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# Does Main Street Benefit from What Benefits Wall Street?

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## Abstract

Yes. We show that aggregate stock returns predict aggregate U.S. employment, despite the industrial composition of publicly traded firms differing markedly from that of all firms, and the representativeness of public firms declining over time. We also show that appropriately reweighted stock returns predict industry and local labor market outcomes. We find the strongest evidence of an alignment of interests between shareholders and workers in the manufacturing sector, despite its declining labor share of output. Our findings suggest that at quarterly frequencies, product demand shocks are more important drivers of industry- and city-level stock returns than technology shocks.

## I. Introduction

Are stock returns relevant for the economic well-being of households? Although stocks account for a negligible fraction of household wealth, they may be important for households because they contain information about human capital.[1] Indeed, standard macroeconomic models that model stock returns based on a

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[1]Kuhn, Schularick, and Steins (2020) provide a detailed breakdown of the composition of U.S. household wealth. See also Poterba (2000) and Smith, Zidar, and Zwick (2022). Households have some indirect exposure to the stock market through pension funds, but publicly traded equities account for slightly less than half of pension fund holdings (Andonov and Rauh (2022). Lustig, Van Nieuwerburgh, and Verdelhan (2013) and Palacios (2015) show that human capital accounts for more than 90% of aggregate wealth. Giglio, Maggiori, Stroebel, and Utkus (2021) show that households' consumption decisions are correlated with stock returns, indicating that households react to information about publicly traded stocks.

representative firm and a balanced growth path suggest that shocks that benefit capital must also benefit labor, on average.[2] For many years, a relatively constant labor share of GDP supported these models as a good first approximation of the macroeconomy, such that the shocks that benefit equity holders would also benefit labor.

However, for two potentially related reasons, economists increasingly question the connection between the labor market and the returns on capital of the large firms that dominate the stock market. First, the rise of superstar firms, which may have different dynamics than private firms (Davis, Haltiwanger, Jarmin, and Miranda (2006), Decker, Haltiwanger, Jarmin, and Miranda (2016), Grullon, Larkin, and Michaely (2019), and Autor, Dorn, Katz, Patterson, and Van Reenen (2020), and a decrease in the number of listed firms (see Doidge, Karolyi, and Stulz (2017)) have led to the possibility that publicly traded firms have become less representative of the firms in the overall economy. Second, recent decades have seen a marked decline in the share of output going to workers in both the United States and other high-income countries, suggesting that, rather than increasing the demand for labor, the shocks that benefit capital may be at the expense of labor.[3] Indeed, Acemoglu and Restrepo (2020) offer compelling empirical evidence that advances in robotic technology in particular are labor-displacing and lead to a decrease in both employment and wages. Perhaps as a result of these trends, the popular press has also questioned the relevance of the stock market for households.[4]

In this article, we use detailed establishment-level panel data to assess the validity and importance of the concerns that the declining representativeness of publicly traded firms and/or the decline in the labor share has made stock returns less relevant for households. We first evaluate the representativeness of publicly traded firms in the United States over time. We find that publicly traded firms are not representative of the industrial composition of the U.S. economy and that the industrial representativeness has declined in recent decades. However, the geographic distribution of employment in publicly traded firms closely resembles the geographic distribution of all U.S. employment.

We then show that despite the lack of industrial representativeness of publicly traded firms, the market excess return has been a good predictor of aggregate employment and wage growth since 1990. Although this finding is consistent with recent evidence on returns and GDP growth (see, e.g., Baron, Verner, and Xiong (2021) for cross-country evidence), it contrasts with earlier work documenting a weaker relationship between returns and output (e.g., Stock and Watson (2003)).[5]

[2] See, for example, Jones (2005).

[3] See, for example, Karabarbounis and Neiman (2013), Autor et al. (2020), Covarrubias and Philippon (2020), and De Loecker, Eeckhout, and Unger (2020). Syverson (2019) reviews the literature thoroughly and concludes that there is robust evidence for a declining labor share of income, but not yet sufficient evidence for a macroeconomy-wide increase in market power. Rossi-Hansberg, Sarte, and Trachter (2021) and Berger, Herkenhoff, and Mongey (2022) find evidence that measures of firm market power in local labor markets have actually declined over time, in contrast to trends at the national level. Eisfeldt, Falato, and Xiaolan (2022) show that high-skilled workers have significant equity-based compensation, which may lead to understating the share of output that goes to labor income.

[4] See, for example, Cohen (2018), Friedberg (2020), Phillips (2020), and Vigna (2020).

[5] A large related literature studies the reaction of stock market returns to news about the real economy. This literature has more success in finding a relationship than does research that uses the information in

The aggregate predictive relationship may hold because the shocks that drive the market return, such as monetary policy news and shifts in aggregate risk tolerance, are beneficial to labor even though many other shocks that increase the returns to capital do not benefit labor. Furthermore, it is possible that technological shocks at the aggregate level lead to a redistribution of workers across industries, which increases labor demand but diminishes the returns to labor within a given industry (Jones (2005), Acemoglu and Restrepo (2019)). To better understand whether the shocks that affect the stock returns of specific industries or cities also benefit labor within those industries or cities, we next look at the predictive content of stock market returns at a more granular level.[6]

To do so, we measure the employment footprint of a given publicly traded firm in each industry and city in which it has employees. We then weigh the stock return for that firm by its employment footprint in those industries and cities. Finally, after doing this for every publicly traded firm, we sum the weighted stock returns across all publicly traded firms with a presence in a given industry/city. We call this the *exposure-weighted stock return* (EWSR) for that industry/city. Our data allow us to use time-fixed effects to control for changes in aggregate discount rates and other macroeconomic factors.

We then estimate the association between the EWSR and the total employment growth and find that a higher EWSR is associated with significant employment growth at both the industry and city levels. A 1-standard-deviation increase in the quarterly EWSR for the average 4-digit NAICS industry is associated with an increase in employment growth of over 90% relative to the mean. An analogous change in quarterly EWSR for the average city, which we define using core-based statistical areas (CBSAs), is associated with an increase in employment growth during the following quarter of 40% relative to the mean. These results are robust to controlling for the market excess return, which indicates that industry- and city-weighted returns have incremental predictive power for employment relative to the overall market. We also find that a higher EWSR predicts faster wage growth, although we find weaker predictive power for wages than for employment. A 1-standard-deviation increase in quarterly EWSR at the industry (city) level is associated with an increase in average nominal wage per worker growth of 14.5% (9.6%) relative to the mean.

Our granular approach allows us to identify whether this positive relationship between the returns to capital and the returns to labor is broad-based or specific to certain industries or cities. Most surprisingly, we find that stock market returns predict employment and wage growth most strongly in the manufacturing sector, a sector that has experienced a significant decline in the labor share of output in recent

stock prices to forecast the real economy. See, for example, Boyd, Hu, and Jagannathan (2005), Cready and Gurun (2010), Savor and Wilson (2013), Brusa, Savor, and Wilson (2019), Kurov, Sancetta, Strasser, and Wolfe (2019), Smajlbegovic (2019), Gürkaynak, Kisacikoğlu, and Wright (2020), and Nagel and Zu (2021).

[6]Alfaro, Chari, Greenland, and Schott (2020) also use disaggregated information from publicly traded firms to make inferences about the macroeconomy. They look at the impact of COVID-19 infections on the economy by using the change in the market value of publicly traded firms within an industry and weighting those changes according to the size of the industry relative to total employment in an area.

decades. Although we find the strongest relation in manufacturing industries, we see the same positive relation across a range of industries with varying skill levels and trends in the labor share.

Our finding of a positive relation in manufacturing industries is insightful about what types of idiosyncratic shocks have benefited capital in recent years. Acemoglu and Restrepo (2019) document that the technology shocks that have affected manufacturing in recent decades have largely been labor displacing. If the shocks that drove stock returns in the manufacturing sector were these same technology shocks, we would observe wages and employment declining with positive abnormal stock returns. We are thus left to conclude that the industry- and city-level shocks that have benefited capital in recent years are most likely product demand shocks.

Product demand shocks may incentivize firms to adopt existing automation technology over the long run. This is because positive demand shocks can force firms to pay higher wages in the short run when labor market frictions make hiring costly. These higher wages can subsequently encourage firms to adopt labor-saving automation technology. We find that negative shocks have stronger predictive power for employment, but that positive shocks have stronger predictive power for wages, consistent with this possibility. Such endogenous technology adoption is in line with recent findings by Zhang (2019) and Ouimet, Simintzi, and Ye (2021). It is also consistent with the long-term divergence between stock market wealth and the labor share of output documented in Greenwald, Lettau, and Ludvigson (2022).

We discuss how different types of shocks might theoretically affect capital and labor in Section II. Section III describes our data and analyzes the representativeness of public firms for economy-wide employment. In Section IV, we document the predictive power of stock market returns for the labor market at the national level. In Section V, we analyze whether the EWSR predicts industry and local labor market changes. Section VI concludes.

## II. Mechanisms

Before turning to the data, we review the economic theory that motivates why shocks that increase stock returns may or may not improve labor market outcomes. We conceive of the firm as owned by the same entity that owns the capital, as in standard asset-pricing models with production (see, e.g., Jermann (1998)), such that firm profits flow directly to the owners of capital. For purposes of exposition, we focus on industries, but our discussion also applies to cities. Heterogeneity in productivity by industry likely arises from the different technologies used in different industries. The divergence in city-level total factor productivity (TFP) documented by Hsieh and Moretti (2019) suggests that there may be significant heterogeneity in production functions across cities as well.

In economic models of asset pricing, there are three different types of shocks that increase stock returns and that may also affect the labor market: i) shocks to the aggregate discount rate, either because of changes in monetary policy expectations or changes in the representative investor's risk preferences; ii) shocks to an industry's technology; and iii) shocks to the demand for an industry's product. A shock to the aggregate discount rate will affect the returns on physical and human capital in the same direction. Even though the most basic asset-pricing model illustrates how a fall in the discount rate increases stock prices, recent work by Hall (2017) and Belo, Donangelo, Lin, and Luo (2022) has demonstrated theoretically and empirically that a fall in the discount rate also increases employment when labor markets have search frictions. Chen and Zhang (2011) also study the relationship between discount rates and the labor market in a model with search frictions and find contrasting effects of a fall in the discount rate in the short run and the long run.

The effect of technology shocks on labor is much more ambiguous, particularly at the industry level. The technology shocks we have in mind are those that introduce new technologies that firms can use. We consider the choice to adopt existing technologies as endogenous to a firm's opportunity cost (see Zhang (2019). Although, at the aggregate level, technological improvements have long thought to be labor-augmenting in the long run (Jones (2005)), it is possible that certain types of technology shocks may decrease labor demand in a particular industry and lead to a reallocation of labor across industries. Perhaps motivated in part by the empirical decline in labor's share of output, economists have recently developed models in which positive technology shocks are labor-displacing rather than labor-augmenting (see Acemoglu and Restrepo (2018), (2019), (2020)).

In Acemoglu and Restrepo (2018), firms in given industries produce output by combining high- and low-skilled tasks, and each task can be produced exclusively with capital or with a combination of capital and labor. They model automation as an increase in the number of tasks that can be produced solely with capital, and they show that an increase in automation can reduce employment and wages. In contrast, an increase in the productivity of labor, which increases the number of high-skilled tasks that cannot be automated, always increases wages. Therefore, technology shocks that increase automation may not benefit labor, whereas shocks that increase the productivity of labor can benefit labor.

Acemoglu and Restrepo (2018) further model dynamics at the aggregate level by endogenizing the investment in automation technology. Although their comparative statics do not rule out the possibility of labor demand going to 0 in the long run, the authors suggest that there is a self-correcting tendency of automation to reduce the demand for further automation by reducing the relative cost of low-skilled labor. Given the comparative statics in the dynamic version of their model, in addition to the possibility of reallocation of labor across industries in response to a sectoral shock, it seems more likely to observe a negative relationship between returns and labor market outcomes at the industry level as compared with the aggregate level.

The third type of shock that can increase stock returns in an equilibrium model with labor demand is a shock to the demand for a firm's product. In standard dynamic general equilibrium models (e.g., Smets and Wouters (2007)), an increase in demand will also increase wages and employment. Recent empirical work by Carlsson, Messina, and Skans (2021) has found that, at the firm level, demand shocks are associated with more hiring than firm-level technology shocks, perhaps because some firm-level technology shocks are the sort of labor-displacing improvements envisioned by Acemoglu and Restrepo (2018).

To summarize, theory predicts that shocks to the aggregate discount rate that increase stock returns will also increase employment and wages. The effect of technological shocks that increase stock returns is theoretically ambiguous, but these shocks are more likely to lead to a decrease in employment at the industry level than at the aggregate level. Thus, finding a positive relationship between stock returns and employment and wage growth at the industry level after controlling for changes in the aggregate discount rate would indicate that the dominant shocks driving returns are unlikely to be automation shocks. Finally, product demand shocks that increase stock returns will also increase employment and wages.

# III. The Industrial and Geographic Composition of Publicly Traded Firms

## A. Data

Our main data set is establishment-level employment data from the YourEconomy Time Series (YTS). YTS data begin in 1997 and cover all U.S. public and private establishments. YTS aggregates data from the Infogroup Business Data historical files, which are provided by the Business Dynamics Research Consortium at the University of Wisconsin–Madison. Kunkle (2018) details Infogroup's methodology to gather the data underlying YTS:

> To develop its data sets, Infogroup operates a 225-seat call center that makes contact with over 55,000 businesses each and every day in order to record and qualify company information. During a typical month, 15% of the entire Infogroup business data set is re-verified. On average, 150,000 new businesses are added while 100,000 businesses are removed each month, capturing the dynamic business churn happening in the economy. Infogroup's team also identifies new companies through the U.S. Yellow Pages, county-level public sources on new business registrations, industry directories, and press releases.

Kunkle (2018) also compares the YTS data with employment data from the U.S. Bureau of Labor Statistics (BLS). Additional information on the YTS data is available at https://wisconsinbdrc.org/data.

We use Compustat to identify publicly traded firms. We take three steps to merge the set of all firms in Compustat with the firms in YTS. We begin with the 15,425 Compustat firms active over the 1997–2017 period that were not missing data on assets, employment, and capital expenditures. Our first step in the merge is to look for a match in the YTS data using stock market tickers. In the second step, we attempt to match the remaining Compustat firms with YTS firms based on headquarters names and ZIP codes. In the third and final step, we match based on the headquarters 2-digit NAICS code, the headquarters ZIP code, and a substring of the headquarters firm name.

