Long Georgia, Short Colorado?
The Geography of Return Predictability*

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ABSTRACT

This study investigates whether local stock returns vary with local business cycles in a predictable manner. We conjecture that, in the presence of local bias and incomplete risk sharing, local macroeconomic variables that characterize local business cycles would predict the returns of local stocks. In particular, during local economic recessions, the average returns of local stocks would increase as local risk aversion increases and the ability of local investors to smooth consumption declines. Consistent with this conjecture, we find that U.S. state portfolios earn higher (lower) returns when state-level unemployment rates are higher (lower) and state investors face stronger (weaker) borrowing constraints. During the 1980-2004 period, trading strategies that exploit this state-level predictability earn annualized risk-adjusted return of over 7 percent. The evidence of predictability is stronger among less visible firms and in regions in which investors exhibit stronger local bias and hold more concentrated portfolios. Overall, our results indicate that the stock return generating process contains a predictable local component.

Are stock returns predictable? This fundamental question has intrigued both academics and practitioners for more than a century and the evidence so far has been mixed. In this paper, we provide an alternative perspective on the return predictability debate. Our main idea is to investigate heterogeneity in return predictability along a geographical dimension. In particular, we examine whether portfolios of U.S. states have predictable patterns that could potentially be exploited to earn abnormal risk-adjusted returns. For example, we test whether the returns of firms headquartered in Texas (i.e., the Texas portfolio) can be predicted using changes in the local macroeconomic indicators of the state of Texas.

Our study is motivated by the traditional literatures on risk sharing and consumption-based asset pricing and the recent literatures on local bias and market segmentation. The key economic intuition behind consumption-based asset pricing models is that during economic downturns investors become more risk averse and require higher returns for holding risky assets (e.g., Campbell and Cochrane (1999)). In addition, because of incomplete risk sharing, investors are unable to fully insure themselves against idiosyncratic income shocks. Thus, periods during which risk sharing is especially difficult, investors' consumption streams become more volatile and they demand a higher risk premium (Lustig and Van Nieuwerburgh (2005)).

Further, the local bias literature documents that investors exhibit a greater propensity to hold stocks that are located in their vicinity (e.g., Coval and Moskowitz (1999, 2001), Grinblatt and Keloharju (2001), Huberman (2001), Zhu (2003), Ivkovich and Weisbenner (2005)). If

investors' local preferences are strong, at least a component of stock returns is likely to be influenced by the behavior of local investors.

We conjecture that in the presence of local bias and incomplete risk sharing, the inability of local investors to smooth consumption, especially during local recessions, will influence the average returns of local stocks. Furthermore, changes in local macro-economic conditions would influence the risk aversion of local investors. When the local economy is in recession, local investors will become more risk averse and require higher returns for holding risky local assets. In sum, the combination of local bias, time-varying local risk aversion, and variation in risk sharing ability of local investors could generate predictable patterns in the returns of local stocks.

To test our main conjecture, we define a region that is local to investors. We use U.S. states as our geographical unit because state-level macroeconomic data are easily available.[1] We form state-level portfolios by adopting the convention in the recent local bias literature (e.g., Coval and Moskowitz (1999, 2001), Loughran and Schultz (2005), Pirinsky and Wang (2006), Hong, Kubik, and Stein (2008)) and use the headquarter location to proxy for firm location.

Our choice of return predictors is guided by the availability of state-level macroeconomic data. We consider three state-level economic indicators that move with the state-level business cycle. This set includes the growth rate of state labor income and the relative unemployment rate in the state. The growth rate of labor income can be interpreted as a proxy for the return to human capital (Jagannathan and Wang (1996), Campbell (1996)). The relative state unemployment rate is the ratio of the current unemployment rate to the moving average of past unemployment rates, where the moving average is a proxy for the expected level of unemployment or the natural rate of unemployment. The unemployment variable can be interpreted as a measure of unemployment news, and it is similar to a regression-based measure of national unemployment news used in Boyd, Hu and Jagannathan (2005).

The third return predictor is the state-level housing collateral ratio measure (hy), which captures investors' borrowing constraints and their ability to engage in risk sharing. It is defined as the log ratio of state-level housing equity to state labor income. Lustig and Van Nieuwerburgh (2005, 2006) show that as hy decreases, the housing collateral becomes scarce and investors find it increasingly more difficult to borrow using their housing equity. Increased borrowing constraints reduce the level of risk sharing and increase the variance of consumption growth because consumption levels cannot be fully shielded against future negative income shocks.

[1] Our economic intuition applies to other geographical units such as metropolitan statistical areas (MSAs) or U.S. Census regions. In an international context, this intuition could also apply at a country level, where the future county-level risk premium would vary cross-sectionally with the level of home bias and changes in country-level macro-economic conditions.

To ensure that the predictable patterns in state portfolios do not merely reflect the known predictability of the aggregate stock market, we conduct our empirical investigation using the state-specific or idiosyncratic component of state portfolio returns. Furthermore, to ensure that our state predictors do not reflect national shocks, we include several U.S.-level macroeconomic variables in our empirical framework.

We test for the predictability of state portfolio returns by estimating panel fixed effects predictive regressions using quarterly data for the 1980 to 2004 time period. Our results indicate that an increase in the relative state unemployment rate and a decline in either the state collateral ratio or the state income growth rate, is followed by higher state portfolio returns in the next quarter. We carry out several tests to show that this evidence of local return predictability is robust.

To measure the economic significance of our predictability evidence, we construct trading strategies that exploit the predictable patterns in state portfolio returns. Specifically, using the return prediction model, we rank state portfolios according to their predicted returns in the next quarter. The trading strategies take a long (short) position in state portfolios with the highest (lowest) predicted returns. We find that during the 1980 to 2004 period, the model-based long-short portfolio generates an economically significant annualized risk-adjusted performance of over 7 percent. In contrast, a "naive" trading strategy based on historical average returns generates insignificant alphas.

Although the predictability regression estimates and the trading strategy results are consistent with our local bias conjectures, we establish the link between local bias and predictability of local returns using more direct approaches. First, we show that both retail and institutional investors exhibit preference for stocks located in their home state. In several states, the local preference is quite strong and local investors have the potential to influence the returns of local stocks.[2] Next, we show that the trading strategy performance is stronger among less visible firms and in regions in which investors exhibit stronger local bias and hold more concentrated portfolios. Further, consistent with our local bias conjecture, we find that the evidence of predictability weakens when we expand the definition of local and use regional macroeconomic variables defined for the four or eight U.S. Census divisions.

In the last part of the paper, we conduct a wide range of tests to identify the mechanism that can generate predictable patterns in local stock returns. First, like previous predictability

[2] For instance, during the 1980 to 2004 period, institutional investors located in the state of Indiana allocate 20.75% of their portfolios to firms headquartered in Indiana even though Indiana firms represent only 1.11% of the aggregate market portfolio. On a value-weighted basis, the institutional local bias measure in Indiana is more than 50%, which indicates that larger institutions exhibit a stronger preference for holding Indiana stocks. Similarly, during the 1991-96 period, retail investors located in Minnesota allocate 13.59% of their portfolios to firms headquartered in Minnesota, even though Minnesota firms represent only 2.48% of the aggregate market portfolio.

studies, we show that our evidence of local predictability does not reflect shifts in future cash flows or changes in local consumption risk. Second, we establish that the predictable return patterns are not generated by an initial mispricing that eventually gets corrected. Third, using a state-level risk aversion measure implied by a regional habit-based asset pricing model, we demonstrate that local risk aversion increases when local economic conditions worsen. Fourth, the negative relation between state-level housing collateral and future state portfolio returns is consistent with the conjecture that risk sharing ability of state investors declines during state-level recessions.

Taken together, our empirical results indicate that the predictable patterns in state portfolio returns are generated by temporal variations in local risk sharing and local risk aversion. We also demonstrate that both of these effects are amplified in the presence of local bias.

The rest of the paper is organized as follows. In the next section, we provide the theoretical motivation for our empirical analysis and summarize the main testable hypotheses. Section II presents the key characteristics of state portfolios. The return predictability model is presented in Section III and in Section IV we construct various trading strategies to examine the economic significance of this return predictability model. We identify the local return predictability channels in Section V. Specifically, we investigate the extent to which the combined effects of local bias, risk sharing, and risk aversion induce predictable patterns in local stock returns. We conclude in Section VI with a brief discussion.

I. Theoretical Motivation and Testable Hypotheses

I.A. Basic Economic Intuition

We derive our key economic intuition from the traditional consumption-based asset-pricing models (CCAPM) and the recent evidence of local bias in the portfolio holdings of retail and institutional investors. In the absence of mispricing, within the CCAPM framework, return predictability at the aggregate market level can arise either due to time-varying consumption beta (i.e., consumption risk) or time-varying risk aversion of the representative U.S. investor (e.g., Constantinides (1990), Campbell and Cochrane (1999), Lettau and Ludvigson (2001a), Cochrane (2008)).[3] Further, time variation in the ability of the representative U.S. investor

[3] For example, in the representative agent model of Campbell and Cochrane (1999), the expected log market return over the risk-free rate can be approximated as $\mathbf{E}_t r_m - r_t^f \approx \eta_t \mathbf{cov}_t(\Delta c, r_m)$,where $\mathbf{cov}_t(\Delta c, r_m)$ is the conditional covariance of the U.S. consumption growth (Δc) with market return (r_m). η is the risk aversion of the U.S. representative investor and is given by γ/S, where γ is the curvature parameter of the utility function and S is the surplus ratio $(C-H)/C$. In this definition of the surplus ratio, C is the U.S. consumption level and H is the habit level.

to share income risks can also generate return predictability (Lustig and Van Nieuwerburgh (2005)). In this one representative investor setting, local bias does not have a role to play.

More recently, consumption-based models have been proposed, which recognize heterogeneity across the U.S. states and allow habit levels to vary geographically. These models are better able to explain the cross-sectional variation in stock returns. In particular, since state-level income shocks are undiversifiable (Asdrubali, Sorensen, and Yosha (1996), Athanasoulis and Van Wincoop (2001)), Korniotis (2008) shows that the U.S. economy is better described as a collection of 50 state-level investors, as opposed to one U.S.-level investor. In this setting, the time-varying risk aversion of state investors and changes in their ability to engage in risk sharing could affect the returns of local stocks held by them.

The combined effect of time-varying local risk aversion and local risk sharing ability on local returns would be amplified if state investors also exhibit a strong preference for local stocks. If local bias is weak or non-existent, the effect of local macroeconomic conditions on risk aversion or investors' risk sharing abilities must be strong to generate return predictability. But if local bias is strong, even if local risk aversion and local risk sharing are only weakly affected by local macroeconomic conditions, there could be predictable patterns in state portfolio returns. We develop several hypotheses to examine whether the interactions among local risk aversion, local degree of risk sharing, and local bias generate predictable patterns in the returns of local stocks.

I.B. CCAPM Motivated Return Predictability Hypotheses

To motivate our key predictability hypotheses, it is useful to assume that there is a representative investor for each U.S. state. In the presence of local bias, the state investor would hold a significant proportion of local firms and the consumption smoothing motives of the state investor could influence local stock returns. Particularly, if her consumption level deteriorates due to state-specific negative income or unemployment shocks, the state investor is likely to become more risk averse. She is then likely to require a higher premium to invest in risky local stocks and would raise her expectations about the future returns of those stocks. This economic argument gives rise to our first testable hypothesis:

> **Hypothesis 1a**: *When local income growth rates are lower and unemployment rates are higher (i.e., the local economy is in recession), local stock prices are depressed and future returns of local stocks are higher.*

Borrowing constraints could also influence investors' portfolio decisions and generate predicable variation in returns. In Lustig and Van Nieuwerburgh (2005, 2006), the housing collateral ratio (the ratio of housing wealth to human wealth or hy) is a proxy for investors' ability to

borrow and engage in risk sharing. When housing collateral is low, investors' ability to borrow against housing collateral decreases and they are unable to effectively smooth future consumption against negative income shocks. As a result, their risk sharing ability declines and the variance of investors' consumption growth increases. In this scenario, risky stocks must offer higher returns in the future to remain attractive to investors.

Consistent with this theoretical prediction, Lustig and Van Nieuwerburgh (2005) find that a decrease in U.S. *hy* is followed by an increase in the U.S. market return. Furthermore, Lustig and Van Nieuwerburgh (2006) show that the time-series variation in the U.S. *hy* is related to the degree of risk sharing across U.S. metropolitan regions.

Motivated by the evidence with the aggregate U.S. *hy*, we conjecture that if investors exhibit local bias, the borrowing constraints at the local level could affect local stock returns. Specifically, a drop in state-level *hy* would limit the risk sharing ability of the state investors and would increase the variance of future state-level consumption growth. Consequently, the state investor would require higher returns to invest in local stocks. We summarize this economic intuition as our second testable hypothesis:

> **Hypothesis 1b**: *When local investors face greater borrowing constraints due to a decline in the housing collateral, their risk sharing ability decreases. Consequently, local stocks yield higher returns in the future to remain attractive to local investors.*

I.C. Tests of Other Assumptions and Implications of CCAPM

The two CCAPM motivated return predictability hypotheses are based on the implicit assumption that return predictability is not induced through cash flow or mispricing channels. Our assumption of no cash flow predictability is based on previous studies (e.g., Menzly, Santos, and Veronesi (2004), Cochrane (2008)), which suggest that any predictability in state-level return indices should be related to changes in future discount rates (i.e., expected return news) and unrelated to changes in cash-flow expectations (i.e., cash flow news). In particular, Vuolteenaho (2002) shows that cash-flow information is largely firm-specific and diversifiable, while discount rate information is mainly driven by systematic, macroeconomic components and thus not fully diversifiable. Therefore, variation in aggregate return indices like our state portfolio return series should be largely related to the discount rate news.

