Star Firms, Information Spillovers, and Predictable Industry-Level Outcomes

Vidhi Chhaochharia, Alok Kumar, Mehrshad Motahari, and Ville Rantala*

Abstract

We study the aggregate impact of information spillovers emerging from industry star firms. Changes in stars' relative earnings growth predict future earnings growth, consensus earnings surprises, and job postings of same-industry nonstar firms. Star-firm performance also predicts industry-level GDP and employment growth. Price markup and innovation spillovers are potential channels underlying these patterns. Our results further show that this performance predictability is not fully incorporated into nonstars' stock prices. A long–short portfolio based on star firms' earnings growth earns an annualized six-factor alpha of 8.64%. Together, our findings provide consistent evidence of the 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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* Chhaochharia, vidhi@miami.edu, University of Miami Herbert Business School; Kumar, akumar@miami.edu, University of Miami Herbert Business School; Mehrshad Motahari, Mehrshad.Motahari@city.ac.uk, City St George's University of London Bayes Business School; and Ville Rantala, vrantala@bus.miami.edu, University of Miami Herbert Business School. We thank an anonymous referee, Scott Guernsey, Bart Lambrecht, Juan Sotes-Paladino, Stephan Siegel (the editor), Rosy Xu, seminar participants at University of Cambridge, and conference participants at the Australasian Banking and Finance Conference, Cambridge Endowment for Research in Finance Alumni Society (CERFAS) Annual Cavalcade, New Zealand Finance Meeting, Research in Behavioral Finance Conference, and Santiago Finance Workshop for useful comments and helpful suggestions. An earlier version of the paper was circulated under the title "Star Firms, Information Externalities, and Predictability." We are responsible for all remaining errors and omissions.

I. Introduction

Very large and dominant "superstar" firms have a significant and sometimes disproportionate impact on various macroeconomic outcomes. In particular, 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, Dorn, Katz, Patterson, and Van Reenen (2017), Grullon, Larkin, and Michaely (2019), De Loecker, Eeckhout, and Unger (2020)).[1] The recent growth in artificial intelligence technologies has further emphasized superstar firms' importance (Babina, Fedyk, He, and Hodson (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, Hitt, Rock, and Brynjolfsson (2020)), easier access to human capital (Choi, Lou, and Mukherjee (2025)), and weakening anti-trust enforcement (Döttling, Gutiérrez, and Philippon (2017)). As large firms attain star status, they can use their market power to create barriers to entry. Because star firms influence the broader economy and industries around them, changes in their operational and earnings performance can predict changes in the future earnings and performance of other related firms. Further, if market

[1] Autor et al. (2017), Autor, Dorn, Katz, Patterson, and Van Reenen (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.

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 spillovers of star firms within industries. Our analysis adopts the industry star firm definition developed by Gutiérrez and Philippon (2019), who classify industry stars as the four largest firms by market capitalization within each of the 60 Bureau of Economic Analysis (BEA) industries. We find that performance shifts of these star firms predict future earnings growth and stock returns of connected nonstar firms, as well as future GDP and employment growth at the industry level. We also investigate the intra-industry mechanisms underlying these spillover effects and assess whether sell-side analysts fully incorporate the information from star firms into their earnings forecasts.

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

The industry-level star firm definition of Gutiérrez and Philippon (2019) offers several advantages for our study. First, their classification avoids concentration in any single industry, ensuring that our results are not driven by industry-specific factors. Second, sell-side security analysts typically specialize in specific industries, meaning the same analysts often issue

[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.

forecasts for both star and nonstar firms within an industry. Third, the number of star firms and industries remains constant over time, which aids in interpreting the empirical results.

Predictability of nonstar earnings. We start our empirical analysis by documenting that changes in star firms' relative earnings performance predict the earnings growth of same-industry nonstar firms. To measure the relative 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, $\Delta EGP\ Difference_{t-1}$ 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). They 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

[3] He and Narayanamoorthy (2020) argue 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.

identical to ours, and another interpretation for the *ΔEGP Difference* variable is that it captures the difference in earnings growth acceleration between star and nonstar firms.[4]

We estimate quarterly industry-level panel regressions of average earnings growth for star and nonstar firms on *ΔEGP* $Difference_{t-1}$, controlling for lagged dependent variables and including year-quarter and industry fixed effects. For nonstar firms, one-quarter lagged *ΔEGP Difference* significantly predicts earnings growth, with coefficients between 0.10 and 0.19 and *t*-values from 3.9 to 5.1. These estimates imply that a one standard deviation increase in *ΔEGP* $Difference_{t-1}$ corresponds to a 0.1–0.2 standard deviation increase in nonstar firms' earnings growth. By contrast, the coefficients in regressions for star firms are negative and insignificant. This contrast suggests that changes in star firms' relative earnings performance predict future earnings growth of nonstar firms but not of star firms themselves.

Evidence on economic channels. We also examine the economic channels that may drive the earnings growth spillover effect. One mechanism supported by empirical evidence is a price markup spillover, where star firms' markup changes influence nonstars' markups and profit margins. This can occur if star firms act as price setters due to their market power, while nonstars follow as price takers. Consistent with this channel, an earnings growth decomposition analysis shows that the earnings growth component driven by profit margin changes is most sensitive to shifts in *ΔEGP Difference*. Using a detailed price markup measure developed by De Loecker, Eeckhout, and Unger (2020), we also find that star firms' markup changes predict nonstars' markup changes at the annual level.

[4] Earnings acceleration-based trading has been viewed as a viable trading strategy in the popular press (He and Narayanamoorthy 2020).

Other channels are also supported by the data. Cross-industry analyses show that earnings predictability is stronger in industries with high technology spillovers and greater vertical integration, suggesting that stars' roles as innovation leaders and supply chain anchors can contribute to the effect. Notably, while our results indicate that *ΔEGP Difference* predicts changes in profit margin-driven earnings growth, we find that this effect is limited to improvements in operating income relative to cost of goods sold. These findings suggest that technology spillovers are more likely associated with product innovation than with broader operational efficiency gains, which would be reflected in other components of the profit margin.

Predictability of industry GDP and employment. Beyond earnings growth, we find that star firms' performance shifts, captured by *ΔEGP Difference,* also predict broader industry-level economic outcomes. First, we test whether *ΔEGP Difference* can forecast changes in nonstar firms' quarterly job postings, which are a timely indicator of firms' growth and growth prospects. Industry-level panel regressions show that a one standard deviation increase in lagged *ΔEGP Difference* predicts a 34% increase in nonstar firms' job postings and the coefficient is statistically significant. We also find that *ΔEGP Difference* predicts industry-level real GDP and employment growth. Specifically, a one standard deviation increase in lagged *ΔEGP Difference* is associated with a 0.5–0.6 percentage point rise in industry GDP growth and a 0.1–0.2 percentage point rise in employment growth, both statistically significant at the 10% level or higher. Importantly, these figures capture the broader industry impact, including non-listed firms.

As further evidence of star firms' information spillovers related to economic growth, we find that the percentage change in star firms' price-to-earnings (P/E) ratio can statistically significantly predict industry GDP growth changes at the annual level. P/E ratios reflect market expectations about long-term growth opportunities, and our results are consistent with findings by Bekaert, Harvey, Lundblad, and Siegel (2007), who show that a country's growth opportunities, measured by its industry mix valued at global P/E ratios, can predict country-specific GDP growth.

Predictability of earnings surprises. In the next set of tests, we examine whether security analysts use the information reflected 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 spillovers from 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 similar 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.

Return predictability. In the last set of tests, we demonstrate that our core findings have 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.

We find that star firms' relative earnings performance contains information that is not fully incorporated into market prices and can therefore predict future stock returns. The long-short portfolio earns an average monthly six-factor alpha of 0.73%, which is statistically significant with a *t*-statistic of 2.35. In line with these results, we also find that there is a 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 0.47% with a *t*-statistic of 2.41.

Finally, we analyze whether the information spillovers of star firms are unique or simply reflect general large-firm effects. We replicate our main analyses using the four next-largest firms in each industry as "substitute" stars. While *ΔEGP Difference* based on these substitutes still predicts nonstars' earnings growth, the effect is only approximately half as large as that of actual stars. Moreover, the substitutes do not significantly predict outcomes related to analyst forecasts or stock returns. All coefficients for nonstar earnings surprises, earnings announcement returns, and abnormal returns are statistically insignificant. These placebo tests confirm that the spillover effects we observe are specific to star firms and not just a feature of large firms in general.

Connections to the literature. Together, these results contribute to several strands of accounting, economics, and finance literature. We provide novel market- and operating-performance-based evidence that shifts in star firms' earnings performance can predict future outcomes of related firms. The industry-level GDP and employment results show that these spillovers extend beyond firm performance to broader economic outcomes, linking to prior work that uses accounting data to forecast macroeconomic indicators such as GDP and employment.[5] We show that a leading indicator based on a small group of star firms can predict industry growth and activity. Our analysis using stars' P/E ratios to predict industry GDP growth also connects to Bekaert et al. (2007), who use countries' industry mix and global P/E ratios to predict their future growth.

[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, Hann, and Li (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.

The results with the *ΔEGP Difference* variable extend the earnings acceleration results of He and Narayanamoorthy (2020) by demonstrating that the relative earnings acceleration of star firms 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 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.

II. Data Sources and Variables

II.A 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. We adjust the CRSP returns for delisting following the procedure of Shumway (1997). In analyses that involve earnings

[6] Lead–lag patterns where one group of stocks leads the returns of another group of stocks have been documented e.g. in Moskowitz and Grinblatt (1999), Cohen and Frazzini (2008), Menzly and Ozbas (2010), Cohen and Lou (2012), Parsons, Sabbatucci, and Titman (2020), Ali and Hirshleifer (2020), and Huang, Lee, Song, and Xiang (2022).

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

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, a vendor that collects postings directly from company websites, covering nearly 160 million advertised positions. Campello, Kankanhalli, and Muthukrishnan (2024) show that LinkUp data are representative of corporate hiring in the U.S.[8] The data include the title, job description, company information, geographic location, creation date, and O*NET job classification code for the postings. 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.

[8] 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).

We utilize quarterly and annual industry-level real GDP data from the Bureau of Economic Analysis (BEA). The quarterly dataset spans from 2005 to 2020, while the annual sample covers our full sample period from 1984 to 2020.[9] Additionally, we source industry-level employment data from the Bureau of Labor Statistics (BLS), covering the period from 1993 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.

Lastly, we use several databases provided by other researchers. We use patent counts and citations from the Kogan, Papanikolaou, Seru, and Stoffman (2017) depository[10] and price markup data from De Loecker et al. (2020). Firm-level *Technology Spillover* scores are sourced from the Bloom, Schankerman, and Van Reenen (2013) depository,[11] while pairwise *Vertical Integration* scores come from the Vertical TNIC (VTNIC) database developed by Frésard, Hoberg, and Phillips (2020).[12] Finally, monthly factor return data are obtained from the Fama and French data library.[13] Table 1 reports descriptive statistics for key variables used in the analyses.

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[9] For detailed information, see https://apps.bea.gov/iTable/?isuri=1&reqid=151&step=1. Although annual industry-level GDP data are available from 1982, allowing us to cover our full sample period starting in 1984, quarterly data are only available from 2005.

[10] Available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

[11] Available at https://people.stanford.edu/nbloom/research.

[12] Available at https://faculty.marshall.usc.edu/Gerard-Hoberg/FresardHobergPhillipsDataSite/index.html.

[13] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[Insert Table 1 here]

II.B Defining Star Firms

To identify dominant star firms at the industry level, we use the industry star definition of Gutiérrez and Philippon (2019). They define star firms as top four firms by the market value of equity within each BEA industry.[14] BEA follows the NAICS classification for grouping firms into industries. We use NAICS codes from Compustat to match firms with their corresponding BEA industry classification.

Following Gutiérrez and Philippon (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 item SALE) ranks within each industry.[15]

Appendix Table IA.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 industries are presented in Appendix Table IA.2 with zero observations. The average number of

[14] Top four firms approximately correspond to the largest 5th percentile of firms based on the average number of firms across all industries.

[15] If an industry–year has fewer than four star firms based on CRSP market-capitalization rankings, we instead rank firms within that industry–year by net sales (Compustat item SALE) and use this ranking to classify firms as stars or nonstars. Our results are similar when we do not fill in missing CRSP market capitalization values using other sources.

nonstar firms ranges from 5 to 543 in industries with stars. Star status is persistent, and 83% of star firms were also star firms in the previous year.

II.C 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.

[Insert Table 2 here]

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 4% (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 share of total capital and R&D expenditure in the industry 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.

II.D 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 quarterly changes in the earnings growth difference between star and nonstar firms. It is defined as follows:

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

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,

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

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.

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 ($EGP_{i,t}$) predicts 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 $\Delta EGP\ Difference\ Monthly_{j,t\text{-}1}$ can also be interpreted as the difference between star firms' and nonstar firms' earnings growth acceleration over the previous quarter according to their measure. Formally, $\Delta EGP\ Difference_{j,t}$ can also be expressed as $\left(\overline{EGP}_{star_{j,\,t}} - \overline{EGP}_{star_{j,\,t\text{-}1}}\right) -$

$\left(\overline{EGP}_{nonstar_{j,\,t}} - \overline{EGP}_{nonstar_{j,\,t\text{-}1}}\right)$ which is simply star firms' earnings growth acceleration minus that of nonstar firms under the He and Narayanamoorthy (2020) definition.[16]

For stock return predictability tests, we create a monthly measure of relative earnings performance called $\Delta EGP\ Difference\ Monthly_{j,t\text{-}1}$.[17] This is similar to the quarterly $\Delta EGP\ Difference_{j,t}$ measure, except that it is updated monthly based on earnings announcements within the past three months. 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 $(EPS_{i,t} - Consensus\ Forecast_{i,t})/Price_{i,t}$, where $EPS_{i,t}$, $\text{Consensus Forecast}_{i,t}$, and $\text{Price}_{i,t}$ 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

[16] Here is a simple example illustrating the properties of *ΔEGP Difference.* For ease of exposition, we ignore the stock-price scaling variable. Suppose star firms' year-over-year earnings growth is $5 per share in quarter 1 and $8 per share in quarter 2, while nonstar firms' earnings growth in those quarters is $5 and $6, respectively. Then *ΔEGP Difference* in quarter 2 is (8−5)−(6−5)=2, a positive value indicating that star firms exhibit faster earnings growth acceleration than nonstar firms. If nonstar firms instead had earnings growth of $10 in quarter 2, their earnings acceleration would exceed that of star firms, and *ΔEGP Difference* would be (8−5)−(10−5)=−2.