In total, we are able to match 9,296 of the Compustat firms to YTS firms. The unmatched Compustat firms tend to be smaller (median assets of $100 million) than the firms in the full sample (median assets of $163 million). The median and average assets of the merged Compustat firms are $240 million and $4.5 billion, respectively. Thus, we match about two-thirds of firms by number and about four-fifths of firms by asset value.

In addition to Compustat and YTS, we use several data sets from the BLS. For our comparison between employment in publicly traded firms and employment in all firms, we use the Quarterly Census of Employment and Wages (QCEW; a comprehensive set of employment and wage data that, according to the BLS, covers "more than 95% of U.S. jobs, available at the county, MSA, state, and national levels by industry"). To construct annual employment at various NAICS levels of aggregation, we use the QCEW Aggregation Level Codes, which provide aggregate employment numbers at the 2-, 4-, or 6-digit NAICS code. To construct annual employment at the state and county levels, we use the FIPS code. In addition to employing the QCEW data to construct aggregate employment, we use them to measure wage compensation within CBSAs and 4-digit NAICS codes.

For our aggregate employment growth regressions, we use the BLS Current Employment Survey (CES) data to construct a quarterly aggregate employment series. The CES data are based on a comprehensive monthly survey of over 145,000 establishments and nearly 700,000 workers. For our aggregate wage growth regressions, we use the Bureau of Economic Analysis (BEA) seasonally adjusted "Compensation of Employees, Received: Wage and Salary Disbursements" series to construct a quarterly nominal wage series.

For our granular employment growth regressions, we rely on two BLS data sources that provide monthly employment at the city and industry levels. For city-level employment, we use the Local Area Unemployment Statistics (LAUS). According to the U.S. BLS, the LAUS data are the "official source of civilian labor force and unemployment data for over 7,500 unique subnational areas." Federal programs use the LAUS to allocate unemployment benefit funds. For industry-level employment, we rely on CES data. We restrict our sample to private-sector (as opposed to government-related) employment by excluding the 2-digit NAICS codes 92 and 99. For our granular wage growth regressions, we use data from the QCEW on city- and industry-level nominal wages.

For our granular wage growth regressions, we use nominal wage data from the QCEW. The QCEW reports both total wages and average *weekly* wage by quarter at the 4-digit NAICS and CBSA levels. Wages are defined as "reported total compensation paid during the calendar quarter, regardless of when the services were performed," and the data exclude proprietors, the unincorporated self-employed, unpaid family members, certain farm and domestic workers, and railroad workers covered by the railroad unemployment insurance system.[7]

We use CRSP to gather stock return data at both the aggregate market level (value-weighted CRSP and S&P 500 indexes) and the individual firm level, as well as the value-weighted CRSP index dividend data. We gather factor returns from Ken French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). We use the St. Louis Federal Reserve Bank's FRED website

[7]The BLS' complete definition of wages is: "in most states covered employers' reported total compensation paid during the calendar quarter, regardless of when the services were performed. A few state laws, however, specify that wages be reported for or be based on the period during which services are performed rather than the period during which compensation is paid. Under most state laws or regulations, wages include bonuses, stock options, severance pay, the cash value of meals and lodging, tips, and other gratuities. In some states, wages also include employer contributions to certain deferred compensation plans, such as 401(k) plans." See https://www.bls.gov/opub/hom/cew/concepts.htm for more information.

(https://fred.stlouisfed.org/) for the construction of the term spread, the default spread, and the relative Treasury bill rate. We gather quarterly GDP data from the BEA and consumption-to-aggregate wealth ratio (CAY) data from Martin Lettau's website (https://sites.google.com/view/martinlettau/data). Finally, we gather quarterly employment forecast data from the Philadelphia Fed's Survey of Professional Forecasters (SPF) database.

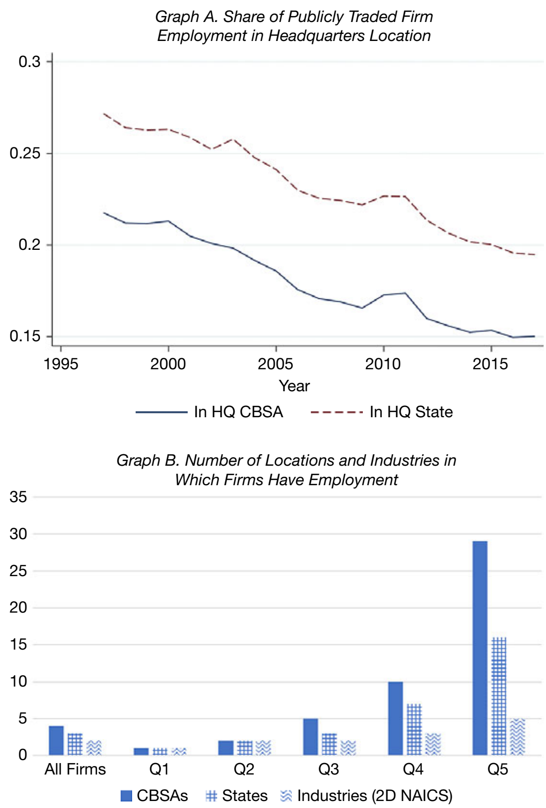
### Headquarters-Level Versus Establishment-Level Information

A key benefit of matching the YTS data to Compustat is that it allows us to identify Compustat firms' employment in geographic areas and industries different than that of their headquarters. For example, if a firm has its headquarters in New York state but also has operations and employees in Texas and California, we are able to use the YTS match to identify the number of employees at the California and Texas locations.

FIGURE 1

Geographic and Industry Dispersion of Employment in Publicly Traded Firms

Graph A of Figure 1 plots the proportion of employees of publicly traded firms in the HQ state or core-based statistical area (CBSA) for the average firm in each year. Graph B plots, for the median firm within each size bucket, the number of states, CBSAs, and 2-digit NAICS industries with at least 1 employee. The size quintiles are based on total assets in Compustat, and YTS–Compustat merged data are used.

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Disaggregating employment into the relevant geographic areas and industries is important because, as Graph A of Figure 1 shows, most employment in publicly traded firms is not at the firm's headquarters location. This graph uses the YTS–Compustat merged data to display, for the average firm in each year, the percentage of all employees located in the headquarters state (top series) or headquarters CBSA (bottom series). At the CBSA level, the average firm has roughly 22% of employees in its headquarters location in 1997, but that number drops to about 15% by 2017. This graph uses firms in all industries, and the finding is not driven by firms with most of their employment in nontradable or construction industries; in fact, the figure looks broadly similar when we exclude firms with NAICS codes that Mian and Sufi (2014) define as falling within those industries. Figure A.1 in the Supplementary Material decomposes the time trends based on whether firms are in nontradable/construction or tradable industries. Graph A illustrates a similar downward trend in nontradable and construction industries, and Graph B displays a decline over time in tradable industries.

As an alternative way to demonstrate the importance of establishment-level aggregation, we show, in Graph B of Figure 1, the number of distinct CBSAs, states, and 2-digit NAICS industries in which publicly traded firms have at least 1 employee. This graph aggregates the Compustat–YTS merged data across the entire 1997–2017 sample period and buckets firm-years into five quintiles based on total assets. The first cluster of bars is for all firms, whereas the Q1 (Q5) cluster summarizes data for the smallest (largest) 20% of firm-years. Within each bucket, the number of CBSAs, states, and 2-digit NAICS industries in which the *median* firm has at least 1 employee is reported. For example, the median firm in the Q3 bucket (which comprises the 40th to 60th percentiles of total assets) has at least 1 employee in five CBSAs, three states, and two industries.

Graph B of Figure 1 also illustrates that the median publicly traded firm has operations in multiple cities and states and that larger firms have more geographically dispersed operations. Similarly, it shows that most firms have operations in multiple industries and that larger firms are more likely to have such operations.[8] These findings are consistent with the fact that the industry code of a firm's headquarters that appears in regulatory filings is usually not the industry code of all the firm's employment, particularly for large firms.[9]

## B. How Representative Are Publicly Traded Firms?

We analyze how representative public firms are of all firms by first measuring the association between publicly traded firm employment and total

[8]García and Norli (2012) and Bernile, Kumar, and Sulaeman (2015) previously studied firm geographic diversification using 10-K statements.

[9]Cohen and Lou (2012) use the Compustat segment data to document that less than half of the value-weighted CRSP universe consists of firms that operate in only one industry. A large literature studies whether industrially diversified stocks have higher or lower returns than firms concentrated in one industry (e.g., Whited (2001), Custódio (2014)). Villalonga (2004) and Tate and Yang (2015) use more detailed data on establishments than is available in Compustat and find a greater degree of diversification, compared with studies that measure industrial diversification based only on the Compustat segment data.

employment. Specifically, we establish the correlation between the share of public firm employment and the share of total employment that each industry and geography account for. We compute two measures of employment for this analysis: COMPUSTAT_SHARE and BLS_SHARE. COMPUSTAT_SHARE measures the percentage of total Compustat (public firm) employees in a given industry or geographic unit in a given year, and BLS_SHARE measures the percentage of total employees (both public and private firms) in a given industry or geographic unit in a given year.

As an example of how we construct the shares, assume that in 2005 there are 1,000 total employees reported in the entire cross section of Compustat. Assume also that 100 of these employees are at firms with 2-digit NAICS code 52 (finance and insurance) and that the other 900 are at firms with different NAICS codes. In this case, the variable COMPUSTAT_SHARE for NAICS code 52 in year 2005 is equal to $100/1,000=0.10$. We treat the geographic units analogously.

For both the industries and geographies, the BLS data on total employment do not allow us to disentangle establishment from headquarters employment. However, using the Compustat–YTS merged data set, we are able to construct *public employment* at both the establishment level and the headquarters level. We do so for both the industry and geographic analyses, which is important because a single firm may have establishments in distinct states or industries. For example, assume that in 2005 there are 1,000 total employees reported in the entire cross section of Compustat. Assume also that 100 of these employees are at firms headquartered in North Carolina, but that the firms headquartered in North Carolina also have establishments in Louisiana. If the establishments in Louisiana are home to 50 of the 100 employees and the establishments in North Carolina are home to the other 50, then the state-level measure of COMPUSTAT_SHARE based on headquarters is 0.10 for NC and 0 for LA. In contrast, the state-level measure of COMPUSTAT_SHARE based on establishments is 0.05 for NC and 0.05 for LA.

Table 1 defines our variables, and Table 2 summarizes the data used in the representativeness analysis. Because the YTS data begin in 1997, we compute statistics at the establishment level over the 1997–2017 period. However, we compute statistics at the HQ level from 1990 to 2017 since we have Compustat data back to 1990, which is also when the disaggregated BLS data start. The statistics in Table 2 illustrate that there is no meaningful difference between public and total employment shares when the data are summarized over the entire sample period.

To investigate time and cross-sectional variation, Figures 2–5 plot the differences over time between public and total employment.[10] In each graph, we plot the total share of employment in a given industry/geography on the horizontal axis and the public share of employment in that industry/geography on the vertical axis. We also plot a line at 45 degrees. If the total employment share is equal to the public employment share, then the dot for a given industry/geography lies on the 45-degree line. However, if the public employment share is larger (smaller) than the total employment share, then the dot lies above (below) the line. A greater deviation from the 45-degree line indicates a larger difference between

[10]Tables A.2 and A.3 in the Supplementary Material provide the data underlying Figures 2 and 3.

TABLE 1

**Variable Definitions**

| Variable | Description |
|---|---|
| COMPUSTAT_SHARE | Employment of Compustat firms within an industry or geographic region as a percentage of total Compustat employment |
| BLS_SHARE | Employment of all firms within an industry or geographic region as a percentage of total BLS employment |
| YTS_SHARE | Employment of all firms within an industry or geographic region as a percentage of total YTS employment |
| EXRET | Excess log return of the value-weighted CRSP index |
| EMP_CHANGE | Aggregate employment growth |
| REL_TB | Current 3-month Treasury bill yield minus its prior 4-quarter average |
| TERM | 10-year Treasury yield minus 3-month Treasury yield |
| BAA_AAA | Difference between Moody's Seasoned Baa and Aaa corporate bond yields |
| CAY | Log consumption-to-aggregate wealth ratio of Lettau and Ludvigson (2001) |
| DP | Log of previous 12 months of dividends per share on the S&P 500 minus logarithm of the current S&P 500 index level |
| GDP_CHANGE | Growth in seasonally adjusted real GDP |
| D_WAGERECEIVED | Growth in aggregate wages |
| NEXTGROWTH | Consensus forecast of next quarter employment growth from the Philadelphia Fed Survey of Professional Forecasters data |
| CBSA_EMP_GR (M) | Monthly employment growth at the core-based statistical area (CBSA) level |
| CBSA_EMP_GR (Q) | Quarterly employment growth at the CBSA level |
| CBSA_EMP_GR (H) | Six-month employment growth at the CBSA level |
| CBSA_EWSR (M) | Monthly EWSR at the CBSA level |
| CBSA_EWSR (Q) | Quarterly EWSR at the CBSA level |
| CBSA_EWSR (H) | Six-month EWSR at the CBSA level |
| IND_EMP_GR (M) | Monthly employment growth at the NAICS4 level |
| IND_EMP_GR (Q) | Quarterly employment growth at the NAICS4 level |
| IND_EMP_GR (H) | Six-month employment growth at the NAICS4 level |
| IND_EWSR (M) | Monthly EWSR at the NAICS4 level |
| IND_EWSR (Q) | Quarterly EWSR at the NAICS4 level |
| IND_EWSR (H) | Six-month EWSR at the NAICS4 level |
| CBSA_TOTAL_WAGE_GR (Q) | Quarterly total wage growth at the CBSA level |
| CBSA_AVG_WK_WAGE_GR (Q) | Quarterly average weekly wage growth at the CBSA level |
| IND_TOTAL_WAGE_GR (Q) | Quarterly total wage growth at the NAICS4 level |
| IND_AVG_WK_WAGE_GR (Q) | Quarterly average weekly wage growth at the NAICS4 level |
| $\text{CBSA\_EWSR}^{\text{HQ}}$ (Q) | Quarterly headquarters EWSR at the CBSA level (see equation (5)) |
| $\text{IND\_EWSR}^{\text{HQ}}$ (Q) | Quarterly headquarters EWSR at the NAICS4 level (see equation (5)) |
| IND_DEVIATION | (COMPUSTAT_SHARE − BLS_SHARE)/BLS_SHARE at the 4-digit NAICS level |
| CBSA_DEVIATION | (COMPUSTAT_SHARE − BLS_SHARE)/BLS_SHARE at the CBSA level |

