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Regional Economic Activity and Stock Returns

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Abstract

This paper studies the diffusion of regional macroeconomic information into stock prices. I identify all U.S. states that are economically relevant for a company through textual analysis of annual reports and find that economic activity forecasts of company-relevant regions positively predict cross-sectional stock returns. Information arising from all relevant states is more important than that relating to the headquarter state alone. These forecasts also predict firms' performance and earnings surprises, suggesting that the return predictability stems from future cash flows that are gradually reflected in prices. Finally, regional information takes longer to be incorporated into prices among difficult-to-arbitrage stocks.

I. Introduction

Asset pricing theory indicates that there is a strong link between macroeconomic variables and equity prices. These variables are ideal candidates for priced risk factors as they arguably capture future changes in the investment opportunity set or consumption (Merton (1973)). Consequently, since the seminal work of Chan, Chen, and Hsieh (1985) and Chen, Roll, and Ross (1986), a large strand of empirical literature has emerged which employs various macro risk factors, and investigates their success and failure in explaining the cross section of equity returns.[1] While most work in empirical asset pricing seeks to make a link between economic indicators as risk factors and equilibrium *expected* rates of return, there

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[1]Harvey, Liu, and Zhu (2016) provide an extensive list of important macro asset pricing factors.

are, surprisingly, very few studies that analyze how efficiently macroeconomic information is translated into individual stock prices. Nevertheless, it is of great importance for both researchers and practitioners to understand whether and how stock prices in the cross section vary in response to changes in *relevant* macroeconomic information. The main challenges in addressing this research question are that i) country-wide macroeconomic indicators do not vary in the cross section of stocks and ii) there is no direct measure to determine the importance of those aggregate macroeconomic indicators for an individual company.

To address this gap in the literature, I utilize the notion of geographically segmented financial markets. Instead of looking at aggregate economic conditions, my study focuses on regions that are economically relevant for a company and their corresponding economic activity. This approach enables me to construct a firm-specific macroeconomic variable and to answer two essential questions: Do forecasts on the economic activity of firm-relevant regions predict the cross section of individual stock returns? If so, how is this macroeconomic information incorporated into stock prices? In particular, I assess how shocks to geographic regions of the United States are translated into both stock returns and overall firm performance (i.e., sales or profitability) of U.S. companies.

To provide an intuition of why regional economic conditions may play an important role in explaining *and* predicting future stock returns, let us consider the case of the former software company viaLink Corp.[2] and the tornado in May 1999 that ravaged the central United States. In addition to the 46 direct fatalities and the 800 people injured,[3] this natural disaster had an extreme impact on the real economy of the region, causing over $1 billion worth of damage. viaLink was directly affected by this disaster because it was operating mainly in Oklahoma during the 1990s. Figure 1 displays the stock price for the firm and the overall financial market (proxied by a 1-dollar investment in the market portfolio) around the time of this event. The shaded region represents the 7-day period of the tornado. The circle- and cross-connected lines indicate viaLink's stock price and the value of a 1-dollar investment in the U.S. market on Apr. 1, 1999, respectively. As is evident from Figure 1, the aggregate market was barely affected by the disastrous event, whereas the company's stock price fell continuously from $22 down to $14 per share after the tornado. As with the market portfolio, this event was not reflected in the aggregate indicators of the U.S. economy. Also, note that the shock was gradually incorporated into the stock price within almost 3 months. To my knowledge, there were no other firm-relevant events or news within this time period. This extreme example aptly illustrates that i) *regional* measures of economic conditions may better capture relevant fundamental news for an individual company than aggregate economic activity of the United States and ii) the market may take a *longer* time period to incorporate these relevant macroeconomic changes into stock prices.

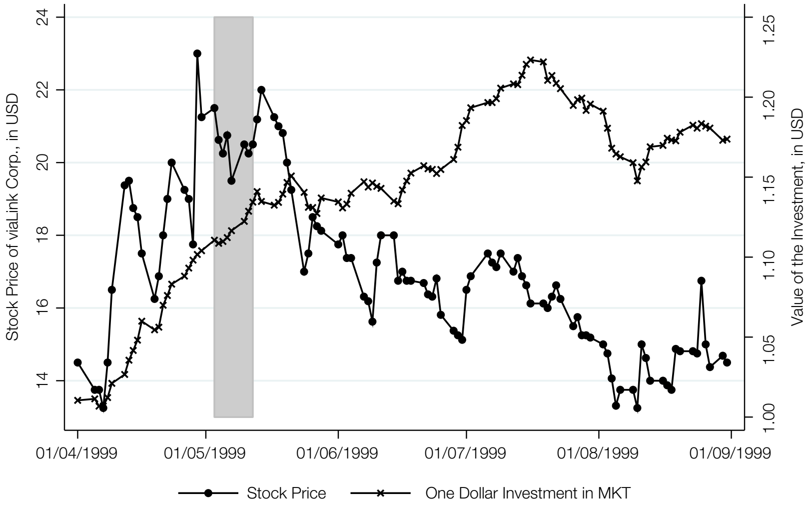
[2]viaLink Corp. was a specialist in supply chain planning that merged with Prescient Systems, Inc. at the beginning of 2005. In 2009 it was acquired by Park City Group, Inc., "a trusted business solutions and services provider that enables retailers and suppliers to work collaboratively as strategic partners to reduce out-of-stocks, shrink, inventory and labor [...]" (www.parkcitygroup.com).

[3]Source: https://www.nssl.noaa.gov/about/history/may3rd/

FIGURE 1

Example of the viaLink Corp. Stock Price during the 1999 Tornado Outbreak

Figure 1 displays the stock price of viaLink Corp. and the overall financial market (proxied by a one dollar investment in the equal-weighted market portfolio) around the tornado breakout in central United States. The shaded region indicates the 7 days of the storm, while viaLink's stock price and the market portfolio investment value are represented by the circle- and cross-connected lines, respectively.



To extend the previous example to the entire cross section of stocks, I decompose the U.S. market into states and obtain the differences in economic activity across the various geographic areas. Identifying economically relevant regions for each firm allows me to match the most important regional macroeconomic figures to each stock. Returning to the previous example, a company that operates mainly in Oklahoma will be influenced by consumer demand and general economic activity in this state, rather than by economic conditions across the country as whole. A similar logic applies to a company that is economically active in both California and Texas. In this case, I focus on the economic conditions of the two states to obtain the impact of macroeconomic changes on firm fundamentals and stock returns.[4]

To identify which states are economically relevant for each firm, I construct a firm-specific measure in which each of the 50 states of the United States are assigned a weight between 0 and 1. For a given company, I measure the economic relevance of a U.S. state by parsing the company's annual reports and counting the number of references to that state in a particular year. The economic relevance is defined as the citation share of the state (i.e., the number of counts of the corresponding state divided by the total number of state counts). For the proxy of economic activity forecasts for the states, I employ the State Leading Indexes developed by Crone and Clayton-Matthews (2005) that predict the

[4]Certainly, multinational companies are also affected by changes in international markets, which in turn may result in changes in stock prices and fundamentals (e.g., Li, Richardson, and Tuna (2014), Huang (2015), and Finke and Weigert (2017)). This study, however, focuses on the heterogeneity in economic activity arising from differences in the regions *within* the United States.

6-month economic growth rates for each U.S. state.[5] Weighting the monthly updated, expected growth rates of the activity indexes by the corresponding citation shares provides a proxy for predicted regional economic activity (PREA). Since this proxy is constructed for each firm on a monthly basis, it enables me to conduct a rich cross-sectional analysis of stock returns and to test how efficiently information on economic activity is translated into stock prices.

Using this novel proxy, I examine the following three key hypotheses. First, I use a cross-sectional analysis to test whether forecasts of regional macroeconomic activity predict the cross section of individual stock returns. By analyzing the operating performance and analyst forecast errors in the second stage of this paper, I seek to understand whether potential price movements predicted by the proxy are a result of investors' underreaction to cash-flow news, or are explained purely by the change in local risk aversion and demand for risky assets (Korniotis and Kumar (2013)). Last, I examine whether limits to arbitrage play a role in explaining how information on regional activity is gradually translated into stock prices (Shleifer and Vishny (1997), Gromb and Vayanos (2010)).

From the Fama–MacBeth (1973) regressions, I find that forecasts of the relevant states' economic conditions positively predict differences in the cross section of individual stock returns. This predictability is explained neither by standard cross-sectional effects, nor by closely related alternative explanations, including industry and geographic momentum, geographic dispersion, and the economic conditions of the headquarter state. I also conduct quintile portfolio sorts and document that the top portfolio of regional economic activity significantly outperforms the bottom portfolio by, on average, 50 basis points per month. This return spread remains after controlling for common risk factors. Importantly, the trading strategy is based on state-specific economic indicators that are publicly available at the time of portfolio formation.

Further tests show that the stock market reaction to regional economic information observed in this study is based on changes in firms' real performance, measured in terms of sales on assets, earnings per share, and return on assets. Namely, a forecast of the regional economic activity growth rate predicts that firm performance in the next quarter will go in the same direction. Without neglecting the role of potential changes in the risk aversion of local investors brought about by regional economic conditions and the resulting change in local discount rates (Korniotis and Kumar (2013)), I provide evidence that the cross-sectional predictability documented in this study is based on news of future cash flows. Moreover, when analyst forecasts are used as a proxy for market expectations, evidence suggests that the predictability based on regional economic activity comes from mispricing due to investors' biased expectations. Furthermore, the cumulative long-run performance of the long–short portfolio is strictly positive and displays no significant reversal over the holding period of 3 years. All these findings together support the hypothesis that the slow diffusion of regional economic activity is the main driver of the return predictability documented in this study.

Finally, to explain the persistence in predictability, I employ various stock characteristics and find that the cross-sectional return predictability is associated

[5] A more detailed description of the indexes is provided in Section II.

with characteristics related to the costs of arbitrage (e.g., idiosyncratic volatility, illiquidity, and market capitalization). This finding is in line with the limits-to-arbitrage literature, suggesting that certain frictions in exploiting arbitrage opportunities may generate temporary return predictability.

The new empirical findings of this paper contribute to the existing literature in several important ways. I add to the emerging literature on geographically segmented financial markets. For instance, Becker (2007) provides evidence relating to segmented U.S. bank loan markets and their effect on economic activity. Additionally, Hong, Kubik, and Stein (2008) find that stock prices are decreasing in the ratio of firms' aggregate book value in their region to the aggregate risk tolerance of investors within that region (the "only-game-in-town" effect). In the context of asset pricing, Pirinsky and Wang (2006) find that stock returns of firms in the same headquarter state comove. Korniotis (2008) uses regional income growth with habit formation to explain the cross section of expected stock returns. Tuzel and Zhang (2017) show that the industrial composition of local markets influences the effect of systematic shocks on firms in those markets. My article is also related to the research of Korniotis and Kumar (2013), who find that state-level stock returns can be predicted by local business cycles. However, using quarterly data, they show that past regional economic conditions *negatively* predict stock returns, due to changes in local risk aversion and coordinated trading by nonlocal investors. These studies exploit the geographic heterogeneity in the cross section of stocks and emphasize that *discount rates* may be influenced by local factors, particularly when investors are geographically concentrated and undiversified, or when there is no mobility of production factors. Parsons, Sabbatucci, and Titman (2017) show that the return comovement of firms headquartered in the same region extends to a lead–lag effect. The authors suggest that their findings are based on common regional variation in cash flows, but do not elaborate on the sources of this variation. I uncover a novel link between regional macroeconomic indicators and equity prices that stems from *cash-flow news*, but is not captured by the lead–lag effect of headquarter regions. Finally, in contrast to all above-mentioned studies, I identify all economically relevant states, rather than just the single headquarter state, and combine these data with comprehensive forecasts of regional economic activity.