Although these two implicit assumptions have prior empirical evidence, given their importance in our empirical analysis, we present two hypotheses that attempt to directly test those assumptions:

Hypothesis 2a: *Changes in local macro-economic variables do not generate a "mis-pricing and correction" pattern in local stock returns.*

Hypothesis 2b: *Changes in local macro-economic conditions have minimal effect on the future cash flows of local firms.*

To further establish that our state-level predictability results are consistent with the economic intuition of the CCAPM, we test other implications of the CCAPM. In particular, similar to the findings in previous studies (e.g., Mehra and Prescott (1985)), we posit that local return predictability is more likely to be induced by time-varying local risk aversion rather than variation in local consumption risk.

Hypothesis 2c: *Local consumption risk (covariance between the consumption growth of local investors and local stock returns) is less sensitive to changes in local macro-economic conditions.*

Further, although local investors can reduce their exposure to risky assets for a variety of reasons (e.g., to satisfy their liquidity needs), an increase in risk aversion would also induce a reduced exposure to risky assets. More formally, we posit that:

Hypothesis 2d: *The local consumption growth rate declines and local risk aversion increases during local economic downturns. Consequently, local investors reduce their exposure to risky assets.*

I.D. Local Bias Motivated Hypotheses

Local bias is one of the key building blocks of our return predictability hypotheses. In the absence of local bias, the marginal investor of all stocks, local and non-local, would be the representative U.S. investor. The constraints faced by the representative U.S. investor would be influenced by changes in U.S. macroeconomic conditions. In this setting, the cross-sectional variation in local macroeconomic conditions would be purely idiosyncratic and would not influence the expected returns of local stocks.

We develop three additional hypotheses to establish a stronger and more direct link between local bias and the predictability of local returns.[4] To develop our first local bias hypothesis, we follow the economic intuition in Hong, Kubik and Stein (2008) and sort firms based on their

[4]In this paper, we remain agnostic about the exact mechanism that induces local bias because our predictability hypotheses do not rely on the type of local bias. Irrespective of the local bias mechanism (superior information or familiarity), deteriorating local economic conditions would adversely affect local investors and they would require higher future returns to hold risky local stocks.

visibility levels. The stock-level visibility measure is defined as the size-adjusted measure of the number of shareholders. All else equal, the visibility would be higher for firms with more shareholders. We conjecture that less visible firms would be more sensitive to the behavior of local investors because non-local investor might not be aware of them. Moreover, if visibility is limited, arbitrage forces generated by non-local investors would also be limited and local investors would have greater influence on the returns of local stocks.[5] More formally, our first local bias hypothesis is:

> **Hypothesis 3a**: *The influence of local investors on local stock returns would be stronger among less visible firms.*

Although firm visibility is a reasonable proxy for local bias, we use the portfolio holdings of a sample of retail investors at a large U.S. discount brokerage house to directly measure the level of local bias across U.S. states. We hypothesize that states in which investors are more locally biased, changes in local economic conditions would have a greater impact on local stock returns. Thus, our second local bias hypothesis is:

> **Hypothesis 3b**: *The influence of local investors on local stock returns will be stronger in states with more locally biased investors.*

Our final local bias test is motivated by the evidence in Hong, Kubik, and Stein (2008), who show that the ratio of regional book equity to regional personal income (RATIO) is negatively correlated with regional stock prices. Stock prices are lower for firms located in regions with higher RATIO levels because of lower regional demand.

While Hong, Kubik, and Stein (2008) show that RATIO induced price effects translate into very small expected return differences across regions, we examine whether the influence of RATIO on expected returns is stronger in our context. Further, if a region continually experiences large *changes* in RATIO, then its expected returns could vary considerably. When aggregated, such changes could translate into substantial expected return differentials. In addition, increased (lowered) competition among local firms, as reflected by a large increase in RATIO, would make the returns of local stocks more (less) sensitive to local demand shifts. With this motivation, we posit our third local bias hypothesis:

> **Hypothesis 3c**: *Local demand shifts influence local stock returns more strongly in states with higher RATIO levels and larger cumulative RATIO changes.*

[5] This prediction is different from the implications of Merton's (1987) model, which predicts that, all else equal, less visible firms have higher expected returns. Our conjecture is that the future returns of less visible stocks are more sensitive to changes in local economic conditions.

II. Characteristics of State Portfolios

To gather empirical support for these three sets of testable hypotheses, we use data from the 1980 to 2004 time period. The state-level housing series that are used to construct the state-level housing collateral ratio are available only for the 1980 to 2004 period. This data constraint determines our sample period.

II.A. Return Characteristics

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) and use them to compute quarterly stock returns. In addition, we obtain the commonly used risk factors from Kenneth French's data library and characteristic-based performance benchmarks from Russell Wermers' web site.[6]

We use quarterly returns in most of our empirical analysis because several state-level macroeconomic variables are only available at the quarterly frequency. The nominal quarterly returns are divided by one plus the inflation rate to obtain real returns. The inflation rate is based on the consumer price index from the Bureau of Labor Statistics (BLS). We also use quarterly market returns, which are the value-weighted returns of all CRSP stocks. Similarly, the quarterly risk-free returns are calculated using the monthly returns of 30-day Treasury bill.

The monthly state portfolio returns are defined as the value-weighted returns of firms located in the state. The state portfolios only include common stocks with CRSP share code of 10 and 11. Following the recent local bias literature (e.g., Coval and Moskowitz (1999), Ivkovich and Weisbenner (2005), Pirinsky and Wang (2006), Hong, Kubik, and Stein (2008)), we use headquarter location to proxy for firm location. The firm location data are obtained from COMPUSTAT. To minimize potential measurement error, we exclude states with fewer than 20 firms and focus on the remaining 35 states.[7]

Table 1 reports the key characteristics of the 35 state portfolios. Panel A reports the return characteristics, including the four-factor alpha estimates, factor exposures, and the adjusted R^2 of the four-factor model. We find that during the 1980 to 2004 sample period, the states with the highest average monthly realized returns are Arkansas, Washington, Nebraska, Minnesota, and Georgia, while the states with the worst performing stocks include Texas, Florida, Kansas, Louisiana, and Colorado.

To examine the robustness of these estimates, we consider an extended time period spanning

[6] The four risk factors are obtained from `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`, while the performance benchmarks for computing characteristic-adjusted stock returns are obtained from `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`.

[7] Our results are not sensitive to the 20 firms cutoff. The results are very similar even when we use a 10 firms cutoff. We choose a higher cutoff to reduce measurement error.

from 1963 to 2005. We find that the mean return and standard deviation estimates of state portfolios over the longer period are very similar to the corresponding estimates during the 1980 to 2004 sample period. In untabulated results we find that the factor exposures and adjusted R^2 values are also similar across the two time periods. This evidence indicates that the return characteristics of state portfolios during the 1980 to 2004 sample period are not specific to the chosen time period and are likely to generalize to other time periods.

Examining the factor model estimates, we find that most state portfolios have a market beta close to one. Moreover, the SMB and HML factor exposures make intuitive sense. For instance, California, with a large concentration of technology and growth firms, has the most negative HML exposure and, Michigan, with a greater concentration of established "old economy" value stocks, has the highest and positive HML estimate.

The average adjusted R^2 for the 35 state portfolios is 0.64 and less than one-quarter of the states have an adjusted R^2 greater than 0.80. This evidence indicates that the state-specific components of state portfolio returns, as measured by the residual returns from the four-factor model, are large and exhibit significant variation. Our main goal in this paper is to investigate whether those residual state portfolio returns have an economically significant predictable component.

II.B. Other Stock Characteristics

In Table 1, Panel B we report other characteristics of state portfolios, including their market capitalization (SIZE), book-to-market ratio (B/M), dividend yield (D/P), the firm size based industry concentration measure or the Herfindahl index (HIDX), institutional ownership (IO), and analyst coverage (ANCOV). The 13(F) institutional ownership data and the I/B/E/S analyst coverage data are from Thompson Financial.

We find that there are important differences in the characteristics of state portfolios, although the Herfindahl index indicates that industry concentration across states do not vary significantly. Comparing the average firm size across states, we note significant differences. We find that the average size of firms in New Hampshire is less than $10 million but the average size of firms located in the New York portfolio is over $1 billion. Similarly, stocks in Connecticut are more likely to be growth stocks, while a greater proportion of stocks in North Carolina are value stocks. Focusing on the dividend yields of state portfolios, we find that stocks in Kentucky pay high dividends (average D/P = 4.10%), while stocks in Colorado pay significantly lower levels of dividends (average D/P = 0.45%).

In terms of the institutional ownership levels, we find that stocks in states such as Illinois, Ohio, Tennessee and Wisconsin have average institutional ownership levels of around 35%,

whereas stocks in Colorado, Mississippi and Nevada have average institutional ownership levels below 20%. Analyst coverage levels are similar to the institutional ownership levels, which is not very surprising because the correlation between the two measures is about 0.73.

II.C. Local Bias Across States

Because local bias is one of the key building blocks of our empirical exercise, we estimate the extent of local ownership across states. We examine the local stock preference of both retail and institutional investors and show that investors exhibit a strong preference for holding local stocks. We calculate the extent of local retail ownership using the Barber and Odean (2000) retail investor data set. The retail data are from a large U.S. discount brokerage house and are available only for the 1991 to 1996 period. For measuring local institutional ownership, we use Thompson Financial 13(F) institutional holdings data set for the 1980 to 2004 time period and hand-collect institutional locations using the *Nelson's Directories of Investment Managers.*

We define the local (or state) bias measure for an investor as the difference between the weights of local stocks (i.e., stocks that are headquartered in the state of residence of the investor) in the investor portfolio and the aggregate market portfolio. The local bias measure is computed for each retail and institutional investor in the sample. Using these investor-level local bias measures, we obtain the state-level averages.

Examining local bias across states, we find that both individual and institutional investors exhibit a preference for holding local stocks. On average, institutional investors over-weight local stocks by 6.36% while retail investors over-weight local stocks by 4.60%.[8] These averages, however, mask the significant heterogeneity in local stock preference across states. For instance, institutional investors located in the state of Indiana allocate, on an equal-weighted basis, 20.75% of their portfolios to firms headquartered in Indiana even though Indiana firms represent only 1.11% of the aggregate market portfolio. On a value-weighted basis, the institutional local bias measure in Indiana is more than 50%, which indicates that larger institutions exhibit a stronger preference for holding Indiana stocks. Similarly, retail investors located in Minnesota allocate 13.59% of their portfolios to firms headquartered in Minnesota, even though Minnesota firms represent only 2.48% of the aggregate market portfolio.

These local bias estimates indicate that the average local bias level is not very high. However, the local bias estimates are large for certain states and, in these instances, local bias could have a perceptible influence on the returns of local stocks. Further, in unreported results, we find that there is significant cross-sectional variation in firm-level local bias even within a state with low average local bias. Overall, our local bias estimates suggest that the interaction be-

[8] The correlation between the retail and institutional local bias measures is 0.42.

tween the behavior of local investors and changes in local economic conditions might influence the returns of local stocks.

III. The Return Prediction Model

In this section, we test our first two hypotheses, which posit that in the presence of local bias, a deterioration in local economic conditions (lower state income growth and higher relative state unemployment) and tightening borrowing constraints (lower state-level housing collateral) would be associated with higher future local returns. We test the hypotheses using one-quarter-ahead predictability regressions.

III.A. Choice of Macroeconomic Indicators

Our first two return predictors are the growth rate of state labor income and the relative state unemployment rate. The state-level labor income data are obtained from the Bureau of Economic Analysis (BEA) and the state-level unemployment data are from the Bureau of Labor Statistics (BLS). The growth rate of labor income can be interpreted as a proxy for the return to human capital (e.g., Jagannathan and Wang (1996), Campbell (1996)).

The relative state unemployment rate measures innovations in unemployment and is a recession indicator for the state economy. It is the ratio of the current state unemployment rate to the moving average of the state unemployment rates in the previous four years (16 quarters). The moving average serves as a proxy for the expected or natural level of unemployment and a deviation from this expected unemployment level signals good (positive deviation) or bad (negative deviation) news for the local economy.[9]

The third state-level return predictor is the state-level version of the housing collateral ratio used in Lustig and Van Nieuwerburgh (2005, 2006). It is defined as the log ratio of housing equity to labor income and is denoted by hy. We construct the state-level hy series using the Lustig and Van Nieuwerburgh (2005) method. It captures how borrowing constraints and the degree of risk sharing vary geographically across the U.S. states. In addition, our return prediction model includes the dividend yield of state portfolios (e.g., Campbell and Shiller (1988), Fama and French (1988)).