TABLE 2

**Employment Shares: Full Sample**

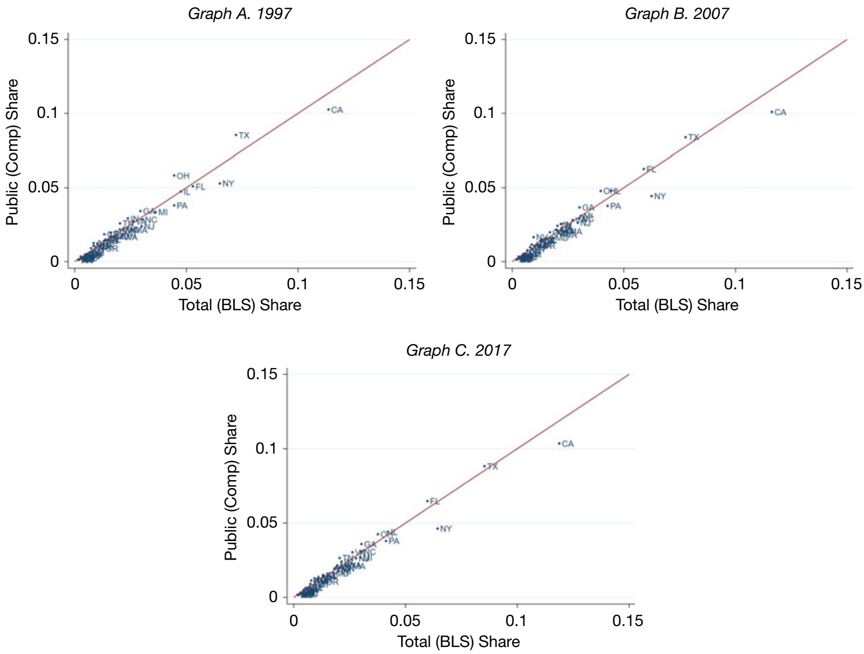
Table 2 reports employment shares for the YTS–Compustat merged, BLS, and full Compustat data sets. For the HQ-level results, the time period is 1990–2017, and the COMPUSTAT_SHARE is based on the full Compustat data set. For the establishment-level results, the time period is 1997–2017, and the COMPUSTAT_SHARE is based on the YTS–Compustat merged data set. All variables are defined in Table 1.

| Variable | *N* | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| NAICS 2-digit (establishment) | | | | | | |
| COMPUSTAT_SHARE | 378 | 0.056 | 0.021 | 0.078 | 0.000 | 0.361 |
| BLS_SHARE | 378 | 0.056 | 0.047 | 0.041 | 0.004 | 0.159 |
| NAICS 2-digit (headquarters) | | | | | | |
| COMPUSTAT_SHARE | 504 | 0.056 | 0.025 | 0.078 | 0.001 | 0.407 |
| BLS_SHARE | 504 | 0.056 | 0.049 | 0.045 | 0.004 | 0.205 |
| State level (establishment) | | | | | | |
| COMPUSTAT_SHARE | 1,071 | 0.020 | 0.014 | 0.020 | 0.001 | 0.104 |
| BLS_SHARE | 1,071 | 0.020 | 0.013 | 0.021 | 0.002 | 0.119 |
| State level (headquarters) | | | | | | |
| COMPUSTAT_SHARE | 1,428 | 0.020 | 0.008 | 0.025 | 0.000 | 0.114 |
| BLS_SHARE | 1,428 | 0.020 | 0.013 | 0.021 | 0.001 | 0.125 |

FIGURE 2

**Employment Shares by State Based on Establishment Location**

In Figure 2, Compustat employment shares are based on location (state) of firm establishments using the YTS–Compustat merged database. BLS_SHARE is plotted on the *x*-axis, and COMPUSTAT_SHARE is plotted on the *y*-axis. All variables are defined in Table 1.




employment in publicly traded companies and employment as a whole. We plot the deviation in 10-year periods that span our sample period for 2-digit NAICS industries and state-level geographic groupings.

To more formally measure the strength of the correlation, we also regress total employment on public employment using the following equation:

$$\text{(1)} \qquad \text{BLS\_SHARE}_{i,t} = \beta_0 + \beta_1 \,\text{COMPUSTAT\_SHARE}_{i,t} + \varepsilon_{i,t},$$

where $\text{BLS\_SHARE}_{i,t}$ is the share of total employment in an industry or geographic region $i$ in year $t$ and $\text{COMPUSTAT\_SHARE}_{i,t}$ is the share of employment in publicly traded firms in an industry or geographic region $i$ in year $t$, using either headquarters- or establishment-level aggregation. When $\text{COMPUSTAT\_SHARE}_{i,t}$ is at the HQ level, we use the full Compustat database, and when $\text{COMPUSTAT\_SHARE}_{i,t}$ is at the establishment level, we use the YTS–Compustat merged database.

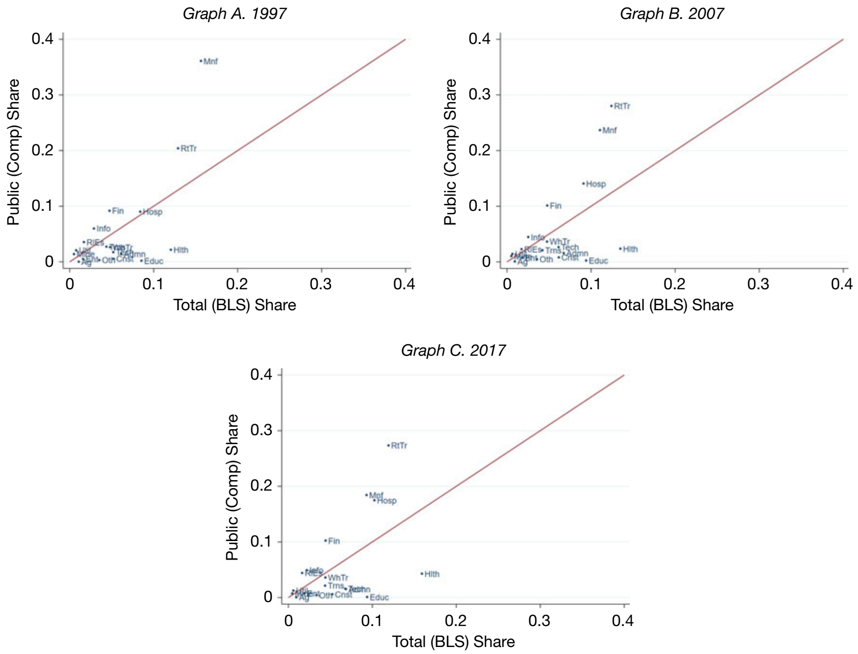
The regressions are weighted by the BLS share of employment in a given state or 2-digit NAICS. Figure 6 plots the $R^2$s for each regression at both the state and 2-digit NAICS levels over time.

At the industry level, two aspects of the graphical and regression results are worth noting. First, Figures 3 and 5 illustrate that, during our sample period, certain

FIGURE 3

Employment Shares by 2-Digit NAICS Based on Establishment Industry

In Figure 3, Compustat employment shares are based on the 2-digit NAICS industry of firm establishments using the YTS–Compustat merged database. BLS_SHARE is plotted on the *x*-axis, and COMPUSTAT_SHARE is plotted on the *y*-axis. All variables are defined in Table 1.




industries are consistently overrepresented or underrepresented in the public market. Specifically, manufacturing (NAICS 31–33) is consistently overrepresented: Its employment share in publicly traded firms is, on average, 2.1 times higher than its share in total U.S. employment. Retail trade (NAICS 44 and 45) is also overrepresented, with a public employment share 1.3 times higher than its share of total firms. Conversely, the health care industry (NAICS 62) is underrepresented: Its share of employment in public firms relative to all firms is less than 0.25.[11]

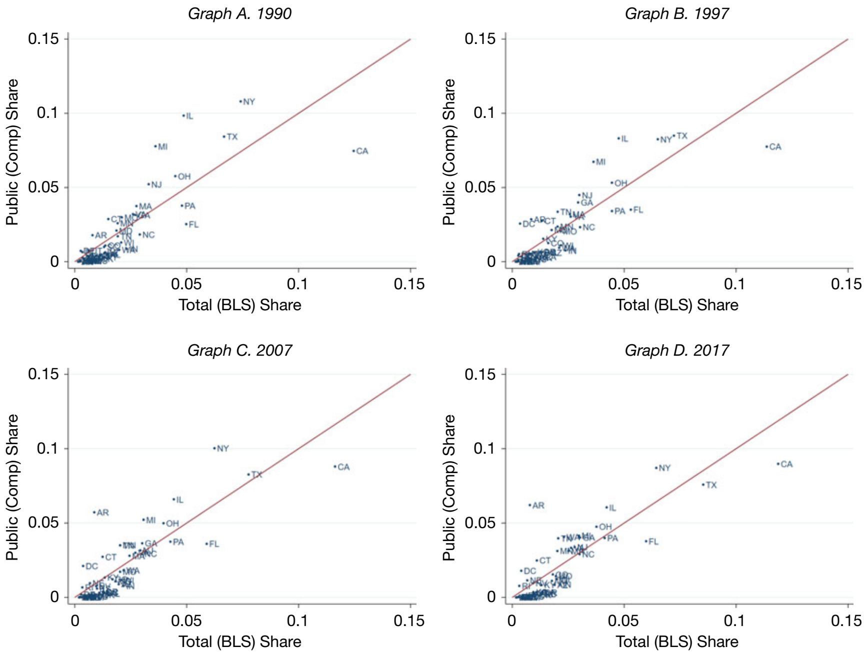
The second key industry-level result is that, cross-sectionally, as Figure 6 illustrates, public employment explains less than 70% of the variation in total employment in all years in the sample. Moreover, the explanatory power of the publicly traded market has declined. The $R^2$s for the 2-digit NAICS regressions decline consistently from 1990 to 2017 and are particularly low following the 2008 financial crisis. By the end of the sample period, the $R^2$s at the HQ level (establishment level) indicate that publicly traded firms explain only about 40%

[11]Our finding that publicly traded firms are significantly overrepresented in some industries and underrepresented in others does not necessarily indicate that public and private firms are dissimilar *within* industries. In Appendix B of the Supplementary Material, we explore the similarity between public and private firms within industries by focusing on employment dynamics.

FIGURE 4

Employment Shares by State Based on Firm HQ Location

In Figure 4, Compustat employment shares are based on location (state) of firm headquarters using the full Compustat database. BLS_SHARE is plotted on the *x*-axis, and COMPUSTAT_SHARE is plotted on the *y*-axis. All variables are defined in Table 1.




(16%) of the variation in total employment.[12] These findings with respect to time variation are consistent with the contemporaneous work of Schlingemann and Stulz (2022), who show, using HQ aggregation, that the industrial representativeness of the public market for the total economy has declined over time.

In contrast to our industry-level results, Figures 2 and 4 reveal that the geographic distribution of the employment of publicly traded firms is similar to that of all firms. This similarity is illustrated by the fact that most states lie close to the diagonal, regardless of whether we use the HQ state (Figure 4) or the establishment state (Figure 2). The similarity is further borne out in Figure 6, which shows a high correlation between public and total employment, particularly when using establishment location. Although the association becomes weaker when we use headquarters location, the average explanatory power of public employment for total employment is still nearly 75%. Thus, there is unlikely to be a significant bias

[12]Although the focus of our article is not on why the industrial composition of public firms differs from that of all firms, in Appendix C of the Supplementary Material, we examine drivers of the likelihood of being public. In particular, we examine whether firm size and age primarily drive whether a firm is public. If older, larger firms are more likely to be public than younger, smaller firms, then the differences in composition across industries may be driven by certain industries' comprising mostly older, larger firms. Our results suggest that size and age do not entirely explain the likelihood of being public and that certain industries are inherently more likely to have public firms.

FIGURE 5

**Employment Shares by 2-Digit NAICS Based on Firm HQ Industry**

In Figure 5, Compustat employment shares are based on the 2-digit NAICS industry of headquarters using the full Compustat database. BLS_SHARE is plotted on the *x*-axis, and COMPUSTAT_SHARE is plotted on the *y*-axis. All variables are defined in Table 1.

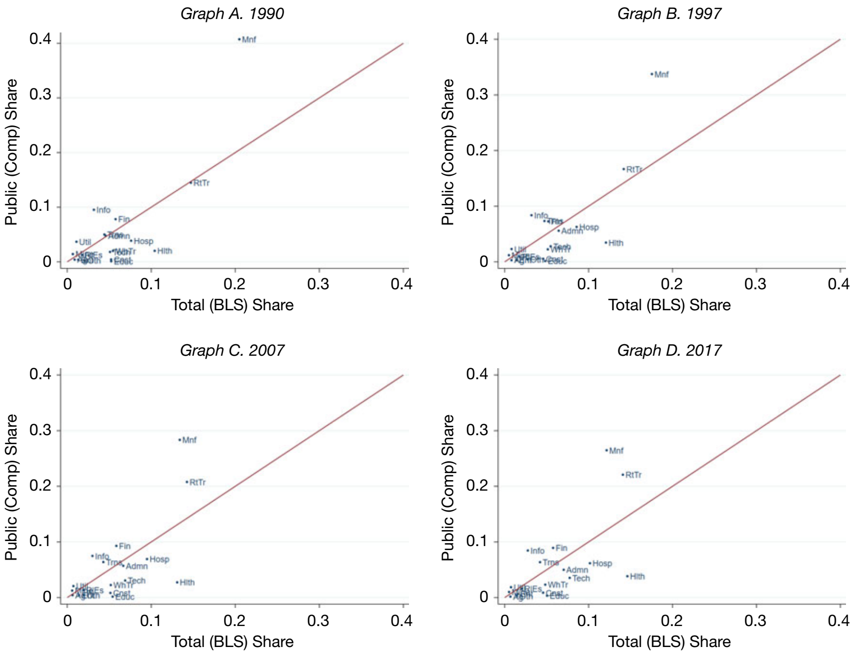
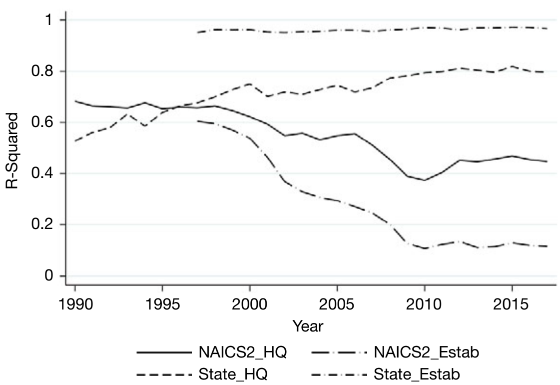



FIGURE 6

**Explanatory Power of Public Employment for Total Employment over Time**

Figure 6 plots the $R^2$ from a weighted cross-sectional regression of the total employment share in a particular NAICS code or geography (BLS_SHARE) on the public firm employment share (COMPUSTAT_SHARE). The weights are based on the total employment share for the given industry or geographic unit. Larger values indicate that employment in publicly traded firms is more representative of all employment. "Estab" indicates that employment is allocated based on the actual establishment location or industry, whereas "HQ" indicates that all employment in the firm is allocated to the location or industry of the headquarters.



https://doi.org/10.1017/S0022109022001569 Published online by Cambridge University Press

against certain U.S. regions when inferring the regions' total employment from data on publicly traded firms.