There are a number of studies that incorporate macroeconomic factors in asset pricing models to explain the cross section of stock returns. A common procedure is to estimate the sensitivity of stock returns to changes in aggregate business cycle variables.[6] This approach aims to identify risk factors associated with business cycle fluctuations. My paper is methodically different and serves a distinct

[6]These estimations have led to mixed results. For instance, while Chen et al. (1986) find that interest rates, expected and unexpected inflation, and industrial production help in pricing size portfolios, Shanken and Weinstein (2006) show that the previous findings are very sensitive to changes in the estimation method. Throughout the last decade, inflation expectation (e.g., Chan et al. (1985), Chen et al. (1986), and Ferson and Harvey (1991)), consumption (e.g., Breeden, Gibbons, and Litzenberger (1989), Lettau and Ludvigson (2001), Parker and Julliard (2005), Yogo (2006), and Darrat, Li, and Park (2011)), income (e.g., Campbell (1996), Jagannathan and Wang (1996), and Eiling (2013)), foreign exchange rates (e.g., Ferson and Harvey (1993), Bartov and Bodnar (1994)), etc., have also served as reasonable factors.

purpose. In particular, I strive for a better understanding of how the market incorporates stock-relevant macroeconomic information into the cross section of stock prices. In the asset pricing literature, there are very few studies that directly assess the processing of firm-specific macro news into financial markets. Li et al. (2014) investigate how gross domestic product (GDP) growth forecasts for the countries to which a company is exposed to affect firm performance and stock returns. I extend this picture by demonstrating that even the heterogeneity within the U.S. economy represents an important source of cash flow and return predictability. To the best of my knowledge, there is no study which applies a similar method to assess exposure to inter-country and regional economic changes and its implications for stock price efficiency. Moreover, by exploiting the regional heterogeneity within the United States, I contribute to the asset pricing literature by constructing a novel macro factor that predicts cash-flow news in the cross section of stocks.

The cross-sectional predictability of stock returns is one of the most intriguing topics in finance. Recently, studies in this area have departed from the rational expectations framework and have utilized sentiment-driven or behavioral explanations, together with market frictions, to rationalize predictability of returns (Nagel (2013)). Alongside various theoretical explanations of stock return predictability in this behavioral framework (e.g., Shleifer and Vishny (1997), Hong and Stein (1999), (2007)), a growing number of studies illustrate different empirical patterns of return predictability and offer explanations as to how information may slowly be translated into asset prices. Economic links between customers and suppliers (Cohen and Frazzini (2008), Menzly and Ozbas (2010)), complicated industry information of conglomerates (Cohen and Lou (2012)), predictable innovation ability (Cohen, Diether, and Malloy (2013), Hirshleifer, Hsu, and Li (2013)) and exposure to foreign countries (Li et al. (2014), Huang (2015)) are just a few examples of how publicly available information predicts the cross section of individual stock returns. To my knowledge, regional *macroeconomic* information has yet to be used to understand the diffusion of information into stock prices.[7]

The remainder of the article is structured as follows: Section II describes the data set and the construction of the novel firm-specific proxy for predicted regional economic activity. In Section III, I analyze the link between the proxy and future stock returns. In Section IV, I study the sources of the abnormal future return spread based on regional economic activity, and Section V concludes the article.

[7]Addoum, Kumar, and Law (2017) also exploit geographically distributed information on firm performance, and find that a firm's *earnings and cash flows* can be predicted using the performance of other firms located in regions that are economically relevant for that firm. Though their measurement of exposure to U.S. regions is similar to that used in my study, there are two important differences between the two studies. First, while Addoum et al. (2017) employ a regional proxy based purely on accounting items, my study builds on the literature examining *macroeconomic* influences on stock prices and presents new evidence on how cash-flow news emerging from macroeconomic information diffuses into the equity market. Second, Addoum et al. (2017) show the predictability of cash flows, yet there is no direct evidence of return predictability based solely on their regional accounting measure.

II. Data

Before analyzing the predictive power of regional economic activity, I need to determine the exact definition of the term *region*. On the one hand, regions should provide sufficient heterogeneity in economic conditions; on the other hand, the choice of regional level is limited by data availability. With this trade-off in mind, defining the 50 U.S. states as regions seems most appropriate for this study, as other available data are not as useful. For example, the 9 U.S. Census Divisions provide less variation in economic activity, whereas information on firms' operations in U.S. metropolitan statistical areas is practically unobservable. Therefore, the terms *region* and *state* are used interchangeably in this study. To construct the proxy for firm-specific economic activity, I first obtain data on the economic relevance of all 50 states for each company and then combine these with data on the economic activity of the respective states.

A. Regional Economic Activity

Using an approach similar to that of Bernile, Kumar, and Sulaeman (2015), I extract the economic relevance of each state for a firm from the 10-K annual reports stored in the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database of the U.S. Securities and Exchange Commission (SEC). Besides balance sheets, income statements and financial footnotes, the reports contain, most importantly for my purpose, data on the location of factories, warehouses, and sales and branch offices. The relevant information is usually found within the descriptions of how the business has developed over the previous year, the financial conditions of the company, major properties, distribution, legal proceedings, and occasionally in extensive supplementary documents. Examples of excerpts from Forms 10-K are provided in Section IA.D of the Supplementary Material.

To extract this geographic information from the 10-K filings, I employ an algorithm to count the number of citations for each of the 50 U.S. states within all items of the annual reports filed between 1994 and 2014.[8] To identify states that are economically relevant for a firm's revenue and future cash flow, I exclude citations relating to production facilities.[9] I expect economic activity to be of particular importance if the state is connected to the demand of the firm's goods and services. Where a state is associated with production, it is not obvious whether this link will still hold. On the one hand, increasing economic activity might result in higher wages or employment costs, and have a negative impact on future cash flows. On the other hand, the states involved in manufacturing in most cases also have sales offices and factory outlets. Consequently, irrespective of whether I exclude production-related states or simply include all citations in the 10-K filings,

[8]I do not search directly for U.S. cities in the 10-K filings, but by manually checking a random sample of annual reports I observe that city names are usually followed by the corresponding U.S. state name.

[9]In particular, I search for terms *plant*, *plants*, *factory*, *factories*, *wage*, *wages*, *production*, *producing*, *construction*, *constructing*, *manufacture*, *manufacturing*, *produce* or *construct* in each sentence and exclude sentences where one of these terms is present, but *sales* or *sale* is not.

the results are essentially the same.[10] In the next step, I define the economic relevance of a U.S. state for a given firm as the citation share for the state extracted from the firm's 10-K report. The citation share of a firm-state observation is simply the ratio of citations of a given U.S. state to the total citations of all U.S. states:

$$\text{CIT\_SHARE}_{i,s,\tau} = \frac{n_{i,s,\tau}}{\sum_{s=1}^{50} n_{i,s,\tau}}, \tag{1}$$

where $n_{i,s,\tau}$ is the number of state s counts in firm i's annual report in year τ. $\text{CIT\_SHARE}_{i,s,\tau}$ is a firm-state-year observation that, per construction, takes a value between 0 and 1. These weights represent the first building block of my main variable.

To capture a coherent picture of the economic activity of each state, I use the State Coincident Indexes (SCI_t) developed by Crone and Clayton-Matthews (2005). The indexes describe the *current* economic conditions using a single statistic. To construct the SCI, the authors employ state-level indicator time series relating to nonagricultural employment, unemployment rate, average hours worked in manufacturing, and real wage and salary disbursement.[11] In addition to these indexes, the Federal Reserve Bank of Philadelphia also publishes the State Leading Indexes (SLI_t or $\widehat{\text{SCI}}_{s,t+6}$) that predict the 6-month growth rate of the states' coincident indexes. To estimate the SLI, the model includes data on the past and present coincident index and other variables that lead the economy: State-level housing permits, state initial unemployment insurance claims, delivery times indicated in the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill. The predicted growth rate for each state is the second element used to construct the firm-level economic activity proxy PREA. This choice is justified by two arguments. First, the indexes are widely accepted as an activity index in the macroeconomic literature, and are described by their authors as "the most *comprehensive* measure of economic activity [emphasis added]" for all 50 states. Second, these are, to my knowledge, the only consistent indexes published on a *monthly basis* for all U.S. states. With very few exceptions, the different indicators for month t are released by the corresponding agencies within month $t+1$ or $t+2$.[12] The time series relating to state economic activity are available on the Web site of the Federal Reserve Bank of Philadelphia.[13]

[10] If more than one filing exists for a specific firm within one fiscal year, I consider all filings as one annual report. In the case of missing reports in year τ, I use citation counts from year $\tau-1$ (no look-ahead bias).

[11] When constructing the state indexes, Crone and Clayton-Matthews (2005) relied on the estimation procedure of Stock and Watson (1989), who developed a similar index for the aggregate U.S. economy.

[12] A notable exception was the government shutdown in Sept. 2013 that forced the agencies to postpone their release announcements by up to 3 months.

[13] The Web sites are: http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/ and http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/leading/.

Finally, I calculate the firm-specific predicted regional economic activity proxy as the citation share-weighted average of economic activity growth rate across all relevant states:

$$(2) \qquad \mathrm{PREA}_{i,t} = \sum_{s=1}^{50} \mathrm{CIT\_SHARE}_{i,s,\tau-1} \times \frac{\Delta \widehat{\mathrm{SCI}_{s,t+6}}}{\mathrm{SCI}_{s,t}},$$

where $\Delta \widehat{\mathrm{SCI}_{s,t+6}}/\mathrm{SCI}_{s,t}$ is the predicted growth rate of the State Coincident Index of state s in month t for the next 6 months and $\mathrm{CIT\_SHARE}_{i,s,\tau-1}$ is the citation share extracted from last year's annual report. This novel proxy measures firms' exposure to future macroeconomic conditions in relevant U.S. states. Specifically, PREA can be interpreted as the average forecast of the economic activity growth rate over all firm-relevant U.S. states.

One concern relating to this proxy is that it might capture sensitivity to systematic risk factors rather than firm-specific forecasts of regional economic activity. For instance, positive forecasts of regional economic activity could be mechanically associated with a high exposure to national economic activity. Similarly, one can argue that the proxy is related to exposure to the market portfolio or other well-known risk factors. To rule out this possibility, I orthogonalize PREA by regressing it on the return sensitivity to the growth rate of the national economic activity, and on the sensitivities to the three common risk factors market, size and value (Fama and French (1993)). For each month, I run a cross-sectional regression with PREA as the dependent variable and the aforementioned exposures as the independent variables. I then define for each stock-month observation the orthogonalized regional activity, $\mathrm{PREA}^{\perp}_{i,t}$, as the sum of the regression residual and constant.