[17] 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. In the monthly version, the timing of earnings announcements is based on I/B/E/S ANNDATS or Compustat RDQ, whichever is earlier if they disagree.

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. A variance composition analysis indicates that over 99% of the variation in $\Delta EGP\ Difference_{j,t}$ is attributable to differences across industries rather than within industries.[18]

III. Star Firms and Industry Spillover Effects

We begin 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 job postings, and industry-level employment and GDP growth.

III.A Predicting Earnings Growth: Baseline Results

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.

[18] We conduct the variance decomposition by regressing $\Delta EGP\ Difference_{j,t}$ on industry fixed effects and comparing the proportion of $\Delta EGP\ Difference_{j,t}$ explained by the fixed effects versus the residuals. We also find no evidence of seasonality in $\Delta EGP\ Difference_{j,t}$, as the year-over-year autocorrelation coefficient is -0.11.

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 *ΔEGP Difference*$_{j,t-1}$ would predict earnings growth of nonstar firms, as star firms' relative earnings performance changes are likely to contain useful information about nonstar firms' future earnings performance.

[Insert Table 3 here]

The estimates in Columns 1 – 3 of Table 3 confirm our conjecture. *ΔEGP 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 magnitude, these coefficient estimates imply that a one standard deviation increase in *ΔEGP 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 *ΔEGP 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 *ΔEGP Difference*$_{j,t-1}$ is unable to predict the earnings growth of star firms. Specifically, the coefficients on *ΔEGP 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.

III.B Earnings Growth Spillover: Additional Analyses and Robustness Checks

We conduct several checks and additional analyses to verify that our results are robust to alternative specifications. To ensure that the results are not affected by outlier observations,

Appendix Table IA.3 repeats the analyses of Table 3 using a sample where *ΔEGP Difference*$_{j,t-1}$ is truncated at the 1% and 99% levels across the panel, and the results remain similar. We also verify that *ΔEGP Difference*$_{j,t-1}$ can predict nonstars' earnings growth at the firm level. Columns 1 to 3 of Appendix Table IA.4 report results from firm-level regressions that correspond to Columns 1 to 3 of Table 3. All the *ΔEGP Difference*$_{j,t-1}$ coefficients are positive and statistically significant.[19]

For additional robustness, we repeat our tests using 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 *ΔEGP Difference*$_{j,t-1}$ (see equation (1)), we use the lagged difference $\left(\overline{EGP}_{star_{j,\ t\text{-}1}} - \overline{EGP}_{nonstar_{j,\ t\text{-}1}}\right)$. The regression estimates are reported in Appendix Table IA.5, Panel A. We find that our results remain qualitatively similar.

As another alternative, 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 $\left(\overline{EGPRCT}_{star_{j,\ t}} - \overline{EGPRCT}_{nonstar_{j,\ t}}\right) - \left(\overline{EGPRCT}_{star_{j,\ t\text{-}1}} - \overline{EGPRCT}_{nonstar_{j,\ t\text{-}1}}\right)$, 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 IA.5 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.

[19] We conduct our main analyses at the industry level because, in the later sections, we use *ΔEGP Difference*$_{j,t-1}$ to predict industry-level outcomes. Industry aggregation also reduces the effect of firm-specific noise earnings growth estimates.

A specific concern with our *ΔEGP Difference* measure is that, because we scale the EPS change by stock price, concurrent stock returns may affect the results through changes in the scaling variable. Changes in stock price can reflect changes in riskiness and long-term expected earnings, which could mean that our results do not accurately capture the effect of changes in earnings growth. To address this concern, we use an alternative earnings growth measure based on firm-level Compustat items. Specifically, our measure captures the change in quarterly operating income before depreciation (Compustat item OIBDPQ), scaled by the book value of assets (Compustat item AT) from the previous fiscal year. Appendix Table IA.6 repeats the analyses of Table 3 using this alternative scaling. The results are consistent with our baseline findings and suggest that the dynamics are driven by earnings, not stock prices, and are not affected by changes in the number of shares outstanding. In both cases, a one standard deviation increase in *ΔEGP Difference* is associated with a 0.1 standard deviation increase in the earnings growth of nonstar firms.[20]

To further understand how different components of $\Delta EGP\ Difference_{t-1}$ contribute to the results of Table 3, we repeat the analysis so that we decompose the variable into subparts and use them to explain nonstars' earnings growth. In Column 1 of Appendix Table IA.7, we first estimate a regression where, instead of using $\Delta EGP\ Difference_{t-1}$ to predict nonstars' earnings growth, we include its subparts stars' earnings growth change ($\overline{EGP}_{star_{j,\ t-1}} - \overline{EGP}_{star_{j,\ t-2}}$) and nonstars' earnings growth change ($\overline{EGP}_{nonstar_{j,\ t-1}} - \overline{EGP}_{nonstar_{j,\ t-2}}$) as separate explanatory

[20] Here we use operating income instead of total earnings to more accurately capture the portion of earnings that may be affected by performance spillovers. Our baseline definition is based on I/B/E/S earnings, as it better reflects the earnings information available at the time of the earnings announcement, which is important for subsequent analyses.

variables. The regression is otherwise similar to Column 3 of Table 3. The coefficient on stars' earnings growth is positive and statistically significant with coefficient value 0.187 and *t*-value 5.0. The nonstar earnings coefficient is -0.05 with *t*-value -1.9.

The economic and statistical significance of the star coefficient suggests that the change in stars' earnings growth is the main driver of the results. However, the negative coefficient on nonstars' earnings growth suggests that relative comparison between stars' and nonstars' growth has additional information value.

In Column 2, we do a further decomposition of $\Delta EGP\ Difference_{t-1}$ and replace it with $\overline{EGP}_{star_{j,\ t-1}}$, $\overline{EGP}_{star_{j,\ t-2}}$, $\overline{EGP}_{nonstar_{j,\ t-1}}$, $\overline{EGP}_{nonstar_{j,\ t-2}}$ as separate variables. The coefficients again make intuitive sense. The coefficient on $\overline{EGP}_{nonstar_{j,\ t-1}}$ is the most economically and statistically significant variable with coefficient value 0.49 and *t*-value 8.4. This is not surprising because it is also the lagged dependent variable. $\overline{EGP}_{nonstar_{j,\ t-2}}$ is statistically insignificant (*t*-value 1.3) and close to zero with coefficient value 0.04. The star firm coefficients $\overline{EGP}_{star_{j,\ t-1}}$ and $\overline{EGP}_{star_{j,\ t-2}}$ are both statistically significant with coefficient values 0.229 (*t*-value 4.9) and -0.139 (*t*-value -2.7), respectively. The results are consistent with our previous findings because the value of $\Delta EGP\ Difference_{t-1}$ increases with the first lag of stars' earnings growth and decreases with the second lag of stars' earnings growth.

Finally, one potential concern with our regression coefficient estimates is that they may suffer from a dynamic panel bias (Nickell 1981) because the lagged dependent variable is included as a control variable. We address this issue in detail in Internet Appendix A where we first discuss the magnitude of the potential bias and show that it is insignificant in our setting. Nickell (1981) shows that the bias is inversely proportional to the number of time periods in the panel, and our quarterly panel has sufficient length to make the potential bias virtually nonexistent. For further robustness, in Appendix Table IA.8 we re-estimate the baseline regression using a two-step Arellano-Bond Generalized Method of Moments estimation procedure following Wintoki, Linck, and Netter (2012). This approach is immune to dynamic panel bias and produces results that are consistent with the findings in Table 3.

III.C Which Components of Earnings Growth Does ΔEGP Difference Predict?

To better understand the nature of the spillover effect, we analyze which components of year-over-year operating income growth are most sensitive to variation in $\Delta EGP\ Difference_{t-1}$. Specifically, we analyze the extent to which the earnings growth spillover effect can be attributed to changes in sales volume, operating profit margin, and its underlying subcomponents. An analysis on earnings growth subcomponents requires data from Compustat, and this analysis builds on the previous operating income/assets analysis in Appendix Table IA.6

In our decomposition, we first divide total operating income before depreciation (*OIBDP*) for each firm *i* and quarter *t* into two subparts: one capturing *OIBDP* growth due to changes in sales volume, and another capturing the effect of changes in operating expense-to-sales ratio. *OIBDP* is based on Compustat item OIBDPQ, which is defined as revenue (*SALE*) measured using item SALEQ minus total operating expenses (*OPEX*) measured using item XOPRQ:

$$OIBDP = SALE - OPEX = SALE \times \left(1 - \frac{OPEX}{SALE}\right) \tag{3}$$

We use this identity as the basis for our decomposition, splitting the year-over-year change in operating income into two components that capture the effect of the change in *SALE* and *OPEX/SALE* while keeping the other variable fixed. The first component, $\Delta OIBDP_{Volume_{i,t}}$, measures the portion of the change driven by changes in *SALE* while holding the previous year's *OPEX/SALE* ratio constant. It captures the *OIBDP* change attributable to sales volume growth under the assumption that sales volume is proportional to *OPEX*. The second component,

$\Delta OIBDP_{Margin_{i,t}}$, captures the effect of changes in the OPEX/SALE ratio itself, reflecting how shifts in operating efficiency or cost structure contribute to the overall change in operating income. By construction, these two components sum to the total change in operating income and the specific formulas are

$$\Delta OIBDP_{Volume_{i,t}} = [SALE_{i,t} - SALE_{i,t-4}] \times \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right) \tag{4}$$

$$\Delta OIBDP_{Margin_{i,t}} = SALE_{i,t} \times \left[\left(1 - \frac{OPEX_{i,t}}{SALE_{i,t}}\right) - \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right)\right] \tag{5}$$

To ensure appropriate comparisons across firms, we scale all variables by total assets from the previous fiscal year (Compustat item AT).[21]

We further break down $\Delta OIBDP_{Margin}$ into two subcomponents, which capture the effect of profit margin change relative to cost of goods sold and relative to other operational factors. Cost of goods sold is defined as Compustat item COGSQ, and it represents a major component of OPEX. The key insight is that the OPEX/SALE ratio can be expressed as the product of OPEX/COGS and COGS/SALE. Accordingly, we decompose $\Delta OIBDP_{Margin}$ to separately capture the impact of changes in the share of COGS relative to sales, and changes in OPEX relative to COGS, which reflect other operational efficiencies.

This decomposition connects to OIBDP through the following identity

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[21] The two components sum up to total OIBDP change. $\Delta OIBDP_{Volume} + \Delta OIBDP_{Margin.}$

$$= [SALE_{i,t} - SALE_{i,t-4}] \times \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right) + SALE_{i,t} \times \left[\left(1 - \frac{OPEX_{i,t}}{SALE_{i,t}}\right) - \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right)\right]$$

$$= [SALE_{i,t} - SALE_{i,t-4}] \times \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right) + SALE_{i,t} \times \left[\frac{OPEX_{i,t-4}}{SALE_{i,t-4}} - \frac{OPEX_{i,t}}{SALE_{i,t}}\right]$$

$$= SALE_{i,t} - SALE_{i,t} \times \frac{OPEX_{i,t-4}}{SALE_{i,t-4}} - SALE_{i,t-4} + OPEX_{i,t-4} + SALE_{i,t} \times \frac{OPEX_{i,t-4}}{SALE_{i,t-4}} - OPEX_{i,t}$$

$$= (SALE_{i,t} - OPEX_{i,t}) - (SALE_{i,t-4} - OPEX_{i,t-4}) = \Delta OIBDP$$

$$OIBDP = SALE \times \left(1 - \frac{COGS}{SALE} \times \frac{OPEX}{COGS}\right) \tag{6}$$

The subcomponents are

$$\Delta OIBDP_{Margin\left(\frac{COGS}{SALE}\right)_{i,t}} = SALE_{i,t} \times \left[\left(1 - \frac{COGS_{i,t}}{SALE_{i,t}}\right) - \left(1 - \frac{COGS_{i,t-4}}{SALE_{i,t-4}}\right)\right] \times \frac{OPEX_{i,t}}{COGS_{i,t}} \tag{7}$$

$$\Delta OIBDP_{Margin\left(\frac{COGS}{OPEX}\right)_{i,t}} = SALE_{i,t} \times \left[\left(1 - \frac{OPEX_{i,t}}{COGS_{i,t}}\right) - \left(1 - \frac{OPEX_{i,t-4}}{COGS_{i,t-4}}\right)\right] \times \frac{COGS_{i,t-4}}{SALE_{i,t-4}} \tag{8}$$

These subcomponents sum up to $\Delta OIBDP_{Margin_{i,t}}$ in Equation (5).[22] The first subcomponent measures the *OIBDP* change that is attributable to profit margin relative to *COGS* and the second component captures any residual change in the $\Delta OIBDP_{Margin}$ component.

Table 4 reports results from industry-level regressions that use $\Delta EGP\ Difference_{j,\ t-1}$ to explain the average value of each of the earnings components and subcomponents among nonstar firms. These regressions are otherwise identical to our baseline earnings growth specification in Column 3 of Table 3. To make it easier to compare the magnitude of *ΔEGP Difference* coefficients across different specifications, we standardize the dependent and independent variables.