## IV. Aggregate Returns and Labor Market Outcomes

We begin by analyzing the relationship between returns and employment at the aggregate level from 1990 to 2017. Based on a survey of literature until the late 1990s, Stock and Watson (2003) suggest that aggregate stock returns perform relatively poorly in consistently predicting changes in aggregate output. More recent findings by Baron et al. (2021) suggest that equity returns do in fact predict GDP. Given the mixed evidence, we examine whether aggregate stock returns strongly predict employment in the United States over a more recent time period.

Our primary independent variable measures the returns to the entire market of U.S. publicly traded companies. In particular, we use the excess log return on the value-weighted CRSP index at either the monthly or quarterly frequency.[13] We subtract the log risk-free return from the log value-weighted CRSP return to construct the excess log returns. We thus compute:

$$\mathrm{EXRET}_t = \mathrm{VWCRSP}_t - \mathrm{RF}_t,$$

where $\mathrm{VWCRSP}_t$ is the logarithm of the value-weighted CRSP index return during time $t$ and $\mathrm{RF}_t$ is the logarithm of the risk-free rate at time $t$.[14]

Columns 1–3 in Panel A of Table 3 report the results of regressing monthly employment growth on 1-month lags of EXRET and controls. Each column includes calendar-month fixed effects to account for the fact that the data are not deseasonalized. In column 1, we use only the 1-month lag of excess market returns, whereas in column 2, we add a 1-month lag of the dependent variable. Finally, column 3 uses three lags of both excess returns and employment growth. The results suggest that the market excess return has explanatory power for aggregate employment since 1990. The variable EXRET is positive and significant in all specifications, indicating that the 1-month lagged market return predicts employment growth.

At the quarterly frequency, rows 1–10 of Table 4 summarize the data, and columns 4–6 in Panel A of Table 3 report the same set of specifications as columns 1–3. Overall, excess returns are positively associated with 1-quarter-ahead employment growth in all specifications. In addition to employment, we investigate the predictive power of returns for aggregate nominal wage growth. Despite a positive relationship between returns and employment, it is unclear whether returns would also be positively correlated with wages. We use the BEA's seasonally adjusted "Compensation of Employees, Received: Wage and Salary Disbursements" series to estimate quarterly nominal wage growth from 1990 to 2017, and we regress it on

[13]The results of our analysis are qualitatively unchanged if we instead use the narrower S&P 500 index.

[14]At the quarterly frequency, we first compute quarterly log returns as the sum of monthly log returns, then estimate the excess return.

TABLE 3

Market Returns and Aggregate Employment and Wages

Panel A of Table 3 reports the results of estimating regressions of employment and wage growth on lagged excess log stock market returns and controls. In columns 1–3, the dependent variable is monthly employment growth; in columns 4–6, the dependent variable is quarterly employment growth; and in columns 7–9, the dependent variable is quarterly wage growth. Data are from CRSP, the BLS, and the BEA from 1990 to 2017. Variables with "L*t*_" prefixes are lagged *t* time periods relative to the dependent variable. Panel B reports the results of estimating regressions of quarterly employment growth on lagged excess log stock market returns and controls. Data in columns 1–3 are from CRSP, the BLS, FRED, the BEA, Martin Lettau's website, and the Philadelphia Fed Survey of Professional Forecasters (SPF) from 2003Q4 to 2017. Data in columns 4–6 exclude the SPF data and are available from 1990 to 2017. Variables with "L*t*_" prefixes are lagged *t* quarters relative to the dependent variable. All variables are defined in Table 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

*Panel A. Market Returns and Aggregate Employment and Wages*

| | Employment Growth | | | | | | Wage Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| | Monthly | | | Quarterly | | | Quarterly | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| L_EXRET | 0.0084** (0.0036) | 0.0059** (0.0024) | 0.0065*** (0.0020) | 0.0191** (0.0087) | 0.0128*** (0.0032) | 0.0132*** (0.0034) | 0.0460** (0.0195) | 0.0436** (0.0185) | 0.0480*** (0.0173) |
| L2_EXRET | | | 0.0035** (0.0015) | | | 0.0059** (0.0027) | | | 0.0204 (0.0127) |
| L3_EXRET | | | 0.0030* (0.0016) | | | 0.0055* (0.0029) | | | 0.0160 (0.0117) |
| L_EMP_CHANGE | | 0.5784*** (0.0519) | 0.2447*** (0.0528) | | 0.8256*** (0.0505) | 0.6509*** (0.1112) | | | |
| L2_EMP_CHANGE | | | 0.1674*** (0.0505) | | | 0.1951 (0.1234) | | | |
| L3_EMP_CHANGE | | | 0.3677*** (0.0502) | | | −0.0916 (0.0928) | | | |
| L_D_WAGERECEIVED | | | | | | | | 0.1444 (0.1013) | −0.0424 (0.1047) |
| L2_D_WAGERECEIVED | | | | | | | | | 0.1904** (0.0924) |
| L3_D_WAGERECEIVED | | | | | | | | | 0.1803** (0.0818) |
| No. of obs. | 336 | 336 | 336 | 112 | 112 | 112 | 112 | 112 | 112 |
| Adj. $R^2$ | 0.9510 | 0.9678 | 0.9753 | 0.9036 | 0.9765 | 0.9783 | 0.1388 | 0.1517 | 0.2580 |
| Cal. time FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Panel B. Market Returns and Aggregate Employment and Wages: Quarterly Frequency Robustness*

| | Employment Growth | | | Wage Growth | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| L_EXRET | 0.0126* (0.0065) | 0.0121* (0.0069) | 0.0121** (0.0059) | 0.0254*** (0.0092) | 0.0229*** (0.0087) | 0.0224** (0.0093) |
| L2_EXRET | | | −0.0019 (0.0061) | | | 0.0035 (0.0122) |
| L3_EXRET | | | 0.0025 (0.0044) | | | 0.0103 (0.0130) |
| L_EMP_CHANGE | | 0.1124 (0.3050) | 0.2855 (0.3351) | | | |
| L2_EMP_CHANGE | | | 0.3983* (0.2016) | | | |
| L3_EMP_CHANGE | | | −0.0071 (0.1324) | | | |
| L_D_WAGERECEIVED | | | | | −0.2781*** (0.0998) | −0.3120*** (0.1040) |
| L2_D_WAGERECEIVED | | | | | | −0.1321 (0.0943) |
| L3_D_WAGERECEIVED | | | | | | −0.0045 (0.0923) |
| L_REL_TB | 0.0013** (0.0005) | 0.0012** (0.0005) | 0.0010* (0.0005) | 0.0019 (0.0012) | 0.0025* (0.0013) | 0.0027** (0.0012) |
| L_TERM | −0.0002 (0.0004) | −0.0002 (0.0004) | 0.0000 (0.0004) | −0.0014* (0.0008) | −0.0018** (0.0008) | −0.0022*** (0.0008) |
| L_BAA_AAA | −0.0029** (0.0013) | −0.0029** (0.0013) | −0.0035** (0.0015) | −0.0040 (0.0036) | −0.0069** (0.0027) | −0.0073* (0.0037) |

*(continued on next page)*

TABLE 3 (continued)

Market Returns and Aggregate Employment and Wages

| | | | | | | |
|---|---|---|---|---|---|---|
| L_CAY | −0.0839<br>(0.0609) | −0.0835<br>(0.0618) | −0.1006*<br>(0.0517) | 0.0039<br>(0.0498) | −0.0243<br>(0.0480) | −0.0156<br>(0.0467) |
| L_DP | 0.0036<br>(0.0032) | 0.0035<br>(0.0033) | 0.0045<br>(0.0029) | 0.0010<br>(0.0011) | 0.0015<br>(0.0011) | 0.0015<br>(0.0011) |
| L_GDP_CHANGE | 0.0061<br>(0.0686) | −0.0000<br>(0.0674) | 0.0152<br>(0.0555) | 0.6566***<br>(0.1474) | 0.7331***<br>(0.1454) | 0.7599***<br>(0.1606) |
| L_NEXTGROWTH | 0.0085***<br>(0.0020) | 0.0070<br>(0.0048) | −0.0006<br>(0.0063) | | | |
| No. of obs. | 56 | 56 | 56 | 112 | 112 | 112 |
| Adj. $R^2$ | 0.9797 | 0.9793 | 0.9814 | 0.4424 | 0.4893 | 0.4826 |
| Cal. qtr FEs | Yes | Yes | Yes | Yes | Yes | Yes |

lags of the market excess return. The results are reported in columns 7–9 in Panel A of Table 3. Overall, the results are consistent with the findings for employment. Market excess returns positively predict nominal wage growth across all three specifications.

To investigate whether the predictive power of the market return since 1990 is sensitive to other financial or macroeconomic information, we focus on the quarterly data. We reestimate the specifications from columns 4–9 in Panel A of Table 3 using a number of additional control variables. First, we include the relative Treasury bill rate REL_TB (e.g., Fama (1981)), which is equal to the current 3-month Treasury bill rate minus its previous 4-quarter average. Second, we include the Treasury term premium TERM and the default spread BAA_AAA (e.g., Fama and French (1989), Fama (1990)). The former is equal to the difference between the 10-year and 3-month Treasury, and the latter is equal to the difference between the Moody's Seasoned Baa Corporate Bond Yield and the Moody's Seasoned Aaa Corporate Bond Yield. Third, we include the dividend yield on the value-weighted CRSP index DP (e.g., Campbell and Shiller (1988), Fama and French (1988)), which, following Chen and Zhang (2011), we compute as the logarithm of the past 12 months of dividends per share minus the logarithm of the S&P 500 index level. Monthly dividends on the value-weighted index are computed by subtracting the value-weighted return without dividends from the value-weighted return with dividends. Fourth, we include the consumption-to-aggregate wealth ratio CAY of Lettau and Ludvigson (2001), which we download from Martin Lettau's website. Fifth, we include the change in real GDP GDP_CHANGE as a macroeconomic control. Finally, in the employment growth regressions, we control for the consensus forecast of quarterly employment growth, which we call NEXTGROWTH, and calculate it using the Philadelphia Fed's SPF data. This data series is only available beginning in the 4th quarter of 2003. Specifically, we control for the quarter $q-1$ mean forecast of employment growth from $q-1$ to $q$, such that the control variable captures the previous quarter's forecast of employment for the quarter in which we measure actual employment growth.[15]

[15]Because the SPF does not produce wage forecasts, we do not include any forecasted variables in the wage growth regressions.

TABLE 4

Summary Statistics for Labor Market Predictions

Table 4 presents summary statistics for variables used in aggregate and geographic/industry-level employment prediction models. The first 10 rows summarize the quarterly data used in the analysis in Section IV, and the remaining rows summarize the data used in the analysis in Section V. Data are from Compustat, CRSP, YTS, BLS, the St. Louis Fed's FRED database, the BEA, Ken French's website, the Philadelphia Fed, and Martin Lettau's website. All EWSRs are computed using log returns. All variables are defined in Table 1.

| Variable | *N* | Mean | p50 | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| EXRET | 112 | 0.011 | 0.023 | 0.082 | −0.280 | 0.179 |
| EMP_CHANGE | 112 | 0.003 | 0.002 | 0.014 | −0.035 | 0.026 |
| D_WAGERECEIVED | 112 | 0.011 | 0.011 | 0.010 | −0.045 | 0.037 |
| REL_TB | 112 | −0.112 | −0.014 | 0.606 | −1.860 | 1.235 |
| TERM | 112 | 1.822 | 1.853 | 1.103 | −0.630 | 3.610 |
| BAA_AAA | 112 | 0.954 | 0.882 | 0.392 | 0.560 | 3.023 |
| CAY | 112 | 0.005 | 0.006 | 0.016 | −0.028 | 0.033 |
| DP | 112 | −10.805 | −11.030 | 0.717 | −11.75 | −9.110 |
| GDP_CHANGE | 112 | 0.006 | 0.006 | 0.006 | −0.022 | 0.018 |
| NEXTGROWTH | 57 | 0.232 | 0.348 | 0.332 | −1.092 | 0.531 |
| CBSA_EMP_GR (M) | 202,826 | 0.0005 | 0.0009 | 0.0143 | −0.0483 | 0.0495 |
| CBSA_EMP_GR (Q) | 67,042 | 0.0012 | 0.0001 | 0.0255 | −0.0763 | 0.0984 |
| CBSA_EMP_GR (H) | 33,096 | 0.0020 | 0.0014 | 0.0365 | −0.1139 | 0.1368 |
| CBSA_EWSR (M) | 210,156 | −0.0007 | −0.0002 | 0.0171 | −0.0485 | 0.0442 |
| CBSA_EWSR (Q) | 70,052 | −0.0020 | −0.0011 | 0.0309 | −0.0887 | 0.0805 |
| CBSA_EWSR (H) | 35,032 | −0.0040 | −0.0033 | 0.0400 | −0.1147 | 0.1004 |
| CBSA_AVG_WAGE_GR (Q) | 63,974 | 0.0092 | 0.0085 | 0.0590 | −0.1376 | 0.1656 |
| CBSA_TOT_WAGE_GR (Q) | 63,974 | 0.0114 | 0.0136 | 0.0709 | −0.1630 | 0.1910 |
| CBSA_EWSR_HQ (Q) | 70,052 | −0.0001 | 0.0000 | 0.0029 | −0.1112 | 0.0641 |
| IND_EMP_GR (M) | 54,969 | 0.0004 | 0.0008 | 0.0213 | −0.0875 | 0.0921 |
| IND_EMP_GR (Q) | 18,177 | 0.0008 | 0.0010 | 0.0426 | −0.1635 | 0.1789 |
| IND_EMP_GR (H) | 8,979 | 0.0024 | 0.0030 | 0.0636 | −0.2116 | 0.2855 |
| IND_EWSR (M) | 70,117 | −0.0010 | −0.0001 | 0.0295 | −0.0936 | 0.0874 |
| IND_EWSR (Q) | 23,373 | −0.0029 | −0.0004 | 0.0519 | −0.1655 | 0.1483 |
| IND_EWSR (H) | 11,687 | −0.0060 | −0.0015 | 0.0727 | −0.2283 | 0.2159 |
| IND_AVG_WAGE_GR (Q) | 18,121 | 0.0119 | 0.0100 | 0.0908 | −0.2854 | 0.3937 |
| IND_TOT_WAGE_GR (Q) | 18,121 | 0.0139 | 0.0151 | 0.1038 | −0.3322 | 0.4633 |
| IND_EWSR_HQ (Q) | 23,373 | −0.0035 | 0.0000 | 0.1091 | −1.6161 | 1.8240 |
| IND_DEVIATION | 15,184 | 0.2539 | −0.3366 | 1.4969 | −0.9997 | 5.9588 |
| CBSA_DEVIATION | 67,872 | −0.0731 | −0.1272 | 0.3942 | −0.7913 | 1.4098 |

Panel B of Table 3 reports the results. The results are broadly consistent with Panel A of Table 3: The market excess return is positive and significant for 1-quarter-ahead employment and wage growth across all six specifications.