Using the data extracted from the annual reports, I also construct two state-related variables that, as shown by García and Norli (2012), explain the cross section of expected stock returns. First, I compute the state dispersion (STATEDISP) for each firm defined as the number of distinct state names mentioned in the 10-K report.[14] An alternative measure to STATEDISP is the Herfindahl–Hirschman concentration measure (HHI) adapted to state counts. This variable incorporates important information on the economic relevance of each state by aggregating the squared citation shares across the 50 states for each firm-year. Specifically, with this measure, a company is defined as local if one state receives nearly all the state counts, despite several other states being mentioned in the firm's annual report. Both dispersion measures are employed as control variables throughout the empirical analyses.

[14]Figure IA.1 in the Supplementary Material shows a histogram of distinct state names cited in the annual reports across all firms and years. Most firms mention three distinct states and, as expected, the distribution is right-skewed. Figure IA.2 in the Supplementary Material shows the average number of distinct state names over the sample period. Note that prior to May 1996, online filing at EDGAR was not mandatory, and it was generally only large and geographically dispersed firms which reported their filing electronically. As expected, Delaware, New York and California are the most cited states in the 10-K filings. A geographic overview of the citation counts of all U.S. states is provided in Figure IA.3. Similar results on regional dispersion can be found in García and Norli (2012) and Bernile, Kumar, and Sulaeman (2015).

B. Other Stock Characteristics and Data Sources

Besides the geographic variables introduced above, I use a list of other firm characteristics commonly used in the asset pricing literature. The list includes market capitalization (Banz (1981)), book-to-market ratio (Fama and French (1992)), market beta (Sharpe (1964), Lintner (1965)), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2009)), short-term reversal (Jegadeesh (1990)), stock, industry, and geographic momentum (Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999), and Parsons et al. (2017)), illiquidity (Amihud and Mendelson (1986)), and institutional ownership (Gompers and Metrick (2001)). For more details of the variables, I refer the reader to Section C of the Supplementary Material.

To calculate the stock-specific characteristics, I obtain daily and monthly stock returns, stock prices, bid and ask quotes, trade volume, and shares outstanding from the Center for Research in Security Prices (CRSP). Accounting variables, such as book value of equity, sales, income, and headquarter information come from the CRSP–Compustat merged (CCM) file. The share of institutional ownership is calculated using data from Thomson Reuters Institutional (13f) Holdings. Analysts' earnings forecasts and actual values are extracted from Thomson Reuters Institutional Brokers Estimate System (IBES).

Following the standard finance literature, I merge monthly stock returns from July in year τ to June in year $\tau+1$ with accounting and annual report data of year $\tau-1$. To match the state information extracted from the SEC filings with the returns and other firm characteristics, I use the Central Index Key (CIK), and the historical link tables of the CCM database and the Wharton Research Data Services (WRDS) SEC Analytics Suite. The final sample consists of all common stocks listed on the NYSE, AMEX, and NASDAQ during the period from July 1995 to June 2014. The average number of firms per month is around 4,100.[15]

Finally, I obtain time series of the well-known Fama–French (1993) factors, market (MKTRF), size (SMB), value (HML), and the momentum factor (UMD), from Kenneth French's Web site. Data on the Pástor–Stambaugh (2003) liquidity factor (LIQ) are downloaded from Ľuboš Pástor's Web site (http://faculty.chicagobooth.edu/lubos.pastor/research/).

C. Summary Statistics

Table 1 reports the summary statistics of state-related characteristics, other stock attributes and the five asset pricing risk factors. According to the figures in Panel A, firms in the sample are associated with a 6-month economic activity growth rate forecast of, on average, 1.08% or 2.15% annually. As a comparison, the average annual GDP growth rate for the United States during the same time period is 2.3%. These two figures are impressively similar, given that GDP includes the market value of all final goods and services produced, whereas the PREA calculation depends strongly on the firm sample. Furthermore, if all the firm-month observations are weighted equally, the average of the regional activity proxy

[15] Prior to May 1996, companies were not obliged to report their 10-K filing electronically. As a consequence, the average number of firms per month from July 1995 to Dec. 1996 is around 1,400.

TABLE 1
Summary Statistics of Explanatory Variables and Risk Factors

Table 1 reports univariate statistics (i.e., mean, standard deviation, and the 1st, 25th, 50th, 75th, and 99th percentiles) for a set of variables. Panel A displays the state-related variables: the predicted regional economic activity proxy (PREA), the orthogonalized predicted regional economic activity proxy (PREA$^{\perp}$), the number of distinct states cited in firms' annual reports (STATEDISP), and the Herfindahl–Hirschman concentration measure based on state citations (HHI). The PREA is constructed from a linear combination of predicted state economic activity growth rates weighted by the citation share of economically relevant states. The orthogonalized proxy is the sum of a constant and the residuals of cross-sectional regressions of PREA on return sensitivities to national economic activity and the Fama–French (1993) risk factors. The additional firm characteristics in Panel B include standard control variables employed throughout the analyses: β_{MKTRF}, β_{SMB}, and β_{HML} are the stock-specific market, SMB and HML beta calculated using rolling regressions with daily returns for the past 125 days. ISVOLA is the standard deviation of the corresponding error term (Ang et al. (2009)). β_{EA} is the return exposure to the growth rate of economic activity calculated using rolling regressions with monthly returns and a 12-month window. SIZE (the market capitalization) and BEME (the book-to-market ratio) are computed as in Fama and French (1992). The BIDASK is calculated as the average difference between the bid and ask price divided by the midquote using daily data for the previous 6 months, as in Amihud and Mendelson (1986). Furthermore, RETRF$_{t-1}$ is the lagged excess return (Jegadeesh (1990)), while RETRF$_{t-12,t-2}$ denotes the cumulative excess return from month $t-12$ to $t-2$, capturing the momentum effect (Jegadeesh and Titman (1993)). INDRET$_{t-1}$ and INDRET$_{t-12,t-2}$ are the lagged returns for the firm's industry (Moskowitz and Grinblatt (1999)). HQRET$_{t-1}$ is the equal-weighted lagged average return across all companies headquartered in the same U.S. state as the corresponding firm (Parsons et al. (2017)), IO is the share of institutional ownership. Panel C displays the descriptive statistics for the five tradable common risk factors MKTRF, SMB, HML, UMD, and LIQ (Fama and French (1993), Carhart (1997), and Pástor and Stambaugh (2003)).

			Percentile				
Variable	Mean	SD	1st	25th	Median	75th	99th
Panel A. State-Related Variables							
PREA	1.077	1.301	−3.615	.53	1.428	1.942	2.887
PREA$^{\perp}$	1.056	1.293	−3.608	.509	1.404	1.915	2.861
STATEDISP	11.392	8.705	2	6	9	14	47
HHI	0.353	0.208	0.061	0.198	0.303	0.459	0.938
Panel B. Other Firm Characteristics							
β_{EA}	18.783	199.533	−600.245	−56.011	2.811	72.742	846.419
β_{MKTRF}	0.855	0.773	−1.106	0.407	0.859	1.269	2.924
β_{SMB}	0.677	1.03	−1.712	0.06	0.583	1.207	3.659
β_{HML}	0.254	1.265	−3.262	−0.338	0.233	0.848	3.838
SIZE	3,067.310	15,300	3.664	58.140	251.087	1,169.802	55,300
BEME	0.832	1.921	0.042	0.331	0.58	0.944	4.817
ISVOLA	0.033	0.026	0.007	0.017	0.026	0.041	0.128
BIDASK	0.022	0.044	0.000	0.002	0.009	0.026	0.182
RETRF$_{t-1}$	0.010	0.186	0.408	0.069	0.001	0.072	0.595
RETRF$_{t-12,t-2}$	0.120	0.800	0.865	0.245	0.026	0.307	2.787
INDRET$_{t-1}$	0.012	0.076	0.196	0.027	0.014	0.05	0.234
INDRET$_{t-12,t-2}$	0.143	0.336	0.485	0.054	0.116	0.282	1.312
HQRET$_{t-1}$	0.01	0.068	−0.184	−0.028	0.012	0.048	0.200
IO	0.397	0.328	0.000	0.062	0.366	0.690	1
Panel C. Asset Pricing Factors							
MKTRF	0.531	4.799	−10.76	−2.315	1.325	3.595	9.24
SMB	0.223	3.680	−6.750	−2.170	−0.110	2.475	7.730
HML	0.249	3.477	−9.780	−1.650	0.220	1.910	9.120
UMD	0.499	5.652	−16.29	−1.325	0.770	3.135	13.200
LIQ	0.750	4.149	−9.257	−1.432	0.598	2.981	11.001

underweights observations in early periods when fewer firms were trading on the exchanges, but there was strong growth in economic activity. The median firm is operating in 9 different U.S. states, with a state concentration of approximately 0.353, according to the Herfindahl–Hirschman index.

Next, I use a simple sorting exercise to examine how regional economic activity is related to stock returns and other explanatory variables. In particular, in each month I divide the cross section into quintiles, depending on the values of PREA. I then compute the average of all the variables within each of the portfolios across time. This exercise not only provides the first evidence of the relation between my proxy for regional economic activity and returns, but also shows how PREA is related to other variables. The results are reported in Table 2. Several interesting observations emerge from the table. The descriptive statistics suggest a positive relation between firm-specific forecasts of regional economic activity and the firm's stock returns. However, due to the simplicity of the method, one should interpret these results with caution. I examine this question in more detail and with greater rigor in Section III. The table also reveals substantial variation in other variables across the quintiles. This observation suggests that one should control for these additional variables before drawing any statistical inference on the relation between returns and regional economic activity. In particular, the return exposures to economic growth and the market portfolio are increasing across the quintiles. I also find similar results for the past stock, state, and industry return. Interestingly, PREA seems to exhibit a U-shaped relation with state concentration and an inverted U-shaped relation with the number of relevant states, the market capitalization of the company, and the share of institutional ownership, yet there is no clear pattern for illiquidity. In other words, the top and bottom PREA portfolios consist of small (but not necessarily illiquid) stocks of geographically concentrated companies.

TABLE 2

Regional Economic Activity and Other Explanatory Variables

Table 2 reports the average value for a list of explanatory variables within each PREA quintile. Quintiles are constructed by sorting the cross section of stock by the predicted regional economic activity proxy (PREA). Variables are described in Table 1 and in Section IA.A of the Supplementary Material.

Variable	Low PREA	2	3	4	High PREA
PREA	0.005	0.009	0.011	0.013	0.016
$RETRF_t$	0.009	0.010	0.011	0.012	0.013
STATEDISP	9.814	12.807	13.192	11.940	9.419
HHI	0.413	0.306	0.298	0.327	0.417
β_{EA}	14.385	16.539	15.436	16.487	18.865
β_{MKTRF}	0.778	0.867	0.894	0.895	0.844
β_{SMB}	0.610	0.646	0.676	0.710	0.705
β_{HML}	0.297	0.246	0.213	0.186	0.236
SIZE	2,367.701	3,927.727	3,945.250	3,298.473	2,095.518
BEME	0.877	0.857	0.829	0.824	0.816
ISVOLA	0.031	0.031	0.032	0.033	0.034
BIDASK	0.023	0.020	0.019	0.020	0.022
$RETRF_{t-1}$	0.008	0.010	0.011	0.012	0.014
$RETRF_{t-12,t-2}$	0.088	0.110	0.119	0.134	0.164
$INDRET_{t-1}$	0.012	0.012	0.012	0.013	0.013
$INDRET_{t-12,t-2}$	0.134	0.144	0.147	0.150	0.156
$HQRET_{t-1}$	0.009	0.010	0.010	0.011	0.012
IO	0.369	0.427	0.433	0.424	0.379

III. Regional Economic Activity and Stock Returns

The sorting exercise in the previous section suggests that forecasts of regional economic activity are positively related to stock returns. I hypothesize that if investors incorporate (publicly available) information on regional activity with a delay, then forecasts of regional economic activity will predict the cross section of stock returns. To test this hypothesis, I use the orthogonalized predicted regional economic activity ($PREA^{\perp}$) to predict stock returns. To ensure that the economic indicators are publicly available before measuring the stock price reaction, I lag

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the proxy by 3 months.[16] I employ two approaches commonly used in the finance literature: Fama–MacBeth (1973) regressions and portfolio sorts.