Besides the four state-level predictors, we consider several U.S.-level macroeconomic indicators. This set includes the U.S. cay residual of Lettau and Ludvigson (2001a, 2001b), the U.S. collateral ratio of Lustig and Van Nieuwerburgh (2005), the growth rate of U.S. labor income,

[9] Since a percentage of the labor force is always unemployed (natural level of unemployment), the level of unemployment is unlikely to be a good indicator of the state of the local economy.

the U.S. relative unemployment rate, and three return spreads (paper-bill, term, and default spreads). The existing predictability literature finds that the U.S.-level macroeconomic variables can predict the aggregate stock market indices (e.g., Campbell and Shiller (1988), Lettau and Ludvigson (2001a)). If the state portfolio returns are correlated with the aggregate stock market indices and if the state predictors are correlated with the U.S.-level macroeconomic indicators, the predictability of the state portfolio returns could simply reflect the predictability of the aggregate U.S. stock market indices. We include these U.S.-level macroeconomic indicators in the prediction model to ensure that the state-level predictors do not simply reflect aggregate U.S.-level economic shocks.

The state-level data are reported with a lag of two quarters but all other variables are reported with a lag of one quarter. The nominal measures of all forecasting variables are transformed into real terms using the regional inflation rates from the Bureau of Labor Statistics. The base year for inflation is 1992(Q1).

Table 2 presents the summary statistics for the quarterly state returns and all the return predictors. The univariate statistics in Panel A show that quarterly state portfolio returns are more volatile than the aggregate market returns. The state-level macroeconomic predictors are also more volatile and less autocorrelated than their U.S. counterparts. Panel B reports the correlations among stock returns and return predictors. We find that state portfolio returns are strongly correlated with market returns. Moreover, state-level macroeconomic predictors are moderately correlated with their U.S. counterparts and with other predicting variables.[10] Of course, this evidence is not surprising because all predictors are affected by the same aggregate-level shocks. Due to these correlations, we include all U.S.-level variables in our empirical analysis and ensure that the state-level predictors only reflect state-specific shocks.

III.B. A First Look: Graphical Evidence

Before estimating the return predictability model, we examine graphically how the risk and return characteristics of state portfolios are affected by changes in state-level macroeconomic conditions. To capture the prevalent economic condition in a state, we define a state-level economic activity index. We compute the state-level index in period t by adding the normalized values of state income growth rate and state-level housing collateral ratio and subtracting the normalized value of relative state unemployment.[11] The states with the highest (lowest) values of the index are assumed to be expanding (contracting).

[10] The state-level variable with the highest level of heterogeneity is hy. The average correlation between the U.S. hy and state-level hy is only 0.09.

[11] In period t, we compute the normalized value of a state-level macroeconomic variable x_{it} as $x^s_{it} = (x_{it} - x_{\min,t})/(x_{\max,t} - x_{\min,t})$. In this definition, $x_{\min,t}$ ($x_{\max,t}$) is the minimum (maximum) value of x across all states in period t.

Each quarter, we rank states according to their economic index estimates. We compute the average monthly return of all states in the top one-third (booming states) and the bottom one-third (depressed states) groups. The state portfolio return is the value-weighted return of all firms headquartered within the state. The cumulative monthly return series for the depressed and booming states portfolios around the ranking period are shown in Figure 1, Panel A. We plot the volatility (standard deviation of daily returns within a month) levels of firms located in booming and depressed states around the ranking period in Panel B.[12]

The graphical results indicate that state portfolio returns are higher (lower) following state-level contractions (expansions). One year after the ranking period, the average return differential between the depressed and booming state portfolios is about 3 percent. This evidence of positive and significant return differential is consistent with our return predictability hypotheses, which posit that local stock returns would be higher (lower) following bad (good) local economic conditions.[13] Around state-level contractions, we also observe an increase in the riskiness of stocks located in depressed states. Therefore, in our main empirical analysis, we focus mainly on risk-adjusted performance measures.

III.C. Predictability Regression Specification

We begin our formal statistical tests by estimating one-quarter ahead predictability regressions. We pool the observations from all states and express the return prediction model as a panel regression with state fixed effects:

$$Y_{j,t} = \alpha_j + X_{j,t-2}\delta_1 + X_{USA,t-1}\delta_2 + \log(1 + D/P)_{j,t-1}\delta_3 + \varepsilon_{j,t}. \tag{1}$$

Here, j is the index to the U.S. states and t refers to the quarterly time period. α_j is the state-specific mean (fixed effect) and captures unobserved differences in the returns of state portfolios (e.g., return differences induced by heterogeneity in the industrial composition of state portfolios). $Y_{j,t}$ is the return of state portfolio j in quarter t. The panel format allows us to utilize both time-series and cross-sectional variations in state portfolio returns and state predictors. This flexibility increases the power of our statistical tests.[14]

To ensure that state portfolio returns are orthogonal to the aggregate U.S. stock returns, we estimate our regressions using the idiosyncratic component of state portfolio returns. The

[12] In each of the three cases, we subtract the return/volatility measure for the ranking quarter from the cumulative measures to shift the plots, such that the ranking quarter return/volatility is equal to zero.

[13] The return differential estimates are similar when we use characteristic-adjusted returns. In Section IV, we use several different methods to account for risk differences between the high and low index portfolios.

[14] In related studies, Balvers, Wu, and Gilliland (2000) and Ang and Bekaert (2007) estimate panel fixed effect models to test for mean-reversion and predictability across national stock markets, respectively.

dependent variable $Y_{j,t}$ reflects state-specific returns obtained using multiple methods. We compute residual return measures using both factor models and estimation-free return adjustment methods.

Our first return measure is the residual from the market model, where the market return excess over the risk-free rate (RMRF) is the only factor. The second return measure is the four-factor residual of state portfolio returns, where the factors are RMRF, the size factor (SMB), the book-to-market factor (HML), plus the momentum factor (UMD). The third return measure is the seven factor residual of state portfolio returns, where the factors are RMRF, SMB, HML, UMD, and three industry factors.[15] In all three instances, we obtain the residual returns by estimating the factor models separately for each state.

For greater accuracy, we estimate the factor models using data for the entire sample period, but this approach introduces a look-ahead bias in the residual return estimates. To avoid this bias, we define residual returns using three performance benchmarks. We compute market-adjusted returns, characteristic-matched returns (Daniel, Grinblatt, Titman, and Wermers (1997)), and industry-matched returns to account for differences in industrial characteristics across states. With this estimation-free approach, we also avoid potential errors-in-variables problems.

The row vector $X_{j,t-2}$ in the predictability regression (1) contains the state-level macroeconomic predictors measured in quarter $t-2$.[16] The vector δ_1 includes the coefficient estimates of the three main state predictors. Specifically, $\delta_{1,dinc}$, $\delta_{1,ru}$, and $\delta_{1,hy}$ represent the coefficient estimate of state income growth, relative state unemployment, and state-level housing collateral, respectively. The row vector $X_{USA,t-1}$ contains the aggregate U.S. predictors, which are measured in quarter $t-1$. $\log(1+D/P)_{j,t}$ is the dividend yield of the portfolio of state j in quarter t.[17] ε_{jt} is the regression error term.

We estimate the pooled panel regressions with state fixed effects using the ordinary least squares (OLS) method. Because of the panel structure of our regression models, the error term can be serially and cross-sectionally correlated. We compute the t-statistics using Driscoll and Kraay (1998) standard errors that can accommodate both sources of correlation. This standard error correction method is an extension of more traditional methods for computing

[15] The three industry factors are calculated using the Pastor and Stambaugh (2002) method and are designed to capture industry momentum (Grinblatt and Moskowitz (1999), Hong, Tourus, and Valkanov (2007)). Specifically, we estimate two time-series regressions for each of the 48 industry portfolios. In these regressions, the dependent variable is either the current or the lagged return of the industry portfolio. The independent variables include the three Fama and French (1992, 1993) factors, and the momentum factor (Jegadeesh and Titman (1993), Carhart (1997)). The industry factors are defined as the first three principal components of the residuals from these 96 regressions.

[16] We use the state predictors from quarter $t-2$ because they are reported with a lag of two quarters.

[17] We follow Lewellen (2004) and use the logarithmic transformation of the dividend-price ratio to reduce its positive skewness.

standard errors that only account for serial correlation in errors (e.g., Hansen and Hodrick (1980), Andrews (1991)).

Like other predictability studies, we are also confronted with strongly autocorrelated return predictors. In our robustness analysis, we deal with potential biases arising from persistent predictors using a bias correction approach proposed in Stambaugh (1999) and by providing bootstrapped critical values using the Mark (1995) method.

The coefficient estimates $\delta_{1,dinc}$, $\delta_{1,ru}$, and $\delta_{1,hy}$ measure the responsiveness of state portfolio returns to changes in state-level economic conditions. Our first two hypotheses conjecture that a decrease in state income growth and state collateral ratio and an increase in relative state unemployment, should be followed by an increase in the returns of the state portfolio. We can test the first two hypotheses using the following one-sided predictability tests:[18]

$$\mathbf{H}_0 : \delta_{1,dinc} = 0,\ \ \delta_{1,ru} = 0, \delta_{1,hy} = 0; \quad \mathbf{H}_A : \delta_{1,dinc} < 0, \delta_{1,ru} > 0, \delta_{1,hy} < 0. \tag{2}$$

III.D. Baseline Predictability Regression Estimates

The baseline predictability regression estimates are presented in Table 3. Consistent with our conjecture in Hypothesis 1a, we find that the coefficient estimates of state labor income growth rate are negative. However, these estimates are statistically insignificant.[19] In contrast, the coefficient estimates of relative state unemployment rate are positive as well as significant. The coefficient estimates of the state collateral ratio hy are also statistically significant in all specifications and have the expected negative sign. These baseline estimates support our first two return predictability hypotheses and confirm that deteriorating state-level economic conditions (higher unemployment rate and lower housing collateral) are followed by higher one-quarter ahead state portfolio returns.

The positive coefficient estimate of our last state predictor (i.e., dividend yield) is consistent with the evidence in the existing literature (e.g.,Campbell and Shiller (1988)). However, the statistical significance of state-level dividend yield is weak. In contrast to the state-level predictors, their U.S. counterparts have weaker and usually insignificant coefficient estimates across all specifications. For instance, in specification (1), all three U.S. predictors have insignificant coefficient estimates.

[18] Campbell and Shiller (1988) and Campbell and Yogo (2006) use similar one-sided tests to examine whether the dividend-yield of aggregate market indices can predict the returns of those indices. Their one-sided tests are motivated by the fact that present-value relations derived from the definition of return imply that an increase in the current dividend yield should be followed by an increase, and not a decrease, in future stock returns.

[19] This evidence is not very surprising because the state income growth rate has low persistence. Its autocorrelation coefficient is only –0.042 (see Table 2, Panel A). Thus, its current value conveys very little information about the future level of state income that affects future discount rates and future returns.

The U.S. *hy* does have significantly positive estimates in other specifications. Lustig and Van Nieuwerburgh (2005) show that a decrease in the U.S. *hy* is followed by an increase in the market return. Thus, for a given level of state return, the residual state return would decrease when the U.S. *hy* decreases and market return increases because the residual state return is roughly the difference between the raw state return and the market return. Our evidence of a positive relation between residual state return and the U.S. *hy* is consistent with this conjecture.

In regression specifications (3) and (6), we investigate whether industry heterogeneity across U.S. states is the key driver of local return predictability. The industry composition of states in the U.S. vary significantly. For example, California has a strong concentration of technology firms, while auto-makers are concentrated in the state of Michigan. Even when we define residual returns using industry benchmarks or factor models with industry factors, relative state unemployment and state-level housing collateral ratio are significant predictors of state portfolio returns. This evidence indicates that predictable patterns in state-level stock returns do not merely reflect the known industry-level return predictability (e.g., Grinblatt and Moskowitz (1999), Hong, Torous, and Valkanov (2007)).[20]

III.E. Panel Regression Estimates for U.S. Census Regions

We conduct a series of additional tests to examine the robustness of our baseline predictability regression estimates. The results from these tests are summarized in Table 4. For brevity, we only report the estimates and t-statistics related to the state-level macroeconomic predictors. To facilitate comparisons with the baseline estimates, in column (1), we report the results from Table 3 (specification (5)).

In our first two tests, we examine the relation between changes in regional macroeconomic conditions and state portfolio returns. We divide the U.S. into eight or four Census divisions. If return predictability at the state-level is primarily driven by changes in local economic conditions, as we widen the region used to define "local" and use regional macroeconomic variables, the evidence of predictability would weaken.

To examine whether this conjecture has empirical support, we estimate the predictability regressions using regional macroeconomic variables. For each state j, we calculate the average labor income growth rate, the average *hy* and the average relative unemployment rate of all states in the Census region of state j. We replace the state predictors with these regional

[20] To examine whether our predictive regressions are merely reflecting the well-known short-term return reversal phenomenon (Jegadeesh (1990), Lehmann (1990)), we consider regression specifications that include lagged portfolio returns. We find that the coefficient estimates of lagged returns are insignificant and only marginally affect the estimates of the other predictive variables. This evidence is consistent with the low average autocorrelation estimate of -0.044 for state portfolio returns (see Table 2, Panel A). We thank Harrison Hong for suggesting the reversal idea.

predictors and re-estimate the predictability regression.

Similar to our baseline results, we find that the regional labor income growth rate has an insignificant coefficient estimate (see specifications (2) and (3)). The regional relative unemployment rate and the regional *hy* have significant coefficient estimates. When we use the regional macroeconomic predictors from the eight Census regions, their statistical significance remains strong. But, when we define regional macroeconomic predictors more coarsely using four Census regions, their statistical significance weakens.