One possible explanation for the difference in our results from those of earlier decades involves households' attention to the stock market. Although 90% of U.S. households have negligible direct stock holdings, the fraction of U.S. households that participate in the stock market is much larger today than it was in the 1980s and 1990s. Accordingly, more households may now pay attention to the stock market and alter their consumption and production decisions as a result. If these changes in household consumption and production are correlated with employment, then aggregate returns may predict employment despite the decline in representativeness. A second possible explanation is that stock prices may have become more informative about the macroeconomy, and thus the market return has become a better predictor of employment. This explanation would be consistent with Bai, Philippon, and Savov (2016), who find that financial markets have become more informative about firm-level cash flows and investment over time. Extrapolating to the aggregate level, this finding may imply that stock prices have also become more informative on a macroeconomic level.

Overall, the results in Panels A and B of Table 3 suggest that, since 1990, stock returns are correlated with future employment and wage growth. This result contrasts with the findings surveyed in Stock and Watson (2003) that returns do not have consistent predictive power for output. However, it is consistent with more recent evidence from Baron et al. (2021). However, even if stock returns predict labor market outcomes in the aggregate, as discussed in Section II, this does not imply that returns should have local or industry predictability. This motivates the importance of studying the returns–labor market relation at a more granular level, which we do in Section V.

## V. Industry and Local Stock Returns and Labor Market Outcomes

To understand whether firm-specific news predicts local or industry-level labor market outcomes, we estimate the relationship between returns and employment and wages at a granular level. We exploit cross-sectional variation at the CBSA (city) and 4-digit NAICS industry level. All of our regressions include time period fixed effects such that we control for the effects of aggregate changes.

Our primary independent variable captures returns to firms with a presence in a particular city or industry. We begin by measuring returns over the time period leading up to when the employment data are measured. For analysis at the monthly frequency, we use the logarithm of monthly returns reported in CRSP. For quarterly and 6-month frequency analysis, we cumulate the log monthly returns to the quarterly or 6-month level. We use abnormal returns in the main analysis, and we compute abnormal returns using the 5-factor model of Fama and French (2015).[16]

To generate a city- or industry-level return, we then weight firms' cumulative abnormal returns according to the importance of that firm to the relevant city or industry. To illustrate this process more concretely, consider measuring the geographic employment change associated with the 29% positive return to the stock of the biotech firm Biogen in July 1999. In 1998, Biogen operated plants in two CBSAs: Durham–Chapel Hill, North Carolina, and Boston–Cambridge–Newton, Massachusetts–New Hampshire. To measure the change associated with this 29% return on these distinct geographic units, we first compute Biogen's portion of total publicly traded firm employment in each city in the year prior to the year of the shock. In 1998, Biogen accounts for 0.277% of Durham–Chapel Hill's and 0.166% of Boston–Cambridge–Newton's employment in publicly traded firms. We then weigh the return based on these proportions to arrive at our localized measure of stock return exposure. For Durham–Chapel Hill, the employment exposure-weighted return is $0.277\% \times 29\% = 0.08\%$, and for Boston–Cambridge–Newton, the employment exposure–weighted return is $0.166\% \times 29\% = 0.05\%$. Though Biogen has most of its employment in Boston–Cambridge–Newton, the shock is more important for Durham–Chapel Hill, because Biogen is more important to Durham–Chapel Hill than to Boston.

[16]We compute the abnormal return for firm $i$ in month $t$ by first estimating the predicted return in $t$ and then subtracting the predicted return from the actual return in $t$. The predicted return is obtained using a regression of realized excess stock returns on the returns of the Fama–French 5-factor portfolios (market-minus-risk-free rate, small-minus-big, high-minus-low, robust-minus-weak, and conservative-minus-aggressive) during a 60-month estimation window from $t-61$ to $t-1$.

We follow this process for each public firm in our sample. Note that by using public firm employment and not total employment (both public and private firm) in the denominator, we obtain weights that sum to 1. As in the example, we lag the employment exposure weights 1 year so that the price shock is allocated based on the previous year's share of total employment for a particular firm. After computing weighted returns for each firm, we sum these returns over cities and industries. The result is a measure that captures the exposure of a city or industry to publicly traded stock returns.

We call this measure the Exposure-Weighted Stock Return (EWSR) of a given city/industry over a given time horizon. Mathematically we express this measure at the city-year or industry-year level as

$$\text{(2)} \qquad \text{EWSR}_{m,t} = \sum_{i=1}^{S} \frac{\text{EMP}_{i,m,y-1}}{\text{PUBEMP}_{m,y-1}} \text{RET}_{i,t} = \sum_{i=1}^{S} \omega_{i,m,y-1} \text{RET}_{i,t},$$

where $\text{RET}_{i,t}$ is the cumulative log abnormal return of publicly traded firm $i$ during period $t$. The weight $\omega_{i,m,y-1}$ is the weight of firm $i$ in unit $m$'s public firm employment during the previous *year* $(y-1)$, which is equal to the number of firm $i$ employees in unit $m$ ($\text{EMP}_{i,m}$) divided by the total number of publicly traded firm employees in unit $m$ ($\text{PUBEMP}_m$). $S$ is the number of publicly traded firms in year $y-1$. If a firm has no employment in unit $m$ in year $y-1$, $\omega_{i,m,y-1}=0$. Note that although the exposure weights are constructed based on $y-1$ employment, we subscript EWSR with $t$ because cumulative returns are measured during a period in the current year.

Our dependent variable is either total employment growth (i.e., the percentage change in employment) or total wage growth in industry/geographic unit $m$ from period $t$ to $t+1$. We estimate the employment regressions at monthly, quarterly, and 6-month horizons, and we average the monthly employment over quarters or half-years for the analysis at the latter two frequencies.[17] We estimate the wage regressions only at the quarterly horizon. Our regressions take the following form:

$$\text{(3)} \qquad Y_{m,t+1} = \beta_0 + \beta_1 \text{EWSR}_{m,t} + \beta_x \text{CONT}_m + \varepsilon_{m,t},$$

where $Y_{m,t+1}$ is employment or wage growth from $t$ to $t+1$. In the wage growth regressions, we define two variables. The first is growth in total quarterly wages, which is equal to the quarterly change in total wages paid by Unemployment Insurance covered employers during the calendar quarter. The second is growth in average weekly wage, defined as the change in the average weekly wage within a quarter. The average weekly wage, in turn, is defined as the ratio of total quarterly wage to total quarterly employment, scaled by 13.

[17]The BLS data do not allow us to decompose total employment into publicly traded firm and private firm employment. Although we can use the YTS data to decompose employment, it is only available at an annual frequency. Because we are interested in the employment–stock return relation at higher frequencies, we use total employment as our primary dependent variables. In Appendix F of the Supplementary Material, we report the results of annual regressions of public firm employment growth, constructed using the YTS data, on annual EWSR.

The term $\mathrm{EWSR}_{m,t}$ in equation (3) is the current period exposure-weighted stock return measure for $m$ (computed from $t-1$ to $t$), and $\mathrm{CONT}_{m,t}$ is a set of controls that include lags of the dependent variable and EWSR, as well as fixed effects. In addition to time period fixed effects, we include unit-by-*calendar time* (month, quarter, or half-year) fixed effects. We do so because the BLS employment data are not deseasonalized, and city or industry employment may have different degrees of seasonality. For example, one would expect Miami, FL, with its dependence on winter tourism, to exhibit different seasonality in employment than Syracuse, NY.

## A. Industry Results

The bottom panel of Table 4 summarizes the data used in the industry employment and wage prediction analysis. Monthly data are summarized at the industry-month level, and quarterly and half-year data are summarized at the industry-quarter or industry-half-year level, respectively.

Panel A of Table 5 reports the results for employment growth and EWSR at the 4-digit NAICS level. We find that EWSR is significantly related to employment at all frequencies. Focusing on the quarterly results, columns 4–6 indicate that an increase in exposure-weighted cumulative returns during quarter $q$ is positively associated with employment growth during quarter $q+1$. Additionally, the coefficient magnitudes increase across frequencies: Quarterly EWSR predicts next-quarter employment growth more strongly than monthly EWSR predicts next-month employment growth. The magnitude at the 6-month frequency is even larger.[18]

As an example of how to interpret the coefficients, consider the specification in column 6. The coefficient on EWSR (Q) indicates that a 1-standard-deviation increase in industry EWSR is associated with a 0.07% increase in quarterly employment growth. This is more than 90% of the mean industry employment growth of 0.08% (IND_EMP_GR (Q) in Table 4).

Turning to the wage results, columns 1 and 2 of Table 6 report industry-level wage growth and EWSR at a quarterly frequency. EWSR is positive and significant for wage growth, indicating that wages also increase after a positive stock return. Given that the average weekly wage per worker increases (column 2), the employment growth we document is associated with an increase in the nominal wage paid to the average worker, in addition to an increase in total wages.

Taken together, the results indicate that the shocks that drive stock returns benefit labor as well. This implies that these shocks are not primarily due to industry automation because if the shocks benefiting shareholders were automation shocks, we would see employment or wages decrease when stock returns increased.

### Heterogeneity Across Industries

To better understand what types of shocks have driven industry-level returns over the past two decades, we exploit the granularity of our data to identify whether the overall relationship we see between EWSR and the labor market is stronger in certain industries. Certain industries are known to be more exposed to the

[18]In Appendix D of the Supplementary Material, we show the results of several sensitivity analyses that establish the robustness of the results in Panel A of Table 5.

automation shocks and declines in the labor share discussed in Section II. As such, identifying whether our results are more pronounced in certain industries can help us understand what types of shocks drive returns and subsequent labor market changes.

We assess whether our results are stronger in certain industries by first defining indicator variables for each 2-digit NAICS sector relative to all other sectors. We then estimate separate regressions for each 2-digit sector in which we interact EWSR with that sector's indicator variable. That is, we estimate 19 separate regressions of the following form:

$$(4) \quad Y_{m,s,t+1} = \beta_0 + \beta_1 \mathrm{EWSR}_{m,s,t} + \beta_2 I(s) + \beta_3 I(s) \times \mathrm{EWSR}_{m,s,t} + \beta_x \mathrm{CONT} + \varepsilon_{m,s,t}.$$

In equation (4), $s$ represents a 2-digit NAICS sector, whereas $m$ represents a 4-digit NAICS industry, as before. The indicator $I(s)$ is equal to 1 for all industries $m$ in 2-digit NAICS sector $s$, and 0 for all other industries. Because there are 19 2-digit NAICS sectors, we estimate 19 different iterations of equation (4) on the full sample of data, and in each iteration, we change the sectors of focus $s$. For example, in the manufacturing equation, we set $I(s)$ equal to 1 for all industries $m$ in the 2-digit NAICS manufacturing sector (NAICS2 codes 31–33), and we set $I(s)$ equal to 0 for all other industries. Similarly, in the health care equation, $I(s) = 1$ for all $m$ in 2-digit NAICS sector 62, and $I(s) = 0$ for all other industries.

The coefficient of interest in each equation is the interaction $\beta_3$. This term tells us the relationship between EWSR and the labor market for the industry in question relative to all other industries. For example, in the regression for the 2-digit NAICS manufacturing sector, the interaction between $I(s)$ and EWSR tells us the predictive power of EWSR for the labor market for manufacturing firms relative to all other firms. We are also interested in the stability of the coefficient $\beta_1$ across specifications to understand whether a single industry drives the relationship we documented in Panel A of Table 5 and in Table 6.

The results of estimating our full specifications at the quarterly level (the equivalent of column 6 in Panel A of Table 5 and columns 1 and 2 of Table 6) are reported in Table 7. Because we include industry-by-calendar quarter fixed effects, the individual industry indicators are excluded from the regressions. For ease of exposition, we label our sector indicators $s$ using a 3-letter abbreviation for the relevant sector. For example, in the manufacturing equation, the sector indicator is $I(\mathrm{MNF})$, whereas in the health care equation, the sector indicator is $I(\mathrm{HLC})$. To account for the fact that certain sectors, such as retail trade and manufacturing, are very large relative to other sectors, we weight each regression by the relative 4-digit NAICS industry size, which is measured as the total number of employees in a given divided by total employment overall. For brevity, for each 2-digit NAICS industry, we report only the unconditional EWSR coefficient and the coefficient on the industry–EWSR interaction term. The results indicate substantial heterogeneity in the labor market–returns relationship across industries.[19] In row 5, columns 1–3 report the results for the manufacturing sector regressions. The positive and significant interaction term $I(\mathrm{MNF}) \times \mathrm{EWSR}$ indicates that when abnormal

[19]We exclude the regression results for NAICS 55 because of an insufficient number of observations.

returns increase, employment and wage growth for manufacturing firms increases relatively more than for nonmanufacturing firms. In contrast to the manufacturing versus nonmanufacturing split, no other sector exhibits consistent differences in labor market outcomes relative to all other sectors. This is evident by the lack of significance, in general, for the interaction terms in all other regressions.