[Insert Table 4 here]

[22] The sum of the two components is $\Delta OIBDP_{Margin\left(\frac{COGS}{SALE}\right)_{i,t}} + \Delta OIBDP_{Margin\left(\frac{COGS}{OPEX}\right)_{i,t}}$

$$= SALE_{i,t} \times \left[\left[\left(1 - \frac{COGS_{i,t}}{SALE_{i,t}}\right) - \left(1 - \frac{COGS_{i,t-4}}{SALE_{i,t-4}}\right)\right] \times \frac{OPEX_{i,t}}{COGS_{i,t}} + \left[\left(1 - \frac{OPEX_{i,t}}{COGS_{i,t}}\right) - \left(1 - \frac{OPEX_{i,t-4}}{COGS_{i,t-4}}\right)\right] \times \frac{COGS_{i,t-4}}{SALE_{i,t-4}}\right]$$

$$= SALE_{i,t} \times \left[\left[\left(\frac{COGS_{i,t-4}}{SALE_{i,t-4}} - \frac{COGS_{i,t}}{SALE_{i,t}}\right)\right] \times \frac{OPEX_{i,t}}{COGS_{i,t}} + \left[\left(\frac{OPEX_{i,t-4}}{COGS_{i,t-4}} - \frac{OPEX_{i,t}}{COGS_{i,t}}\right)\right] \times \frac{COGS_{i,t-4}}{SALE_{i,t-4}}\right]$$

$$= SALE_{i,t} \times \left[\frac{COGS_{i,t-4}}{SALE_{i,t-4}} \times \frac{OPEX_{i,t}}{COGS_{i,t}} - \frac{OPEX_{i,t}}{SALE_{i,t}} + \frac{OPEX_{i,t-4}}{SALE_{i,t-4}} - \frac{COGS_{i,t-4}}{SALE_{i,t-4}} \times \frac{OPEX_{i,t}}{COGS_{i,t}}\right]$$

$$= SALE_{i,t} \times \left[\left(1 - \frac{OPEX_{i,t}}{SALE_{i,t}}\right) - \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right)\right] = \Delta OIBDP_{Margin_{i,t}}$$

Column 1 first verifies that *ΔEGP Difference* can predict *OIBDP* growth in addition to earnings growth. The earnings growth coefficient is 0.146 with *t*-value of 4.63, indicating that a one standard deviation increase in *ΔEGP Difference* is associated with a 0.15 standard deviation increase in *OIBDP* growth. When we decompose total *OIBDP* growth into $\Delta OIBDP_{Volume}$ and $\Delta OIBDP_{Margin}$ in Columns 2 and 3, we find that *ΔEGP Difference* can statistically significantly predict changes in both components, but the profit margin component is more responsive to changes in *ΔEGP Difference*. The coefficient on the profit margin component is 45% higher than the coefficient on the volume component (0.096 vs. 0.066). The *t*-values of the two components are 3.83 and 2.18, respectively.

The additional decomposition into profit margin subcomponents in Columns 4 and 5 reveals that the profit margin effect is based on changes in profit relative to cost of goods sold rather than on other operational efficiencies. *ΔEGP Difference* can statistically significantly predict changes in the *COGS/SALE* subcomponent with coefficient values 0.087 and *t*-value of 3.17 whereas the coefficient on the *COGS/OPEX* subcomponent is statistically insignificant with coefficient value –0.006 and *t*-value of –0.29. Altogether, the *OIBDP* decomposition results indicate that the earnings growth changes predicted by *ΔEGP Difference* are related to changes in profit margins and sales volume, and the profit margin component is more sensitive to *ΔEGP Difference*. The impact on the profit margin component is related to markup relative to cost of goods sold rather than other operational efficiencies.[23]

[23] We conduct further analyses related to volume growth and *COGS/OPEX* changes in Appendix Table IA.9, where we regress nonstar firms' *COGS* growth, *OPEX* growth and *COGS/OPEX* change on $\Delta EGP\ Difference_{j,\,t\text{-}1}$ using similar industry-level quarterly regressions. Higher sales volume should result in an increase in *COGS* and *OPEX* and, consistent with the volume component results, we find that *ΔEGP Difference* statistically significantly predicts

III.D Predicting Job Postings

So far, our results show that star firms' relative earnings performance predicts nonstar firms' earnings growth. We next test whether *ΔEGP Difference* also predicts nonstar firms' job postings — a timely indicator of firm growth and labor demand. Shifts in star firms' performance may affect nonstar hiring through profitability spillovers and local multiplier effects (Moretti, 2010).

To test this conjecture, we estimate quarterly industry-level panel regressions where we explain the relative change in the average number of job postings for nonstar and star firms with *ΔEGP Difference*. Specifically, the dependent variable 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*. 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.

Table 5 shows that lagged *ΔEGP Difference* statistically significantly predicts nonstar firms' job postings. The coefficient ranges from 24.32 (*t*-statistic = 2.33) to 25.32 (*t*-statistic = 2.22) implying a one standard deviation increase in *ΔEGP Difference* raises nonstar job postings by 34–36%. In contrast, the effect on star firms' own postings is negative and insignificant. This is consistent with the hypothesis that star firms' relative performance predicts nonstar firms' hiring but not their own.

[Insert Table 5 here]

COGS and *OPEX* growth. The coefficient on *COGS/OPEX* change is statistically insignificant, suggesting that *ΔEGP Difference* does not predict changes in cost structure.

III.E Predicting Industry-Level GDP and Employment Growth with ΔEGP Difference

Building on the predictability 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 industry aggregates include listed and unlisted firms, and we cannot isolate star and nonstar effects separately. Also, the GDP time series starts in 2006 due to data limitations.

[Insert Table 6 here]

Table 6 reports regressions of quarterly year-over-year industry GDP growth (Panel A) and employment growth (Panel B) on lagged *ΔEGP Difference*, with controls for past industry earnings growth and lagged GDP or employment growth. In Panel A, *ΔEGP Difference* is positively and statistically significantly related to future industry GDP growth, with coefficients from 0.345 to 0.442 (significant at the 10% level or higher). Economically, a one standard deviation increase predicts a 0.5–0.6% rise in GDP growth. This response is comparatively higher than the effect of a one standard deviation change on future earnings growth in the regressions of Table 3.

Panel B shows a similar positive link for employment: higher relative star firm earnings growth predicts higher industry employment growth next quarter. The coefficients (0.079–0.135) imply a 0.1–0.2% increase in employment growth per standard deviation increase in *ΔEGP Difference*. The results are statistically significant at the 10% level or higher. Together, these findings indicate that star firms' relative performance predicts not only nonstar firm outcomes but also broader industry-level growth and labor market trends.

III.F Predicting Industry-Level GDP with the Change in Star Firms' P/E Ratios

We also examine stars' ability to predict GDP growth using an alternative measure based on growth expectations embedded in firm valuations. Previously, Bekaert et al. (2007) measure a country's growth opportunities using a price-to-earnings (P/E) ratio based on its industry mix valued at global P/E ratios. They find that the country-specific P/E ratio can predict future GDP growth and investment, which indicates that aggregate P/E ratios contain information that is relevant for predicting future economic growth.

Building on this idea, we test whether changes in star firms' P/E ratios signal broader industry growth opportunities. If star firms' growth spills over to other firms, then stars' P/E ratios may better capture industry-level growth expectations than nonstars' P/E ratios, especially if markets underreact to these spillovers.

P/E ratios reflect long-term growth opportunities, and we test the hypothesis by estimating regressions where we explain change in annual GDP growth at the industry level ($\Delta GDP\ Ann\ Growth_{j,t}$) with the change in star firms' and nonstar firms' P/E ratio. Specifically, we define $P/E\ Growth_{star/nonstar_{j,t-1}}$ as $(P/E_{star/nonstar_{j,\ t-1}} - P/E_{star/nonstar_{j,\ t-2}})\ /\ P/E_{star/nonstar_{j,\ t-2}}$. The variable $P/E_{star/nonstar_{j,\ t}}$ refers to industry j's sum of star/nonstar firms' market capitalization in December of fiscal year t divided by their sum of earnings before extraordinary items (Compustat item EPSPX times shares outstanding, item CSHO) for fiscal year t. Regressions include industry fixed effects and lagged P/E growth, and are estimated both with and without time fixed effects.

[Insert Table 7 here]

The results in Table 7 show that star firms' relative P/E changes statistically significantly predict industry GDP changes, whereas nonstars' P/E changes do not. The coefficient on

$P/E\ Growth_{star\ j,t-1}$ is 0.011 with t-value of 2.66 when time fixed effects are included and 0.011 with t-value of 2.80 without the time fixed effects. In contrast, the corresponding nonstar coefficients are statistically insignificant with coefficient value 0.006 and t-values of 1.39 and 1.32, respectively. Columns 3 and 6 include both the star and nonstar variables as separate predictors in regressions estimated with and without time fixed effects. In both cases, the coefficient value on $P/E\ Growth_{star\ j,t-1}$ remains unchanged and statistically significant whereas the $P/E\ Growth_{nonstar\ j,t-1}$coefficients are statistically insignificant. In economic terms, a one standard deviation change in $P/E\ Growth_{star\ j,t-1}$ predicts a 0.8 percentage point change in annual GDP growth. This effect corresponds to 9.3% of the standard deviation of annual industry GDP growth.

These results reinforce our earlier findings: star firms provide predictive signals about broader economic outcomes, not just about firm-specific performance. Together, the GDP and employment results highlight the wider economic importance of star firms' information spillovers. The findings also show that star firms' predictive ability extends to performance in non-financial outcomes.

IV. Economic Channels Behind the Industry Spillover Effect

In this section, we analyze the economic channels and industry dynamics that can contribute to the earnings growth spillover effect documented in Section III. We first describe the potential mechanisms through which star firms' information predicts nonstar firms' earnings and then assess the empirical support for each channel.

IV.A Potential Economic Channels Behind the Spillover Effect

Stars as price setters and price markup spillover. Previous literature provides evidence that the largest firms in the economy have higher price markups (Autor et al. (2020), De Loecker et al. (2020)), suggesting market power is central to star firms' dominance. If star firms have greater pricing power, they may act as price setters within industries, while nonstar firms adjust their prices accordingly. When star firms raise or lower prices, nonstars' profits would change in tandem as they follow the stars' pricing decisions.

Technology spillover related to product market innovation. Product market innovation spillovers where new products, services or technologies developed by star firms are adopted by nonstar firms can potentially result in earnings spillovers. Improved products can result in higher sales volume, as well as higher price markups. Easier access to human capital (Choi et al. (2025)) and better management quality can contribute to stars' innovativeness.[24]

Technology spillover related to productivity innovation. Technology spillovers can also stem from productivity innovations. If star firms develop cost-saving production techniques that nonstars can imitate, this may lower unit costs across the industry, resulting in earnings spillovers.

Supply chain and vertical integration effects. Positive shocks to star firms' profitability can affect other firms that are connected to them through the supply chain or other intra-industry connections.

Schumpeterian competition with negative externalities on nonstar firms. Star firms' innovations could trigger Schumpeterian competition, spurring creative destruction that reduces nonstar firms' future earnings (Aghion and Howitt (1992), Cheng, Vyas, Wittenberg-Moerman, and Zhao (2025)).

[24] Bloom and Van Reenen (2010) report that management quality increases with firm size in cross-sectional statistics.

IV.B Empirical Evidence on Economic Channels

Our previous earnings growth decomposition results are consistent with the price markup channel where stars function as price setters. The finding that the *COGS* profit margin component is most responsive to changes in *ΔEGP Difference* is in line with this explanation because it captures price markup relative to unit costs. To further test the price markup spillover hypothesis, we analyze whether star firms' price markup changes predict nonstars' price markup changes using a detailed price markup definition introduced by De Loecker et al. (2020). Their markup variable accounts for user cost of capital and complements Compustat with other data sources.[25] Because these data are annual, we conduct the analysis at the annual level.

In Appendix Table IA.10 we estimate regressions where we explain nonstars' and stars' average change in annual markup at the industry level with a variable labeled $\Delta MU\ Difference_{j,\ t-1},$ which is defined similarly as $\Delta EGP\ Difference_{j,\ t-1}$. It captures the difference between stars' and nonstars' average markup growth over the previous year. The regressions include year and firm fixed effects, and control for three lagged values of markup growth. The results show that $\Delta MU\ Difference_{j,\ t-1}$ can statistically significantly predict nonstars' markup change with coefficient value 0.053 and *t*-value of 2.33, whereas the coefficient in the regression explaining

[25] The measure is defined as sales (Compustat item SALE) divided by the sum of cost of goods sold (Compustat item COGS), selling, general, and administrative expense (Compustat item XSGA), and the user cost of capital. De Loecker et al. (2020) compute the user cost of capital as a function of the nominal interest rate minus the inflation rate plus a depreciation rate, which is set at 12% to account for exogenous depreciation rate and risk premium. All variables are US dollar deflated using the GDP deflator with base year 2010.

stars' markup growth is negative and statistically insignificant. These results provide further evidence that stars' price markup changes lead nonstars' price markup changes.[26]

We also find evidence consistent with technology spillovers from star firms to nonstars, but only related to product market innovation. To analyze the relevance of the technology spillover channel, we classify industries as high and low technology spillover industries using the *Technology Spillover* score developed by Bloom et al. (2013). Specifically, we calculate nonstar firms' average *Technology Spillover* score with the same-industry stars within each industry-quarter. We then use the median industry scores to split industries into *High Technology Spillover* (above median) and *Low Technology Spillover* (below median) industries.

[Insert Table 8 here]

Panel A of Table 8 reports results from regressions explaining the main *OIBDP* growth subcomponents ($\Delta Revenue_{Volume}$ and $\Delta Revenue_{Margin}$) with *ΔEGP Difference* among *High* and *Low Technology Spillover* industries. We find that *ΔEGP Difference* coefficients in *High Technology Spillover* industries are higher both for the markup growth (0.121 vs. 0.054) and volume growth (0.172 vs. 0.048) components and the coefficients in the *Low Technology Spillover* industries are statistically insignificant.[27] These results provide evidence that *ΔEGP Difference* has a stronger ability to predict volume and markup growth in industries with high

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[26] Changes in the De Loecker et al. (2020) markup measure could also reflect shifts in cost structure if movements in variable costs are offset by changes in fixed costs. However, the cost-structure results in Section III.C indicate that such shifts cannot explain our findings. We do not find that *ΔEGP Difference* predicts changes in firms' cost structure.

[27] Regressions in Appendix Table IA.11 further confirm that the difference between subsamples reported in Table 8 are statistically significant based on pooled regressions with interaction terms.

technological similarity. However, our evidence does not indicate that the technology spillovers are related to productivity innovation. Production can become more efficient either through the reduction of unit costs or through other operational efficiencies, but as discussed in Section III.C, we find no evidence that *ΔEGP Difference* predicts cost structure changes.

Next, we test the supply chain channel using Frésard et al.'s (2020) Vertical Integration scores to classify industries. Again, we split industries by median score and compare results (Table 8, Panel B).[28] We find that the *ΔEGP Difference* coefficient in regressions explaining $\Delta OIBDP_{Margin}$ in *High Vertical Integration* industries (0.129 with *t*-value of 3.04) is higher than the corresponding coefficient in *Low Vertical Integration* industries (0.052 with *t*-value of 2.36). The coefficients on volume growth are close to each other (0.061 vs. 0.085), with only the *Low Vertical Integration* coefficient being statistically significant. These results suggest that profitability spillovers are larger in *High Vertical Integration* industries, and stars' markup changes can potentially spread through the supply chain.

Our results are not consistent with the Schumpeterian competition channel where star firms' innovation spurs creative destruction. Such effects may have an impact over a longer time period, but they are contrary to our findings because the *ΔEGP Difference* results suggest that positive earnings shocks to star firms predict positive future performance for nonstar firms.