These results indicate that both state-level and regional predictors are successful in predicting state returns. The predictive power of regional predictors, however, declines as our definition of "local" becomes coarser. Thus, changes in local macroeconomic conditions are important determinants of local stock returns, but this results does not depend upon a strict and perhaps artificial definition of geographical units along state boundaries.

III.F. Panel Regression Estimates from Other Robustness Tests

We conduct four additional robustness tests. In the first test, we ensure that our results are not driven by a handful of large U.S. states. We exclude California, New York, and Texas (the three largest states based on the total market capitalization of firms headquartered in the state) and re-estimate the predictability regression. The results reported in Table 4, column (4) are qualitatively similar to the baseline results reported in column (1). Both the state unemployment and the state-level *hy* measures continue to have significant coefficient estimates.

In the second test, we examine whether our predictability results are contaminated by spurious predictors. A variable can spuriously predict returns if it is highly persistent and if its innovations are correlated with the errors in the predictability regression. The persistence and endogeneity of a spurious predictor can inflate both its estimate and t-statistic (e.g., Stambaugh (1999), Campbell and Yogo (2006)). To ensure that our estimates do not suffer from this bias, we follow correct the OLS estimates using the Stambaugh (1999) bias correction formula. The bias corrected estimates of the baseline coefficient estimates are reported in column (5). We find that these estimates are remarkably similar to our baseline estimates. This evidence indicates that our coefficient estimates are not inflated by the existence of persistent predictors.

An alternative way to ensure that our t-statistics are not spuriously inflated is to bootstrap their critical values. Section A.I of the appendix summarizes the bootstrapping method. Column (6) reports the bootstrapped critical values and the actual t-statistics beneath the actual estimates of all three state-level predictors. The magnitudes of bootstrapped critical values are typically greater than the normal critical value for one-sided tests (= 1.64). The bootstrapped critical values confirm that in one-quarter-ahead forecasting regressions, the coefficient estimate

of state labor income growth rate is statistically insignificant. In addition, the state *hy* and the relative state unemployment remain significant predictors of state portfolio returns.

In the last robustness test, we measure the U.S. and state-level unemployment news using the Boyd, Hu and Jagannathan (2005) method.[21] When we replace the relative unemployment measures in the predictability regressions with the regression-based measures of unemployment news and re-estimate the regressions, we find results that are similar to the baseline estimates (see column (7)). Although the two methods for measuring unemployment news produce very similar results, we prefer to use our unemployment news measure because it is simpler to compute and does not suffer from potential errors-in-variables problems.

Collectively, the results from our predictability regressions indicate that local economic conditions can predict local stock returns. In particular, local stocks perform well following local contractions and local stocks earn lower returns following periods of local economic expansions. These results provide empirical support to our return predictability hypotheses (Hypotheses 1a and 1b).

IV. Economic Significance of the Prediction Model

In this section, we examine the economic significance of the predictability regression estimates. We use the ranking of state portfolios implied by our return prediction models and construct different types of trading strategies. The performance estimates of these trading strategies allow us to evaluate the economic significance of the return predictability models.

IV.A. Construction of Trading Strategies

We construct the trading strategy in three steps. First, at the end of each quarter t, we estimate the predictability regression (1) in Section III.C using characteristic-adjusted state portfolio returns. We estimate the return prediction model in quarter t using all available data until quarter t.

Second, using the model estimated in quarter t, we predict the state portfolio returns for quarter $t+1$ and rank the U.S. states using their predicted quarterly returns. Using these predicted state ranking, we construct four portfolios. The "Long" portfolio contains stocks located in three states with the best predicted performance next quarter and the "Short"

[21] This alternative news measure is defined as the innovations e_t from the following regression: $\Delta U_t = b_0 + \sum_{l=1}^{3} b_l IPG_{t-l} + b_4 \Delta U_{t-1} + b_5 \Delta TB_t + b_6 \Delta RP_t + e_t$. Here, ΔU is the change in either the U.S. unemployment rate or the unemployment rate of state j. The set of unemployment predictors include IPG, which is the growth rate of the industrial production index; ΔTB, which is the change in the 90-day T-bill rate; and ΔRP, which is the change in the corporate bond spread or the default risk premium (Baa – Aaa).

portfolio contains stocks located in three states with the worst predicted performance next quarter (i.e., $N_s = 3$, where N_s is the number of states in the extreme portfolios). The stocks in the remaining states are used to define the "Others" portfolio. The "Long − Short" portfolio represents the difference between the returns of Long and Short portfolios.[22] Since our state-level data are quarterly, we hold the composition of all portfolios fixed for three months and rebalance them quarterly. In our robustness tests, we examine the sensitivity of our results to longer rebalancing periods.

In the last step, we compute the value-weighted portfolio returns for each of the four portfolios. The portfolio weights are determined using the market capitalizations of firms at the end of the previous month. For robustness, we also measure portfolio performance as the equal-weighted average of state portfolio return indices.

IV.B. Performance Evaluation: Baseline Results

We evaluate the performance of our trading strategies using multiple performance measures. The evaluation period is from 1984 to 2004 because we need at least three years of quarterly data to estimate the initial return prediction model. The performance estimates are reported in Table 5. In Panel A, we report the raw monthly returns, the monthly characteristic-adjusted returns computed using the Daniel, Grinblatt, Titman and Wermers (1997) method, and the risk-adjusted performance estimates from the market model. In Panels B, C, and D, we report the estimates from the four-factor, the seven-factor, and the nine-factor models, respectively. The four-factor model contains the market factor (RMRF), the size factor (SMB), the value factor (HML), and the momentum factor (UMD). The seven-factor model contains three additional industry factors (IND1, IND2, and IND3) obtained using the Pastor and Stambaugh (2002) method. The nine-factor model contains the short-term and the long-term reversal factors in addition to the four standard factors and the three industry factors.

We find that the performance estimates from trading strategies constructed using the return prediction model are robust and economically significant. The evidence in Panel A indicates that during the 21-year evaluation period, the Long portfolio earns a monthly return of 1.325 percent, while the Short portfolio earns only 0.723 percent per month. The monthly performance differential of 0.603 percent translates into an annual performance differential of over 7 percent. The characteristic-adjusted performance differential is also large (over 8 percent on an annualized basis) and economically significant.

When we examine the risk-adjusted performance estimates, the results are somewhat

[22] Balvers, Wu, and Gilliland (2000) follow a similar approach in constructing their parametric contrarian investment strategies in which they first rank the return indices of various countries and then use the predicted expected returns to form portfolios.

stronger (see Panels B, C and D). The strength of the performance estimates increases as we include additional factors in the risk adjustment factor models. For example, the monthly nine-factor alpha (t-statistic) estimates for Long, Short, and Long − Short portfolios are 0.442 (2.59), −0.374 (−2.39), and 0.816 (3.50), respectively (see Panel D). This translates into an annual, risk-adjusted performance of 9.79 percent for the Long − Short portfolio.

Because both the Long and the Short portfolios have economically significant returns, our trading strategies do not rely exclusively on the ability to take a short position. Further, the factor exposure estimates indicate that the Long portfolio contains mid-cap, growth stocks, while the Short portfolio contains larger stocks. This evidence indicates that our strategy does not primarily recommend portfolios with small stocks that could be difficult to short and are likely to be more sensitive to microstructure biases (e.g., large bid-ask bounce, illiquidity, etc.).

IV.C. Robustness of Performance Estimates

We conduct several additional tests to examine the robustness of our trading strategy performance estimates. In the first robustness test, we compute the Long and Short portfolio returns by averaging the state portfolio return indices in the two extreme categories. Conceptually, with this approach, we are trading the same state return indices that are predicted in our one-quarter ahead prediction model. We find economically significant performance estimates even with this alternative method for computing portfolio returns. The results reported in column (1) of Table 6, Panel A indicate that the Long − Short portfolio has a monthly nine-factor alpha of 0.597 (t-statistic = 2.97), which translates into an annual performance differential of over 7 percent.

In the second test, we compare the performance of our predictability model to the performance of a "naive" model, which simply uses the historical average return of state portfolio returns until period $t-1$ to predict the state ranking in period t. We find that the nine-factor alpha (t-statistic) for the "naive" Long, Short, and Long − Short portfolios are 0.035 (0.77), −0.063 (−0.92), and 0.098 (0.50), respectively (see Table 6, Panel A, column (2)). This evidence indicates that our trading strategy performance estimates are not somehow mechanically produced.

In the third test, we examine whether the qualitative features of the return prediction model alone can be used to construct a profitable trading strategy. We use the state-level economic index, which is defined as the signed average of the normalized measures of state income growth, relative state unemployment, and state-level housing collateral (see Section III.B). We rank states according to the quarterly levels of the state-level economic indices and form the Long, Short, and Long − Short portfolios. These portfolios are redefined every quarter.

The performance estimates of the qualitative return prediction model indicate that the index-based trading strategy is also able to generate economically significant performance (see column (3)). The monthly nine-factor alpha (t-statistic) estimates for the Long, Short, and Long − Short portfolios are 0.252 (2.20), −0.412 (−2.91), and 0.664 (3.21), respectively. These performance estimates are weaker than the baseline trading strategy results obtained using the estimated return prediction model. However, it is somewhat remarkable that a relatively simple indicator of local macroeconomic conditions is able to generate economically significant evidence of return predictability.

In the fourth test, we examine whether the definition of "local" extends beyond rigid state boundaries. We estimate the return prediction model using the regional macroeconomic indicators instead of state-level macroeconomic variables and construct the trading strategy using the state ranking determined by this regional prediction model. When we consider the eight Census regions, the performance estimates for the Long, Short, and Long − Short portfolios are weaker than the corresponding baseline estimates (see Table 6, Panel A, column (4)). The estimates weaken further and are barely significant when we measure regional macroeconomic conditions using the four Census regions. In this instance, the monthly nine-factor alpha (t-statistic) estimates for the Long, Short, and Long − Short portfolios are 0.050 (0.31), −0.181 (−1.01), and 0.231 (1.63), respectively (see column (5)).

In the fifth test, we examine the incremental role of our three state-level macroeconomic predictors over the previously known predictors of stock returns. We re-estimate the prediction model without the three state-level predictors and obtain a new set of state ranking. We then estimate the performance of the trading strategy using these new ranking. The results reported in column (6) indicate that the Long portfolio has an insignificant performance estimate (alpha = 0.075, t-statistic = 1.04), the Short portfolio has a barely significant alpha estimate (alpha = −0.256, t-statistic = −1.81), and the monthly risk-adjusted performance of the Long − Short portfolio decreases significantly from 0.816 to 0.331 percent (t-statistic = 2.02). This evidence indicates that our state-level predictors are very important for predicting cross-sectional differences in state portfolio returns.

In the sixth test, we examine whether the trading strategy performance is significant across 1984-1994 and 1995-2004 sub-periods. The nine-factor alpha estimates for three different estimation periods are reported in Figure 2, Panel A. We find that the Long portfolio is strongly significant in both sub-periods, while the Short portfolio is only marginally significant in the first sub-period but significant during the second sub-period. The performance differential estimate, however, is significant in both sub-periods and somewhat stronger during the second sub-period.

In the seventh robustness test, we examine the sensitivity of our performance estimates

to the choice of number of state portfolios (N_s) in the extreme portfolios. If N_s is high, the estimation risk would be lower but the distinction between extreme portfolios would weaken. If N_s is low, the estimation risk would be high, but the performance differentials would be reflected more accurately. Thus, we face a risk-accuracy trade-off (e.g., Kandel and Stambaugh (1996), Barberis (2000)). Figure 2, Panel B reports the trading strategy performance estimates for different values of N_s.

We find that the Long − Short performance differential is statistically significant even for larger values of N_s. For example, when $N_s = 6$, the monthly nine-factor alpha (t-statistic) estimates for the Long, Short, and Long − Short portfolios are 0.215 (2.81), −0.156 (−1.86), and 0.371 (2.89), respectively. When $N_s = 12$, the corresponding alpha (t-statistic) estimates are 0.136 (3.11), −0.147 (−2.77), and 0.283 (3.69), respectively. The decline in the trading strategy performance is not surprising because, as N_s increases, the extreme portfolios become similar to each other and the performance differentials decline. However, the variability in the monthly performance estimate also declines and, as a result, the statistical significance of the performance estimates improves.

In the last robustness test, we vary the portfolio rebalancing period. Figure 2, Panel C shows the nine-factor alpha estimates for the Long, Short, and Long − Short portfolios. We find that the performance estimates are significant even when the portfolios are rebalanced only every six quarters. With an eight-quarter rebalancing period, however, the Long − Short portfolio no longer has a significant performance estimate. In this case, the monthly nine-factor alpha (t-statistic) estimates for the Long, Short, and Long − Short portfolios are 0.066 (0.85), −0.071 (−1.04), and 0.137 (1.09), respectively.

IV.D. Trading Strategy Performance and Firm Characteristics

To examine whether the evidence of return predictability and the performance of our trading strategy is stronger among certain types of stocks, we examine the trading strategy performance estimates for sub-samples based on different stock characteristics. Our main objective is to determine whether the trading strategy performance is realizable or whether the predictability is concentrated primarily among subsets of stocks that are difficult to trade. We also use the stock characteristics based sub-samples to indirectly examine the effects of local bias on local return predictability. The trading strategy performance estimates for these sub-samples are reported in Table 6, Panel B.