TABLE 5

Industry (NAICS4) and City (CBSA) Employment Growth and Stock Returns

Table 5 reports the results of estimating linear regressions of employment growth on EWSR and controls. The dependent variable is measured over the period following when EWSR is measured. All EWSRs are computed using log returns. In Panel A, an observation is a 4-digit NAICS industry-period. Data are from Compustat and YTS from 1997 to 2017. In Panel B, an observation is a CBSA-period, and we limit the data to CBSA-periods with greater than 10,000 total employees. Data are from Compustat, BLS, and YTS from 1997 to 2017. All variables are defined in Table 1. Variables are winsorized at the 1% level in each tail. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

*Panel A. Industry (NAICS4) Employment Growth and Stock Returns*

| | 1-Period-Ahead Employment Growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Monthly | | | Quarterly | | | Six-Month | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| EWSR (M) | 0.0035** (0.0017) | 0.0035** (0.0017) | 0.0035** (0.0017) | | | | | | |
| EWSR (Q) | | | | 0.0150*** (0.0030) | 0.0140*** (0.0030) | 0.0140*** (0.0030) | | | |
| EWSR (H) | | | | | | | 0.0360*** (0.0046) | 0.0360*** (0.0046) | 0.0370*** (0.0044) |
| L_EMP_GR (M) | | 0.0200** (0.0086) | 0.0200** (0.0086) | | | | | | |
| L_EWSR (M) | | | 0.0054*** (0.0017) | | | | | | |
| L2_EWSR (M) | | | 0.0059*** (0.0017) | | | | | | |
| L2_EMP_GR (M) | | | 0.0240*** (0.0079) | | | | | | |
| L3_EMP_GR (M) | | | −0.0079 (0.0082) | | | | | | |
| L_EMP_GR (Q) | | | | | 0.058*** (0.014) | 0.055*** (0.014) | | | |
| L2_EMP_GR (Q) | | | | | | 0.011 (0.013) | | | |
| L3_EMP_GR (Q) | | | | | | 0.058*** (0.012) | | | |
| L_EWSR (Q) | | | | | | 0.0160*** (0.0030) | | | |
| L2_EWSR (Q) | | | | | | 0.0160*** (0.0030) | | | |
| L_EMP_GR (H) | | | | | | | | −0.0190 (0.0200) | 0.0078 (0.0190) |
| L2_EMP_GR (H) | | | | | | | | | 0.300*** (0.019) |
| L3_EMP_GR (H) | | | | | | | | | −0.075*** (0.018) |
| L_EWSR (H) | | | | | | | | | 0.0160*** (0.0047) |
| L2_EWSR (H) | | | | | | | | | 0.0062 (0.0043) |
| No. of obs. | 52,341 | 52,334 | 51,882 | 17,301 | 17,294 | 16,842 | 8,541 | 8,534 | 8,083 |
| $R^2$ | 0.782 | 0.782 | 0.782 | 0.831 | 0.832 | 0.833 | 0.826 | 0.826 | 0.845 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| NAICS4 × cal. mo. FE | Yes | Yes | Yes | Yes | No | No | No | No | No |
| NAICS4 × cal. qtr FE | No | No | No | No | Yes | Yes | Yes | No | No |
| NAICS4 × cal. half FE | No | No | No | No | No | No | No | Yes | Yes |

(continued on next page)

TABLE 5 (continued)

Industry (NAICS4) and City (CBSA) Employment Growth and Stock Returns

*Panel B. City (CBSA) Employment Growth and Stock Returns*

| | 1-Period-Ahead Employment Growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Monthly | | | Quarterly | | | Six-Month | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| EWSR (M) | 0.0036** | 0.0036** | 0.0034** | | | | | | |
| | (0.0017) | (0.0017) | (0.0017) | | | | | | |
| EWSR (Q) | | | | 0.0180*** | 0.0170*** | 0.0160*** | | | |
| | | | | (0.0031) | (0.0031) | (0.0032) | | | |
| EWSR (H) | | | | | | | 0.0310*** | 0.0320*** | 0.0310*** |
| | | | | | | | (0.0045) | (0.0046) | (0.0047) |
| L_EMP_GR (M) | | −0.0840*** | −0.0860*** | | | | | | |
| | | (0.0032) | (0.0032) | | | | | | |
| L_EWSR (M) | | | 0.0039** | | | | | | |
| | | | (0.0017) | | | | | | |
| L2_EWSR (M) | | | 0.0076*** | | | | | | |
| | | | (0.0017) | | | | | | |
| L2_EMP_GR (M) | | | −0.0320*** | | | | | | |
| | | | (0.0029) | | | | | | |
| L3_EMP_GR (M) | | | −0.0300*** | | | | | | |
| | | | (0.0031) | | | | | | |
| L_EMP_GR (Q) | | | | | −0.1000*** | −0.0970*** | | | |
| | | | | | (0.0059) | (0.0059) | | | |
| L2_EMP_GR (Q) | | | | | | −0.0200*** | | | |
| | | | | | | (0.0055) | | | |
| L3_EMP_GR (Q) | | | | | | −0.0240*** | | | |
| | | | | | | (0.0054) | | | |
| L_EWSR (Q) | | | | | | 0.0130*** | | | |
| | | | | | | (0.0032) | | | |
| L2_EWSR (Q) | | | | | | 0.0190*** | | | |
| | | | | | | (0.0031) | | | |
| L_EMP_GR (H) | | | | | | | | −0.1100*** | −0.0770*** |
| | | | | | | | | (0.0080) | (0.0080) |
| L2_EMP_GR (H) | | | | | | | | | 0.0890*** |
| | | | | | | | | | (0.0086) |
| L3_EMP_GR (H) | | | | | | | | | −0.0830*** |
| | | | | | | | | | (0.0073) |
| L_EWSR (H) | | | | | | | | | 0.0130** |
| | | | | | | | | | (0.0050) |
| L2_EWSR (H) | | | | | | | | | −0.0091* |
| | | | | | | | | | (0.0050) |
| No. of obs. | 202,826 | 201,910 | 200,078 | 67,042 | 66,126 | 64,294 | 33,096 | 32,180 | 30,341 |
| $R^2$ | 0.631 | 0.634 | 0.636 | 0.649 | 0.651 | 0.654 | 0.653 | 0.658 | 0.668 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| CBSA × cal. mo. FE | Yes | Yes | Yes | Yes | No | No | No | No | No |
| CBSA × cal. qtr FE | No | No | No | No | Yes | Yes | Yes | No | No |
| CBSA × cal. half FE | No | No | No | No | No | No | No | Yes | Yes |

Overall, the results in Table 7 are consistent with different industries being exposed to different types of shocks at the quarterly frequency. The results in manufacturing industries are the strongest: Compared with all other firms, manufacturing firms experience higher employment and wage growth following higher stock returns. Table 8 splits the sample into nonmanufacturing and manufacturing industries. We continue to find a generally positive relationship between stock returns and the labor market even when we exclude manufacturing (columns 1–3), but the magnitude of the relationship is strongest in manufacturing (columns 4–6).

The fact that the relationship is strongest in the manufacturing sector illustrates what types of shocks benefit shareholders at the frequencies we are studying. If

TABLE 6

Wage Growth and Stock Returns

Table 6 reports the results of estimating linear regressions of nominal wage growth on EWSR and controls. The dependent variable is measured over the period following when EWSR is measured. All EWSRs are computed using log returns. An observation in columns 1 and 2 is a 4-digit NAICS industry-quarter, and an observation in columns 3 and 4 is a CBSA-quarter. We limit the CBSA data to CBSA periods with greater than 10,000 total employees. Data are from Compustat, BLS, and YTS from 1997 to 2017. All variables are defined in Table 1. Right-hand-side variables are winsorized at the 1% level in each tail. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

| | 1-Quarter-Ahead NAICS4 Wage Growth | | 1-Quarter-Ahead CBSA Wage Growth | |
|---|---|---|---|---|
| | Total Wages | Avg. Weekly Wage | Total Wages | Avg. Weekly Wage |
| | 1 | 2 | 3 | 4 |
| EWSR (Q) | 0.0280*** | 0.0190*** | 0.0190*** | 0.0150*** |
| | (0.0054) | (0.0042) | (0.0056) | (0.0045) |
| L_EWSR (Q) | 0.0370*** | 0.0230*** | 0.0320*** | 0.0190*** |
| | (0.0055) | (0.0044) | (0.0056) | (0.0043) |
| L2_EWSR (Q) | 0.0220*** | 0.0110** | 0.0430*** | 0.0250*** |
| | (0.0056) | (0.0044) | (0.0056) | (0.0044) |
| L_TOTAL_WAGE_GR (Q) | −0.3100*** | | −0.4000*** | |
| | (0.0150) | | (0.0076) | |
| L2_TOTAL_WAGE_GR (Q) | −0.0770*** | | −0.0320*** | |
| | (0.0130) | | (0.0078) | |
| L3_TOTAL_WAGE_GR (Q) | −0.0930*** | | −0.1400*** | |
| | (0.0130) | | (0.0065) | |
| L_AVG_WK_WAGE_GR (Q) | | −0.5900*** | | −0.6400*** |
| | | (0.0150) | | (0.0060) |
| L2_AVG_WK_WAGE GR (Q) | | −0.3800*** | | −0.3100*** |
| | | (0.0160) | | (0.0073) |
| L3_AVG_WK_WAGE_GR (Q) | | −0.3100*** | | −0.3000*** |
| | | (0.0160) | | (0.0064) |
| No. of obs. | 16,789 | 16,789 | 61,269 | 61,269 |
| $R^2$ | 0.907 | 0.921 | 0.867 | 0.871 |
| Time FE | Yes | Yes | Yes | Yes |
| NAICS4 × cal. qtr FE | Yes | Yes | No | No |
| CBSA × cal. qtr FE | No | No | Yes | Yes |

returns primarily reflected technology shocks, then we would expect a reduction in employment and wage growth in the manufacturing sector, given the evidence in Acemoglu and Restrepo (2019) that technology shocks to manufacturing industries from 1987 to 2017 largely reduced labor demand. In particular, Graph C of Figure 5 in Acemoglu and Restrepo (2019) shows that labor-displacing technology reduced net labor demand between 1987 and 2017. In contrast, because we observe significantly higher employment and wage growth in manufacturing following increases in returns, stock returns most likely reflect product demand shocks that increase demand for labor.

To investigate whether certain characteristics of the manufacturing sector account for the differential predictive power of returns for those firms, we focus on three aspects of industries that could be correlated with returns and the labor market: labor shares, representativeness, and education levels. It may be the case that the decline in the manufacturing labor share over the past few decades is really what drives the differential predictive power. Alternatively, the differential predictive power may be due to the relatively lower levels of education, on average, for manufacturing firms. Finally, it may be that the fact that manufacturing firms are overrepresented in the public sector drives the difference. We define three variables

## TABLE 7

### Industry Variation: Distinct NAICS Sectors

Table 7 reports the results of estimating 19 sets of linear regressions of labor market outcomes on EWSR and controls. Each regression is estimated on the full sample of data and varies only by the sector $s$ for which $I(s) = 1$. The dependent variable is measured over the period following when the EWSR is measured. An observation is a 4-digit NAICS industry-quarter. $I()$ variables are indicators equal to 1 for the relevant 2-digit NAICS industry, and 0 otherwise. Industry dummies are defined as follows: AGR = 1 for NAICS2 = 11, MIN = 1 for NAICS2 = 21, UTL = 1 for NAICS2 = 22, CON = 1 for NAICS2 = 23, MNF = 1 for NAICS2 = 31–33, WTD = 1 for NAICS2 = 42, RTD = 1 for NAICS2 = 44 and 45, TRN = 1 for NAICS2 = 48 and 49, INF = 1 for NAICS2 = 51, FIN = 1 for NAICS2 = 52, RST = 1 for NAICS2 = 53, PRF = 1 for NAICS2 = 54, ADM = 1 for NAICS2 = 56, EDU = 1 for NAICS2 = 61, HLC = 1 for NAICS2 = 62, ENT = 1 for NAICS2 = 71, HSP = 1 for NAICS2 = 72, and OTH = 1 for NAICS2 = 81. Results for NAICS 55 are excluded due to insufficient observations. Each regression is weighted by the relative 4-digit NAICS size. All other variables are defined in Table 1. Right-hand-side variables are winsorized at the 1% level in each tail. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

| | | Emp. | Tot. Wg. | Avg. Wk. Wg. | | | Emp. | Tot. Wg. | Avg. Wk. Wg. |
|---|---|---|---|---|---|---|---|---|---|
| MIN | EWSR (Q) | 0.0130*** | 0.0230*** | 0.0054 | FIN | EWSR (Q) | 0.0130*** | 0.0230*** | 0.0051 |
| | | (0.0031) | (0.0067) | (0.0049) | | | (0.0031) | (0.0066) | (0.0048) |
| | $I$(MIN) × EWSR | 0.067*** | 0.014 | 0.019 | | $I$(FIN) × EWSR | 0.077 | 0.320 | 0.340 |
| | | (0.023) | (0.041) | (0.023) | | | (0.074) | (0.390) | (0.290) |
| AGR | EWSR (Q) | 0.0140*** | 0.0240*** | 0.0055 | RST | EWSR (Q) | 0.0140*** | 0.0240*** | 0.0056 |
| | | (0.0031) | (0.0066) | (0.0048) | | | (0.0031) | (0.0067) | (0.0049) |
| | $I$(AGR) × EWSR | −0.0810 | −0.0360 | −0.0069 | | $I$(RST) × EWSR | −0.0055 | −0.0190 | −0.0098 |
| | | (0.0700) | (0.0840) | (0.0420) | | | (0.0180) | (0.0230) | (0.0190) |
| UTL | EWSR (Q) | 0.0130*** | 0.0240*** | 0.0054 | PRF | EWSR (Q) | 0.0150*** | 0.0250*** | 0.0080* |
| | | (0.0031) | (0.0066) | (0.0048) | | | (0.0032) | (0.0064) | (0.0047) |
| | $I$(UTL) × EWSR | −0.014 | 0.073 | 0.190 | | $I$(PRF) × EWSR | −0.035*** | −0.036 | −0.059 |
| | | (0.110) | (0.360) | (0.320) | | | (0.013) | (0.054) | (0.037) |
| CON | EWSR (Q) | 0.0130*** | 0.0220*** | 0.0056 | HSP | EWSR (Q) | 0.0130*** | 0.0250*** | 0.0063 |
| | | (0.0032) | (0.0069) | (0.0051) | | | (0.0031) | (0.0068) | (0.0050) |
| | $I$(CON) × EWSR | 0.00070 | 0.02800 | −0.00260 | | $I$(HSP) × EWSR | 0.00330 | −0.02800 | −0.02300 |
| | | (0.01300) | (0.02300) | (0.01300) | | | (0.01300) | (0.02200) | (0.01700) |
| MNF | EWSR (Q) | 0.0120*** | 0.0160** | −0.0037 | ADM | EWSR (Q) | 0.0120*** | 0.0250*** | 0.0090* |
| | | (0.0034) | (0.0072) | (0.0052) | | | (0.0029) | (0.0069) | (0.0050) |
| | $I$(MNF) × EWSR | 0.0120* | 0.0620*** | 0.0800*** | | $I$(ADM) × EWSR | 0.0220 | −0.0160 | −0.0480*** |
| | | (0.0070) | (0.0160) | (0.0140) | | | (0.0220) | (0.0250) | (0.0180) |
| WTD | EWSR (Q) | 0.0140*** | 0.0240*** | 0.0048 | EDU | EWSR (Q) | 0.0130*** | 0.0260*** | 0.0069 |
| | | (0.0032) | (0.0068) | (0.0050) | | | (0.0032) | (0.0070) | (0.0052) |
| | $I$(WTD) × EWSR | −0.0052 | −0.0100 | 0.0200 | | $I$(EDU) × EWSR | 0.0110 | −0.0330* | −0.0170 |
| | | (0.0073) | (0.0190) | (0.0150) | | | (0.0160) | (0.0190) | (0.0130) |
| RTD | EWSR (Q) | 0.0120*** | 0.0250*** | 0.0060 | HLC | EWSR (Q) | 0.0170*** | 0.0210*** | 0.0064 |
| | | (0.0034) | (0.0074) | (0.0054) | | | (0.0038) | (0.0069) | (0.0051) |
| | $I$(RTD) × EWSR | 0.0090 | −0.0120 | −0.0039 | | $I$(HLC) × EWSR | −0.0140** | 0.0084 | −0.0038 |
| | | (0.0077) | (0.0140) | (0.0110) | | | (0.0064) | (0.0190) | (0.0140) |
| TRN | EWSR (Q) | 0.0130*** | 0.0250*** | 0.0056 | ENT | EWSR (Q) | 0.0140*** | 0.0230*** | 0.0051 |
| | | (0.0032) | (0.0068) | (0.0049) | | | (0.0032) | (0.0068) | (0.0050) |
| | $I$(TRN) × EWSR | 0.0013 | −0.0220 | −0.0034 | | $I$(ENT) × EWSR | −0.0260 | 0.0022 | 0.0150 |
| | | (0.0130) | (0.0270) | (0.0240) | | | (0.0160) | (0.0190) | (0.0160) |
| INF | EWSR (Q) | 0.0140*** | 0.0240*** | 0.0049 | OTH | EWSR (Q) | 0.0140*** | 0.0250*** | 0.0060 |
| | | (0.0031) | (0.0067) | (0.0049) | | | (0.0032) | (0.0068) | (0.0050) |
| | $I$(INF) × EWSR | −0.0230* | 0.0015 | 0.0460 | | $I$(OTH) × EWSR | −0.0130 | −0.0270* | −0.0160 |
| | | (0.0120) | (0.0480) | (0.0420) | | | (0.0089) | (0.0140) | (0.0100) |