Altogether, we find support for channels related to star firms as price setters, technology spillovers, and vertical integration effects. Any potential technology spillover effects seem to

[28] By construction, the Frésard et al. (2020) pairwise scores are directional and can be used to measure either upstream or downstream pairwise vertical integration potential between two firms. We measure the scores based on star firms' "upstream potential" relative to nonstar firms. Upstream potential can be more relevant in our setting if larger firms are generally higher (more upstream) in the supply chain.

arise from product market innovation rather than from productivity innovation. Notably, all the spillover effects we find are positive, even in earnings growth subcomponents. While we cannot rule out that star firms' dominance has negative effects on nonstar firms over the long run, in the short-term, star firms' performance improvements predict positive earnings for nonstar firms in the future.

V. Star Firms and Earnings Surprises

Our earnings growth regression estimates indicate that star firms reflect 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.

In the earnings surprise analysis, we use $\Delta EGP\ Difference_{j,t-1}$ 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 3. We separately regress year-quarter earnings surprise average for industry-level star and nonstar firms on $\Delta EGP\ Difference_{j,t-1}$. We include lagged earnings surprises as control variables and include industry as well as year-quarter fixed effects.

[Insert Table 9 here]

In Columns 1 – 3 of Table 9, we regress the average earnings surprise of nonstar firms (i.e., $\overline{ES}_{nonstar\,j,t}$) on $\Delta EGP\ Difference_{j,t-1}$. We find that the $\Delta EGP\ Difference_{j,t-1}$ statistically 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 reflected in star firms' earnings growth. In economic terms, a 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.[29] 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 IA.13 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 star firms' predictive ability is not limited to small firms. This evidence 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 (e.g., Lo and MacKinlay (1990) and Hou (2007)).

If analysts underreact to shifts in star firms' relative earnings performance, markets may not fully incorporate this information into prices. As a result, star firms' relative earnings could predict short-term returns of nonstar firms. To test this, we regress cumulative abnormal returns

[29] Similarly as with the earnings growth results in Section III.A, we verify that the results are robust to alternative specifications. Appendix Table IA.12 repeats the analyses of Table 9 using total assets per share as scaling variable instead of stock price. The results remain similar. Columns 5 and 6 of Appendix Table IA.4 verify that *ΔEGP Difference*$_{j,t-1}$ can also statistically significantly predict nonstars' earnings surprises in firm-level regressions.

of nonstar firms around earnings announcements, aggregated at the industry level, on our key $\Delta EGP\ Difference_{j,t-1}$ measure. Some specifications add average earnings announcement returns of star and nonstar firms from the prior quarter as controls. All regressions include year-quarter and industry fixed effects, with standard errors clustered by year-quarter and industry.

Table 10 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 firms' 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).

[Insert Table 10 here]

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

VI. 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 explore the asset pricing implications, we develop a trading strategy that leverages cross-sectional differences in star firms' performance shifts and examine potential lead–lag relationships between same-industry stars' and nonstars' returns.

VI.A Earnings Performance Shifts and Stock Returns

We start by creating market value-weighted quintile portfolios of nonstar firms with CRSP share codes 10 or 11 in industries with the highest and lowest lagged values of *ΔEGP Difference.* Each month, we form quintiles by sorting all industries using the *ΔEGP difference* measured at the end of the previous month (i.e., *ΔEGP Difference* $Monthly_{j,t-1}$). *ΔEGP Difference Monthly* is calculated using earnings announcements from months *t-1* to *t-3*.

We construct a value-weighted long portfolio that invests in nonstar portfolios from the eleven highest-ranked industries and a value-weighted short portfolio that invests in nonstar portfolios from the eleven lowest-ranked industries. These portfolios correspond to the top and bottom quintile within the 55 industries for which we have sufficient observations. Within each value-weighted quintile, an industry's non-star portfolio weight is based on the sum of the market capitalizations of all non-star firms in that industry at the beginning of the month. We then define a long-short portfolio strategy that takes a long position in the quintile of industries with the highest lagged *ΔEGP Difference Monthly* values and takes a short position in 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 IA.14), 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 11 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 loadings on size and negative loadings on momentum.

[Insert Table 11 here]

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.

VI.B 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) and Hameed, Morck, Shen, and Yeung (2015)), we posit that underreaction related to information spillover between connected firms may generate a 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.

[Insert Table 12 here]

Table 12, 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 47 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 firms' returns predict star firms' returns. In this case, we form star firm quintiles by sorting on lagged value-weighted nonstar firms' returns. We find an insignificant long-short portfolio alpha, suggesting that nonstar firms' 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.

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

In the last set of tests, we examine whether other large firms exhibit the same ability to predict the outcomes of other firms as star firms. We repeat our main analyses using an alternative specification 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 IA.15 reports results from regressions where we explain nonstar firms' earnings growth, earnings surprises, and earnings announcement returns with $\Delta EGP\ Difference_{j,t-1}$ calculated using these star substitutes and Appendix Table IA.16 reports six-factor alphas from nonstar firm portfolios formed based on the corresponding $\Delta EGP\ Difference\ Monthly_{j,t-1.}$ The regressions in these Appendix tables are identical to the specifications in Tables 3, 9, 10, and 11.

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 IA.15 shows that star substitutes can predict nonstars' earnings growth, but the coefficient magnitudes are 40-60% 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 IA.15, Panel B) and earnings announcement returns (Appendix Table IA.15, 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 IA.16). Together, these placebo tests confirm that the effects we identify are specific to star firms and are not merely general large-firm effects.

VIII. Summary and Conclusions

This study examines whether information from very large and dominant "star" firms can predict 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 affect other firms through various spillover and multiplier effects. Our key conjecture is that changes in star firms' earnings performance predict the future earnings and growth of other related firms. Further, market participants, such as sell-side equity analysts, may not fully incorporate information from star firms into their earnings forecasts of related firms. Consequently, financial information of industry star firms would predict 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. We find that spillover effects related to price markups, technology, and vertical integration are potential economic channels behind these patterns.

Notably, these predictive signals are not fully reflected in stock prices: a long–short trading strategy based on changes in star firms' relative earnings achieves an annualized risk-adjusted return exceeding 8%. Overall, these findings provide market- and operating-performance-based evidence of the economic importance of star firms and highlight the broader role of very large firms in financial markets.

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TABLE 1

Summary Statistics

This table presents summary statistics for our main variables. Panel A reports statistics on quarterly and monthly variables and Panel B reports on annual variables. All variables are measured at the industry 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, $Quarterly\ GDP\ YoY\ Growth_{j,t}$, which is available from 2006 to 2020, and annual variables, which are reported for the 1984 to 2020 period. Definitions of all variables are presented in Appendix Table IA.1. Industry star firms are defined following the definition of Gutiérrez and Philippon (2019) and all other firms are classified as nonstars.

Variable	Mean	Median	Std. Dev.	1st Pctl.	25th Pctl.	75th Pctl.	99th Pctl.	Min.	Max.	N
Panel A: Quarterly and Monthly Variables										
Statistics based on industry-quarter observations:										
ΔEGP Difference$_{j,t}$ (× 100)	0.017	0.006	1.409	-4.113	-0.382	0.413	4.214	-15.196	20.918	4,478
$\overline{EGP}_{star_{j,t}}$ (× 100)	-0.032	0.121	1.179	-5.159	-0.080	0.292	2.312	-13.760	5.813	4,616
$\overline{EGP}_{nonstar_{j,t}}$ (× 100)	-0.259	0.011	1.469	-6.258	-0.460	0.315	2.954	-13.760	7.152	4,710
$\overline{ES}_{star_{j,t}}$ (× 100)	0.042	0.046	0.278	-1.043	-0.008	0.120	0.744	-3.381	2.205	4,764
$\overline{ES}_{nonstar_{j,t}}$ (× 100)	-0.016	0.013	0.296	-1.094	-0.113	0.117	0.723	-2.351	2.153	4,793
GDP YoY Growth$_{j,t}$	0.011	0.018	0.085	-0.276	-0.014	0.047	0.207	-0.752	0.515	2,601
EMPL YoY Growth$_{j,t}$	0.005	0.011	0.064	-0.180	-0.015	0.030	0.158	-0.465	1.250	4,728
$\overline{JPG}_{star_{j,t}}$	0.541	0.002	3.905	-0.979	-0.246	0.329	12.369	-1.000	77.500	1,975
$\overline{JPG}_{nonstar_{j,t}}$	0.528	0.023	5.680	-0.880	-0.219	0.320	9.135	-1.000	152.000	1,995
Star Firms' Announcement Return (× 100)	0.054	0.055	3.809	-10.084	-1.868	2.002	10.142	-30.893	36.248	4,764
Nonstar Firms' Announcement Return (× 100)	0.011	0.029	2.690	-7.998	-1.280	1.333	7.180	-13.592	19.710	4,793
Statistics based on industry-month observations:										
ΔEGP Difference Monthly$_{j,t}$ (× 100)	0.011	0.007	1.333	-3.909	-0.377	0.386	4.252	-15.196	15.125	12,439
Panel B: Annual Variables										
ΔGDP Ann Growth$_{j,t}$	-0.003	0.107	-0.794	0.903	-0.327	-0.033	-0.001	0.029	0.335	1,767
P/E Growth$_{star_{j,t}}$	0.170	0.041	0.682	-0.712	-0.199	0.289	3.824	-0.712	3.824	1,797
P/E Growth$_{nonstar_{j,t}}$	0.420	0.062	1.355	-0.823	-0.209	0.473	7.758	-0.823	7.758	1,765

TABLE 2

Star Firm Characteristics

This table compares firm and industry characteristics of all firms, star firms, and large nonstar firms. Panel A reports means and medians of firm-level variables, based on annual firm observations. Panel B reports industry-level means for star firms and large same-industry nonstar firms, based on annual industry observations. Star firms are defined as industry stars following Gutiérrez and Philippon (2019), while large nonstar firms are those in the top 30% of market capitalization within each industry. Patent and citation data are from Kogan et al. (2017). Patents filed and issued refer to the number of patents filed or granted in a calendar year. Variable definitions are in Appendix Table IA.1. The last columns in Panel A report *p*-values from Satterthwaite *t*-tests and Kruskal-Wallis median tests comparing star and large firms. Panel B reports *p*-values from pairwise *t*-tests comparing industry-level means of star and large nonstar firms. The sample covers 1984–2020.

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 Share	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 Share	0.28	0.10	0.00
Citations of patents filed (past year)	2482.80	286.17	0.00
Citations of patents filed (cumulative)	45329	4683.70	0.00
Number of patents filed (past year)	101.96	7.91	0.00
Number of patents filed (cumulative)	2222.90	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 $\Delta EGP\ Difference_{j,t-1}$ 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 $\Delta EGP\ Difference_{j,t-1}$ 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. Other explanatory variables include three lagged values of $\overline{EGP}_{star/nonstar\ j,t}$. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, 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
	(3.90)	(5.07)	(4.97)	(-0.85)	(-1.13)	(-0.87)
$\overline{EGP}_{g_{j,t-1}}$	0.582***	0.703***	0.698***	0.585***	0.597***	0.589***
	(13.59)	(15.00)	(15.55)	(14.19)	(8.36)	(8.91)
$\overline{EGP}_{g_{j,t-2}}$		-0.163***	-0.137***		-0.021	0.031
		(-4.68)	(-3.39)		(-0.25)	(0.40)
$\overline{EGP}_{g_{j,t-3}}$			-0.050			-0.087**
			(-1.09)			(-2.23)
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 Change in Earnings Growth Components

This table reports results from regressions explaining different components of nonstar firms' earnings growth. The variables are measured as industry-quarter observations based on averages among nonstar firms. In Column 1, the dependent variable is operating income growth. In Columns 2 and 3, the dependent variables are operating income growth components that capture the effect of sales volume growth and profit margin growth. Columns 4 and 5 further decompose the profit margin component in Column 3 into subcomponents that capture the effect of COGS/OPEX margin change and residual profit margin change. The exact formulas for these components are provided in Section III.C. We scale all variables by total assets (Compustat item AT) from the previous fiscal year to ensure comparability across firms. The main explanatory variable *ΔEGP Difference*$_{j,t\text{-}1}$ 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 nonstar firms' quarterly earnings growth ($\overline{EGP}_{nonstar_{j,\ t}}$). To improve comparability, all variables are standardized across the pooled panel to have a mean of zero and a standard deviation of one. The sample period is from 1994 to 2020. We include industry-quarter observations with at least five nonstar firms. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	ΔOperating Income Total	*ΔOperating Income* Volume Growth Component	*ΔOperating Income* Profit Margin Component	*ΔOperating Income* COGS/OPEX Profit Margin Subcomponent	*ΔOperating Income* Residual Profit Margin Subcomponent
	1	2	3	4	5
ΔEGP Difference$_{j,\ t\text{-}1}$	0.146***	0.066**	0.096***	0.087***	-0.006
	(4.63)	(2.18)	(3.83)	(3.17)	(-0.29)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-1}}$	0.465***	0.222***	0.359***	0.290***	0.037
	(6.86)	(3.57)	(7.15)	(6.38)	(1.57)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-2}}$	-0.087***	-0.025	-0.095***	-0.091***	0.040***
	(-3.68)	(-0.82)	(-5.86)	(-3.71)	(2.68)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-3}}$	-0.034*	0.017	-0.054**	-0.061***	0.013
	(-1.71)	(0.98)	(-2.46)	(-3.13)	(1.19)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	4,445	4,446	4,446	4,446	4,446
R2	0.280	0.369	0.175	0.151	0.112

TABLE 5

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 ($\overline{JPG}_{star/nonstar_{j,\ t}}$). The dependent variable is defined as $(\overline{JP}_{star/nonstar_{j,\ t}} - \overline{JP}_{star/nonstar_{j,\ t\text{-}1}})/\overline{JP}_{star/nonstar_{j,\ t\text{-}1}}$, 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 $\Delta EGP\ Difference_{j,t\text{-}1}$ 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 $\overline{EGP}_{star/nonstar_{j,\ t}}$ and $\overline{JPG}_{star/nonstar_{j,\ t}}$ (in Columns 2 and 4). Detailed variable definitions are presented in Appendix Table IA.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% levels, 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
	(2.34)	(2.23)	(-0.92)	(0.93)
$\overline{EGP}_{g_{j,t-1}}$	1.156	1.330	-400.879	-25.915
	(0.13)	(0.09)	(-1.04)	(-0.46)
$\overline{EGP}_{g_{j,t-2}}$	-46.908	-54.610	595.721	-20.766
	(-1.50)	(-1.59)	(0.96)	(-0.89)
$\overline{EGP}_{g_{j,t-3}}$	-30.347	-29.464	307.975	42.974
	(-1.14)	(-0.96)	(0.99)	(1.23)
$\overline{JPG}_{g_{j,t-1}}$		-0.096		0.000
		(-1.47)		(-0.86)
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 6