In the first sub-sample, we obtain the performance estimates after excluding all stocks priced below \$5. We find that the trading strategy performance estimates become weaker but remain significant. For instance, the monthly nine-factor alpha estimate drops from 0.816 percent to

0.772 percent (see column (1)). In the second sub-sample, we exclude stocks with low (bottom one third) institutional ownership. Because of institutional constraints (e.g., due to prudent man rules), the low institutional ownership stocks are likely to be smaller, low priced, and relatively illiquid. Again, we observe a deterioration in the trading strategy performance, but the estimates are still significant (see column (2)). These results indicate that our predictability evidence is not primarily driven by small, illiquid, and hard-to-trade stocks.

In the next three tests, we exclude stocks that are known to have a more local clientele (smaller and less visible growth stocks). We find that the trading strategy performance declines but remains significant (see columns (3)-(5)).[23] This evidence in consistent with our conjecture that local bias is an important determinant of predictable patterns in local stock returns.

Taken together, the robustness test results indicate that the relation between local macroeconomy and local stock returns is robust and economically significant. The trading strategies based on our return prediction models generate high and statistically significant risk-adjusted returns under many different scenarios. These results provide additional support to our return predictability hypotheses (Hypotheses 1a and 1b).

V. Why Are State Portfolio Returns Predictable?

In this section, we attempt to identify the mechanism that generates the predictable patterns in state portfolio returns. We use the key CCAPM economic intuition that in the absence of mispricing, return predictability can arise due to time-varying risk aversion, time-varying consumption beta (i.e., consumption risk), or temporal variation in local risk sharing. In addition, although cash flow based explanations of return predictability have not found much empirical support, if firms' business operations are local, return predictability at least theoretically could also reflect the ability of state-level macroeconomic indicators to predict future cash flows. Further, investors' strong preference for local stocks can amplify these effects.

We have already shown in Section III.D that changes in local risk sharing, as reflected by state-level hy, can influence local stock returns. Thus, local return predictability at least partially reflects changes in state-level risk sharing opportunities. In this section, we focus on the remaining predictability mechanisms.

We first estimate mispricing regressions and show that our empirical evidence is inconsistent with a mispricing based explanation for local return predictability. We also show that state-level predictors are unable to predict future cash flows. These results rule out two potential predictability channels. Next, we show that consumption risk is not strongly affected by

[23] We use the Hong, Kubik, and Stein (2008) proxy of firm visibility. It is defined as the size-adjusted measure of number of shareholders.

changes in local macro-economic indicators. However, as local economic conditions worsen, the consumption levels of local investors decline and, consequently, their risk aversion increases. This evidence supports the conjecture that predictable patterns in state portfolio returns are induced by the changing risk aversion of local investors. In the last set of tests, we show that local return predictability is stronger when local investors exhibit a greater propensity to hold local stocks.

V.A. Mispricing Regression Estimates

We estimate long horizon predictive regressions to test Hypothesis 2a, which posits that local return predictability is unlikely to reflect mispricing. The dependent variable in the mispricing regression is the h-horizon cumulative characteristic-adjusted return for state portfolio j ($\overline{Y}_{j,t,h}$).[24] Similar to the one-quarter ahead predictability regressions (see equation (1)), we pool the observations from all states and formulate the h-horizon prediction models as panel regressions with state fixed effects:

$$\overline{Y}_{j,t,h} = \alpha_{j,h} + X_{j,t-2}\delta_{1,h} + X_{USA,t-1}\delta_{2,h} + \log(1 + D/P)_{j,t-1}\delta_{3,h} + \varepsilon_{j,t,h}. \tag{3}$$

Here, $h = \{1, 2, ..., 24\}$, j is the index for the U.S. states, t is the index for the quarterly time periods, and $\alpha_{j,h}$ is state-specific mean of the h-horizon returns. The explanatory variables in the long-horizon regression are identical to those employed in the short-horizon predictability regressions. If the local predictability is driven by mispricing and subsequent correction, the coefficient estimates of the three state predictors would have significant coefficient estimates for shorter horizons, but they would lose statistical significance as the forecasting horizon increases.

The panel models are estimated using OLS. Because the mispricing regressions are estimated with overlapping observations, errors are serially correlated. We calculate the t-statistics of the parameter estimates using standard errors that have been corrected for cross-sectional and serial auto-correlations using the Driscoll and Kraay (1998) method. In addition, to account for potential small sample biases, we calculate bootstrapped critical values (see Appendix section A.I) for the corrected t-statistics.

To further ensure that our long horizon predictability evidence is robust, we estimate long-run regressions with only the hth quarter return as the dependent variable. These regressions are not estimated with overlapping data and potential concerns about biased inference due to serial auto-correlation in the error terms are mitigated. To be conservative, however, even in this setting, we use the Driscoll and Kraay (1998) standard errors to compute the t-statistics and

[24] We get very similar results when the dependent variable is computed using residuals from one of the factor models or by using other performance benchmarks.

also use bootstrapped critical values to examine statistical significance. In these long-horizon regressions, if there is an initial mispricing, we expect the coefficient estimates of state-level macroeconomic variables to reverse signs as the time horizon increases as initial mispricing eventually gets corrected.

For both types of long-horizon regression specifications, we estimate 24 regressions, one for each horizon h. For brevity, we consider the characteristic-adjusted return measures and report the estimates for only a few values of h. The results are presented in Table 7, Panels A and B.

When the dependent variable is the cumulative h-quarter return, we find that the coefficient estimates for growth rate of state labor income are insignificant across all horizons (see Panel A). In contrast, the long-horizon estimates for relative state unemployment rate are always positive and statistically significant. The state hy is also a significant predictor of long-term returns across all horizons. When the dependent variable is the hth quarter return, we find that the coefficient estimates for all three state-level predictors are either weakly significant or insignificant in most instances (see Panel B). For the 24th quarter regressions, the coefficient estimates switch signs but neither of the three estimates are statistically significant.

These results from long-horizon regressions indicate that the evidence of state-level return predictability does not disappear in the long-term. This evidence supports Hypothesis 2a and appears inconsistent with the mispricing interpretation because it is quite unlikely that mispricing would persist for up to six years.

V.B. Cash Flow and Consumption Beta Related Tests

In the absence of mispricing, the local return predictability could reflect cash flow predictability, changes in local consumption risk, or shifts in local risk aversion. Hypotheses 2b, 2c, and 2d formally state these conjectures.

To test Hypothesis 2b, we estimate panel regressions with the hth quarter state-level cash flow growth rate as the dependent variable.[25] Other details of this specification are identical to the mispricing regressions estimated earlier. The estimation results from the cash flow panel regressions are presented in Table 7, Panel C. We find that neither of the three state-level predictors have statistically significant coefficient estimates. This evidence supports Hypothesis 2b and indicates that changes in local macroeconomic conditions are unlikely to have an incremental effect on the cash flows of local firms.

Next, we test Hypothesis 2c and investigate whether consumption risk is affected by changes in local macroeconomic conditions. We estimate a panel regression in which the dependent variable is the state-level consumption growth beta. The consumption growth beta is estimated

[25] Our cash flow measure is the earnings before extraordinary items minus total accruals, scaled by average total assets.

using a univariate regression of the state portfolio return on the corresponding state consumption growth. The regression is estimated every quarter using a rolling estimator with a look-back window of 24 quarters.[26] We use the state-level retail sales to proxy for state consumption. The annual data for the 1965 to 1998 period are obtained from the Statistical Abstracts of the U.S.[27] To transform the annual consumption growth to quarterly growth rate, we assume that the consumption growth in quarter q of year t is one fourth of the annual growth rate in year t.

The consumption growth beta regression estimates for the 1980 to 1998 period are reported in Table 8, Panel A, column (1). The evidence indicates that any time-variation in consumption beta is only weakly captured by changes in state-level macroeconomic indicators. Thus, consistent with Hypothesis 2c, the evidence indicates that local return predictability is unlikely to be driven by shifts in consumption risk.

V.C. Tests for Time-Varying Risk Aversion

In the next set of tests, we test Hypothesis 2d and examine whether local return predictability is generated through the risk aversion channel. We do not have direct measures of state-level risk aversion. However, we obtain state-level risk aversion estimates from a regional habit-based CCAPM (Korniotis (2008)). This habit model extends the Campbell and Cochrane (1999) habit formation model and allows for uninsurable income shocks in the spirit of Constantinides and Duffie (1996). In this model, risk aversion is given by γ/S_{jt}, where γ is the curvature parameter of the utility function and S_{jt} is defined as $(C_{jt} - H_{4,jt})/C_{jt}$. C_{jt} is the state-level consumption of state j and $H_{4,jt}$ is the average consumption of one of the four Census divisions (North-East, Mid-West, South, and West) to which state j belongs. The key economic intuition from this regional habit model is that as the consumption level moves closer to the regional habit level, the risk aversion of the state representative investor increases.

Korniotis (2008) estimates the model using annual state-level retails sales. To transform the annual risk aversion estimate to a quarterly measure, we assume that risk aversion in quarter q of year t is equal to the risk aversion estimate for year t. Using the quarterly consumption growth and risk aversion estimates, we estimate two panel regression specifications. In the first specification, the dependent variable is the state-level consumption growth rate and in the second specification the dependent variable is the state-level risk aversion estimate.[28] The inde-

[26] Since there are no high-frequency consumption data available, the rolling-regression approach is the only feasible alternative to the Fama and French (1997) short-window regressions used in Lewellen and Nagel (2006) to compute time-varying CAPM betas.

[27] See Korniotis (2008) for more details on the state retail sales data.

[28] Unlike state consumption growth, the consumption betas and state-risk aversion are serially correlated. For robustness, we estimate regressions (1) and (3) in Table 8, Panel A, by adding a lagged dependent variable in the regression specification. We estimate the extended regression specifications using the Hahn and Kuersteiner (2002) estimator, which corrects the OLS estimates from biases arising in panel models with fixed effects and a

pendent variables are identical to those used in the one-quarter ahead predictability regressions (see equation (1)). The regression results obtained using data for the 1980 to 1998 period are reported in Table 8, Panel A, columns (2) and (3).

We find that, in both specifications, all three state-level macroeconomic variables have significant coefficient estimates. Specifically, the estimates in column (2) indicate that the state consumption growth rate declines as the state-level macroeconomic conditions worsen. Because of this decline in the consumption growth rate, the consumption level would move closer to the slow-varying habit level, and the state-level risk aversion is likely to increase.

Consistent with this economic intuition, the evidence in column (3) shows a strong association between state-level risk aversion and state macroeconomic variables. In particular, like the original Campbell and Cochrane (1999) model, when a state economy is experiencing a recession (low state income growth, high relative state unemployment, and low state collateral ratio), state-level risk aversion is high. Taken together, the results in Table 8, Panel A indicate that local return predictability is more strongly related to the variation in risk aversion than the variation in the joint distribution of local consumption and local stock returns. These results are consistent with the conjecture in Hypothesis 2d.

Because we use an indirect and model-implied risk aversion measure, we perform several checks to examine the robustness of these results. In the first test, we use direct trading data to examine whether the trading behavior of local investors is consistent with our risk aversion hypothesis. We measure the trading activities of both local retail and local institutional investors using the buy-sell imbalance (BSI) measure.[29] The quarterly BSI for a stock is defined as the ratio of the quarterly buy-sell volume differential and the total quarterly trading volume. The local institutional buy (sell) trading volume is computed by aggregating the buy (sell) volumes of all local institutions in the sample. The volume measures for local retail investors are defined in an analogous manner using the monthly trading data.

If the risk aversion of local investors increases, they are likely to reduce their exposure to local risky assets. The trading regression estimates reported in Table 8, Panel B are consistent with this conjecture. Like the return predictability regressions, the coefficient estimates of state income growth rate are statistically insignificant in all instances. The relative unemployment rate has the strongest coefficient estimate, while the state-level hy has only weakly significant coefficient estimates. In specification (2), however, neither of the coefficient estimates are statistically significant.

The estimates from trading regressions indicate that when the relative state unemployment

lagged dependent variable. The results from these alternative specification are very similar to those reported in Table 8, Panel B.

[29] We use the Barber and Odean (2000) discount brokerage data to capture retail trading and the 13(F) institutional holdings data to capture institutional trades (quarterly position changes).

is high and state housing collateral is low (borrowing constraints are high), local retail and local institutional investors are less bullish about local stocks. Consequently, local investors sell local stocks with greater intensity (or buy them with relatively lower intensity). Although trading intensity could be affected by numerous other factors (e.g., liquidity needs), the trading regression estimates support our risk aversion conjecture.

V.D. Return Based Tests for Time-Varying Risk Aversion

In the next risk aversion test, we examine the relation between local risk aversion and local stock returns using our return predictability regressions. We re-estimate the return predictability regressions using a residual return measure as the dependent variable, which accounts for time-varying risk aversion. The estimation period is from 1980 to 1999.

The results reported in Table 8, Panel C indicate that when we include a risk aversion based factor in either the CAPM or the four-factor model, the ability of state macroeconomic variables to predict residual state portfolio returns diminishes. For example, the state hy estimate is -0.040 when we do not account for state-level risk aversion (column (1)), but this estimate becomes -0.022 when the state-level risk aversion is included in the factor model (column (3)). The estimates in column (5) indicate that the two hy estimates are statistically different. We obtain similar results for the relative state unemployment estimates and when we define the residuals using the four-factor model (see columns (2), (4), and (6)). These results indicate that local risk aversion is an important determinant of local return predictability.