based on these characteristics. First, $I(\text{LSDECREASE}_m)$ is equal to 1 if industry $m$'s labor share decreased from 1975 to the beginning of our sample period, and 0 otherwise. We compute the change in labor share from 1975 to 1996 (the period preceding our sample period) using the data from Karabarbounis and Neiman (2013). Labor share data are at the 2-digit NAICS sector level, so for each 4-digit NAICS industry $m$, we apply the labor share for the respective 2-digit NAICS sector. Second, $\text{DEVIATION}_{m,t}$ is equal to the difference between the public firm employment share and the total firm employment share, scaled by total share, in

TABLE 8

Industry Variation: Manufacturing Split

Table 8 reports the results of estimating linear regressions of employment and wage growth on EWSR and controls. Columns 1–3 exclude manufacturing industries, and columns 4–6 include only manufacturing industries. Each regression is weighted by the relative 4-digit NAICS size. The dependent variable is measured over the period following when EWSR is measured. All EWSRs are computed using log returns. An observation is a 4-digit NAICS industry-period. Data are from Compustat and YTS from 1997 to 2017. All variables are defined in Table 1. Variables are winsorized at the 1% level in each tail. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

| | Excluding Manufacturing Sector | | | Manufacturing Sector Only | | |
|---|---|---|---|---|---|---|
| | Emp. | Tot. Wg. | Avg. Wk. Wg. | Emp. | Tot. Wg. | Avg. Wk. Wg. |
| | 1 | 2 | 3 | 4 | 5 | 6 |
| EWSR (Q) | 0.0120*** (0.0034) | 0.0170** (0.0072) | −0.0030 (0.0053) | 0.0240*** (0.0059) | 0.0710*** (0.0150) | 0.0640*** (0.0130) |
| L_EMP_GR (Q) | 0.120*** (0.025) | | | 0.180*** (0.029) | | |
| L2_EMP_GR (Q) | 0.049** (0.020) | | | 0.120*** (0.024) | | |
| L3_EMP_GR (Q) | 0.055** (0.022) | | | 0.100*** (0.022) | | |
| L_EWSR (Q) | 0.0088** (0.0035) | 0.0290*** (0.0072) | 0.0096* (0.0052) | 0.0230*** (0.0059) | 0.0500*** (0.0150) | 0.0380*** (0.0130) |
| L2_EWSR (Q) | 0.00700* (0.00370) | 0.01200* (0.00670) | 0.00056 (0.00490) | 0.02000*** (0.00550) | 0.04400** (0.01700) | 0.02700* (0.01500) |
| L_TOTAL_WAGE_GR (Q) | | −0.280*** (0.033) | | | −0.350*** (0.027) | |
| L2_TOTAL_WAGE_GR (Q) | | −0.039* (0.023) | | | −0.077*** (0.027) | |
| L3_TOTAL_WAGE_GR (Q) | | −0.092*** (0.020) | | | −0.100*** (0.027) | |
| L_AVG_WK_WAGE_GR (Q) | | | −0.570*** (0.017) | | | −0.590*** (0.031) |
| L2_AVG_WK_WAGE_GR (Q) | | | −0.370*** (0.021) | | | −0.340*** (0.037) |
| L3_AVG_WK_WAGE_GR (Q) | | | −0.330*** (0.024) | | | −0.290*** (0.034) |
| No. of obs. | 11,621 | 11,568 | 11,568 | 5,221 | 5,221 | 5,221 |
| $R^2$ | 0.910 | 0.941 | 0.952 | 0.726 | 0.849 | 0.879 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| NAICS4 × cal. qtr FE | Yes | Yes | Yes | Yes | Yes | Yes |

4-digit NAICS industry $m$ in year $t-1$.[20] This means that firms in $m$ are overrepresented in public markets when $\text{DEVIATION}_{m,t}$ is positive. Finally, $I(\text{HIGHED}_m)$ is equal to 1 if the average educational attainment in industry $m$ in 2004 is above the median, and 0 otherwise.[21]

Using these variables, we estimate a variation of the manufacturing sector equation in Table 7 that includes both the $I(\text{MNF}) \times \text{EWSR}$ term and an interaction between EWSR and the relevant variable. The results are reported in Table 9. In columns 1–3, we include DEVIATION × EWSR; in columns 4–6, we include $I(\text{LSDECREASE}) \times \text{EWSR}$; and in columns 7–9, we include $I(\text{HIGHED}) \times$

[20]That is, $(\text{COMPUSTAT\_SHARE} - \text{BLS\_SHARE})/\text{BLS\_SHARE}$ for $m$ in year $t-1$; see Section V.B for more details.

[21]Educational attainment data are from the 2004 Census American Community Survey and were provided by Lindsey Oldenski based on Oldenski (2012). Because the data are from the 2004 Census, we exclude the years prior to 2004 in the analysis that uses these data.

EWSR. In all but two specifications, the $I(\text{MNF}) \times \text{EWSR}$ term is positive and significant, and the other interaction terms are largely insignificant. This result indicates that returns in the manufacturing sector consistently have greater predictive power for employment and wage growth relative to nonmanufacturing and that this predictive power is not due to other characteristics of manufacturing firms. Specifically, neither the fact that the labor share in manufacturing has declined since 1975, nor the fact that manufacturing has on average lower educational attainment, nor the fact that manufacturing is overrepresented in publicly traded firms explains the differential predictive power of manufacturing firm returns. Further evidence that the strong relationship between stock returns and labor in manufacturing does not simply result from representativeness comes from comparing the results for the other significantly overrepresented industry (retail trade). As Table 7 reports, the coefficient on the interaction between the indicator for retail trade and the EWSR is far from statistically significant for all three labor market outcomes.

### 2. Asymmetry in Returns

Firms may respond differently to positive shocks to product demand compared with negative shocks. One reason responses may be asymmetric is that firms may be able to quickly lay off workers in downturns but unable to quickly hire workers in upturns. If firms cannot easily hire workers in good times, they may choose to adopt existing automation technology over the longer term so that they are able to adapt more quickly. If this is the case, short-run product demand shocks may lead to automation using existing technology over the longer term.[22]

To explore this possibility, we estimate a variation of equation (3) in which, in place of EWSR, we include two variables that capture asymmetry in returns. The variable EWSR+ is equal to EWSR when EWSR$\geq$0, and 0 otherwise, and the variable EWSR− is equal to EWSR when EWSR $<$ 0, and 0 otherwise. The results are reported in Table 10. In columns 1–3, the regressions are unweighted, whereas in columns 4–6, the regressions are weighted by 4-digit NAICS size. With the exception of column 6, EWSR− is positive and highly significant, which indicates that as returns become *more negative*, employment and wage growth declines. The second and third lags of EWSR− are also significant, suggesting that this predictive power persists for several quarters. In contrast, the predictive power for average wages is stronger for positive shocks than for negative shocks.

The asymmetry in the relationship between returns and the labor market is consistent with long-run automation, leading to lower labor demand. However, because the impact of automation is unlikely to be fully realized at the shorter-term frequencies we study, we are unable to clearly identify whether and when firms choose to automate in response to positive product demand shocks.

## B. City Results

At the city level, the middle panel of Table 4 summarizes the data used in the city employment and wage prediction analysis. Monthly data are summarized at the CBSA-month level, and quarterly and half-year data are summarized at the CBSA-

[22]A large literature in economics studies the slow adoption of existing technologies and the consequences of adoption speeds. See Foster and Rosenzweig (2010) for a review.

TABLE 9

Industry Variation: Manufacturing and Other Industry Characteristics

Table 9 reports the results of estimating linear regressions of labor market outcomes on EWSR and controls. Each regression is weighted by the relative 4-digit NAICS size. The dependent variable is measured over the period following when EWSR is measured. All EWSRs are computed using log returns. An observation is a 4-digit NAICS industry-quarter. Data are from Compustat, BLS, and YTS from 1997 to 2017. *I*(MNF) is equal to 1 for manufacturing sector firms, and 0 otherwise. *I*(OVERREP) is equal to 1 for industries overrepresented in public markets, and 0 otherwise. *I*(LSINCREASE) is equal to 1 for industries in which the labor share of income increased from 1975 to 1996, and 0 otherwise. *I*(HIGHED) is equal to 1 for industries with average educational attainment above the median, and 0 otherwise. All other variables are defined in Table 1. Variables are winsorized at the 1% level in each tail. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

| | Emp. | Tot. Wg. | Avg. Wk. Wg. | Emp. | Tot. Wg. | Avg. Wk. Wg. | Emp. | Tot. Wg. | Avg. Wk. Wg. |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| EWSR (Q) | 0.01300*** | 0.01500** | −0.00039 | 0.00830* | 0.01600 | −0.00800 | −0.00068 | 0.00490 | −0.0120* |
| | (0.00360) | (0.00750) | (0.00530) | (0.00480) | (0.01000) | (0.00740) | (0.00570) | (0.00930) | (0.00680) |
| *I*(MNF) × EWSR | 0.0055 | 0.0530*** | 0.0650*** | 0.0086 | 0.0590*** | 0.0740*** | 0.0240*** | 0.0690*** | 0.0870*** |
| | (0.0081) | (0.0160) | (0.0130) | (0.0079) | (0.0170) | (0.0140) | (0.0078) | (0.0180) | (0.0160) |
| DEVIATION × EWSR | 0.0043 | 0.0081* | 0.0095** | | | | | | |
| | (0.0027) | (0.0048) | (0.0037) | | | | | | |
| *I*(LSDECREASE) × EWSR | | | | 0.0084 | 0.0040 | 0.010 | | | |
| | | | | (0.0070) | (0.013) | (0.0094) | | | |
| *I*(HIGHED) × EWSR | | | | | | | 0.0110 | 0.0120 | 0.0022 |
| | | | | | | | (0.0077) | (0.0150) | (0.0120) |
| DEVIATION | 0.00033 | 0.00045 | 0.00097 | | | | | | |
| | (0.00032) | (0.00082) | (0.00067) | | | | | | |
| L_EWSR (Q) | 0.0088*** | 0.0330*** | 0.0180*** | 0.0097*** | 0.0320*** | 0.0150*** | 0.0070* | 0.0320*** | 0.0150** |
| | (0.0034) | (0.0071) | (0.0051) | (0.0033) | (0.0067) | (0.0048) | (0.0042) | (0.0082) | (0.0061) |
| L2_EWSR (Q) | 0.0078** | 0.0170** | 0.0063 | 0.0085** | 0.0170*** | 0.0053 | 0.0130*** | 0.0130 | 0.0025 |
| | (0.0036) | (0.0067) | (0.0050) | (0.0035) | (0.0064) | (0.0047) | (0.0046) | (0.0079) | (0.0060) |
| L_EMP_GR (Q) | 0.160*** | | | 0.170*** | | | 0.180*** | | |
| | (0.023) | | | (0.021) | | | (0.027) | | |
| L2_EMP_GR (Q) | 0.067*** | | | 0.066*** | | | 0.083*** | | |
| | (0.018) | | | (0.017) | | | (0.022) | | |
| L3_EMP_GR (Q) | 0.060*** | | | 0.085*** | | | 0.061** | | |
| | (0.021) | | | (0.019) | | | (0.024) | | |
| L_TOTAL_WAGE_GR (Q) | | −0.300*** | | | −0.280*** | | | −0.310*** | |
| | | (0.027) | | | (0.028) | | | (0.032) | |
| L2_TOTAL_WAGE_GR (Q) | | −0.046** | | | −0.016 | | | −0.053** | |
| | | (0.020) | | | (0.020) | | | (0.023) | |
| L3_TOTAL_WAGE_GR (Q) | | −0.094*** | | | −0.084*** | | | −0.110*** | |
| | | (0.018) | | | (0.017) | | | (0.021) | |
| L_AVG_WK_WAGE_GR (Q) | | | −0.580*** | | | −0.560*** | | | −0.560*** |
| | | | (0.015) | | | (0.016) | | | (0.018) |
| L2_AVG_WK_WAGE_GR (Q) | | | −0.370*** | | | −0.340*** | | | −0.340*** |
| | | | (0.018) | | | (0.018) | | | (0.021) |
| L3_AVG_WK_WAGE_GR (Q) | | | −0.320*** | | | −0.310*** | | | −0.300*** |
| | | | (0.021) | | | (0.021) | | | (0.024) |
| No. of obs. | 14,608 | 14,555 | 14,555 | 15,968 | 15,915 | 15,915 | 11,425 | 11,425 | 11,425 |
| $R^2$ | 0.905 | 0.927 | 0.941 | 0.904 | 0.932 | 0.945 | 0.892 | 0.927 | 0.943 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Ind × cal. qtr FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

quarter or CBSA-half-year level, respectively. We only include in our regressions CBSA periods in excess of 10,000 total employees.