A. Regression-Based Tests

I conduct a regression analysis along the lines of Fama and MacBeth (1973), with monthly excess returns as the dependent variable:

$$\text{RETRF}_{i,t} = \alpha_t + \beta_t \text{PREA}^{\perp}_{i,t-3} + \mathbf{x}'_{\mathbf{i,t-1}} \mathbf{b_t} + \varepsilon_{i,t}, \tag{3}$$

where $\text{PREA}^{\perp}_{i,t-3}$ denotes the regional economic activity of stock i lagged by 3 months and $\mathbf{x_i}$ represents a vector of control variables depending on the specification. I then calculate the time-series average of each estimated regression coefficient and its t-statistic using the Newey–West (1987) standard error correction. If macroeconomic activity forecasts for economically relevant U.S. states are incorporated into stock prices with a delay, I expect a significant positive estimate of β. I report the estimation results for different specifications in Table 3.

In the first specification in column 1 of Table 3 only $\text{PREA}^{\perp}_{t-3}$ is considered as the explanatory variable. Using this simple design, I find that the economic activity forecasts for relevant states significantly and positively predict individual stock returns. The regression coefficient associated with the proxy is 0.457, with a corresponding t-value of 2.92. To interpret the regression coefficient economically, I sort the stocks in each month into quintiles, according to the regional activity variable. The average difference in the proxy between the lowest and highest quintiles is 0.011. Multiplying this difference by the regression coefficient of 0.457 shows that a change in state economic activity from the bottom to the top portfolio is associated with a meaningful increase in the average return of 0.503 percentage points.

The next specification includes a set of standard control variables introduced in Section II.B. Column 2 of Table 3 reports the regression results. Controlling for standard cross-sectional asset pricing effects, I find that the coefficient on the lagged state activity proxy decreases to 0.381, but is highly significant at the level of 1%, with a t-statistic of 4.31. Thus, the effect of regional activity is robust to common firm and stock characteristics. Furthermore, including the standard controls allows the regional activity effect to be measured with greater precision and substantially increases the statistical significance of the estimated coefficient. The other regression coefficients only partially explain the cross section of individual stock returns. Consistent with previous findings in the asset pricing literature, historical market beta has little predictive power for returns. I also find no significant estimation coefficients for idiosyncratic volatility, cumulative past return, or the bid–ask spread. Moreover, firm size, book-to-market, institutional ownership, and particularly the short-term reversal, exhibit a strong effect on returns in the expected direction.[17]

[16] I require the index components to be publicly available (but not necessarily the indexes). The rationale behind this assumption is that the components are sufficient for the investors to construct the regional forecasts. In the robustness tests, I further discuss the availability of PREA.

[17] The mixed results across the other well-known standard controls could be partially attributed to the differing time period from that used in the original studies.

TABLE 3
Predicted Regional Economic Activity and Stock Returns

Table 3 reports the average cross-sectional regression coefficients using the Fama–MacBeth (1973) framework:

$$\mathrm{RETRF}_{i,t} = \alpha_t + \beta_t \mathrm{PREA}^{\perp}_{i,t-3} + \mathbf{x}'_{i,t-1}\mathbf{b}_t + \varepsilon_{i,t},$$

where $\mathrm{RETRF}_{i,t}$ is the excess return of stock i in month t, and $\mathbf{x}'_i$ is a vector of other firm characteristics. $\mathrm{PREA}^{\perp}$ is the orthogonalized predicted regional economic activity proxy. The other variables are described in Table 1 and in Section IA.A of the Supplementary Material. The t-statistics computed with the Newey–West (1987) standard errors are reported in parentheses. The sample period is July 1995 through June 2014.

Variable	1	2	3	4	5	6
$\mathrm{PREA}^{\perp}_{t-3}$	0.457	0.381	0.347	0.384	0.389	
	(2.92)	(4.31)	(5.90)	(4.70)	(4.60)	
$\mathrm{PREA}^{\mathrm{ExHQ}}_{t-3}$						0.198
						(3.78)
$\mathrm{PREA}^{\mathrm{HQ}}_{t-3}$						0.117
						(3.83)
β		−0.001	−0.001	−0.001	−0.001	−0.001
		(−0.84)	(−0.82)	(−0.78)	(−0.82)	(−0.82)
ln(SIZE)		−0.002	−0.002	−0.002	−0.002	−0.001
		(−3.05)	(−3.07)	(−2.58)	(−2.80)	(−2.66)
ln(BEME)		0.002	0.002	0.002	0.002	0.002
		(1.68)	(2.07)	(1.75)	(1.70)	(2.11)
ln(ISVOLA)		0.000	−0.000	−0.000	0.000	−0.000
		(0.02)	(−0.05)	(−0.00)	(0.01)	(−0.13)
$\mathrm{RETRF}_{t-12,t-2}$		0.002	0.001	0.002	0.002	0.001
		(0.57)	(0.26)	(0.56)	(0.56)	(0.29)
RETRF_{t-1}		−0.043	−0.050	−0.043	−0.043	−0.050
		(−5.86)	(−6.78)	(−5.93)	(−5.91)	(−6.84)
ln(BIDASK)		−0.000	0.000	0.000	0.000	0.000
		(−0.11)	(0.11)	(0.11)	(0.14)	(0.40)
IO		0.006	0.006	0.006	0.006	0.006
		(2.98)	(2.99)	(3.16)	(3.18)	(3.04)
INDRET_{t-1}			0.148			0.142
			(9.11)			(8.77)
$\mathrm{INDRET}_{t-12,t-2}$			0.012			0.011
			(2.87)			(2.67)
HQRET_{t-1}			0.041			0.041
			(3.95)			(4.13)
ln(STATEDISP)				−0.000		−0.000
				(−0.36)		(−0.37)
HHI					−0.000	−0.000
					(−0.02)	(−0.16)
Constant	0.005	0.023	0.019	0.023	0.022	0.020
	(1.06)	(1.49)	(1.38)	(1.50)	(1.41)	(1.32)
Avg. R^2	0.001	0.055	0.061	0.056	0.056	0.063
No. of obs.	874,072	874,072	874,072	874,072	874,072	877,011

Besides the variables in column 2 of Table 3, it is important to account for the potentially confounding effect of other characteristics that are closely related to economic activity in the relevant regions, such as industry and geographic momentum, geographic dispersion, or the economic conditions of the headquarter state. These variables could potentially lead to a spurious correlation between $\mathrm{PREA}^{\perp}$ and stock returns. To alleviate this concern, in the remainder of this section, I add closely related control variables in alternative specifications.

1. Industry and Geographic Momentum

In the third specification, in addition to the standard controls, I include the industry return for the past month and the cumulative past industry return from month $t-12$ to month $t-2$ to account for the industry momentum. Moskowitz and Grinblatt (1999) show that a strategy that involves buying winning industry stocks and selling losing industry stocks is highly profitable and partially explains the individual stock momentum. Therefore, given that industries tend to be clustered geographically (Ellison and Glaeser (1997)), the predictive power of regional economic activity may be driven by the effect of industry momentum on individual stock returns. Moreover, I control for the past month's return averaged across all companies located in the same headquarter state. Parsons et al. (2017) document a lead–lag return effect among companies headquartered in the same region. Given that regional economic activity and contemporaneous returns are also positively related, it is interesting to note if the PREA effect remains, even after controlling for this cross-predictability.

The empirical results in column 3 of Table 3 confirm the findings of Moskowitz and Grinblatt (1999) and Parsons et al. (2017). The three variables, that is, the two past industry returns and the lagged headquarter state return, are significantly related to contemporaneous stock returns, with regression coefficients of 0.148, 0.012, and 0.041, respectively. Nevertheless, the lagged economic activity coefficient remains significant at the 1% significance level and decreases only slightly to 0.347. This empirical finding suggests that the state activity effect cannot be explained by industry and geographic momentum.

2. State Dispersion

As described in Section II.A, the construction of the state activity proxy requires two underlying variables: the economic relevance of the U.S. states for each firm, and the predicted growth rates in the relevant state coincident indexes. Thus, $\text{PREA}^{\perp}$ is indirectly related to the number of distinct state names mentioned in the SEC filings. Moreover, in light of the Merton (1987) model, García and Norli (2012) show that firms which operate in fewer U.S. states are less recognized by investors and outperform geographically dispersed firms. To account for the possibility that the return predictability with PREA is driven purely by the geographic dispersion of a given firm, I introduce the natural logarithm of STATEDISP into the fourth regression specification. Additionally, in column 5 of Table 3, I use an alternative measure of geographic dispersion; the Herfindahl–Hirschman index adapted to state counts.

Columns 4 and 5 of Table 3 present the regression estimates with the predicted state activity proxy, the standard controls and the two geographic dispersion measures as independent variables. The coefficient of main interest remains highly significant in the two specifications, with values of 0.384 and 0.389, respectively. This finding implies that $\text{PREA}^{\perp}$ plays an important role in explaining returns and that the effect is not driven by the state dispersion of the firm. Furthermore, I find very weak evidence of the effect originally reported by García and Norli (2012). The coefficient of ln(STATEDISP) is negative but not significant by standard confidence levels. A similar result is obtained when HHI is included as an explanatory variable. However, this result can be attributed mainly to the different sample period.[18]

[18]Namely, when restricting the sample of this study to the period up to Dec. 2008, as in García and Norli (2012), I find that state dispersion negatively predicts stock returns at the 5% significance level. As suggested by García and Norli (2012), the weaker effect of state dispersion in the recent sample

3. Headquarter State Activity

Pirinsky and Wang (2006) document return comovement of firms headquartered in the same U.S. state. Moreover, many studies dealing with local bias or the informational advantage of local investors focus on the headquarter region as the variable of interest, neglecting other states or regions. Therefore, the correlation between the state economic activity across all relevant states and returns could be driven fully by the economic conditions of the headquarter state. To address this point, I break down the regional activity proxy into two parts. The first measures only the predicted regional economic activity of the headquarter state, $\text{PREA}_{i,t}^{\text{HQ}}$, whereas the second captures the predicted economic activity of all relevant states with the exception of the headquarter state, $\text{PREA}_{i,t}^{\text{ExHQ}}$.[19] I conjecture that the economic activity of *all* relevant states better explains the impact of regional macroeconomic conditions on returns compared to the economic activity of the headquarter state alone. In other words, I expect that the regression coefficients associated with both $\text{PREA}_{i,t-3}^{\text{HQ}}$ *and* $\text{PREA}_{i,t-3}^{\text{ExHQ}}$ are economically and statistically significant.