To further understand the link between time-varying local risk aversion and local return predictability, we form trading strategies using the state-level risk aversion estimates. Although our risk aversion measures are somewhat coarse and are derived from a specific habit model, this approach allows us to identify the relation between local risk aversion and local stock returns more directly. At the beginning of year t, we form the Long and Short portfolios by ranking states using their annual risk aversion estimates during year $t-1$. The set of stocks located in states with the highest risk aversion levels are in the Long portfolio, while the stocks located in lowest risk aversion states are included in the Short portfolio. The portfolios are rebalanced every year because the state-level risk aversion data are only available annually.

The trading strategy performance estimates for two evaluation periods are reported in Table 8, Panel D. Consistent with our key economic intuition, we find that firms located in high risk aversion states (Long portfolio) earn significantly positive risk-adjusted returns. In contrast, firms located in low risk aversion states (Short portfolio) earn negative risk-adjusted returns, although the statistical significance is weak. During the 1980-1999 evaluation period, the Long $-$ Short portfolio has a monthly nine-factor alpha of 0.362 (t-statistic $= 2.56$). The

alpha estimate remains significant (alpha = 0.342, t-statistic = 2.32) even when we consider a longer time period from 1966 to 1999 for which we have the risk aversion data.

In our last risk aversion motivated test, we estimate the performance of our baseline trading strategy (see Table 5, Panel D) after excluding time periods in which the U.S. economy was in recession. Because our time-varying risk aversion measure attempts to capture local recessions, we conjecture that the effect of local recessions on local stock returns would be stronger when the U.S. economy is also contracting. When both the state and the U.S. economy experience a contraction, non-local investors would have limited ability to mitigate the effects of local economic conditions on local returns. Consequently, the impact of changes in local economic conditions on local stock returns would be higher.

We test this conjecture by excluding quarters in which the U.S. economy was in a recession during the 1984 to 2004 period.[30] We identify the U.S. recession periods using data from the National Bureau of Economic Research (NBER).[31] We find that the trading strategy performance declines when we exclude the recession quarters from the sample (see Table 8, Panel D, column (3)). The nine-factor alpha estimate drops from 0.816 to 0.671 (t-statistic = 2.77). This evidence is consistent with our conjecture and indicates that local return predictability and trading strategy performance are both stronger during time-periods in which both the state and the U.S. economies are contracting.

V.E. Firm Visibility, Local Betas, and Local Return Predictability

Our predictability hypotheses rely critically on the existence of local bias among investors. In our next set of tests, we evaluate the three local bias hypotheses (Hypotheses 3a, 3b, and 3c) and examine whether local bias amplifies the predictable patterns in local stock returns.

The first local bias hypothesis (Hypothesis 3a) examines whether the effects of changes in state-level macroeconomic variables on returns are stronger among less visible firms because, all else equal, those firms are likely to have a more local investor clientele.[32] We measure firm visibility using the Hong, Kubik and Stein (2008) visibility index, which is the residual from a regression of the log of number of shareholders on the log of firm size. The visibility regression

[30] We focus on expansions rather than contractions because the U.S. economy was in contraction for only seven quarters during our sample period. This does not give us a sufficient number of monthly observations to accurately estimate the factor model.

[31] The data are available at `http://www.nber.org/cycles.html`. NBER defines a recession when there is a significant decline in the economic activity (visible in real GDP, real income, employment, industrial production, and wholesale-retail sales), which spread across the economy and lasts for more than a few months.

[32] Using the Barber and Odean (2000) discount brokerage data, we do find that stocks with lower visibility have a more local clientele, after accounting for other stock characteristics such as size, B/M, past returns, etc. In particular, during the 1991 to 1996 period, the average cross-sectional correlation between stock-level visibility proxy and stock-level local bias is −0.108 (t-statistic = −4.54).

is estimated each quarter using data on number of shareholders from COMPUSTAT and firm size (number of shares outstanding multiplied by stock price) data from CRSP.

We re-estimate the trading strategy performance for sub-samples of high (top third) and low (bottom third) visibility firms. We report the results in Table 9, Panel A. Consistent with Hypothesis 3a, we find that the returns of less visible local firms are more sensitive to changes in local economic conditions. When we consider a sample of low visibility firms, the monthly nine-factor alpha (t-statistic) for the Long − Short portfolio is 0.907 (3.52). This performance estimate is significantly lower (alpha = 0.493, t-statistic = 2.17) when we consider a sub-sample of highly visible firms. This evidence indicates that local bias is likely to be an important determinant of local return predictability.

For robustness, we use another indirect method to test our local bias hypothesis. Pirinsky and Wang (2006) show that the returns of firms headquartered in a certain region are correlated with other firms in that region. They find that the local comovement is not influenced by local economic fundamentals and conjecture that this comovement could be induced by the correlated trading behavior of local investors. Motivated by this evidence, we test whether firms that are more strongly correlated with the state index (i.e., have higher local beta) exhibit stronger predictable patterns. We measure quarterly local beta using a rolling 36-month window and estimate a factor model that contains the market factor and a state-level value-weighted return index.

When we re-estimate the performance of the trading strategy for sub-samples of high (top third) and low (bottom third) local beta firms, we find that the returns of firms with high local betas are more sensitive to changes in local economic conditions. For the sample of high local beta firms, the monthly nine-factor alpha (t-statistic) for the Long − Short portfolio is 0.912 (2.98). The performance of the Long − Short portfolio is significant even for the low local beta sub-sample but the estimate is significantly lower (alpha = 0.437, t-statistic = 2.47). This evidence indicates that stocks that are more sensitive to the trading activities of local investors exhibit stronger predictable return patterns.[33]

V.F. More Direct Local BiasTests

In the next test, we examine the effects of local bias on local return predictability more directly.

[33] We also find direct evidence to support the Pirinsky and Wang (2006) conjecture. Like their study, we find that our state-level predictors have little ability to predict the local beta, but the buy-sell imbalance of local institutional investors in a given quarter has a strong ability to predict the local beta in the following quarter. Specifically, we estimate local beta predictability regression similar to our return predictability regression in which the local beta is the dependent variable. We use all independent variables from the return predictability regression and add the institutional trading (BSI) measure to the set. We find that the institutional trading variable has the strongest coefficient estimate (estimate = 0.148, t-statistic = 5.18), while most of the economic indicators have insignificant coefficient estimates.

Our second local bias hypothesis (Hypothesis 3b) posits that the impact of changes in local economic conditions on local returns would be higher in states with higher local bias. To test this hypothesis, we use the Barber and Odean (2000) discount brokerage data and obtain direct measures of monthly firm-level local bias.[34] The firm-level local bias measure indicates whether the actual shareholders of a firm are closer than what one would expect to observe by chance. Because the brokerage data are available only for the 1991-1996 period, we estimate the trading strategy performance for the 1991 to 2004 period to avoid a look-ahead bias in our performance estimates.

The local bias based sub-sample estimates are presented in Table 9, Panel C. When we re-estimate the performance of the trading strategy for sub-samples of high (top third) and low (bottom third) local bias firms, we find that the monthly nine-factor alpha (t-statistic) for the Long $-$ Short portfolio is 0.932 (2.96) for high local bias firms and only 0.059 (0.32) for low bias firms. These results are broadly consistent with our second local bias hypothesis (Hypothesis 3b) and indicate that local bias is a critical determinant of local return predictability.

For additional robustness, we consider an alternative local bias proxy. This test is motivated by Van Nieuwerburgh and Veldkamp (2008), who show that investors with a strong preference for local stocks would hold concentrated portfolios. Thus, portfolio concentration could serve as an alternative proxy for local bias and, furthermore, investors who hold more concentrated portfolios would be more sensitive to idiosyncratic, state-specific macroeconomic shocks.[35] Consistent with Hypothesis 3b, we find that the trading strategy performance is insignificant (alpha $= -0.008$, t-statistic $= -0.17$) when we consider stocks with low portfolio concentration but strongly significant (alpha $= 1.098$, t-statistic $= 3.16$) for firms that are held by investors with concentrated portfolios (see Panel C).

Our next local bias test is motivated by the evidence in Hong, Kubik, and Stein (2008), who show that, in the presence of local bias, stock prices are lower for firms located in regions with high RATIO (ratio of state book equity to state personal income) because there is more competition among local firms for local investments. We conjecture that future local returns would be higher when the RATIO measure increases and competition among local firms for local investments rises.[36]

[34] The firm level local bias is the difference between (i) the average distance between the firm headquarter and all individual investors in the sample and (ii) the average distance between the firm headquarter and the firm's retail shareholders in the sample. A positive difference indicates that the actual shareholders of the firm are closer than potential shareholders. See Ivkovich and Weisbenner (2005) for additional details of this measure.

[35] We use the discount brokerage sample of retail investors and the normalized portfolio variance measure to quantify portfolio concentration. Normalized portfolio variance is defined as the ratio of portfolio variance and average variance of stocks in the portfolio. The stock-level portfolio concentration measure is the equal-weighted average of the normalized portfolio variance of investors holding the stock.

[36] The RATIO data are obtained from Hong, Kubik and Stein (2008) for five-year intervals: 1975, 1980, 1985, 1990, 1995, 2000, and 2005. Using these data, for each state, we compute the change in its ratio measure between 1980 and 1975, 1985 and 1980, etc. Then, for each state, we calculate the average change in its ratio

We estimate the performance of our trading strategy for states with low (bottom third) average RATIO levels and states with high (top third) average RATIO levels. We repeat the analysis using RATIO change measures. The trading strategy results for both the RATIO level and RATIO change sub-samples are reported in Table 9, Panel D. Consistent with our last local bias hypothesis (Hypothesis 3c), we find that the trading strategy performance is stronger when we restrict our attention to states that have high RATIO levels or have experienced a large increase in the RATIO level.

V.G. Local Bias, Local Risk Aversion, and Local Predictability

In our last empirical test, we directly examine how the interaction between local bias and local risk aversion affects local stock returns. Although our local bias and risk aversion measures are available for different time periods, the interaction between the two measures could help us better identify the predictability mechanism. We measure the performance of the Long, Short, and Long − Short portfolios for high and low local bias sub-samples, where the state ranking is obtained using the state-level risk aversion estimates instead of a return prediction model. This approach is similar to the method used to generate the local bias conditional performance estimates in Table 9, Panel C.

We find that the performance of the Long − Short portfolio is significant only for the high local bias sub-sample (see Table 9, Panel E). This evidence supports our conjecture that local bias strengthens the relation between time-varying local risk aversion and local stock returns. Overall, the empirical results from our local bias motivated tests indicate that the predictable patterns in local stock returns are generated by the joint effects of time-varying local risk aversion and local bias.

VI. Summary and Conclusion

In this study, we examine the asset pricing implications of local bias using the economic intuition from recent consumption-based asset pricing models. We conjecture that, in the presence of local bias and incomplete risk sharing, local macroeconomic variables that capture local business cycles can be used to predict the returns of local stocks. In particular, when local economic conditions deteriorate, the average returns of local stocks increase because local risk aversion increases and the ability of local investors to smooth consumption declines.

Consistent with this conjecture, we find that U.S. state portfolios earn higher (lower) returns when state-level unemployment rates are higher (lower) and state investors face stronger

measure over the 1980 to 2005 period, and the average ratio over the 1975 to 2005 period.

(weaker) borrowing constraints. During the 1980-2004 period, trading strategies that exploit this state-level predictability earn annualized risk-adjusted return of over 7 percent. The evidence of predictability is stronger among less visible firms and in regions in which investors exhibit stronger local bias and hold more concentrated portfolios.

Overall, our empirical findings indicate that the stock return generating process contains a predictable local component. This local component is jointly influenced by state-specific business cycles and the investment behavior of state investors. In broader terms, our predictability results suggest that the explanatory power of existing asset pricing models could be improved by including a geographical component.

These results make important contributions to several strands of research. First, our results suggest that local bias generates local investor clienteles and frictions that segment the market along a geographical dimension. Because of state-level segmentation, at least a component of stock returns is determined by the preferences and trading behavior of the local clientele. Our evidence of segmentation induced by local bias complements the evidence of market segmentation in other related settings (e.g., Becker (2007), Becker, Ivkovich, and Weisbenner (2007)).

Second, our results contribute to the emerging literature on the asset-pricing implications of local bias. We provide more direct evidence to show that local return comovements identified in Pirinsky and Wang (2006) could be induced by local bias. We also extend the results in Hong, Kubik and Stein (2008), who show that stock price levels are lower in regions with stronger local bias and higher supply of risky assets. Our evidence indicates that in the presence of local bias, the returns of firms located in regions with an increased supply of risky assets react more strongly to local demand shifts. Therefore, local bias has important implications not only for price levels and return comovements, but also for expected returns.

Last, the paper contributes to the literature on the predictability of stock returns. We establish a strong geographical dimension to return predictability and show that the state-specific component of state portfolio returns can be predicted using state-level macroeconomic indicators. This evidence indicates that in the presence of local bias, state-level versions of recently proposed predictors of aggregate U.S. stock market returns (e.g., the hy collateral of Lustig and Van Nieuwerburgh (2005)) can be effectively applied to more disaggregated portfolios.