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, star firms, and nonstar 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 IA.1. The sample period is 2006 to 2020 in Panel A and 1994 to 2020 in Panel B. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, 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*
	(3.26)	(2.32)	(2.35)	(2.36)	(2.27)	(1.83)
$\overline{\text{EGP}}_{j,t-1}$	2.140***	2.204**	2.203**	2.238**	1.160**	0.797*
	(2.81)	(2.63)	(2.61)	(2.68)	(2.09)	(1.76)
$\overline{\text{EGP}}_{j,t-2}$		-0.097	-0.099	-0.193	-0.378	-0.680
		(-0.24)	(-0.23)	(-0.41)	(-0.94)	(-1.62)
$\overline{\text{EGP}}_{j,t-3}$			0.002	0.211	0.587**	0.249
			(0.01)	(0.71)	(2.06)	(1.06)
GDP YoY Growth$_{j,t-4}$				-0.174***	-0.106***	-0.228***
				(-3.55)	(-2.80)	(-10.00)
GDP Qtr Growth$_{j,t-1}$					1.081***	0.341*
					(5.18)	(1.80)
GDP YoY Growth$_{j,t-1}$						0.698***
						(19.81)
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*
	(3.35)	(2.60)	(2.26)	(2.39)	(2.68)	(1.76)
$\overline{\text{EGP}}_{j,t-1}$	0.948**	0.760*	0.791*	0.817**	0.722**	0.507**
	(2.19)	(1.94)	(2.01)	(2.05)	(2.09)	(2.46)
$\overline{\text{EGP}}_{j,t-2}$		0.289*	0.071	0.073	0.007	-0.247
		(1.81)	(0.45)	(0.47)	(0.05)	(-1.49)
$\overline{\text{EGP}}_{j,t-3}$			0.324**	0.255**	0.280***	0.109
			(2.66)	(2.24)	(2.69)	(1.48)
EMPL YoY Growth$_{j,t-4}$				0.168**	0.160**	-0.108*
				(2.43)	(2.45)	(-1.79)
EMPL Qtr Growth$_{j,t-1}$					0.397**	0.021
					(2.51)	(0.32)
EMPL YoY Growth$_{j,t-1}$						0.750***
						(10.80)
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 7

Using Star Firms' P/E Ratio Changes to Predict Industry-Level GDP Growth

This table reports results from regressions explaining changes in industry-level annual real GDP growth (*ΔGDP Ann Growth*$_{j,t}$). GDP growth is measured as the percentage change in real GDP relative to the previous year (expressed as a decimal). The main explanatory variable $P/E\ Growth_{star/nonstar\ j,t-1}$ is calculated as $((P/E_{star/nonstar_{j,\ t-1}}) - (P/E_{star/nonstar_{j,\ t-2}}))/(P/E_{star/nonstar_{j,\ t-2}})$. $P/E_{star/nonstar_{j,\ t}}$ refers to industry *j*'s sum of star/nonstar firms' market capitalization in December of fiscal year *t* divided by their sum of earnings before extraordinary items (Compustat item EPSPX times shares outstanding, item CSHO) for fiscal year *t*. To control for the impact of outliers, $P/E_{star/nonstar_{j,\ t}}$ is winsorized at the 1st and 99th percentiles. All models control for the lagged dependent variable (coefficients not reported for brevity). Detailed variable definitions are presented in Appendix Table IA.1. The annual industry GDP data are available from 1984 and the annual observations in the regression cover 1986 to 2020. In regression specifications 1–3, we include industry fixed effects, while specifications 4–6 contain year and industry fixed effects. *t*-statistics based on standard errors that are two-way clustered by year and industry are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6
$\text{P/E Growth}_{\text{star}_{j,t-1}}$	0.012**		0.011**	0.010**		0.009**
	(2.18)		(2.11)	(2.57)		(2.53)
$\text{P/E Growth}_{\text{nonstar}_{j,t-1}}$		0.005	0.005		0.005	0.006
		(1.20)	(1.19)		(1.35)	(1.42)
Year FE	No	No	No	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,811	1,842	1,794	1,811	1,842	1,794
R^2	0.132	0.126	0.134	0.338	0.337	0.346

TABLE 8

Technology Spillover, Vertical Integration, and Earnings Growth Changes

This table reports results from regressions explaining the change in nonstar firms' operating income growth components defined in Section III.C. The regressions use industry-quarter observations based on averages among nonstar firms. The dependent variable in Columns 1 and 2 is the sales volume component of operating income growth, and the dependent variable in Columns 3 and 4 is the profit margin component. Panel A reports results using subsamples based on nonstar firms' average *Technology Spillover* scores relative to same-industry stars. *Technology Spillover* scores are based on a pairwise measure developed by Bloom et al. (2013). Panel B reports results using subsamples based on nonstar firms' average vertical relatedness relative to same-industry stars. Vertical relatedness is measured based on Frésard et al. (2020) pairwise *Vertical Integration* scores in the previous fiscal year. Each quarter, we split industries into High (above median) and Low (below median) industries using the two scores. 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. Other explanatory variables include three lagged values of nonstar firms' quarterly earnings growth ($\overline{EGP}_{nonstar_{j,\ t}}$). To improve comparability, all dependent and independent variables are standardized across the pooled panel to have a mean of zero and a standard deviation of one. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. We include industry-quarter observations with at least five nonstar firms. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Technology Spillover Subsamples				
	Regressions Explaining *ΔOperating Income*$_{Volume}$		Regressions Explaining *ΔOperating Income*$_{Margin}$	
	High Technology Spillover	Low Technology Spillover	High Technology Spillover	Low Technology Spillover
	1	2	3	4
ΔEGP Difference$_{j,\ t-1}$	0.121***	0.054	0.172***	0.048
	(3.32)	(1.45)	(3.31)	(1.32)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-1}}$	0.324***	0.186**	0.411***	0.376***
	(3.26)	(2.35)	(4.62)	(6.98)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-2}}$	-0.068	-0.014	-0.080*	-0.076**
	(-1.60)	(-0.45)	(-1.71)	(-2.53)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-3}}$	0.040	-0.005	-0.091***	-0.037
	(1.38)	(-0.33)	(-3.86)	(-1.07)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2,035	1,980	2,035	1,980
R^2	0.448	0.365	0.245	0.207

Panel B: Vertical Integration Subsamples				
	Regressions Explaining *ΔOperating Income*$_{Volume}$		Regressions Explaining *ΔOperating Income*$_{Margin}$	
	High Vertical Integration	Low Vertical Integration	High Vertical Integration	Low Vertical Integration
	1	2	3	4
ΔEGP Difference$_{j,\ t-1}$	0.061	0.085**	0.129***	0.052**
	(1.63)	(2.65)	(3.04)	(2.36)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-1}}$	0.183***	0.316***	0.428***	0.256***
	(2.99)	(3.93)	(7.51)	(3.12)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-2}}$	-0.022	-0.033	-0.112***	-0.054*
	(-0.71)	(-0.88)	(-19.62)	(-1.89)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-3}}$	0.025	0.013	-0.085***	-0.016
	(0.98)	(0.49)	(-3.52)	(-0.52)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	2,226	2,175	2,226	2,175
R^2	0.358	0.447	0.221	0.188

TABLE 9

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 $(\overline{EGP}_{star_{j,\,t-1}} - \overline{EGP}_{nonstar_{j,\,t-1}}) - (\overline{EGP}_{star_{j,\,t-2}} - \overline{EGP}_{nonstar_{j,\,t-2}})$. $\overline{EGP}_{star_{j,\,t}}$ 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 $\overline{EGP}_{nonstar_{j,\,t}}$ 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 IA.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, 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
	(2.48)	(2.55)	(-0.74)	(-0.78)
$\overline{EGP}_{g_{j,t-1}}$	0.033***	0.019**	0.032**	0.014**
	(3.87)	(2.36)	(2.65)	(2.37)
$\overline{EGP}_{g_{j,t-2}}$	-0.021**	-0.017*	0.003	0.007
	(-2.26)	(-1.75)	(0.13)	(0.31)
$\overline{EGP}_{g_{j,t-3}}$	0.015**	0.015**	-0.007	-0.006
	(2.55)	(2.53)	(-1.02)	(-0.71)
$\overline{ES}_{g_{j,t-1}}$		0.162***		0.183***
		(3.31)		(2.95)
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 10

Predicting Earnings Announcement Returns of Star and Nonstar Firms

This table reports regression results explaining star firms' and nonstar firms' average quarterly earnings announcement returns at the industry level. Earnings announcement returns are market-adjusted cumulative abnormal returns within the [0, 2] window around the announcement date. The main explanatory variable *ΔEGP Difference*$_{j,t-1}$ is defined as in Section II.D. The control variables include stars' and nonstars' average announcement returns in the previous quarter. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, 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 11

Performance Estimates for Star Earnings Performance-Based Portfolios

This table reports 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 $(\overline{EGP}_{m_{star_{j,\,t\text{-}1}}} - \overline{EGP}_{m_{nonstar_{j,\,t\text{-}1}}}) - (\overline{EGP}_{m_{star_{j,\,t\text{-}4}}} - \overline{EGP}_{m_{nonstar_{j,\,t\text{-}4}}})$ 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 based on earnings announcements made during the months from *t* to *t-2.* The portfolios are updated monthly, and the sample includes stocks with CRSP share code 10 or 11. We regress the monthly excess returns of quintile portfolios on 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% levels, respectively.

	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Alpha	0.725**	-0.384*	0.148	-0.010	-0.129	0.341
	(2.35)	(-1.89)	(0.78)	(-0.07)	(-0.80)	(1.44)
RMRF	-0.081	1.172***	1.119***	1.106***	1.109***	1.091***
	(-0.61)	(20.73)	(20.09)	(24.76)	(26.23)	(9.45)
SMB	-0.148	0.621***	0.424***	0.314***	0.426***	0.474***
	(-1.21)	(8.10)	(4.78)	(3.70)	(6.12)	(4.50)
HML	-0.100	0.248**	0.036	0.124	0.129	0.148
	(-0.46)	(2.19)	(0.41)	(1.51)	(1.26)	(0.94)
CMA	-0.241	0.014	0.220	-0.041	-0.056	-0.227
	(-0.94)	(0.09)	(1.58)	(-0.34)	(-0.42)	(-1.07)
RMW	0.327	0.083	0.068	0.110	-0.124	0.411**
	(1.52)	(0.77)	(0.55)	(0.87)	(-1.31)	(2.28)
MOM	-0.285***	-0.220***	-0.213***	-0.085	-0.206***	-0.505***
	(-3.11)	(-4.97)	(-3.55)	(-1.43)	(-3.97)	(-6.05)
N	324	324	324	324	324	324
Adj R^2	0.081	0.778	0.794	0.814	0.826	0.695

TABLE 12

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. The sample includes stocks with CRSP share code 10 or 11. 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% levels, 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**
	(2.41)	(-1.77)	(0.29)	(-0.67)	(-0.04)	(2.02)
RMRF	-0.139***	1.104***	1.022***	1.043***	1.004***	0.965***
	(-2.86)	(29.78)	(28.82)	(26.27)	(26.82)	(34.62)
SMB	-0.011	0.311***	0.321***	0.171***	0.096	0.299***
	(-0.13)	(6.16)	(5.79)	(2.82)	(1.58)	(5.61)
HML	-0.047	0.066	0.035	0.071	0.011	0.019
	(-0.39)	(0.78)	(0.37)	(0.86)	(0.19)	(0.25)
CMA	-0.108	0.024	-0.081	0.016	-0.020	-0.084
	(-0.53)	(0.23)	(-0.75)	(0.13)	(-0.21)	(-0.67)
RMW	-0.224*	-0.043	0.048	0.017	0.024	-0.267***
	(-1.79)	(-0.63)	(0.73)	(0.20)	(0.37)	(-2.90)
MOM	0.095	-0.030	-0.057	0.018	-0.053	0.064
	(1.07)	(-0.56)	(-1.49)	(0.27)	(-1.18)	(1.44)
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
	(1.31)	(-2.07)	(0.20)	(0.08)	(-0.06)	(-0.15)
RMRF	-0.123**	1.060***	1.042***	0.994***	1.015***	0.937***
	(-2.07)	(23.86)	(32.17)	(31.54)	(28.57)	(28.24)
SMB	0.022	-0.083	-0.303***	-0.194***	-0.126**	-0.061
	(0.21)	(-1.18)	(-5.55)	(-4.65)	(-2.36)	(-1.16)
HML	-0.050	0.081	0.136*	0.022	-0.227***	0.031
	(-0.34)	(0.77)	(1.87)	(0.39)	(-3.82)	(0.40)
CMA	-0.048	0.039	-0.083	0.055	0.157	-0.009
	(-0.21)	(0.31)	(-0.99)	(0.46)	(1.59)	(-0.06)
RMW	0.018	0.162**	0.041	0.121*	0.170**	0.180**
	(0.12)	(1.97)	(0.38)	(1.90)	(2.05)	(2.13)
MOM	0.101	-0.112*	0.018	-0.029	0.002	-0.012
	(0.98)	(-1.74)	(0.29)	(-0.74)	(0.03)	(-0.24)
N	444	444	444	444	444	444
Adj R^2	0.016	0.736	0.782	0.814	0.780	0.674

Internet Appendix for

Star Firms, Information Spillovers, and Predictable Industry-Level Outcomes

Vidhi Chhaochharia, Alok Kumar, Mehrshad Motahari, and Ville Rantala

A. Potential Effect of Dynamic Panel Bias

The earnings growth regressions of Table 3 include the lagged dependent variable as a predictor, and a potential concern is that, while it is an important control variable, it may cause a bias in the estimated regression coefficients. In this Appendix, we discuss the potential magnitude of the bias. We also provide results from a robustness check where we estimate comparable regressions using Arellano-Bond Generalized Method of Moments (GMM) estimation that is free from any potential dynamic panel bias.