As expected, column 6 of Table 3 shows that the effects of the two regional activity variables are highly significant. Moreover, the coefficient to PREA excluding the headquarter state is nearly twice as large as the corresponding coefficient of the headquarter state.[20] These results have the following important implication in terms of explaining the cross section of individual stock returns: A proxy that captures expected economic conditions of all relevant states provides more valuable information compared to that which incorporates only information on the economic conditions of the headquarter state.[21]

B. Portfolio Tests

Besides the regression framework of Fama and MacBeth (1973), portfolio tests provide an alternative way of using cross-sectional data to test asset pricing predictions. At the beginning of each month t, I sort the stocks into quintiles according to their $\text{PREA}^{\perp}$ proxy in month $t-3$. To analyze whether state activity forecasts positively predict stock returns across different asset pricing models, I compare the returns of the two extreme portfolios across different asset pricing models. Columns 1 to 5 of Table 4 report average excess returns over the risk-free rate of the equal- and value-weighted portfolios, respectively. The univariate sorts show that the relation between the state activity and the returns increases monotonically. In the case of equal-weighted portfolios, one can observe that the average monthly excess return increases from 0.88% to 1.376 when moving from the lowest to the highest $\text{PREA}^{\perp}$ portfolio. The value-weighted portfolios yield a

indicates that the trading strategy relating to state dispersion was spotted and extensively implemented by arbitrageurs after the publication of their study. Most importantly, the economic and statistical significance of regional economic activity remains unchanged after restricting the sample period.

[19]Section B of the Supplementary Material contains detailed information about the variable construction.

[20]The average cross-sectional variances of the proxies are essentially identical, while the two variables are, interestingly, not significantly cross-correlated.

[21]In untabulated estimations, I observe that including $\text{PREA}_{i,t-3}$ (instead of $\text{PREA}_{i,t-3}^{\text{ExHQ}}$) causes the effect of the headquarter state activity to vanish.

TABLE 4
Portfolio Sorts Based on PREA$^{\perp}$

Table 4 reports the average monthly portfolio returns (in percentages) and their corresponding t-statistics for both equal-weighted and value-weighted portfolios. The portfolios are sorted according to PREA$^{\perp}$ lagged by 3 months into quintiles. The last row reports the average monthly portfolio return (in percentages) and the corresponding t-statistic of a portfolio that goes long in the highest and short in the lowest quintile. PREA$^{\perp}$ is the orthogonalized predicted regional economic activity proxy. The sample period is July 1995 through June 2014.

Portfolio	Low PREA$^{\perp}$	2	3	4	High PREA$^{\perp}$	High − Low
Panel A. Equal-Weighted Portfolio						
RETRF	0.878	0.979	1.087	1.222	1.376	0.498
	(2.45)	(2.43)	(2.64)	(2.97)	(3.53)	(4.42)
Panel B. Value-Weighted Portfolio						
RETRF	0.520	0.644	0.728	0.787	0.966	0.446
	(1.62)	(2.07)	(2.30)	(2.38)	(2.82)	(2.93)

similar result. To test the hypothesis that forecasts of regional economic activity may be positively associated with the cross section of returns, I form a hypothetical portfolio strategy that goes long in the highest quintile and short in the lowest quintile. If regional economic activity positively predicts stock returns, I expect this strategy to yield, on average, an economically and statistically significant positive return. The last row of Table 4 shows that the difference in return between the fifth and the first portfolio is positive and statistically significant, regardless of the weighting method. The equal-weighted long–short portfolio gives a monthly return of 0.498% ($t = 4.42$), whereas the value-weighted portfolio yields a slightly lower return of 0.446% ($t = 2.93$). The t-statistic of the value-weighted long–short portfolio is slightly lower than the hurdle t-ratio of 3.0 proposed by Harvey et al. (2016). However, the statistical significance of the return spread increases when I adjust for common risk factors. The decrease in economic and statistical significance when using the value-weighted portfolio formation indicates that the state activity effect is stronger among small stocks. Overall, portfolio sorts yield results of similar economic magnitude to the effects found in the regression analysis.

Next, I run time-series regressions to risk-adjust the excess returns with well-known asset pricing factors. In Table 5, I account for the market risk (columns 1–3), the Fama–French (1993) factors (columns 4–6), the Carhart (1997) factor (columns 7–9), and the Pástor–Stambaugh (2003) factor (columns 10–12), respectively. The α rows of Panels A and B show that the abnormal returns remain significant when all four asset pricing models are employed. For instance, in Panel A for the equal-weighted portfolio, the intercept (alpha) for the five-factor model is 0.467% ($t = 4.85$), while the same time-series regression for the value-weighted portfolio yields a risk-adjusted return of 0.431% ($t = 3.03$). Taking a closer look at the long and short portfolios, I observe that the differences in return come from both the underperformance of the low PREA$^{\perp}$ and the overperformance of the high PREA$^{\perp}$ portfolio, rather than being driven purely by one side of the strategy. This finding is surprising because most existing misvaluation factors in the literature can be attributed mainly to the strong negative returns of the short portfolio (Stambaugh, Yu, and Yuan (2012)). Finally, when I compare these results to Table 4, the returns decrease slightly after the risk-adjustments, but remain statistically significant at the 1% level.

TABLE 5

PREA$^{\perp}$ Portfolio Time-Series Regression

Table 5 reports the coefficient estimates (Jensen's alpha and regression coefficients) of the following regression model:

$$\mathrm{LS}_{\mathrm{PREA}^{\perp},t} \quad = \quad \alpha + \mathbf{X}_t' \boldsymbol{\beta} + \varepsilon,$$

where LS is the long–short portfolio return formed according to $\mathrm{PREA}_{t-3}^{\perp}$ reported in Table 4, and $\mathbf{X}_t'$ is a set of the five tradable common risk factors MKTRF, SMB, HML, UMD, and LIQ (Fama and French (1993), Carhart (1997), and Pástor and Stambaugh (2003)). Panel A shows the results for the equal-weighted long–short portfolio, $\mathrm{LS}^{\mathrm{EW}}_{\mathrm{PREA}^{\perp},t}$, and Panel B shows the results for the value-weighted counterpart, $\mathrm{LS}^{\mathrm{VW}}_{\mathrm{PREA}^{\perp},t}$. The t-statistics are reported in parentheses. The sample period is July 1995 through June 2014.

	Low	High	High – Low	Low	High	High – Low	Low	High	High – Low	Low	High	High – Low
Variable	1	2	3	4	5	6	7	8	9	10	11	12
Panel A. Equal-Weighted Portfolio												
α	0.247	0.715	0.469	0.043	0.568	0.525	0.229	0.710	0.480	0.201	0.668	0.467
	(1.31)	(3.19)	(4.15)	(0.33)	(3.73)	(5.45)	(2.32)	(5.08)	(5.03)	(2.03)	(4.77)	(4.85)
MKTRF	1.008	1.055	0.047	0.950	0.937	−0.014	0.849	0.859	0.010	0.845	0.854	0.009
	(24.77)	(21.81)	(1.93)	(32.98)	(27.48)	(−0.64)	(36.44)	(26.06)	(0.46)	(36.44)	(26.04)	(0.38)
SMB				0.620	0.764	0.144	0.658	0.793	0.135	0.658	0.793	0.135
				(15.85)	(16.50)	(4.90)	(22.00)	(18.73)	(4.67)	(22.16)	(18.88)	(4.66)
HML				0.377	0.182	−0.195	0.297	0.122	−0.176	0.303	0.129	−0.173
				(9.13)	(3.73)	(−6.30)	(9.30)	(2.69)	(−5.69)	(9.51)	(2.87)	(−5.60)
UMD							−0.245	−0.186	0.058	−0.246	−0.189	0.058
							(−12.82)	(−6.90)	(3.17)	(−12.98)	(−7.03)	(3.13)
LIQ										0.049	0.073	0.024
										(2.10)	(2.21)	(1.06)
Panel B. Value-Weighted Portfolio												
α	−0.113	0.316	0.428	−0.181	0.308	0.488	−0.116	0.303	0.420	−0.153	0.278	0.431
	(−1.17)	(2.36)	(2.78)	(−1.98)	(2.44)	(3.43)	(−1.33)	(2.38)	(2.98)	(−1.76)	(2.16)	(3.03)
MKTRF	1.010	1.038	0.028	1.026	0.992	−0.034	0.991	0.994	0.003	0.986	0.991	0.004
	(48.53)	(35.84)	(0.85)	(50.21)	(35.13)	(−1.08)	(47.98)	(33.05)	(0.09)	(48.51)	(32.92)	(0.13)
SMB				0.062	0.207	0.145	0.075	0.206	0.131	0.075	0.206	0.131
				(2.23)	(5.40)	(3.34)	(2.82)	(5.33)	(3.08)	(2.86)	(5.34)	(3.07)
HML				0.167	−0.037	−0.205	0.140	−0.035	−0.175	0.147	−0.031	−0.177
				(5.72)	(−0.92)	(−4.48)	(4.94)	(−0.86)	(−3.85)	(5.26)	(−0.75)	(−3.88)
UMD							−0.084	0.006	0.090	−0.086	0.005	0.091
							(−4.97)	(0.24)	(3.31)	(−5.17)	(0.19)	(3.33)
LIQ										0.064	0.044	−0.019
										(3.10)	(1.45)	(−0.58)

A natural question that arises is how the portfolio strategy is exposed to other risk factors. Table 5 also reports the factor loadings across all the models, and the long and short portfolios. In interest of brevity, I focus on the full model with all five factors (columns 10–12). Both the equal-weighted and the value-weighted long–short portfolios do not load significantly on the market, indicating that the portfolios are well diversified with respect to market risk. The PREA portfolio is positively related to the size and momentum factors, while the exposure to value is strongly negative. As reported in Panel B, the returns of the value-weighted portfolio exhibit very similar exposures to the risk factors.[22]

[22] In additional tests, I conduct time-series regressions using only stocks with a price higher than 5 USD. The magnitude of the alpha decreases for the equal-weighted portfolios. Nevertheless, as evident from Table IA.5 in the Supplementary Material, the risk-adjusted returns remain economically and statistically significant. Also, I add the factors of profitability and investment (Fama and French (2015)), and two mispricing factors related to firm performance and managerial decisions, as proposed

To summarize, I find that a trading strategy based on lagged economic activity forecasts, combined with information on regions that are economically relevant for firms, is partially correlated with important risk factors. However, the explanatory power of the factors is very low, and the risk-adjusted alpha amounts to 5.75% (5.30%) per annum for the equal-weighted (value-weighted) portfolio. These findings confirm the regression results in Section III.A.

In Figure 2, I compare the returns of the two PREA long–short portfolios with the returns of the market and the momentum portfolio (Jegadeesh and Titman (1993)). I find that the performance of both the equal-weighted and the value-weighted regional economic activity portfolios is very similar in quantitative terms to that of the prominent momentum strategy. However, even more importantly, the PREA strategy does not experience the same severe crashes as the momentum portfolio (Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016)). Thus, the crash risk explanation that is often alleged for momentum returns is unlikely to apply to the effect documented in this study.