Panel B of Table 5 reports the employment regression results at the city level. We find that the EWSR is significantly related to employment at all frequencies. In terms of economic magnitudes, the coefficient on EWSR (Q) in column 6 shows that a 1-standard-deviation increase in the quarterly EWSR is associated with an increase in employment growth in the following quarter of 0.05%. Because the average quarterly employment growth within a city during the sample period is 0.12% (see CBSA_EMP_GR (Q) in Table 4), this increase is roughly 40% relative to the mean. In terms of wages, columns 3 and 4 of Table 6 indicate that CSBA-level wage growth follows higher stock returns, which is consistent with the industry-level results. Overall, the CBSA labor market results mirror those at the industry level.[23]

### C. Headquarters Versus Establishment Measure of EWSR

Our primary measure of EWSR weights the abnormal return of publicly traded firm $i$ based on the proportion of employment in all publicly traded firms that firm $i$ accounts for in unit $m$. This weighting takes advantage of the establishment-level YTS data and allows us to allocate employment based on actual industry/location rather than headquarters industry/location. However, an alternative weighting scheme would assign all employees of firm $i$ to the industry and city in which firm $i$'s headquarters resides. The advantage of such a weighting scheme is that it can be produced by relying solely on the Compustat data. In order to understand whether our primary weighting method is superior to an approach that relies only on headquarters location, we construct an alternative measure of EWSR that we call HQ_EWSR, or $\text{EWSR}^{\text{HQ}}$.

$$(5)\quad \forall i \text{ with HQ in } m, \text{EWSR}_{m,t}^{\text{HQ}} = \sum_{i=1}^{S} \frac{\text{EMP}_{i,m,y-1}}{\text{PUBEMP}_{m,y-1}} \text{RET}_{i,t} = \sum_{i=1}^{S} \omega_{i,m,y-1}^{\text{HQ}} \text{RET}_{i,t}.$$

This measure specifically weights returns positively only when firm $i$ is headquartered in $m$. That is, for any firm $j$ not headquartered in $m$, $\text{RET}_{j,t}$ is multiplied by 0 even if firm $j$ has employees in $m$.

We then estimate equation (3) using this additional measure of EWSR and report the results in Panels A and B of Table 11. In columns 1, 3, and 5, we include only the variable $\text{EWSR}^{\text{HQ}}$, whereas in the remaining columns, we include both $\text{EWSR}^{\text{HQ}}$ and our main measure of EWSR. When included on its own, $\text{EWSR}^{\text{HQ}}$ is positive and significant in the industry results, but it loses significance in the city results. However, when we include our main, granular measure in the same regression (columns 2, 4, and 6 of each table), the coefficient on $\text{EWSR}^{\text{HQ}}$ falls in the industry results and becomes insignificant in the city results. In contrast, the main EWSR measure is positive and highly significant across industry and city specifications. This illustrates the importance of using the granular establishment-level data to weight returns, instead of relying on a more naive approach that assumes that all employment is in the headquarters location and/or industry.

## VI. Conclusions

We find that there is information about the U.S. labor market in publicly traded firms' stock returns. The predictive power of returns for the labor market exists despite publicly traded firms having become less representative of the industrial

[23]In Appendix D of the Supplementary Material, we show the results of sensitivity analysis that establish the robustness of the city-level results. Additionally, Appendix E of the Supplementary Material examines heterogeneity in the city-level results along a number of dimensions.

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TABLE 10

Asymmetric Predictive Power of EWSR

Table 10 reports the results of estimating linear regressions of labor market outcomes on EWSR and controls. The dependent variable is measured over the period following when EWSR is measured. All EWSRs are computed using log returns. An observation is an industry-quarter. Data are from Compustat, BLS, and YTS from 1997 to 2017. EWSR+ equals EWSR when EWSR≥0, and 0 otherwise. EWSR− equals EWSR when EWSR < 0, and 0 otherwise. All other variables are defined in Table 1. Variables are winsorized at the 1% level in each tail. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

| | Emp. | Tot. Wg. | Avg. Wk. Wg. | Emp. | Tot. Wg. | Avg. Wk. Wg. |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| EWSR+ | 0.0060 | 0.0170* | 0.0200** | 0.0063 | 0.0110 | −0.0018 |
| | (0.0056) | (0.0100) | (0.0083) | (0.0062) | (0.0120) | (0.0095) |
| L_EWSR+ | 0.00690 | 0.03100*** | 0.02800*** | 0.00064 | 0.02900** | 0.02200** |
| | (0.00570) | (0.01100) | (0.00870) | (0.00640) | (0.01400) | (0.01100) |
| L2_EWSR+ | 0.00770 | 0.01500 | 0.02300*** | 0.00097 | 0.00220 | 0.00350 |
| | (0.00550) | (0.01100) | (0.00850) | (0.00670) | (0.01300) | (0.00980) |
| EWSR− | 0.0210*** | 0.0380*** | 0.0190*** | 0.0200*** | 0.0350*** | 0.0120 |
| | (0.0054) | (0.0096) | (0.0071) | (0.0062) | (0.0130) | (0.0086) |
| L_EWSR− | 0.0250*** | 0.0420*** | 0.0190** | 0.0190*** | 0.0360*** | 0.0076 |
| | (0.0055) | (0.0095) | (0.0074) | (0.0057) | (0.0120) | (0.0086) |
| L2_EWSR− | 0.02400*** | 0.02700*** | 0.00064 | 0.01600*** | 0.02800** | 0.00550 |
| | (0.00530) | (0.01000) | (0.00780) | (0.00590) | (0.01200) | (0.00890) |
| L_EMP_GR (Q) | 0.054*** | | | 0.140*** | | |
| | (0.014) | | | (0.021) | | |
| L2_EMP_GR (Q) | 0.010 | | | 0.064*** | | |
| | (0.013) | | | (0.016) | | |
| L3_EMP_GR (Q) | 0.058*** | | | 0.065*** | | |
| | (0.012) | | | (0.019) | | |
| L_TOTAL_WAGE_GR (Q) | | −0.320*** | | | −0.280*** | |
| | | (0.015) | | | (0.026) | |
| L2_TOTAL_WAGE_GR (Q) | | −0.077*** | | | −0.036* | |
| | | (0.013) | | | (0.019) | |
| L3_TOTAL_WAGE_GR (Q) | | −0.093*** | | | −0.086*** | |
| | | (0.013) | | | (0.017) | |
| L_AVG_WK_WAGE_GR (Q) | | | −0.590*** | | | −0.570*** |
| | | | (0.015) | | | (0.015) |
| L2_AVG_WK_WAGE_GR (Q) | | | −0.380*** | | | −0.360*** |
| | | | (0.016) | | | (0.018) |
| L3_AVG_WK_WAGE_GR (Q) | | | −0.310*** | | | −0.310*** |
| | | | (0.016) | | | (0.020) |
| No. of obs. | 16,842 | 16,789 | 16,789 | 16,842 | 16,789 | 16,789 |
| $R^2$ | 0.834 | 0.907 | 0.921 | 0.898 | 0.930 | 0.942 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| NAICS4 × cal. qtr FE | Yes | Yes | Yes | Yes | Yes | Yes |
| NAICS4 size weight | No | No | No | Yes | Yes | Yes |

composition of all U.S. firms over the past three decades. Using establishment-level data on the exposure of specific industries and cities to the stock market, we show that the information in industry- and city-level returns predicts employment and wage growth.

Our results show that good news in the stock market translates into at least a short-term increase in labor demand in the cities and industries most exposed to that news. We find the strongest and most robust relationship in the manufacturing sector, suggesting that, at the quarterly frequency, positive shocks to the manufacturing sector that most benefit shareholders also increase labor market demand. Given existing evidence on the effect of technology shocks on manufacturing, the shocks driving stock market returns are therefore likely to be product demand shocks rather than labor-saving technology shocks.

We do not study changes in the association between stock market returns and the labor market over a long period, nor do we use stock market returns to structurally estimate the labor share of output. As a result, we are unable to assess whether labor is receiving a fair share of increases in output. However, our evidence indicates that there is still some alignment of interests between shareholders and labor. The findings thus indicate that the stock market remains highly relevant even for the majority of U.S. households that do not own a significant amount of stock.

TABLE 11

HQ EWSR and Industry and City Labor Market Outcomes

Table 11 reports the results of estimating linear regressions of labor market outcomes on EWSR and controls. The dependent variable is measured over the period following when EWSR is measured. All EWSRs are computed using log returns. In Panel A, an observation is an industry-quarter, whereas in Panel B, an observation is a CBSA-quarter. Data are from Compustat, BLS, and YTS from 1997 to 2017. All variables are defined in Table 1. Variables are winsorized at the 1% level in each tail. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors are reported in parentheses.

*Panel A. HQ EWSR and Industry Labor Market Outcomes*

| | Emp. | | Tot. Wg. | | Avg. Wk. Wg. | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| EWSR (Q) | | 0.0089** | | 0.0200*** | | 0.0120*** |
| | | (0.0036) | | (0.0060) | | (0.0047) |
| $EWSR^{HQ}$ (Q) | 0.0063*** | 0.0040** | 0.0120*** | 0.0070** | 0.0090*** | 0.0060** |
| | (0.0014) | (0.0017) | (0.0030) | (0.0034) | (0.0025) | (0.0029) |
| L_EWSR (Q) | | 0.0140*** | | 0.0330*** | | 0.0210*** |
| | | (0.0036) | | (0.0063) | | (0.0050) |
| L2_EWSR (Q) | | 0.0120*** | | 0.0098 | | 0.0028 |
| | | (0.0037) | | (0.0062) | | (0.0048) |
| L_$EWSR^{HQ}$ (Q) | 0.0057*** | 0.0022 | 0.0110*** | 0.0028 | 0.0073*** | 0.0021 |
| | (0.0015) | (0.0018) | (0.0032) | (0.0036) | (0.0026) | (0.0030) |
| L2_$EWSR^{HQ}$ (Q) | 0.0066*** | 0.0035* | 0.0130*** | 0.0100*** | 0.0077*** | 0.0069** |
| | (0.0016) | (0.0020) | (0.0034) | (0.0038) | (0.0027) | (0.0031) |
| L_EMP_GR (Q) | 0.056*** | 0.054*** | | | | |
| | (0.014) | (0.014) | | | | |
| L2_EMP_GR (Q) | 0.011 | 0.010 | | | | |
| | (0.013) | (0.013) | | | | |
| L3_EMP_GR (Q) | 0.058*** | 0.059*** | | | | |
| | (0.012) | (0.012) | | | | |
| L_TOTAL_WAGE gr (Q) | | | −0.310*** | −0.320*** | | |
| | | | (0.015) | (0.015) | | |
| L2_TOTAL_WAGE_GR (Q) | | | −0.076*** | −0.077*** | | |
| | | | (0.013) | (0.013) | | |
| L3_TOTAL_WAGE_GR (Q) | | | −0.093*** | −0.093*** | | |
| | | | (0.013) | (0.013) | | |
| L_AVG_WK_WAGE_GR (Q) | | | | | −0.590*** | −0.590*** |
| | | | | | (0.015) | (0.015) |
| L2_AVG_WK_WAGE_GR (Q) | | | | | −0.380*** | −0.380*** |
| | | | | | (0.016) | (0.016) |
| L3_AVG_WK_WAGE_GR (Q) | | | | | −0.310*** | −0.310*** |
| | | | | | (0.016) | (0.016) |
| No. of obs. | 16,842 | 16,842 | 16,789 | 16,789 | 16,789 | 16,789 |
| $R^2$ | 0.833 | 0.834 | 0.907 | 0.907 | 0.921 | 0.921 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| NAICS4 × cal. qtr FE | Yes | Yes | Yes | Yes | Yes | Yes |

*(continued on next page)*

TABLE 11 (continued)

HQ EWSR and Industry and City Labor Market Outcomes

*Panel B. HQ EWSR and City Labor Market Outcomes*

| | Emp. | | Tot. Wg. | | Avg. Wk. Wg. | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| EWSR (Q) | | 0.0150*** (0.0032) | | 0.0180*** (0.0057) | | 0.0140*** (0.0045) |
| $EWSR^{HQ}$ (Q) | 0.0240* (0.0140) | 0.0054 (0.0140) | 0.0580 (0.0370) | 0.0380 (0.0370) | 0.0660* (0.0340) | 0.0500 (0.0340) |
| L_EWSR (Q) | | 0.0120*** (0.0033) | | 0.0300*** (0.0056) | | 0.0170*** (0.0044) |
| L2_EWSR (Q) | | 0.0190*** (0.0032) | | 0.0430*** (0.0056) | | 0.0250*** (0.0044) |
| $L\_EWSR^{HQ}$ (Q) | 0.0490*** (0.0150) | 0.0360** (0.0150) | 0.1500*** (0.0400) | 0.1200*** (0.0400) | 0.1300*** (0.0380) | 0.1100*** (0.0380) |
| $L2\_EWSR^{HQ}$ (Q) | 0.0083 (0.0140) | −0.0160 (0.0140) | 0.0250 (0.0370) | −0.0290 (0.0380) | 0.0370 (0.0350) | 0.0058 (0.0360) |
| L_EMP_GR (Q) | −0.0960*** (0.0059) | −0.0970*** (0.0059) | | | | |
| L2_EMP_GR (Q) | −0.0200*** (0.0055) | −0.0200*** (0.0055) | | | | |
| L3_EMP_GR (Q) | −0.0250*** (0.0054) | −0.0240*** (0.0054) | | | | |
| L_TOTAL_WAGE_GR (Q) | | | −0.4000*** (0.0077) | −0.4000*** (0.0076) | | |
| L2_TOTAL_WAGE_GR (Q) | | | −0.0310*** (0.0079) | −0.0320*** (0.0078) | | |
| L3_TOTAL_WAGE_GR (Q) | | | −0.1400*** (0.0065) | −0.1400*** (0.0065) | | |
| L_AVG_WK_WAGE_GR (Q) | | | | | −0.6400*** (0.0060) | −0.6400*** (0.0060) |
| L2_AVG_WK_WAGE_GR (Q) | | | | | −0.3100*** (0.0073) | −0.3100*** (0.0073) |
| L3_AVG_WK_WAGE_GR (Q) | | | | | −0.3000*** (0.0064) | −0.3000*** (0.0064) |
| No. of obs. | 64,294 | 64,294 | 61,269 | 61,269 | 61,269 | 61,269 |
| $R^2$ | 0.653 | 0.654 | 0.866 | 0.867 | 0.871 | 0.871 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| CBSA × cal. qtr FE | Yes | Yes | Yes | Yes | Yes | Yes |

## Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001569.

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