A. 1. Panel Length and Dynamic Panel Bias

In a seminal paper, Nickell (1981) shows that the coefficient estimate bias in dynamic panel models that include the lagged dependent variable is decreasing with panel length (*T*), and approaches zero as T approaches infinity. Our panel has a relatively large *T*, which mitigates the concern that the bias has any significant impact on our results. Previous papers that show an economically significant bias typically have a much shorter panel length.[30]

Nickell (1981) provides analytic formulae for the bias in the coefficient estimate on the lagged dependent variables in a first-order autoregressive model as a function of the true autocorrelation coefficient ρ. For reasonably large values of *T*, the formula for the bias expressed as $\hat{\rho} - \rho$ is

$$plim_{N\rightarrow\infty}(\hat{\rho} - \rho) = \frac{-(1+\rho)}{T-1} \qquad (1)$$

[30] E.g., Flannery and Hankins (2013) mention that "The bias is inversely related to panel length ("*T*"), but potentially severe biases remain even with $T = 30$", which is still only 27% of our panel length. As another example, Wintoki, Linck, and Netter (2012) study dynamic panel biases in corporate governance settings and their sample has a *T* of 7.

Even in the hypothetical extreme case where the true autocorrelation coefficient ρ = 1, the maximum value for the bias with our T of 104 would be -0.01942. This value is tiny compared to the lagged dependent variable coefficient estimates we have in our regression. In Column 1 of Table 3, the coefficient is 0.582 so even with ρ = 1, the bias would amount at most to 3.3% of the coefficient estimate. Such a bias would not be sufficient to change any of our key findings.

A.2. A robustness check using Arellano-Bond estimation

To further alleviate the concern, we estimate our baseline result using Arellano-Bond estimation following the framework of Wintoki et al. (2012). We use a two-step GMM estimator with robust standard errors clustered at the industry level. Both $\overline{EGP}_{star/nonstar_{j,\,t}}$ and $\Delta EGP\ Difference_{j,t-1}$ are treated as endogenous and $\overline{EGP}_{star/nonstar_{j,\,t}}$ is instrumented using its second to fourth lags, while $\Delta EGP\ Difference_{j,t-1}$ is instrumented using its first and second lags.

To validate the instruments, we use two tests commonly used in dynamic panel GMM estimation: the AR (2) test for second-order serial correlation and the Hansen J test for over-identification. The AR (2) test checks whether there is second-order serial correlation in the residuals of the differenced equation, which would indicate that the instruments are not valid. A lack of second-order serial correlation suggests that the instruments are correctly specified. The Hansen J test, on the other hand, evaluates the overall validity of the instruments by testing whether they are uncorrelated with the error term. Together, these tests provide evidence that our model's instruments are valid and that the GMM estimator is appropriately specified.

We present our results in Appendix Table IA.8. The diagnostic tests confirm the GMM specification of our models. The AR (1) test for first-order serial correlation is significant across all models, as expected, while the AR (2) test shows no evidence of second-order serial correlation, suggesting the absence of misspecification. The Hansen test of over-identification yields p-values greater than 0.05 in all cases, indicating that the instruments used are valid. Additionally, the difference-in-Hansen test supports the exogeneity of instruments for the levels equations, with *p*-values generally above 0.05.

Column 1 of Appendix Table IA.8 shows that $\Delta EGP\ Difference_{j,t-1}$ can statistically significantly predict nonstar firms' earnings growth also when using Arellano-Bond estimation. The $\Delta EGP\ Difference_{j,t-1}$ coefficient is positive and statistically significant at the 1% level. Additionally, similar to our previous results, Column 2 shows that $\Delta EGP\ Difference_{j,t-1}$ does not statistically significantly predict star firms' earnings growth.

Internet Appendix Tables

Table IA.1
Variable Definitions

This table describes our variables and data sources.

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

Variable Name	Source	Description
$\overline{\text{EGPA}}_{star}$	I/B/E/S, and Compustat	The equal-weighted average earnings growth per total assets per share *(EGPA)* of star firms in the industry. *EGPA* is the earnings per share (EPS) in quarter *t* minus EPS in quarter *t*–4 scaled by total assets per share, defined as total assets (Compustat item AT) from the previous fiscal year divided by shares outstanding ten days before the earnings announcement date.
$\overline{\text{EGPA}}_{nonstar}$	I/B/E/S, and Compustat	The equal-weighted average earnings growth per total assets per share *(EGPA)* of nonstar firms in the industry. *EGPA* is the earnings per share (EPS) in quarter *t* minus EPS in quarter *t*–4 scaled by total assets per share, defined as total assets (Compustat item AT) from the previous fiscal year divided by shares outstanding ten days before the earnings announcement date.
EGPRCT	I/B/E/S	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*.
ES	I/B/E/S and CRSP	Quarterly consensus earnings surprise defined as ($EPS_{i,t}$ – $Consensus\ Forecast_{i,t}$)/$Price_{i,t}$. $Consensus\ Forecast_{i,t}$ is the median analyst earnings per share (EPS) forecast, $EPS_{i,t}$ is firm *i*'s actual EPS, and $Price_{i,t}$ is the share price ten days before the earnings announcement date.
$\overline{\text{ES}}_{nonstar}$	I/B/E/S and CRSP	The equal-weighted average consensus earnings surprise *(ES)* of nonstar firms in the industry.
$\overline{\text{ES}}_{star}$	I/B/E/S and CRSP	The equal-weighted average consensus earnings surprise *(ES)* of star firms in the industry.
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*.

Variable Name	Source	Description
$\overline{\text{JPG}}_{\text{star}}$	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*.
$\overline{\text{MU}}_{\text{star}}$	Compustat and Federal Reserve Economic Data	The equal-weighted average *MU* of star firms in the industry. *MU* is an industry-level annual markup measure based on the production approach of De Loecker et al. (2020) defined as sales (Compustat item SALE) divided by the sum of cost of goods sold (Compustat item COGS), selling, general, and administrative expense (Compustat item XSGA), and the user cost of capital. De Loecker et al. (2020) compute the user cost of capital as a function of the nominal interest rate minus the inflation rate plus a depreciation rate, which is set at 12% to account for exogenous depreciation rate and risk premium. All variables are US dollar deflated using the GDP deflator with base year 2010.
$\overline{\text{MU}}_{\text{nonstar}}$	Compustat and Federal Reserve Economic Data	The equal-weighted average *MU* of nonstar firms in the industry. *MU* is an industry-level annual markup measure based on the production approach of De Loecker et al. (2020) defined as sales (Compustat item SALE) divided by the sum of cost of goods sold (Compustat item COGS), selling, general, and administrative expense (Compustat item XSGA), and the user cost of capital. De Loecker et al. (2020) compute the user cost of capital as a function of the nominal interest rate minus the inflation rate plus a depreciation rate, which is set at 12% to account for exogenous depreciation rate and risk premium. All variables are US dollar deflated using the GDP deflator with base year 2010.
Number of patents filed	Kogan et al. (2017)	This is the number of patents filed during a calendar year. The data are 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 are from the Kogan et al. (2017) depository available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
$\overline{\text{OIA}}_{\text{star}}$	Compustat	The equal-weighted average, across star firms in industry *j* and quarter *t*, of the change in operating income before depreciation (Compustat item OIBDPQ) from quarter *t–4* to *t*, scaled by lagged total assets (Compustat item AT) from the previous fiscal year.

Variable Name	Source	Description
$\overline{\text{OIA}}_{\text{nonstar}}$	Compustat	The equal-weighted average, across nonstar firms in industry *j* and quarter *t*, of the change in operating income before depreciation (Compustat item OIBDPQ) from quarter *t–4* to *t*, scaled by lagged total assets (Compustat item AT) from the previous fiscal year.
OPEX Growth	Compustat	The change in operating expenses (Compustat item XOPRQ) relative to four quarters ago, scaled by total assets (Compustat item AT).
$\text{P/E Growth}_{\text{star}}$	CRSP and Compustat	$P/E\ Growth_{star\ j,t}$ is calculated as $(P/E_{star_{j,\ t}} - P/E_{star_{j,\ t\text{-}1}})/P/E_{star_{j,\ t\text{-}1}}$. $P/E_{star_{j,\ t}}$ refers to industry *j*'s sum of star firms' market capitalization in December of fiscal year *t* divided by their sum of earnings before extraordinary items (Compustat item EPSPX times shares outstanding, item CSHO) for fiscal year *t*. If $P/E_{star_{j,\ t}}$ or $P/E_{star_{j,\ t\text{-}1}}$ is negative, we replace $P/E\ Growth_{star\ j,t}$ with its most recent lag that has positive components.
$\text{P/E Growth}_{\text{nonstar}}$	CRSP and Compustat	$P/E\ Growth_{nonstar\ j,t}$ is calculated as $(P/E_{nonstar_{j,\ t}} - P/E_{nonstar_{j,\ t\text{-}1}})/P/E_{nonstar_{j,\ t\text{-}1}}$. $P/E_{nonstar_{j,\ t}}$ refers to industry *j*'s sum of nonstar firms' market capitalization in December of fiscal year *t* divided by their sum of earnings before extraordinary items (Compustat item EPSPX times shares outstanding, item CSHO) for fiscal year *t*. If $P/E_{nonstar_{j,\ t}}$ or $P/E_{nonstar_{j,\ t\text{-}1}}$ is negative, we replace $P/E\ Growth_{nonstar\ j,t}$ with its most recent lag that has positive components.
ROA	Compustat	Income before extraordinary items (Compustat item IB) divided by total assets (Compustat item AT).
ROE	Compustat	Income before extraordinary items (Compustat item IB) divided by book equity (defined as Compustat item SEQ + Compustat item TXDITC - Compustat item PSTK, where we set TXDITC and PSTK to zero if missing).
SG&A/Sales	Compustat	Selling, general, and administrative expenses (Compustat item XSGA) divided by sales (Compustat item SALE).
Technology Spillover	Bloom et al. (2013)	Pairwise score of firms' research and development (R&D) spillover measured by comparing their patents across different technology classes. The data are from the Bloom et al. (2013) depository available at https://people.stanford.edu/nbloom/research.

Variable Name	Source	Description
Vertical Integration	Frésard et al. (2020)	Pairwise vertical relatedness score measuring the annual upstream and downstream potential between firms based on textual analysis of product descriptions in 10-K filings. The data are from the VTNIC (Vertical TNIC) database, developed by Frésard et al. (2020), available at https://faculty.marshall.usc.edu/Gerard-Hoberg/FresardHobergPhillipsDataSite/index.html.
ΔCOGS/OPEX	Compustat	The change in the ratio of cost of goods sold (Compustat item COGS) to operating expenses (Compustat item XOPRQ) compared to its value four quarters earlier.
ΔEGPRCT Difference	I/B/E/S and CRSP	$\Delta EGPRCT\ Difference_{j,t}$ 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 CRSP	$\Delta EGP\ Difference_{j,t}$ 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 $\overline{EGP}_{star\ j,t}$ and $\overline{EGP}_{nonstar\ j,t}$ 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 CRSP	*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 based on earnings announcements during months from *t* to *t-2*. *EGP* is defined similarly as in *ΔEGP Difference.*
ΔEGPA Difference	I/B/E/S, and Compustat	*ΔEGPA Difference* $_{j,t}$ is calculated as follows: $$\Delta EGPA\ Difference_{j,t} = \left(\overline{EGPA}_{star\ j,t} - \overline{EGPA}_{nonstar\ j,t}\right) - \left(\overline{EGPA}_{star\ j,t-1} - \overline{EGPA}_{nonstar\ j,t-1}\right),$$ where $\overline{EGPA}_{star\ j,t}$ and $\overline{EGPA}_{nonstar\ j,t}$ are *EGPA*s of quarter *t* averaged across all star and nonstar firms in each industry, respectively.
ΔGDP Ann Growth	Bureau of Economic Analysis	The annual GDP growth in industry *j* in year *t* minus the annual GDP growth in the same industry in year *t-1*.
ΔMU Difference	Compustat and Federal Reserve Economic Data	*ΔMU Difference* $_{j,t}$ is calculated as follows: $$\Delta MU\ Difference_{j,t} = \left(\overline{MU}_{star\ j,t} - \overline{MU}_{nonstar\ j,t}\right) - \left(\overline{MU}_{star\ j,t-1} - \overline{MU}_{nonstar\ j,t-1}\right),$$ where $\overline{MU}_{star\ j,t}$ and $\overline{MU}_{nonstar\ j,t}$ are De Loecker et al. (2020) markup (*MU*) measures of year *t* averaged across all star and nonstar firms in each industry, respectively (see the $\overline{MU}_{star\ j,t}$ and $\overline{MU}_{nonstar\ j,t}$ definitions above for details).