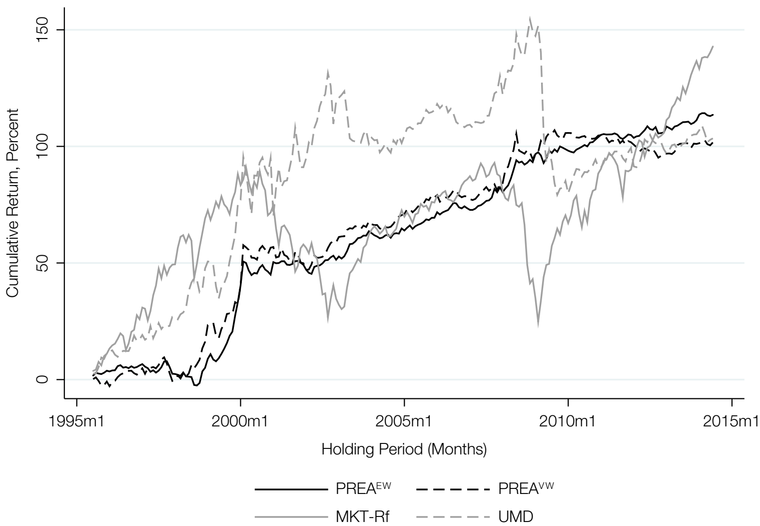
C. Robustness Tests

To examine the stability of the relation between regional economic activity and stock returns, I conduct a battery of robustness tests. In particular, I assess whether the results in Table 3 are sensitive to return adjustments, sample selection and alternative proxies. The estimation results for the main robustness tests are

FIGURE 2

Cumulative Return of the PREA-Based Portfolio, the Market, and the Momentum Portfolio

Figure 2 shows the cumulative return performance of the equal- and value-weighted long–short $\text{PREA}^{\perp}_{t-3}$ portfolio (black solid and black dashed lines, respectively), the value-weighted market portfolio over the risk-free rate (gray solid line), and the momentum portfolio (gray dashed line). The sample period is July 1995 through June 2014.



by Stambaugh and Yuan (2017). The results are reported in the Supplementary Material in Table IA.6 of the PREA portfolio to the profitability factor.

provided in Table 6. Results of further robustness tests are available in Section B of the Supplementary Material.

1. Return Adjustments

As shown in Section III.A, the PREA effect is not driven by the past return of clustered industries. Nevertheless, I now address this issue from a different perspective by adjusting the returns and all other variables by the 49 Fama–French industry benchmark portfolios, as suggested by Gormley and Matsa (2014). I repeat the regression using the full specification model of equation (3) with industry effects. I observe in column 1 of Table 6 a slight decrease in the PREA effect, yet the results remain highly significant at the 1% level.

TABLE 6
Robustness Tests

Table 6 reports the average cross-sectional regression coefficients using the Fama–MacBeth (1973) framework, as in Table 3. The values in this table represent the robustness tests related to Table 3. Specification 1 includes industry fixed effects using the 49 Fama–French industry classification, specification 2 includes the 125 size-value-momentum portfolio fixed effects (Daniel, Grinblatt, Titman, and Wermers (1997)), and specification 3 uses $\text{PREA}^{\perp}$ with a lag of 4 months for predicting all April returns and the return of Dec. 2013, and a standard lag of 3 months to predict all other monthly returns. The t-statistics computed with the Newey–West (1987) standard errors are reported in parentheses. The sample period is July 1995 through June 2014.

Variable	1	2	3
$\text{PREA}^{\perp}_{t-3}$	0.337	0.345	
	(7.15)	(6.49)	
$\text{PREA}^{\perp}_{t-3\vee t-4}$			0.343
			(5.62)
β	−0.000	−0.000	−0.001
	(−0.51)	(−0.09)	(−0.79)
ln(SIZE)	−0.001		−0.001
	(−2.81)		(−2.60)
ln(BEME)	0.002		0.002
	(3.08)		(2.10)
ln(ISVOLA)	−0.001	0.001	−0.000
	(−0.37)	(0.33)	(−0.08)
$\text{RETRF}_{t-12,t-2}$	0.001		0.001
	(0.24)		(0.27)
RETRF_{t-1}	−0.051	−0.050	−0.050
	(−6.95)	(−7.00)	(−6.82)
ln(BIDASK)	0.001	0.002	0.000
	(0.68)	(2.58)	(0.35)
IO	0.005	0.005	0.006
	(2.82)	(2.72)	(3.08)
INDRET_{t-1}		0.141	0.142
		(8.56)	(8.83)
$\text{INDRET}_{t-12t-2}$		0.010	0.011
		(1.78)	(2.60)
HQRET_{t-1}	0.036	0.047	0.041
	(3.48)	(4.60)	(4.19)
ln(STATEDISP)	0.000	−0.001	−0.000
	(0.21)	(−1.04)	(−0.39)
HHI	0.002	−0.000	−0.000
	(1.16)	(−0.05)	(−0.17)
Constant	0.018	0.014	0.019
	(1.25)	(0.90)	(1.30)
Avg. R^2	0.092	0.084	0.062
No. of obs.	874,055	868,800	874,061

Furthermore, as suggested by Daniel et al. (1997) and Wermers (2004), I first adjust all variables by the 125 ($5 \times 5 \times 5$) benchmark portfolios based on market capitalization, book-to-market and past cumulative return, and subsequently run the return regression.[23] I find in column 2 of Table 6 that the adjustments leave the initial results largely unaffected.

2. Availability of PREA

In the main specification I use PREA of month $t-3$ to predict returns in t. This 3-month lag ensures that the *components* underlying the regional forecasts are available to the investors at the time when stock returns are predicted. Although the availability of the index components is an important requirement for the predictability exercise, in this subsection I take a closer look at the public disclosure dates of the indexes since the date they were first published. From the start of regular index publications in Jan. 2011 to the end of my sample period in June 2014, the indexes were available to the public within the required lag of $t-3$, with one exception: the period of the federal government shutdown in 2013. The Sept. 2013 forecasts were not available on the first day of Dec. 2013. Although not the case for my sample, over the last few years the January forecasts have also been reported late relative to other months. Now, one could raise the concern that such a January delay was also present in my sample period before 2011, and that even the underlying components of the indexes were not observable in April of each year.

To address this concern, in an alternative proxy I use the December (instead of January) forecasts to predict the next year's April stock returns and a standard lag of 3 months for other forecasts. Also, I use the Aug. 2013, rather than the Sept. 2013, forecasts to predict the Dec. 2013 returns because of the government shutdown.[24] As evident from column 3 of Table 6, the coefficient estimate of $\text{PREA}^{\perp}_{t-3 \vee t-4}$ and its t-statistic change only slightly to 0.353 (4.88). Therefore, a look-ahead bias due to *potential* reporting delays is unlikely to explain the predictive power of PREA.

3. Further Robustness Tests

In further tests I find that the regression results are robust to sample selection and adjustments to the construction of PREA along different dimensions. For a detailed discussion of the results, please see Section B of the Supplementary Material.

IV. Understanding the Effect of Regional Economic Activity

The findings of the previous sections show that firms exposed to regions that are expected to perform well (or badly) in the future generate higher (or lower) returns in the subsequent month. There are two possible explanations

[23]The Daniel et al. (1997) benchmarks are available via http://terpconnect.umd.edu/~wermers/ftpsite/Dgtw/coverpage.htm

[24]Importantly, for most of the months, the forecasts for month $t-2$ are already publicly available at t, and the 3- or 4-month lag represents a conservative approach to test the predictability of stock returns. The history of SLI publication dates is reported in the Supplementary Material in Table IA.1.

for the positive relation between predicted state activity and stock returns. The first is that the economic activity of relevant regions has a positive effect on expected consumer demand and on firms' cash flows in those regions. Consequently, news of positive cash flows drives the stock prices and increases the returns. In other words, the increase in stock returns is based on the rise in firms' expected future profitability. The second potential explanation is that stock price reaction may be attributable to a combination of local bias and time-region-varying risk aversion (see, e.g., Korniotis and Kumar (2013)). The notion here is that positive regional economic conditions decrease the risk aversion of regional investors and increase the demand for risky assets. Assuming that investors prefer trading stocks of regional firms over stocks of other firms, they buy local stocks and drive up the prices of those stocks while there is no change in the fundamental value. As a consequence, after a positive price reaction, nonlocal investors trade against this mispricing, leading to subsequent negative returns.

To distinguish between these two possible hypotheses, I first test whether the forecasts of regional economic activity predict the real operations of firms. If the predicted price changes are purely based on changes in local risk aversion, I should not find any effect on firm profitability. However, if the returns are driven by changes in the fundamental value of the companies, I would expect there to be a positive link between regional economic activity and firm profitability. Second, if the return predictability is driven, at least partially, by information underreaction and investors' biased expectations about the fundamentals, I expect that PREA will also predict the discrepancy between market expectations and observed fundamentals. In the third step, I examine the long-run performance of the PREA long–short portfolio. If the return predictability is driven solely by changes in local risk aversion, I should observe a reversal of the trading strategy in the long run, as suggested by Korniotis and Kumar (2013). If there is no such reversal, a temporary change in local risk aversion and coordinated trading by nonlocal investors are unlikely to explain the return predictability documented in this article.

A. Regional Economic Activity and Firm Profitability

To study whether the return predictability in Section III relates to changes in firm fundamentals, I test whether regional economic activity also predicts firms' profitability. In particular, I run regressions with firm and quarter fixed effects:

$$\text{(4)} \qquad \begin{aligned} \text{PROFIT}_{i,q} &= \alpha + \beta_1 \text{PROFIT}_{i,q-1} + \beta_2 \text{PREA}^{\perp}_{i,q-1} \\ &\quad + \mathbf{y}'_{\mathbf{i,q-1}}\mathbf{b} + \mu_i + \eta_q + \varepsilon_{i,q}, \end{aligned}$$

where firm profitability (PROFIT) is measured by sales scaled by assets (SOA), earnings per share (EPS), and operating income before depreciation scaled by assets (ROA). $\text{PREA}^{\perp}_{i,q-1}$ is the value of the orthogonalized PREA at the end of the previous quarter. $\mathbf{y}'_{\mathbf{i,q-1}}$ denotes the vector of control variables, and μ_i and η_q denote the firm fixed effect and the quarter fixed effect, respectively. The main coefficient of interest in this analysis is β_2, which is expected to be positive if the return predictability stems from expectations of future cash flows. Besides a list

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of common control variables employed in the literature,[25] $\mathbf{y}'_{\mathbf{i,q-1}}$ also includes the lagged regional profitability proxy in the spirit of Addoum et al. (2017).[26]

Columns 1–3 of Table 7 report the empirical results for SOA as the dependent variable. The regional economic activity coefficient in columns 1–3 are positive, stable and statistically significant across the different regression specifications. In particular, even after controlling for the past quarter's SOA and regional SOA_{reg}, $\text{PREA}_i^{\perp}$ significantly and positively predicts the scaled sales of the firm. The results in columns 4–6 of Table 7 confirm the predictive power of the lagged regional activity forecast when EPS is used as the dependent variable. In all three regression specifications, the coefficient associated with the proxy is statistically significant at least at the 5% level, suggesting that $\text{PREA}_i^{\perp}$ positively predicts the future profitability of firms. As shown in columns 7–9, I obtain similar results when using ROA as the dependent variable. Finding an effect of regional economic activity on the future firm performance suggests that the stock market reaction documented in Sections III.A and III.B is based on the change in the fundamental value of the firms.[27]

B. Regional Economic Activity and Analysts' Earnings Forecast Errors

The findings thus far suggest that the predictability of stock returns with regional economic activity stems from changes in the fundamentals of the companies. A simple decomposition of cash flows implies that each stock's expected return is determined by its price-to-book ratio and *expectations of its future profitability* and investment, irrespective whether prices are rational or irrational (Campbell and Shiller (1988), Fama and French (2015)). In this section, I ask whether mispricing due to the slow diffusion of regional information into prices at least partially explains the return predictability. For this purpose, I link PREA to future analyst forecast errors. If mispricing due to biased market expectations explains this predictability, and if analysts' earnings forecasts proxy for the expectations of investors, then I expect analysts' earnings forecast errors to be positively associated with $\text{PREA}^{\perp}$.