Appendix

A.I. Bootstrapped Standard Errors

We follow Mark (1995) and apply a non-parametric bootstrap to calculate the critical values of the t-statistic of our OLS estimates. We generate data under the hypothesis that the state-level portfolio returns ($r_{j,t}^{loc}$) follow a random walk, i.e., $r_{j,t}^{loc} = a_{j,0} + e_{j,1t}$, where $a_{j,0}$ is the mean return of the jth state, and $e_{j,1t}$ is an innovation sequence generated by the mean deviations ($r_{j,t}^{loc} - a_{j,0}$). The predictive variables X are generated from AR(1) models, $X_t = b_0 + b_1 X_{t-1} + e_{2t}$, where b_0 and b_1 are OLS estimates from AR(1) models, and e_{2t} is the innovation sequence generated from the sequence of fitted residuals. For state-specific predictors like the state hy, we estimate a separate AR(1) for each state.

We create bootstrapped samples by choosing states randomly with replacement. By bootstrapping on the cross-sectional dimension, we preserve the persistence and the endogeneity in the original sample within each cross-sectional unit. For each bootstrapped sample, we estimate a fixed effect regression with OLS and calculate the Driscoll and Kraay (1998) t-statistic for each predictor. We collect theses t-statistics and obtain their empirical distributions by repeating the experiment 1,000 times. For each t-statistic, we use these empirical distributions to compute the bootstrapped critical value at the 5% significance level.

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Table 1
Characteristics of State Portfolios

The table reports the average monthly characteristics of 35 U.S. state portfolios. A state portfolio contains firms headquartered in the state. U.S. states with fewer than 20 stocks are excluded from the analysis. **Panel A** reports the average number of firms in each state (N), average monthly returns (AvgRet), standard deviation (SD), and the average characteristic adjusted returns computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method. We also estimate the four-factor model for each state portfolio (the factors are RMRF, SMB, HML, and UMD) and report the alphas, factor exposures, and the adjusted R^2 (AdjR^2). Average characteristic-adjusted returns and alphas, which are significant at the 5 and 10 percent levels, are indicated by ** and *, respectively. We consider two time-periods: 1980 to 2004, and 1963 to 2005. **Panel B** reports additional characteristics of state portfolios averaged over the 1980 to 2004 sample period. They include market capitalization in millions of dollars (Size), market share of the firms in the state portfolio (% of Market), book-to-market ratio (B/M), dividend yield in percent (D/P), firm size based industry concentration or Herfindahl index (HIDX) multiplied by hundred, and analyst coverage (ANCOV). Panel B also reports the following three statistics for local institutional investors: average percentage institutional ownership among local firms (IO), the average number of state-based institutions (Num of Insti.), and the size of the state-based institutional investors relative to all institutions in our sample (% of Tot Insti. Holdings). **Panel C** reports state-level local bias measures. EWLB and VWLB are equal-weighted and value-weighted averages of the local bias measure of institutional investors. Retail EWLB is a state-level local bias measure for retail investors. It is the equal-weighted average of investor-level local bias measures. The local bias of retail (institutional) investors is the differential between the percentage of local stocks they hold and the percentage of the same local stocks in the market portfolio. The value-weighted local bias measure uses the size of the institutional portfolio to determine the weight assigned to the institution. The retail EWLB is computed over the 1991 to 1996 period, the other statistics in Panel B and C are computed over the 1980 to 2004 period.

Panel A: Return Characteristics

		1980 - 2004									1963-2005	
State	*N*	*AvgRet*	*SD*	*Char. Adj.*	*Alpha*	*RMRF*	*SMB*	*HML*	*UMD*	*Adj R^2*	*AvgRet*	*SD*
AR	22	1.72	5.99	0.54**	0.64**	0.93	-0.23	0.00	0.03	0.67	1.44	6.44
WA	81	1.44	6.12	0.12	0.46**	1.01	0.15	-0.34	-0.04	0.80	1.25	5.99
MN	170	1.30	4.25	0.28**	0.19	0.88	0.01	0.17	-0.01	0.65	1.06	4.58
GA	132	1.29	4.11	0.09	0.21	0.85	-0.12	0.18	-0.01	0.86	1.07	4.43
WI	76	1.28	4.16	0.03	0.17	0.89	0.14	0.37	-0.14	0.66	1.08	4.55
TN	64	1.27	5.22	-0.03	-0.10	1.01	0.22	0.52	-0.02	0.40	1.14	5.70
IA	35	1.24	4.37	0.01	0.06	0.85	0.20	0.43	-0.06	0.85	0.99	4.66
NC	93	1.24	4.36	0.10	0.01	0.93	-0.02	0.43	-0.04	0.74	0.94	4.48
IN	80	1.23	4.83	-0.02	0.14	0.77	-0.11	0.08	0.10	0.45	0.97	4.81
KY	36	1.21	5.00	-0.01	0.03	0.88	0.21	0.17	0.03	0.47	1.05	4.86
CA	816	1.21	6.41	0.16	0.18	1.07	0.35	-0.44	-0.02	0.62	1.02	5.80
NY	552	1.21	4.60	0.08	0.11	1.01	-0.14	0.05	-0.05	0.66	0.96	4.49
NJ	280	1.20	4.30	0.04	0.27**	0.83	-0.29	-0.03	-0.04	0.61	0.96	4.28
MO	92	1.20	4.02	0.04	0.16	0.84	-0.10	0.14	-0.03	0.56	0.96	4.15
CT	162	1.16	4.84	0.04	-0.05	1.05	-0.01	0.17	-0.01	0.72	0.99	4.78
NV	42	1.15	6.30	0.02	-0.11	0.96	0.59	0.37	-0.10	0.90	1.12	6.84
IL	236	1.13	4.15	-0.01	-0.07	0.95	-0.09	0.27	0.01	0.77	0.97	4.16
AL	42	1.13	4.84	-0.08	-0.14	0.99	0.10	0.45	-0.05	0.34	1.06	4.86
VA	127	1.10	4.57	0.00	-0.16	1.00	0.10	0.20	0.04	0.30	0.97	4.47
OH	203	1.09	4.06	-0.06	-0.13	0.90	-0.02	0.38	0.01	0.50	0.91	4.00
MI	120	1.05	4.98	-0.08	-0.27*	1.09	0.08	0.54	-0.12	0.51	0.86	4.86
PA	244	1.05	4.55	-0.12	-0.18*	1.00	0.14	0.23	-0.01	0.61	0.90	4.46
OR	52	1.02	5.20	-0.11	-0.07	0.97	0.26	0.04	-0.09	0.75	0.96	5.78
NH	28	1.02	7.37	-0.13	0.03	0.89	0.75	-0.31	-0.06	0.38	1.05	7.66
AZ	65	1.01	5.41	-0.17	-0.27	1.03	0.56	0.29	-0.08	0.93	0.84	5.40
UT	47	0.98	6.14	-0.06	-0.18	0.96	0.38	-0.08	0.05	0.71	0.86	5.52
MA	271	0.98	6.15	-0.10	-0.08	1.07	0.32	-0.33	-0.04	0.21	0.90	5.83
MD	87	0.96	5.79	-0.07	-0.21	0.85	0.58	-0.12	0.13	0.78	0.81	5.41
OK	53	0.94	5.71	-0.27	-0.35	0.96	0.04	0.35	0.04	0.77	1.02	5.71
SC	36	0.93	5.00	-0.15	-0.21	0.94	0.34	0.38	-0.17	0.87	0.75	5.05
TX	451	0.92	4.73	-0.12	-0.26**	1.00	0.02	0.14	0.00	0.68	0.89	4.56
FL	256	0.88	4.76	-0.16	-0.28**	0.92	0.49	0.20	-0.07	0.82	0.74	5.09
KS	34	0.84	4.80	-0.30*	-0.44**	0.89	0.39	0.34	0.04	0.38	0.79	4.98
LA	35	0.79	5.23	-0.18	-0.56**	1.00	0.04	0.50	0.02	0.76	0.82	5.45
CO	153	0.50	6.60	-0.40**	-0.64**	1.07	0.28	-0.14	-0.02	0.80	0.53	5.79
Avg	**151**	**1.10**	**5.11**	**-0.01**	**-0.02**	**0.95**	**0.16**	**0.16**	**-0.02**	**0.64**	**0.96**	**5.14**

	Panel B: Other Characteristics									Panel C: State Local Bias		
State	*Size ($m)*	*% of Market*	*B/M*	*D/P (%)*	*HIDX*	*ANCOV*	*IO (%)*	*Num of Insti.*	*% of Tot Insti. Holdings*	*Insti. EWLB*	*Insti. VWLB*	*Retail EWLB*
AR	114.70	1.42	0.83	1.29	8.51	6.70	27.50	92	0.13	17.56	14.02	19.46
WA	203.58	2.05	0.68	1.37	9.41	5.46	27.26	68	0.63	7.78	4.67	12.49
MN	185.90	2.48	0.63	1.13	10.41	4.23	27.55	60	0.98	8.04	13.31	11.11
GA	248.34	3.27	0.86	2.78	9.65	4.79	27.07	68	1.17	9.24	8.09	7.69
WI	58.74	0.87	0.73	2.21	9.14	4.55	33.26	64	1.27	4.46	2.86	3.55
TN	73.79	1.04	0.73	1.95	9.80	6.41	35.48	75	0.32	6.38	6.50	7.56
IA	17.98	0.29	0.94	2.56	8.28	3.47	22.91	47	0.11	9.46	6.67	3.15
NC	164.14	1.84	0.96	2.10	9.54	4.92	26.93	67	2.39	14.50	7.83	2.20
IN	79.01	1.11	0.90	2.19	7.79	3.82	27.21	53	0.45	19.64	50.70	4.99
KY	22.55	0.38	0.86	4.10	8.59	4.39	28.36	59	0.28	8.91	9.56	2.20
CA	953.12	11.87	0.60	0.73	10.33	4.23	27.06	57	11.74	5.81	2.52	6.32
NY	1119.47	16.36	0.64	1.40	10.13	3.81	24.94	61	28.79	-0.57	0.87	-2.77
NJ	452.92	7.08	0.58	1.25	9.71	3.50	22.02	56	2.29	4.70	3.60	0.45
MO	103.70	1.69	0.56	2.78	9.18	5.16	32.76	78	0.87	4.94	2.90	3.82
CT	290.25	4.10	0.35	1.80	10.23	3.82	30.38	64	2.49	1.91	1.43	1.29
NV	24.26	0.30	0.71	1.03	16.51	3.84	19.32	44	0.94	0.26	-0.07	6.38
IL	440.44	7.96	0.70	2.23	8.83	6.11	34.77	72	6.42	5.23	5.57	0.79
AL	28.47	0.38	0.78	2.14	8.02	4.82	25.82	56	0.29	13.21	13.07	5.73
VA	172.30	2.53	0.76	1.75	10.82	5.06	27.59	68	0.46	10.94	11.26	0.82
OH	245.65	3.85	0.75	2.21	8.96	5.01	32.31	70	2.62	11.87	9.75	5.14
MI	144.38	2.68	0.87	1.97	10.04	4.44	27.30	62	0.83	13.28	7.93	4.97
PA	196.58	3.47	0.76	2.05	8.21	4.49	29.41	60	4.93	6.28	5.54	3.86
OR	24.45	0.39	0.72	1.65	10.71	5.15	29.27	51	0.15	1.61	0.90	4.84
NH	6.37	0.14	0.70	1.59	8.86	1.98	25.04	31	0.76	0.03	-0.02	1.48
AZ	28.88	0.40	0.61	1.86	10.78	3.52	24.55	46	0.22	2.18	2.29	3.14
UT	12.26	0.22	0.65	0.97	10.20	2.51	20.30	36	0.08	4.88	7.12	7.47
MA	189.66	3.03	0.68	1.06	9.88	4.06	29.13	48	11.72	3.24	1.17	6.72
MD	61.15	1.00	0.71	1.38	9.95	3.97	25.60	50	2.04	2.38	1.14	4.42
OK	25.98	0.40	0.56	0.77	9.61	3.49	22.86	50	0.29	3.95	4.04	4.56
SC	13.61	0.25	0.83	1.81	8.78	3.90	26.83	42	0.10	5.65	5.90	1.42
TX	652.93	10.52	0.61	1.12	10.56	5.17	28.81	67	3.35	5.69	3.72	3.93
FL	85.16	1.43	0.68	1.11	10.57	2.43	20.92	39	0.77	1.54	1.21	2.91
KS	8.77	0.15	0.87	1.35	9.72	2.86	23.58	35	0.31	0.95	0.30	1.43
LA	24.38	0.41	0.82	1.77	8.91	5.04	30.85	62	0.06	5.55	5.31	3.31
CO	78.44	1.25	0.61	0.45	12.27	2.82	19.92	41	1.85	1.09	0.98	4.15
Avg	**187.21**	**2.76**	**0.72**	**1.71**	**9.80**	**4.28**	**27.00**	**57**	**2.63**	**6.36**	**6.36**	**4.60**

Table 2

Descriptive Statistics For State Portfolio Returns and Return Predictors

The table reports univariate statistics (Panel A) and correlation coefficients (Panel B) for state portfolio returns and return predictors. The sample period is from 1980(Q3) to 2004(Q4). The two return variables reported are the state portfolio returns over the risk-free rate ($\mathrm{R}^{loc} - \mathrm{R}_f$) and the market return over the risk-free rate ($\mathrm{R}_m - \mathrm{R}_f$). R^{loc} is the value-weighted state portfolio return, where firms headquartered in the state are included in the state portfolio. The market return is the value-weighted average return of all CRSP stocks. The risk-free rate is the rate of return of 30-day Treasury bills obtained from Ibbotson Associates. All return measures are divided by one plus the inflation rate computed using the U.S. consumer price index from the Bureau of Labor Statistics (BLS). The return predictors include the U.S. and state relative unemployment rate (U.S. Rel Un, State Rel. Un.), U.S. and state labor income growth rate (U.S. Inc Gr, State Inc Gr), the U.S. and state housing collateral ratio (U.S. *hy*, state *hy*), the paper-bill spread (30-day commercial paper minus 30-day Treasury bill return), the term spread (10-year government bond yield minus 1-year government bond yield), default spread (Baa-rated corporate bond yield minus 10-year government bond yield), the U.S. *cay* residual of Lettau and Ludvigson (2001a, 2001b), and the state dividend-price ratio (log-value of $(1 + D/P)$). D is the sum of the past four quarterly dividends and P is the stock price. The state housing collateral ratio is computed using the Lustig and Van Nieuwerburgh (2005) method. The unemployment rates are from the BLS. The relative unemployment rate is the ratio of current unemployment rate to the moving average of the unemployment rates of the previous 16 quarters. Labor income is from the Bureau of Economic Analysis (BEA). The U.S. *cay* and U.S. *hy* are downloaded from Sydney Ludvigson's and Stijn Van Nieuwerburg's web sites, respectively. The three spreads use quarterly returns obtained from the Board of Governors of the Federal Reserve System web site.