Variable Name	Source	Description
ΔOIA Difference	Compustat	*ΔOIA Difference*$_{j,t}$ is calculated as follows: $\Delta OIA\ Difference_{j,t} = \left(\overline{OIA}_{star\ j,t} - \overline{OIA}_{nonstar\ j,t}\right) - \left(\overline{OIA}_{star\ j,t-1} - \overline{OIA}_{nonstar\ j,t-1}\right),$ where $\overline{OIA}_{star\ j,t}$ and $\overline{OIA}_{nonstar\ j,t}$ are *OIA* measures of quarter *t* averaged across all star and nonstar firms in each industry, respectively (see the $\overline{OIA}_{star\ j,t}$ and $\overline{OIA}_{nonstar\ j,t}$ definitions above for details).
ΔOperating Income COGS/OPEX Profit Margin Subcomponent	Compustat	This variable is calculated for each firm *i* as follows: $\Delta OIBDP_{Margin\left(\frac{COGS}{SALE}\right)_{i,t}} = \left[SALE_{i,t} \times \left[\left(1 - \frac{COGS_{i,t}}{SALE_{i,t}}\right) - \left(1 - \frac{COGS_{i,t-4}}{SALE_{i,t-4}}\right)\right] \times \frac{OPEX_{i,t}}{COGS_{i,t}}\right] / AT_{i,t},$ where $AT_{i,t}$ is the total assets (Compustat item AT) from the previous fiscal year, $COGS_{i,t}$ is the cost of goods sold (Compustat item COGSQ) in quarter *t*, $OPEX_{i,t}$ is the operating expenses (Compustat item XOPRQ) in quarter *t*, and $Sale_{i,t}$ is the total sales (Compustat item SALEQ) in quarter *t.*
ΔOperaring Income Profit Margin Component	Compustat	This variable is calculated for each firm *i* as follows: $\Delta OIBDP_{Margin_{i,t}} = \left[SALE_{i,t} \times \left[\left(1 - \frac{OPEX_{i,t}}{SALE_{i,t}}\right) - \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right)\right]\right] / AT_{i,t},$ where $AT_{i,t}$ is the total assets (Compustat item AT) from the previous fiscal year, $OPEX_{i,t}$ is the operating expenses (Compustat item XOPRQ) in quarter *t*, and $SALE_{i,t}$ is the total sales (Compustat item SALEQ) in quarter *t.*

Variable Name	Source	Description
ΔOperating Income Residual Profit Margin Subcomponent	Compustat	This variable is calculated for each firm *i* as follows: $$\Delta OIBDP_{Margin\left(\frac{COGS}{OPEX}\right)_{i,t}} = \left[SALE_{i,t} \times \left[\left(1 - \frac{OPEX_{i,t}}{COGS_{i,t}}\right) - \left(1 - \frac{OPEX_{i,t-4}}{COGS_{i,t-4}}\right)\right] \times \frac{COGS_{i,t-4}}{SALE_{i,t-4}}\right] / AT_{i,t},$$ where $AT_{i,t}$ is the total assets (Compustat item AT) from the previous fiscal year *t*, $COGS_{i,t}$ is the cost of goods sold (Compustat item COGSQ) in quarter *t*, $OPEX_{i,t}$ is the operating expenses (Compustat item XOPRQ) in quarter *t*, and $Sale_{i,t}$ is the total sales (Compustat item SALEQ) in quarter *t*.
ΔOperating Income Total	Compustat	This variable is calculated for each firm *i* as follows: $$\Delta OIBDP = \left(OIBDP_{i,t} - OIBDP_{i,t-4}\right) / AT_{i,t},$$ where $AT_{i,t}$ is the total assets (Compustat item AT) from the previous fiscal year and $OIBDP_t$ is the quarterly operating income before depreciation (Compustat item OIBDPQ) in quarter *t*.
ΔOperating Income Volume Growth Component	Compustat	This variable is calculated for each firm *i* as follows: $$\Delta OIBDP_{Volume_{i,t}} = \left[\left[SALE_{i,t} - SALE_{i,t-4}\right] \times \left(1 - \frac{OPEX_{i,t-4}}{SALE_{i,t-4}}\right)\right] / AT_{i,t},$$ where $AT_{i,t}$ is the total assets (Compustat item AT) from the previous fiscal year, $OPEX_{i,t}$ is the operating expenses (Compustat item XOPRQ) in quarter *t*, and $SALE_{i,t}$ is the sales in quarter *t* (SALEQ).

Table IA.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	0.22	28	0.78
2	Food services and drinking places	4	0.11	68	0.89
3	Administrative and support services	4	0.10	73	0.90
4	Farms	4	0.41	11	0.59
5	Forestry, fishing, and related activities	0	0.00	0	0.00
6	Performing arts, spectator sports, museums, and related activities	4	0.51	8	0.49
7	Amusements, gambling, and recreation industries	4	0.26	20	0.74
8	Federal Reserve banks, credit intermediation, and related activities	4	0.02	543	0.98
9	Computer systems design and related services	4	0.09	95	0.92
10	Construction	4	0.10	64	0.90
11	Computer and electronic products	4	0.02	513	0.98
12	Electrical equipment, appliances, and components	4	0.11	63	0.89
13	Fabricated metal products	4	0.10	67	0.90
14	Furniture and related products	4	0.23	23	0.77
15	Machinery	4	0.03	258	0.97
16	Miscellaneous manufacturing	4	0.19	40	0.81
17	Nonmetallic mineral products	4	0.27	20	0.73
18	Primary metals	4	0.14	44	0.86
19	Motor vehicles, bodies and trailers, and parts	4	0.07	102	0.93
20	Wood products	4	0.31	18	0.70
21	Educational services	4	0.33	15	0.67
22	Funds, trusts, and other financial vehicles	0	0.00	0	0.00
23	Ambulatory health care services	4	0.12	62	0.88
24	Hospitals and nursing and residential care facilities	4	0.22	26	0.79
25	Social assistance	4	0.51	5	0.49
26	Data processing, internet publishing, and other information services	4	0.11	103	0.89
27	Motion picture and sound recording industries	4	0.31	25	0.69
28	Publishing industries, except internet (includes software)	4	0.05	175	0.95
29	Broadcasting and telecommunications	4	0.06	130	0.94
30	Insurance carriers and related activities	4	0.05	140	0.95
31	Legal services	0	0.00	0	0.00
32	Mining, except oil and gas	4	0.17	35	0.83
33	Oil and gas extraction	4	0.06	136	0.94
34	Support activities for mining	4	0.20	30	0.81
35	Miscellaneous professional, scientific, and technical services	4	0.08	98	0.92
36	Apparel and leather and allied products	4	0.13	56	0.87

#	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	0.02	357	0.98
38	Food and beverage and tobacco products	4	0.08	93	0.93
39	Paper products	4	0.19	32	0.81
40	Petroleum and coal products	4	0.26	21	0.74
41	Plastics and rubber products	4	0.19	41	0.82
42	Printing and related support activities	4	0.27	21	0.73
43	Textile mills and textile product mills	4	0.29	24	0.71
44	Other	4	0.24	47	0.76
45	Other services, except government	4	0.32	18	0.68
46	Real estate	4	0.03	214	0.97
47	Rental and leasing services and lessors of intangible assets	4	0.10	63	0.90
48	Retail trade	4	0.04	223	0.96
49	Securities, commodity contracts, and investments	4	0.07	106	0.94
50	Warehousing and storage	0	0.00	0	0.00
51	Air transportation	4	0.25	21	0.75
52	Transit and ground passenger transportation	0	0.00	0	0.00
53	Other transportation and support activities	4	0.39	13	0.61
54	Pipeline transportation	4	0.29	18	0.71
55	Rail transportation	4	0.44	9	0.56
56	Truck transportation	4	0.23	23	0.77
57	Water transportation	4	0.43	9	0.57
58	Utilities	4	0.05	135	0.96
59	Waste management and remediation services	4	0.33	22	0.67
60	Wholesale trade	4	0.05	164	0.95

Table IA.3
Predicting Earnings Growth with Truncated *ΔEGP Difference*

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 $\Delta EGP\ Difference_{j,t-1}$ 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 $\Delta EGP\ Difference_{j,t-1}$ 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. In the regressions of this table, *ΔEGP Differencej,t-1* is truncated at the 1st and 99th percentiles. Other explanatory variables include three lagged values of $\overline{EGP}_{star/nonstar_{j,t}}$. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	Nonstar Firms (g = nonstar)			Star Firms (g = star)		
	1	2	3	4	5	6
ΔEGP Difference$_{j,\ t-1}$	0.060*	0.192***	0.183***	0.000	-0.050	-0.045
	(1.76)	(5.48)	(5.45)	(0.01)	(-1.57)	(-1.46)
$\overline{EGP}_{g_{j,t-1}}$	0.637***	0.816***	0.808***	0.645***	0.765***	0.757***
	(21.86)	(20.21)	(21.79)	(25.73)	(12.32)	(12.85)
$\overline{EGP}_{g_{j,t-2}}$		-0.230***	-0.188***		-0.179***	-0.128**
		(-6.45)	(-4.83)		(-2.71)	(-2.29)
$\overline{EGP}_{g_{j,t-3}}$			-0.069**			-0.080**
			(-2.08)			(-2.05)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,381	4,381	4,351	4,361	4,361	4,333
R^2	0.458	0.470	0.472	0.430	0.441	0.445

Table IA.4
Predicting Nonstar Firms' Earnings Growth and Earnings Surprises at the Firm Level

This table reports results from firm-level regressions explaining nonstar firms' quarterly earnings growth ($\overline{EGP}_{nonstar_{i,\ t}}$) in Columns 1–3 and earnings surprises ($\overline{ES}_{nonstar_{i,\ t}}$) in Columns 4–5. The main explanatory variable *ΔEGP Difference*$_{j,t-1}$ is defined as in Section II.D. The control variables include lagged values of $\overline{EGP}_{nonstar_{j,\ t}}$ in all models and $\overline{ES}_{nonstar_{i,\ t}}$ in Column 5. The firm-level panel regressions are weighted so that the weight applied is the inverse of the total number of nonstar firms within each industry-quarter. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. The regressions include firm and year-quarter fixed effects. Standard errors are clustered by firm. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	Earnings Growth (EGP)			Earnings Surprise (ES)	
	1	2	3	4	5
ΔEGP Difference$_{j,\ t-1}$	0.045***	0.087***	0.079***	0.014**	0.014**
	(3.10)	(4.56)	(4.12)	(2.42)	(2.41)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-1}}$	0.613***	0.692***	0.680***	0.026***	0.018**
	(23.34)	(20.84)	(21.01)	(3.32)	(2.20)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-2}}$		-0.114***	-0.043*	-0.021***	-0.019**
		(-4.30)	(-1.76)	(-2.71)	(-2.38)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-3}}$			-0.107***	0.011**	0.011**
			(-5.36)	(2.18)	(2.20)
$\overline{\mathrm{ES}}_{\mathrm{nonstar}_{j,t-1}}$					0.092***
					(2.98)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	99,346	99,346	99,264	99,346	99,346
R^2	0.224	0.225	0.226	0.255	0.258

Table IA.5
Predicting Earnings Growth Using Alternative Measures

This table reports the results of model specifications 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 two-way 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% levels, respectively.

Panel A: Earnings performance measured using difference in earnings growth						
	Nonstar Firms			Star Firms		
	1	2	3	4	5	6
EGP Difference$_{j,\,t-1}$	0.150***	0.157***	0.162***	-0.061*	-0.060*	-0.058*
	(3.07)	(3.25)	(3.43)	(-1.98)	(-1.92)	(-1.86)
$\overline{EGP}_{j,t-1}$	0.654***	0.665***	0.665***	0.602***	0.609***	0.605***
	(15.11)	(-14.45)	(-14.70)	(-13.73)	(-9.21)	(-9.91)
$\overline{EGP}_{j,t-2}$		-0.02	0.009		-0.007	0.040
		(-0.66)	(-0.34)		(-0.09)	(-0.52)
$\overline{EGP}_{j,t-3}$			-0.061			-0.088**
			(-1.34)			(-2.14)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,526	4,496	4,464	4,502	4,475	4,445
R^2	0.409	0.409	0.41	0.387	0.389	0.393

Panel B: Earnings performance measured using earnings growth percentage						
	Nonstar Firms			Star Firms		
	1	2	3	4	5	6
ΔEGPRCT Difference$_{j,\,t-1}$	0.001*	0.001*	0.001*	-0.000	-0.000	-0.000
	(1.69)	(1.93)	(1.93)	(-0.38)	(-0.59)	(-0.61)
$\overline{EGP}_{j,t-1}$	0.591***	0.620***	0.618***	0.549***	0.566***	0.564***
	(14.23)	(12.68)	(13.10)	(-14.19)	(-8.05)	(-8.66)
$\overline{EGP}_{j,t-2}$		-0.050	-0.010		-0.030	0.017
		(-1.65)	(-0.35)		(-0.42)	(-0.28)
$\overline{EGP}_{j,t-3}$			-0.069			-0.088**
			(-1.67)			(-2.05)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,317	4,317	4,292	4,295	4,295	4,271
R^2	0.430	0.431	0.435	0.366	0.367	0.372

Table IA.6
Predicting Earnings Growth Based on Operating Income Growth Scaled by Total Assets

This table reports regression results explaining star and nonstar firms' growth in operating income scaled by total assets (*OIA*) at the industry level ($\overline{OIA}_{star/nonstar\ j,t}$). Columns 1 to 3 and 4 to 6 use the *ΔOIA Difference*$_{j,t-1}$ to explain nonstar and star firms' growth in operating income to assets, respectively. *OIA* is defined as the operating income before depreciation (Compustat item OIBDPQ*)* in quarter *t* minus the operating income in quarter *t*–4, scaled by total assets (Compustat item AT) from the previous fiscal year. The main explanatory variable *ΔOIA Difference*$_{j,t-1}$ is calculated as ($\overline{OIA}_{star_{j,\ t-1}} - \overline{OIA}_{nonstar_{j,\ t-1}}$)−($\overline{OIA}_{star_{j,\ t-2}} - \overline{OIA}_{nonstar_{j,\ t-2}}$). $\overline{OIA}_{star_{j,\ t}}$ and $\overline{OIA}_{nonstar_{j,\ t}}$ refer to the equal-weighted average OIA of star firms and nonstar firms in industry *j* in quarter *t*, respectively. Other explanatory variables include three lagged values of $\overline{OIA}_{star/nonstar\ j,t}$. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	Nonstar Firms (g = nonstar)			Star Firms (g = star)		
	1	2	3	4	5	6
ΔOIA Difference$_{j,\ t-1}$	0.073***	0.070***	0.067***	-0.044*	-0.039	-0.036
	(7.00)	(3.61)	(3.63)	(-1.93)	(-1.15)	(-1.11)
$\overline{OIA}_{g_{j,t-1}}$	0.551***	0.546***	0.546***	0.550***	0.543***	0.547***
	(11.86)	(9.41)	(9.48)	(14.63)	(7.86)	(8.14)
$\overline{OIA}_{g_{j,t-2}}$		0.008	0.039		0.010	0.045
		(0.21)	(1.01)		(0.17)	(0.88)
$\overline{OIA}_{g_{j,t-3}}$			-0.048			-0.069*
			(-1.43)			(-1.83)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,581	4,581	4,562	4,545	4,545	4,503
R^2	0.402	0.402	0.406	0.392	0.392	0.395

Table IA.7
Predicting Earnings Growth with Subcomponents of *ΔEGP Difference*

This table reports the results of model specification 3 of Table 3 using subcomponents of the main explanatory variable as separate predictors. $\Delta EGP_{star/nonstar\ j,t-1}$ is calculated as ($\overline{EGP}_{star/nonstar_{j,\ t-1}} - \overline{EGP}_{star/nonstar_{j,\ t-2}}$). $\overline{EGP}_{star_{j,\ t}}$ 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. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	1	2
$\Delta EGP_{star_{j,t-1}}$	0.187***	
	(4.97)	
$\Delta EGP_{nonstar_{j,t-1}}$	-0.050*	
	(-1.90)	
$\overline{EGP}_{star_{j,t-1}}$		0.229***
		(4.94)
$\overline{EGP}_{star_{j,t-2}}$		-0.139***
		(-2.72)
$\overline{EGP}_{nonstar_{j,t-1}}$	0.561***	0.494***
	(9.15)	(8.46)
$\overline{EGP}_{nonstar_{j,t-2}}$		0.038
		(1.28)
$\overline{EGP}_{nonstar_{j,t-3}}$	-0.050	-0.054
	(-1.09)	(-1.22)
Year-Quarter FE	Yes	Yes
Industry FE	Yes	Yes
N	4,438	4,438
R^2	0.415	0.417