I employ three proxies for earnings forecast errors. For the first two, I rely on IBES summary statistics of analyst forecasts. The first proxy, SUE^{AFD}, denotes the difference between the actual earnings per share and the mean estimate across all analysts scaled by the standard deviation of the estimates. For the second proxy, SUE^{AFP}, I scale the numerator by the stock price of the previous month instead of by the standard deviation of the forecasts. For my third proxy of earnings surprise, I use the stock market reaction on the earnings announcement day. In the

[25]I control for lagged profitability, market capitalization, book-to-market ratio, change in net operating assets, dividend yield, and a dummy variable that takes a value 1 if the firm reports a loss in the last quarter (e.g., Fama and French (1995), (2000), Richardson, Sloan, Soliman, and Tuna (2005)). Additionally, the list of variables includes the cumulative past stock return and the cumulative industry return, in order to disentangle the effect of state activity from information already incorporated into the stock market.

[26]The regional profitability of each company is the CIT_SHARE-weighted average of profitability across all states that are economically relevant for the company.

[27]Results are robust to the Fama–MacBeth (1973) estimation procedure that relies on the cross-sectional heterogeneity across the companies. Table IA.7 in the Supplementary Material reports these estimates.

TABLE 7

Regional Economic Activity and Firm Profitability

Table 7 reports the regression coefficients using 2-way fixed effect estimation with the following specification:

$$\text{PROFIT}_{i,q} \quad = \quad \alpha+\beta_1\text{PROFIT}_{i,q-1}+\beta_2\text{PREA}^{\perp}_{i,q-1}+\mathbf{y}'_{\mathrm{i,q-1}}\mathbf{b}+\mu_i+\eta_q+\varepsilon_{i,q},$$

where firm profitability is measured by sales scaled by assets (SOA), earnings per share (EPS), and operating income before depreciation scaled by assets (ROA). PREA$^{\perp}$ is the orthogonalized predicted regional economic activity proxy. $\mathbf{y}'_{\mathrm{i,q-1}}$ denotes the vector of control variables, while μ_i and η_q denote the firm fixed effect and quarter fixed effect, respectively. The standard control variables include lagged profitability, the citation-share weighted profitability measure across all company-relevant U.S. states (PROFIT$^{\text{reg}}$) calculated as in Addoum et al. (2017), the natural logarithm of market capitalization (ln(SIZE)), the natural logarithm of book-to-market ratio (ln(BEME)), the change in net operating assets (DNOA), a dummy variable that takes a value of 1 if the firm reported a loss in the last quarter (LOSS) and 0 otherwise, and the dividend yield (DIV). Additionally, I include firms' excess stock return (RET) and the corresponding industry return (INDRET) of the past quarter. All explanatory variables are lagged by one quarter. All specifications include stock and quarter fixed effects. The t-statistics are calculated using 2-way clustered standard errors and reported in parentheses. The sample period is July 1995 through June 2014.

	SOA			EPS			ROA		
Variable	1	2	3	4	5	6	7	8	9
SOA	0.666 (52.49)	0.664 (52.29)	0.641 (48.07)						
EPS				0.338 (33.47)	0.337 (33.34)	0.276 (29.09)			
ROA							0.520 (46.02)	0.518 (45.73)	0.488 (41.50)
PREA$^{\perp}$	4.764 (5.87)	4.443 (5.34)	3.349 (3.84)	1.121 (4.50)	1.083 (4.36)	0.772 (3.32)	5.533 (3.45)	5.250 (3.21)	3.385 (2.03)
SOA$^{\text{reg}}$		0.031 (3.33)	0.029 (2.88)						
EPS$^{\text{reg}}$					0.083 (2.65)	0.058 (2.06)			
ROA$^{\text{reg}}$								0.046 (2.50)	0.036 (1.85)
ln(SIZE)			−0.343 (−18.97)			0.040 (7.58)			0.171 (6.41)
ln(BEME)			−0.481 (−23.04)			−0.070 (−14.29)			−0.335 (−10.88)
DNOA			0.294 (1.91)			−0.049 (−2.04)			−0.508 (−3.13)
LOSS			0.381 (14.58)			−0.050 (−9.72)			−0.076 (−1.80)
DIV			0.052 (2.31)			0.051 (4.30)			0.076 (3.32)
RET			−0.013 (−0.77)			0.001 (0.23)			0.086 (2.75)
INDRET			0.097 (0.95)			0.073 (1.95)			0.275 (1.33)
R^2	0.921	0.921	0.924	0.491	0.491	0.514	0.742	0.743	0.750

regressions, I control for the earnings surprises of the previous quarter and a number of standard firm-level variables, including information from the IBES database if possible. Also, all specifications include both stock and month fixed effects.

The coefficients in Table 8 show that, irrespective of which earnings surprise proxy I employ, PREA$^{\perp}$ significantly predicts the forecast errors and the returns on announcement days in the right direction. In particular, I find that analysts underestimate the information on regional economic activity. In addition to this, the effect is economically significant. For instance, a 1-standard-deviation increase in PREA$^{\perp}$ is associated with an increase in the SUE$^{\text{AFD}}$ forecast error of 0.20.[28]

[28]The distance between the median and 75th percentile of this forecast error amounts to 1.67.

TABLE 8

Regional Economic Activity and Earnings Surprise

Table 8 reports the regression coefficients using 2-way fixed effect estimation with the following specification:

$$\text{ESURP}_{i,q} = \alpha + \beta_1 \text{ESURP}_{i,q-1} + \beta_2 \text{PREA}^{\perp}_{i,t-3} + \mathbf{y}'_{i,t-1}\mathbf{b} + \mu_i + \eta_t + \varepsilon_{i,t},$$

where earnings surprise is measured using three different proxies. The first proxy is the difference between the actual earnings per share and the mean estimate across all analysts scaled by the standard deviation of the estimates (SUE^{AFD}). The second proxy is the difference between the actual earnings per share and the mean estimate across all analysts scaled by the last month's stock price (SUE^{AFP}). The third proxy is the stock market reaction on the earnings announcement day (CAR). The vector $\mathbf{y}'_i$ represents other firm characteristics. $\text{PREA}^{\perp}$ is the orthogonalized predicted regional economic activity proxy. ln(NUMEST) is the logarithmized number of analyst estimates. ln(ANALYST_DISP) is the natural logarithmized standard deviation of the corresponding estimates, and SINGLE denotes a dummy variable, taking a value of 1 if there is only one analyst covering the stock, and 0 otherwise. The other variables are described in Table 1 and in Section IA.A of the Supplementary Material. All explanatory variables are lagged by either 1 quarter or 1 month, depending on the data frequency. All specifications include stock and month fixed effects. The t-statistics are calculated using 2-way clustered standard errors and are reported in parentheses. The sample period is July 1995 through June 2014.

	SUE^{AFD}		SUE^{AFP}		CAR	
Variable	1	2	3	4	5	6
SUE^{AFD}	0.133 (22.85)	0.109 (19.00)				
SUE^{AFP}			0.178 (15.13)	0.170 (13.80)		
CAR					−0.030 (−8.02)	−0.032 (−8.13)
$\text{PREA}^{\perp}_{t-3}$	18.113 (3.22)	15.249 (2.60)	0.131 (2.79)	0.104 (2.32)	0.184 (3.37)	0.184 (3.41)
ln(SIZE)		−0.380 (−7.77)		0.002 (3.10)		−0.011 (−14.87)
ln(BEME)		−0.149 (−3.54)		−0.003 (−5.41)		−0.001 (−1.00)
$\text{RETRF}_{t-12,t-2}$		0.642 (8.27)		0.003 (5.93)		−0.001 (−1.24)
RETRF_{t-1}		2.550 (11.16)		0.014 (4.89)		−0.010 (−3.99)
β		0.032 (0.77)		0.001 (1.34)		−0.001 (−2.24)
ln(ISVOLA)		−0.476 (−4.94)		−0.009 (−6.46)		0.002 (1.28)
INDRET_{t-1}		0.754 (0.84)		0.006 (1.06)		0.009 (0.78)
ln(NUMEST)		0.078 (1.43)		0.000 (0.31)		
ln(ANALYST_DISP)				−0.005 (−7.25)		
SINGLE				−0.007 (−8.26)		
R^2	0.168	0.181	0.275	0.284	0.068	0.074

This finding suggests that the market, as proxied by the estimates of analysts, does not immediately incorporate fundamental and relevant information about regional economic activity into its expectations. As a consequence, evidence from this section suggests that the return predictability using PREA is at least partially due to slow diffusion of regional information into stock prices.

C. Long-Run Effect

Investors' reactions to changes in regional conditions are predictable in the cross section of stock returns. Further, I find that the positive relation between economic state activity and return is based on fundamental changes in firms' profitability that are not incorporated immediately into prices. Thus, I expect that regional economic activity will have a permanent impact on prices, but will reflect the change in fundamental value only with a lag. Alternatively, one might argue that local investors overreact to information on regional activity and/or temporarily change their risk aversion, as suggested by Korniotis and Kumar (2013). According to this hypothesis, the long-run return reaction should show a reversal. The one-month horizon analysis of Section III did not allow to distinguish between these two explanations.

To examine the return pattern in the long run, I use the $PREA^{\perp}$ long–short portfolio as the explanatory variable and obtain monthly returns for the 36 months after portfolio formation. I then run time-series regressions with the full five-factor model for the corresponding months. Figure 3 shows the average risk-adjusted holding period returns for the equal-weighted and value-weighted long–short portfolios for different holding periods k. Overall, the average cumulative abnormal return of the portfolios increases over the holding period, but with decreasing monthly returns. After 36 months, the average risk-adjusted holding period returns are approximately 4.1% and 1.5% for the equal- and value-weighted portfolio, respectively. The difference in returns between the long and short portfolios is even more pronounced in the long run. The results also suggest that the information diffusion process for small stocks is longer and drives the stronger performance of the equal-weighted portfolio. Most importantly, however, both portfolios show no significant reversal in their patterns, and both remain positive throughout the entire investment period.

The results of the long-horizon investment, combined with the findings of cash-flow predictability and analysts' forecast errors, are most consistent with the idea that the return predictability with regional economic activity comes from the gradual incorporation of fundamental geographic information into the stock market.[29]

D. Difficult-to-Arbitrage Stocks

A question that naturally arises is that, if a profitable trading strategy based on mispricing exists, such as the one discussed in this study, what prevents investors from investing and arbitraging away the profits? In this section, I explore the role of frictions that prevent arbitrage from fully eliminating mispricing (Gromb and Vayanos (2010)), which might sustain the predictability of stock returns when using PREA. In efficient markets, arbitrage opportunities vanish immediately as a large number of investors active in the market take positions against the mispricing, driving the stock price back to its fundamental value. However, in reality investors might face systematic noise trader risk (De Long, Shleifer, Summers, and Waldmann (1990)), causing stock prices to perhaps diverge in the short run even further from the fundamental value. Idiosyncratic risk and trading costs create further frictions that prevent arbitrage (Pontiff (1996), (2006)).

