics in parentheses are computed based on standard errors with Newey-West correction with three lags. ***, **, and * report significance at the 1%, 5%, and 10%, respectively.

	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Value-weighted average returns	0.594**	0.698*	1.195***	1.031***	0.806**	1.292***
	(2.030)	(1.810)	(3.460)	(3.060)	(2.100)	(3.200)
N	324	324	324	324	324	324

Table A.8
Substitute Star Firms' Ability to Predict Nonstar Firms' Earnings Growth, Earnings Surprises, and Earnings Announcement Returns

This table reports results on analyses where we replace industry star firms with substitute star firms consisting of the four next largest firms in each industry. Panel A reports the results of model specifications (1) to (3) of Table 3 that predict nonstar firms' earnings growth and Panel B reports the results of model specifications (1) to (2) of Table 6 that predict consensus earnings surprises. Panel C reports the results of model specifications (1) to (3) of Table 8 that predict nonstar firms' earnings announcement returns. Panels D and E report the results of Panels A and B of Table 5 predicting industry-level real GDP growth and employment growth, respectively. Details of the specifications and control variables are reported in Tables 3, 4, 7, and 8. We include all industry-quarter observations where we have at least five nonstar firms.

Panel A: Regressions Explaining Nonstar Firms' Average Earnings Growth

	(1)	(2)	(3)
ΔEGP Difference$_{j,\,t-1}$	0.039	0.090***	0.112***
	(1.36)	(2.93)	(3.59)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-1}}$	0.544***	0.612***	0.644***
	(11.27)	(12.49)	(16.44)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-2}}$		-0.095**	-0.102***
		(-2.56)	(-3.69)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-3}}$			0.011
			(0.27)
Year-Quarter FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	3,837	3,837	3,739
R^2	0.378	0.381	0.409

Panel B: Regressions Explaining Nonstar Firms' Average Consensus Earnings Surprise

	(1)	(2)
ΔEGP Difference$_{j,\,t-1}$	0.011	0.010
	(1.65)	(1.41)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-1}}$	0.043***	0.033***
	(5.87)	(3.20)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-2}}$	-0.023***	-0.020**
	(-2.70)	(-2.45)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-3}}$	0.002	0.003
	(0.37)	(0.52)
$\overline{\mathrm{ES}}_{\mathrm{nonstar}_{j,t-1}}$		0.104
		(1.22)
Year-Quarter FE	Yes	Yes
Industry FE	Yes	Yes
N	3,801	3,801
R-squared	0.144	0.151

Panel C: Regressions Explaining Nonstar Firms' Average Earnings Announcement Returns			
	(1)	(2)	(3)
ΔEGP Difference$_{j,\ t-1}$	0.008	0.007	0.007
	(0.24)	(0.20)	(0.20)
Nonstars' Avg Announcement Return$_{j,\ t\text{-}1}$		-0.014	-0.012
		(-0.56)	(-0.44)
Stars' Avg Announcement Return$_{j,\ t\text{-}1}$			-0.004
			(-0.24)
Year-Quarter FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	3,922	3,922	3,922
R-squared	0.090	0.090	0.090

Table A.9
Substitute Star Firms' Performance in Star Earnings Performance-Based Portfolios

This table provides results from a portfolio analysis that is identical to Table 10 except that we replace industry star firms with substitute star firms consisting of the next four largest firms in each industry. We then form *ΔEGP Difference Monthly* using the substitute stars as star firms. The table reports factor model estimates for nonstar firm quintile portfolios and a long-short portfolio (Q5-Q1) formed based on lagged values of *ΔEGP Difference Monthly.* Details of the analysis are reported in Table 10.

	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Alpha	-0.133	0.092	-0.147	-0.109	0.387**	-0.041
	(-0.400)	(0.330)	(-0.880)	(-0.680)	(2.290)	(-0.170)
RMRF	0.148	1.093***	1.089***	1.139***	0.985***	1.241***
	(1.270)	(12.920)	(19.860)	(21.430)	(16.690)	(15.020)
SMB	-0.498**	0.938***	0.486***	0.376***	0.279***	0.439***
	(-2.390)	(7.160)	(6.380)	(4.960)	(3.460)	(3.220)
HML	-0.045	0.273*	0.227**	0.125	0.050	0.228
	(-0.250)	(1.850)	(2.580)	(1.290)	(0.580)	(1.350)
CMA	-0.088	-0.243	0.092	0.064	-0.049	-0.331*
	(-0.300)	(-1.080)	(0.560)	(0.490)	(-0.330)	(-1.660)
RMW	0.341	-0.061	0.016	-0.027	-0.157	0.281**
	(1.300)	(-0.280)	(0.130)	(-0.260)	(-1.110)	(2.200)
Mom	-0.089	-0.314***	-0.149***	-0.104	-0.340***	-0.403***
	(-0.620)	(-2.950)	(-2.600)	(-1.500)	(-6.810)	(-6.090)
N	324	324	324	324	324	324
Adj R^2	0.089	0.731	0.808	0.823	0.783	0.728