Table IA.8
Predicting Earnings Growth Using Arellano–Bond Dynamic Panel Estimation

This table reports results from Arellano–Bond dynamic panel regressions explaining star and nonstar firms' average quarterly earnings growth ($\overline{EGP}_{star/nonstar_{j,\ t}}$) at the industry level. The model is estimated using two-step GMM estimation. The main explanatory variable is *ΔEGP Difference*$_{j,t-1}$. The endogenous variables, $\overline{EGP}_{star/nonstar_{j,\ t}}$ and *ΔEGP Difference*$_{j,t-1}$, are instrumented using their 2nd–4th and 1st–2nd lags, respectively. The reported AR(1) and AR(2) statistics are for first-order and second-order serial correlation tests in the first-differenced residuals, with the null hypothesis of no serial correlation. The Hansen test of over-identification is based on the null hypothesis that all instruments are valid. The difference-in-Hansen test for exogeneity is conducted under the null hypothesis that the instruments used for the equations in levels are exogenous. The sample period is from 1994 to 2020. The regressions include year fixed effects, treated as exogenous instruments. Detailed variable definitions are presented in Appendix Table IA.1. All *t*-statistics are based on robust industry-clustered standard errors and are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	Earnings Growth (EGP)	
	Nonstar	Star
	1	2
ΔEGP Difference$_{j,\ t-1}$	0.091***	-0.034
	(3.21)	(-1.33)
$\overline{EGP}_{nonstar_{j,t-1}}$	0.784***	
	(10.18)	
$\overline{EGP}_{star_{j,t-1}}$		0.747***
		(18.43)
$\overline{ES}_{nonstar_{j,t-1}}$		
$\overline{ES}_{star_{j,t-1}}$		
Year FE	Yes	Yes
AR(1) test (*p*-value)	0.000	0.000
AR(2) test (*p*-value)	0.350	0.760
Hansen test of over-identification (*p*-value)	0.080	0.560
Diff-in-Hansen tests of exogeneity (*p*-value)	0.065	0.815
N	4,335	4,315

Table IA.9
Predicting Cost Structure Changes

This table presents results from regressions explaining nonstar firms' average *COGS Growth*, *OPEX Growth*, and *ΔCOGS/OPEX*. *COGS Growth* is defined as the change in cost of goods sold (Compustat item COGS) relative to its value four quarters ago, scaled by total assets (Compustat item AT). *OPEX Growth* is defined similarly, as the change in operating expenses (Compustat item XOPRQ) relative to four quarters ago, scaled by total assets (Compustat item AT). *ΔCOGS/OPEX* measures the change in the ratio of cost of goods sold (Compustat item COGS) to operating expenses (Compustat item XOPRQ) compared to its value four quarters earlier. 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 nonstar firms' quarterly earnings growth ($\overline{EGP}_{nonstar_{j,\ t}}$). All dependent and independent variables are standardized across the pooled panel to have a mean of zero and a standard deviation of one. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. We include industry-quarter observations with at least five nonstar firms. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	COGS Growth	OPEX Growth	ΔCOGS/OPEX
	1	2	3
ΔEGP Difference$_{j,\ t-1}$	0.070**	0.072**	0.016
	(2.23)	(2.41)	(0.54)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-1}}$	0.142***	0.127***	0.062
	(2.81)	(2.77)	(1.19)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-2}}$	-0.036	-0.041**	0.005
	(-1.52)	(-2.10)	(0.13)
$\overline{\mathrm{EGP}}_{\mathrm{nonstar}_{j,t-3}}$	0.045**	0.045**	0.013
	(2.16)	(2.04)	(1.28)
Year-Quarter FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	4,446	4,446	4,446
R^2	0.427	0.442	0.095

Table IA.10
Predicting Price Markup Changes

This table reports results from regressions explaining nonstar and star firms' change in annual price markup ($\Delta MU_{star/nonstar_{i,\,t}}$), defined as ($\overline{MU}_{star/nonstar_{j,\,t}} - \overline{MU}_{star/nonstar_{j,\,t\text{-}1}}$) at the industry level. $\overline{MU}_{star_{j,\,t}}$ and $\overline{MU}_{nonstar_{j,\,t}}$ refer to the equal-weighted average *MU* of star firms and nonstar firms in industry *j* in year *t*, respectively. *MU* is an industry-level annual markup measure based on the production approach of De Loecker et al. (2020). Specifically, *MU* is defined as sales (Compustat item SALE) divided by the sum of cost of goods sold (Compustat item COGS), selling, general, and administrative expense (Compustat item XSGA), and the user cost of capital. All variables are US dollar deflated using the GDP deflator with base year 2010. The main explanatory variable $\Delta MU\ Difference_{j,t\text{-}1}$ is calculated as ($\overline{MU}_{star_{j,\,t\text{-}1}} - \overline{MU}_{nonstar_{j,\,t\text{-}1}}$)$-$($\overline{MU}_{star_{j,\,t\text{-}2}} - \overline{MU}_{nonstar_{j,\,t\text{-}2}}$). The control variables include lagged values of the dependent variable. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1984 to 2020. The regressions include firm and year fixed effects. Standard errors are two-way clustered by year and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	Nonstar Firms (g = nonstar)	**Star Firms** (g = star)
	1	2
ΔMU Difference$_{j,\,t-1}$	0.053**	-0.001
	(2.33)	(-0.03)
$\overline{MU}_{g_{j,t-1}}$	-0.089*	-0.012
	(-1.76)	(-0.19)
$\overline{MU}_{g_{j,t-2}}$	-0.134*	-0.092
	(-1.74)	(-1.47)
$\overline{MU}_{g_{j,t-3}}$	-0.061	-0.146***
	(-1.62)	(-3.20)
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	1,371	1,325
R^2	0.125	0.148

Table IA.11

Technology Spillover, Vertical Integration, and Earnings Growth: Alternative Specifications

This table reports results from regressions explaining change in nonstar firms' operating income growth components defined in Section III.C. The regressions use industry-quarter observations based on averages among nonstar firms. The dependent variable in Columns 1 and 2 is the volume component of operating income growth and the dependent variable in Columns 3 and 4 is the profit margin component. The main explanatory variable $\Delta EGP\ Difference_{j,t-1}$ is defined as in Section II.D. $High\ Technology\ Spillover_{nonstar_{j,t-1}}$ is a dummy variable that takes the value one if the industry's *Technology Spillover* score is above the quarter-specific median among all industries. $High\ Vertical\ Integration_{nonstar_{j,t-1}}$ is a dummy variable that takes the value one if the industry's quarter-specific *Vertical Integration* score is above median. Details about the calculation of these scores are provided in Table 8. The regressions include interaction terms between these variables and $\Delta EGP\ Difference_{j,t-1}$. We also include pairwise interaction terms between the two dummies and all control variables to account for subsample heterogeneity (coefficients are omitted for brevity). All continuous dependent and independent variables are standardized across the pooled panel to have a mean of zero and a standard deviation of one. Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. We include industry-quarter observations with at least five nonstar firms. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	$\Delta Operating\ Income_{Volume}$		$\Delta Operating\ Income_{Margin}$	
	1	2	3	4
ΔEGP $\text{Difference}_{j,\,t-1}$	0.055	0.080**	0.045	0.048**
	(1.44)	(2.44)	(1.36)	(2.17)
High Technology $\text{Spillover}_{\text{nonstar}_{j,t-1}}$	0.101		-0.041	
	(1.07)		(-0.59)	
High Vertical $\text{Integration}_{\text{nonstar}_{j,t-1}}$		0.004		-0.030
		(0.04)		(-0.47)
ΔEGP $\text{Difference}_{j,\,t-1}$ × High Technology $\text{Spillover}_{\text{nonstar}_{j,t-1}}$	0.075*		0.123**	
	(1.68)		(2.17)	
ΔEGP $\text{Difference}_{j,\,t-1}$ × High Vertical $\text{Integration}_{\text{nonstar}_{j,t-1}}$		-0.013		0.081*
		(-0.33)		(1.96)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-1}}$	0.177**	0.298***	0.384***	0.244***
	(2.17)	(3.73)	(7.22)	(3.13)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-2}}$	-0.014	-0.028	-0.073***	-0.050*
	(-0.43)	(-0.69)	(-2.88)	(-1.98)
$\overline{\text{EGP}}_{\text{nonstar}_{j,t-3}}$	0.014	0.015	-0.046	-0.014
	(0.71)	(0.53)	(-1.22)	(-0.42)
Year-Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	4,015	4,401	4,015	4,400
R^2	0.369	0.371	0.187	0.191

Table IA.12

Predicting Earnings Surprises Using Variables Scaled by Total Assets

This table reports results from regressions explaining industry star and nonstar firms' average quarterly earnings surprises scaled by total assets per share ($\overline{ESA}_{star/nonstar_{j,\,t}}$) at the industry level. *ESA* is the difference between actual earnings per share and analysts' consensus forecast, scaled by total assets per share, defined as total assets (Compustat AT) from the previous fiscal year divided by shares outstanding ten days before the earnings announcement date. The main explanatory variable *ΔEGPA Difference*$_{j,t-1}$ is calculated as $(\overline{EGPA}_{star_{j,\,t-1}} - \overline{EGPA}_{nonstar_{j,\,t-1}}) - (\overline{EGPA}_{star_{j,\,t-2}} - \overline{EGPA}_{nonstar_{j,\,t-2}})$. $\overline{EGPA}_{star_{j,\,t}}$ and $\overline{EGPA}_{nonstar_{j,\,t}}$ refer to the equal-weighted average earnings growth per total assets per share *(EGPA)* of star firms and nonstar firms in industry *j* in quarter *t*, respectively. *EGPA* is the earnings per share (EPS) in quarter *t* minus EPS in quarter *t*–4 scaled by total assets per share. The control variables include lagged values of $\overline{EGPA}_{nonstar_{j,\,t}}$ and $\overline{ESA}_{nonstar_{j,\,t}}$ (in Columns 1–2) or $\overline{EGPA}_{star_{j,\,t}}$ and $\overline{ESA}_{star_{j,\,t}}$ (in Columns 3–4). Detailed variable definitions are presented in Appendix Table IA.1. The sample period is from 1994 to 2020. The regressions include industry and year-quarter fixed effects. Standard errors are two-way clustered by year-quarter and industry. *t*-statistics are reported in parentheses below the coefficients. ***, **, and * report significance at the 1%, 5%, and 10% levels, respectively.

	Earnings Surprise (ES)			
	Nonstar Firms (1-2) (g=nonstar)		Star Firms (3-4) (g=star)	
	1	2	3	4
ΔEGPA Difference$_{j,\,t-1}$	0.021***	0.022***	-0.004	-0.005
	(3.88)	(3.97)	(-0.55)	(-0.63)
$\overline{\mathrm{EGPA}}_{g_{j,t-1}}$	0.048***	0.034***	0.023*	0.013
	(5.78)	(3.77)	(2.00)	(1.28)
$\overline{\mathrm{EGPA}}_{g_{j,t-2}}$	-0.026***	-0.023***	-0.011	-0.007
	(-3.14)	(-2.69)	(-0.80)	(-0.44)
$\overline{\mathrm{EGPA}}_{g_{j,t-3}}$	0.017**	0.017**	0.010	0.011
	(2.16)	(2.16)	(1.08)	(1.16)
		0.144***		0.082*
		(3.49)		(1.72)
Year-Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	4,443	4,443	4,435	4,435
R^2	0.207	0.222	0.130	0.135

Table IA.13
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 1–3 of Table 3 that predict nonstar firms' earnings growth and Panel B reports the results of model specifications 1–2 of Table 9 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 IA.14
Raw Returns of Earnings Performance-Based Portfolios

This table reports the 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 based on earnings announcements during months *t*, *t-1*, and *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% levels, respectively.

	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Value-weighted average returns	0.594**	0.698*	1.195***	1.031***	0.806**	1.292***
	(2.03)	(1.81)	(3.46)	(3.06)	(2.10)	(3.20)
N	324	324	324	324	324	324

Table IA.15
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 corresponding to model specifications 1–3 of Table 3 that predict nonstar firms' earnings growth and Panel B reports the results corresponding to specifications 1–2 of Table 9 that predict consensus earnings surprises. Panel C reports the results corresponding to model specifications 1–3 of Table 10 that predict nonstar firms' earnings announcement returns. Details of the specifications and control variables are reported in Tables 3, 9, and 10. 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$_{j, t-1}$		-0.014	-0.012
		(-0.56)	(-0.44)
Stars' Avg Announcement Return$_{j, t-1}$			-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 IA.16
Substitute Star Firms' Performance in Star Earnings Performance-Based Portfolios

This table provides results from a portfolio analysis that is identical to Table 12 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 12.

	Q5 - Q1	Q1	Q2	Q3	Q4	Q5
Alpha	-0.133	0.092	-0.147	-0.109	0.387**	-0.041
	(-0.40)	(0.33)	(-0.88)	(-0.68)	(2.29)	(-0.17)
RMRF	0.148	1.093***	1.089***	1.139***	0.985***	1.241***
	(1.27)	(12.92)	(19.86)	(21.43)	(16.69)	(15.02)
SMB	-0.498**	0.938***	0.486***	0.376***	0.279***	0.439***
	(-2.39)	(7.16)	(6.38)	(4.96)	(3.46)	(3.22)
HML	-0.045	0.273*	0.227**	0.125	0.050	0.228
	(-0.25)	(1.85)	(2.58)	(1.29)	(0.58)	(1.35)
CMA	-0.088	-0.243	0.092	0.064	-0.049	-0.331*
	(-0.30)	(-1.08)	(0.56)	(0.49)	(-0.33)	(-1.66)
RMW	0.341	-0.061	0.016	-0.027	-0.157	0.281**
	(1.30)	(-0.28)	(0.13)	(-0.26)	(-1.11)	(2.20)
MOM	-0.089	-0.314***	-0.149***	-0.104	-0.340***	-0.403***
	(-0.62)	(-2.95)	(-2.60)	(-1.50)	(-6.81)	(-6.09)
N	324	324	324	324	324	324
Adj R^2	0.089	0.731	0.808	0.823	0.783	0.728