[29]Note that there may be other macroeconomic indicators that proxy for changes in local risk aversion (see, e.g., Korniotis and Kumar (2013)) that could cause a reversal of local portfolios in the long run. Nevertheless, the results of this article, and particularly this section, show that regional macroeconomic indicators can affect the real operations of firms and the corresponding stock prices in the same way.

FIGURE 3

Long-Horizon Performance of the Predicted Regional Activity Portfolio

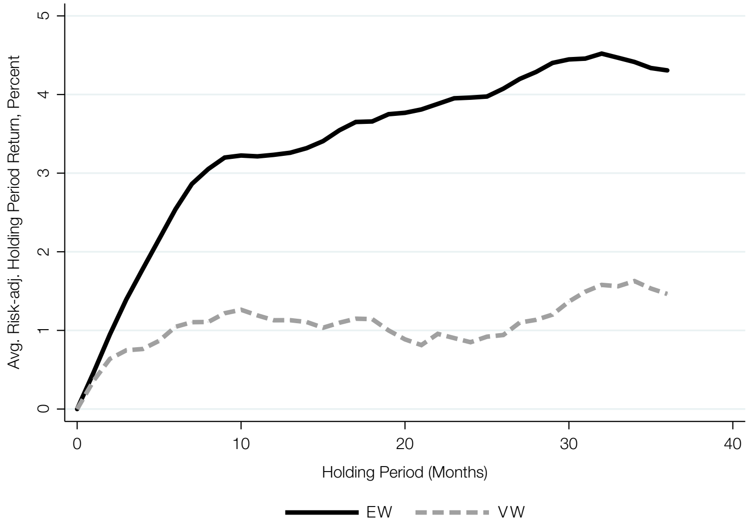
Figure 3 plots the average cumulative risk-adjusted return of the $\text{PREA}^{\perp}_{t-3}$ long–short portfolio. To calculate the long-horizon performance, I first construct for each month the long–short portfolio according to $\text{PREA}^{\perp}_{t-3}$ and obtain the monthly returns in the months $t+k-1$, where $k \in \{1,\ldots,36\}$. Second, for each horizon I run a time-series regression with the 5-factor model for the corresponding months. The regression intercept is defined as the average risk-adjusted portfolio return for the long–short portfolio at month $t+k$:

$$\begin{aligned} \text{LS}_{t+k-1} &= \alpha_k + \beta_{\text{MKTRF},k}(\text{MKTRF})_{t+k-1} + \beta_{\text{SMB},k}\text{SMB}_{t+k-1} \\ &\quad + \beta_{\text{HML},k}\text{HML}_{t+k-1} + \beta_{\text{UMD},k}\text{UMD}_{t+k-1} + \beta_{\text{LIQ},k}\text{LIQ}_{t+k-1} + \varepsilon_{t+k-1,k}. \end{aligned}$$

In the third and final step, the average holding period (cumulative) risk-adjusted return for the next k months since formation is defined as:

$$\text{ACR}_k := \sum_{j=1}^{k} \alpha_j.$$

The sample period is July 1995 through June 2014.



These limits to arbitrage can be amplified by principal–agent problems between investors and investment professionals (Shleifer and Vishny (1997)).

To test the idea of limits to arbitrage, I define variables relating to costly arbitrage and use them in an interaction with PREA within the Fama–MacBeth (1973) framework:

$$(5) \qquad \begin{aligned} \text{RETRF}_{i,t} &= \alpha_t + \beta_1 \text{PREA}^{\perp}_{i,t-3} + \beta_2 \text{PREA}^{\perp}_{i,t-3} \times \text{M}_{i,t-2} \\ &\quad + \beta_3 \text{M}_{i,t-2} + \mathbf{x}_{\mathbf{i}}'\mathbf{b} + \epsilon_{i,t}, \end{aligned}$$

where M denotes the interaction variable and β_2 is the coefficient of interest. I now consider three different variables, all commonly used in the literature, that are closely related to the mechanism of limits to arbitrage: idiosyncratic volatility, the bid–ask spread, and the firm's market capitalization. The three variables are standardized with a mean of 0 and standard deviation of 1 in order to help interpret the results.

Column 1 of Table 9 reports the regression coefficients of the interaction term between the standardized log idiosyncratic volatility and the predicted

TABLE 9

Predictability of Returns and Difficult-to-Arbitrage Stocks

Table 9 reports the relevant average cross-sectional regression coefficients using the Fama–MacBeth (1973) framework:

$$\text{RETRF}_{i,t} \quad = \quad \alpha_t + \beta_1 \text{PREA}^{\perp}_{i,t-3} + \beta_2 \text{PREA}^{\perp}_{i,t-3} \times \text{M}_{i,t-2} + \beta_3 \text{M}_{i,t-2} + \mathbf{x}_i' \mathbf{b} + \epsilon_{i,t},$$

where $\text{RETRF}_{i,t}$ is the excess return of stock i in month t, and $\mathbf{x}_i'$ is a vector of other firm characteristics. $\text{PREA}^{\perp}$ is the orthogonalized predicted regional economic activity proxy. M is a stock characteristic, defined according to the specifications below. STD denotes that the corresponding variables is orthogonalized for the sake of convenient economic interpretation. The other control variables are described in Table 1 and in Section IA.A of the Supplementary Material. This table reports only the regression coefficients β_1 and β_2. The t-statistics computed with the Newey–West (1987) standard errors are reported in parentheses. The sample period is July 1995 through June 2014.

Variable	1	2	3	4
$\text{PREA}^{\perp}_{t-3}$	0.369	0.336	0.347	0.370
	(6.20)	(5.60)	(5.74)	(5.72)
$\text{PREA}^{\perp}_{t-3} \times \ln(\text{ISVOLA})^{\text{STD}}$	0.118			
	(2.12)			
$\text{PREA}^{\perp}_{t-3} \times \ln(\text{BIDASK})^{\text{STD}}$		0.178		
		(4.08)		
$\text{PREA}^{\perp}_{t-3} \times \ln(\text{SIZE})^{\text{STD}}$			−0.132	
			(−2.97)	
$\text{PREA}^{\perp}_{t-3} \times \text{LTA}^{\text{STD}}$				0.152
				(3.30)
Standard controls	Yes	Yes	Yes	Yes
Avg. R^2	0.060	0.060	0.060	0.051
No. of obs.	874,072	874,072	874,072	874,072

regional activity proxy. In line with my prediction, the estimated coefficient on the interaction term is positive and statistically significant. In terms of the economic magnitude, a 1-standard-deviation increase in the logarithmized stock volatility is associated with a 32.98% (0.118/0.369) increase in the PREA effect compared to the average idiosyncratic volatility stock. The intuition behind this finding is that stocks with higher idiosyncratic risk are less attractive to arbitrageurs and exhibit a larger predictable return. This finding is in line with previous studies suggesting that idiosyncratic risk is an important cost faced by arbitrageurs (e.g., Pontiff (2006)). Furthermore, the greater the illiquidity of a stock, the more slowly it is traded on the market, and the greater the costs involved. These additional costs could prevent investors from fully exploiting arbitrage opportunities and taking advantage of the return predictability (Sadka and Scherbina (2007)). Therefore, the hypothesis is that the predictability effect is stronger among illiquid stocks. I measure illiquidity by the natural logarithm of the average daily bid–ask spread over the previous 6 months. The figures in column 2 are in line with this hypothesis, and show there to be a coefficient estimate of 0.178 ($t = 4.08$) on the interaction term between standardized ln(BIDASK) and PREA. This coefficient translates into an increase in the predictability effect of 52.98% (0.177/0.346) for a 1-standard-deviation increase in the logarithmized bid–ask spread. Finally, since illiquid and volatile stocks are in most cases stocks with a low market capitalization, I expect the stocks of small firms to be more difficult to arbitrage. The immediate implication is that the return effect of lagged PREA is stronger for smaller firms. The figures in column 3 provide evidence to support this prediction. The Fama–MacBeth (1973) regression coefficient of the interaction term between $\ln(\text{SIZE})^{\text{STD}}$ and PREA is -0.132 ($t = -2.97$). Volatility, illiquidity, and market capitalization are well-known proxies for limits to arbitrage.

However, since all three variables are highly correlated, it is difficult to disentangle the effect of each proxy. Nevertheless, I argue that the variables have a mutual influence on the effect of predictability. Specifically, stocks that are small, volatile and illiquid are more difficult to arbitrage and display higher predictable returns.[30] I construct a limits-to-arbitrage index (LTA) using a linear combination of the percentile ranks of idiosyncratic volatility, illiquidity, and negative size. Column 4 shows a positive and significant coefficient of the LTA interaction term, confirming the findings shown in the first three columns: Stocks associated with stronger limits to arbitrage characteristics exhibit stronger predictability.

V. Conclusion

This study investigates the link between stock returns and economic conditions of firm-relevant U.S. regions. By combining textual analysis of companies' annual financial reports with regional economic indicators, I construct a novel proxy that measures firm-specific exposure to the regional economy. I find that economic forecasts for relevant regions are a positive predictor of stock returns. This predictability is not subsumed by industry and geographic momentum, geographic dispersion, economic activity in the headquarter state and various other well-known cross-sectional asset pricing effects. Using quintile portfolios based on predicted regional economic activity, a long–short portfolio yields an annual risk-adjusted return of more than 5%. Consistent with Shleifer and Vishny (1997), the predictability is stronger among difficult-to-arbitrage stocks. Finally, this study indicates that the economic activity in regions where firms are located has a strong impact on the firms' profitability and positively predicts analysts' forecast errors. These findings provide evidence that the stock market reaction is based on news about future cash flows, rather than on changes in discount rate news. Besides uncovering new links between regional economic conditions, firm profitability and stock returns, this study demonstrates that all economically relevant regions are of importance, not just the headquarter location (similar to Bernile, Kumar, and Sulaeman (2015)).

In addition to the new empirical findings, this study also poses some interesting questions concerning geographically segmented markets. For instance, whether investors require compensation for holding stocks that are more sensitive to regional economic conditions remains unanswered. Specifically, it is particularly interesting to compare asset pricing models with regional and aggregate macroeconomic factors. Although this study reveals there to be certain correlations between the regional economic activity portfolios and common risk factors, there are still some areas that require further investigation: in particular, the reasons for the strong loadings on the book-to-market and momentum portfolios.

[30]A nonmutually exclusive hypothesis relating to market capitalization is that the impact of economic conditions on firms' performance and stock returns is more relevant for small and regional companies than for large and dispersed companies. Employing the number of economically relevant states as a more direct proxy for dispersion, I do not find evidence to support the alternative explanation. If anything, the predictability of stock returns is stronger, though statistically insignificant, for more dispersed firms. Although this test does not entirely rule out the possibility that economic conditions might affect different companies in different ways, evidence suggests that the predictability is at least partially driven by limits to arbitrage.

Similarly, the role of geographic regions in explaining the heterogeneity in other firm or stock characteristics, such as liquidity (Bernile, Korniotis, Kumar, and Wang (2015)), provides an interesting area for future research.

Supplementary Material

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