Panel A: Average Univariate Statistics Across States

	Mean	*Std. Dev.*	*Autocorrel.*
$R^{loc} - R_f$	1.933	0.094	-0.051
$R_m - R_f$	1.972	0.086	-0.025
US Rel Un	1.000	0.196	0.877
State Rel Un	1.009	0.246	0.871
US Inc Gr	0.486	0.008	-0.236
State Inc Gr	0.380	0.010	-0.034
US hy	0.025	0.062	0.982
State hy	0.002	0.086	0.954
Paper-Bill Spd	0.049	0.026	0.959
Term Spd	0.013	0.011	0.907
Default Spd	0.022	0.005	0.873
U.S. cay	0.003	0.016	0.890
log(1 + D/P)	0.025	0.011	0.956

Panel B: Correlations Among Returns and Predicting Variables

	TIMING:	$R^{loc} - R_f$	$R_m - R_f$	*US Rel Un*	*State Rel Un*	*US Inc Gr*	*State Inc Gr*	*US hy*	*State hy*
$R^{loc} - R_f$	t	1	0.838	0.053	0.039	-0.064	0.028	0.025	-0.027
$R_m - R_f$	t		1	-0.001	-0.015	-0.076	0.053	-0.007	-0.028
US Rel Un	t - 1			1	0.759	-0.076	-0.185	0.146	0.215
State Rel Un	t - 2				1	-0.015	-0.227	0.130	0.281
US Inc Gr	t - 1					1	0.497	-0.116	0.029
State Inc Gr	t - 2						1	-0.118	-0.075
US hy	t - 1							1	0.091
State hy	t - 2								1
Paper-Bill Spd	t - 1	-0.061	-0.076	-0.036	-0.024	-0.129	-0.103	0.034	-0.172
Term Spd	t - 1	0.097	0.099	0.341	0.288	0.094	0.075	0.278	0.058
Default Spd	t - 1	0.073	0.020	0.564	0.456	-0.086	-0.166	0.229	0.271
U.S. cay	t - 1	0.102	0.082	0.201	0.185	-0.170	-0.154	0.312	-0.160
log(1 + D/P)	t - 1	0.157	0.196	0.051	0.004	-0.317	-0.118	0.193	-0.260

Table 3

Panel Predictive Regressions: Baseline Estimates

This table reports the results from one-quarter ahead panel predictive regressions of the form: $Y_{j,t} = \alpha_j + X_{j,t-2}\delta_1 + X_{USA,t-1}\delta_2 + \log(1+D/P)_{j,t-1}\delta_3 + \varepsilon_{j,t}$. The dependent variable $Y_{j,t}$ is either **(1)** the CAPM residual, **(2)** the four-factor residual, or **(3)** the seven-factor residual. In regressions **(4)** to **(6)**, the state-specific returns are the difference between the state returns and a benchmark return. In the "Market Adj." column, the benchmark return is the value-weighted return of all CRSP stocks. In the "Char. Adj." column, the benchmark is the size, book-to-market, and momentum matched portfolio. In the "Ind. Adj." column, we use the 48 Fama and French (1997) industry returns as benchmarks. The row vectors $X_{j,t-2}$ and $X_{USA,t-1}$ contain the state macroeconomic predictors and U.S.-level predictors, respectively. See Table 2 for the definitions of all variables. The panel models are estimated using OLS. The t-statistics, reported beneath the estimates in smaller font, use serial and cross-sectional correlation adjusted Driscoll and Kraay (1998) standard errors. The estimation period is from 1980(Q3) to 2004(Q4).

	(1)	(2)	(3)	(4)	(5)	(6)
		Residual R^{loc}				
	CAPM	*4 Factor*	*7 Factor*	*Market Adj.*	*Char. Adj.*	*Ind. Adj.*
State-Level Predictors						
Inc Gr	-0.099	-0.060	0.038	-0.105	0.029	0.017
	-0.97	-0.91	0.47	-0.85	0.35	0.23
Rel Un	0.014	0.014	0.013	0.012	0.012	0.009
	3.94	2.95	3.09	3.49	3.99	2.99
hy	-0.032	-0.036	-0.034	-0.028	-0.031	-0.023
	-2.66	-5.26	-3.66	-2.08	-2.98	-2.11
U.S. Macro Predictors						
Inc Gr	0.161	-0.030	-0.091	0.187	0.033	0.083
	0.83	-0.20	-0.80	1.26	0.39	0.68
Rel Un	0.007	-0.003	-0.003	0.010	0.007	0.006
	0.97	-0.46	-0.35	1.33	1.38	1.44
hy	0.042	0.061	0.036	0.046	0.056	0.022
	1.61	3.67	2.97	1.56	4.23	1.75
Other Predictors						
log(1 + D/P)	0.238	0.291	0.112	0.089	-0.058	0.073
	1.05	1.14	0.70	0.40	-0.51	0.46
U.S. cay	-0.040	-0.046	-0.110	-0.113	-0.062	0.053
	-0.28	-0.41	-1.71	-0.75	-0.73	0.73
Paper-Bill Spd	-0.431	-0.505	-0.395	-0.099	-0.026	-0.087
	-2.64	-3.32	-4.69	-0.63	-0.43	-0.82
Term Spd	-0.348	-0.487	-0.192	-0.272	-0.086	-0.189
	-0.85	-1.72	-1.15	-0.70	-0.58	-0.80
Default Spd	0.755	0.068	-0.078	0.522	-0.193	0.421
	1.70	0.24	-0.30	1.12	-0.87	1.71
Adj R^2	0.037	0.029	0.036	0.015	0.009	0.009

Table 4
Panel Predictive Regressions: Estimates from Robustness Tests

The table reports the coefficient estimates of state-level predictors from one-quarter ahead predictive regressions of the form: $Y_{j,t} = \alpha_j + X_{j,t-2}\delta_1 + X_{USA,t-1}\delta_2 + \log(1 + D/P)_{j,t-1}\delta_3 + \varepsilon_{j,t}$, where the dependent variable $Y_{j,t}$ is the difference between the state portfolio return and the size, book-to-market, and momentum matched benchmark return (Daniel, Grinblatt, Titman, and Wermers (1997)). The t-statistics are reported beneath the estimates in smaller font. The estimation period is from 1980(Q3) to 2004(Q4). The predictors are defined in Table 2 and the estimation method for regressions (1) to (5), and (7) is described in Table 3. **Regression (1)** is our baseline regression from Table 3, column (5). **Regressions (2) and (3)**. The state-level predictors in $X_{j,t-2}$ are replaced with their regional averages. The regions are either the four or eight divisions of the U.S. Census Bureau. **Regression (4)** excludes the states of California, New York, and Texas. **Regression (5)** uses the Stambaugh (1999) bias-correction method and the Driscoll and Kraay (1998) t-statistics use residuals computed with the bias-corrected estimates. In **Regression (6),** the first row contains the OLS estimates from the baseline regression, the second row reports the t-statistics, and the last row (reported within square brackets) is the bootstrapped critical values for these t-statistics (Mark (1995)). Appendix A.I provides details of the bootstrapping method. **Regression (7)**. The U.S. and state relative unemployment rates are replaced with the regression-based unemployment news measure of Boyd, Hu and Jagannathan (2005).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	*8 Census Divisions*	*4 Census Divisions*	*Exclude CA, NY, TX*	*Stambaugh Correction*	*Bootstrapped Critical Value*	*BHJ Unemp. News*
State-Level Predictors							
Inc Gr	0.029	0.065	0.043	0.030	0.029	0.029	0.028
	0.35	0.52	0.32	0.34	0.36	0.35	0.33
						[1.11]	
Rel Un	0.012	0.016	0.011	0.010	0.012	0.012	0.015
	3.99	3.78	2.28	3.66	3.92	3.99	6.72
						[2.71]	
hy	-0.031	-0.043	-0.028	-0.034	-0.031	-0.031	-0.031
	-2.98	-3.34	-2.26	-2.38	-3.06	-2.98	-2.92
						[-2.21]	

Table 5

Performance of Trading Strategies: Baseline Estimates

The table reports the performance estimates of trading strategies defined using our return prediction model. We report the performance estimates of three portfolios: (i) the "Long" portfolio, which is a value-weighted portfolio of firms located in states predicted to have the highest three ($N_s = 3$) characteristic-adjusted returns, (ii) the "Short" portfolio, which is a value-weighted portfolio of firms in states predicted to have the lowest three characteristic-adjusted portfolio returns, and (iii) the "Long − Short" portfolio, which is the difference between the "Long" and "Short" portfolio returns. In Panel D, we also consider the "Others" portfolio, which includes stocks not included in the long and short portfolios. To rank the state portfolios, we use the one-quarter-ahead prediction model estimated with characteristic adjusted returns (see Table 3, column (5)). See Section IV.A for additional details on the construction of the trading strategy. The evaluation period is from 1984 to 2004. State portfolios with fewer than ten firms are excluded from the sample. In **Panel A**, we report the mean and standard deviation of the raw and characteristic adjusted returns of the Long, Short, and Long − Short portfolios. We also consider four different factor models to obtain risk-adjusted performance: (i) the CAPM (**Panel A**), (ii) the four-factor model, where the factors are the market factor (RMRF), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) (**Panel B**), (iii) the seven-factor model, which contains the four factors in (ii) and three industry factors (IND1, IND2, and IND 3) (**Panels C**), (iv) the nine-factor model, which contains the seven factors in (iii) and two reversal factors (short-term reversal (STR), long-term reversal (LTR)) (**Panels D**). We report the estimated monthly alphas, the factor exposures (estimates are in a large font and t-statistics are in smaller font beneath the estimates), and the adjusted R^2.

$N_s = 3$	**Panel A: Raw Returns, Characteristic-Adjusted Returns, and CAPM Model Estimates**						
	Raw Return		*Char Adj. Return*		*CAPM*		
	Mean	*St. Dev.*	*Mean*	*St. Dev.*	*α*	*RMRF*	*Adj R^2*
Long	1.325	5.736	0.358	1.813	0.294	1.097	0.738
					3.04	26.59	
Short	0.723	5.289	-0.372	2.059	-0.360	1.023	0.749
					-2.13	27.42	
Long - Short	0.603	4.028	0.730	2.858	0.654	0.075	0.003
					2.16	1.32	

$N_s = 3$	**Panel B: Four Factor Model Estimates**					
	α	*RMRF*	*SMB*	*HML*	*UMD*	*Adj R^2*
Long	0.421	0.931	0.005	-0.479	0.071	0.798
	2.44	21.90	0.10	-7.53	1.91	
Short	-0.363	1.012	0.300	0.099	-0.047	0.778
	-2.17	24.61	5.86	1.60	-1.31	
Long - Short	0.784	-0.082	-0.295	-0.578	0.117	0.160
	3.18	-1.34	-3.89	-6.34	2.22	

$N_s = 3$	**Panel C: Four Factors and Industry Factors**								
	α	*RMRF*	*SMB*	*HML*	*UMD*	*IND1*	*IND2*	*IND3*	*Adj R^2*
Long	0.429	0.918	0.011	-0.463	0.064	0.104	0.013	0.014	0.806
	2.54	21.98	0.21	-7.40	1.78	3.65	0.46	0.52	
Short	-0.381	1.029	0.288	0.106	-0.041	-0.070	-0.150	-0.057	0.809
	-2.46	26.85	6.06	1.85	-1.22	-2.69	-5.82	-2.25	
Long - Short	0.809	-0.110	-0.277	-0.570	0.105	0.175	0.163	0.071	0.266
	3.51	-1.93	-3.91	-6.65	2.12	4.47	4.24	1.89	

$N_s = 3$	**Panel D: Four Factors, Industry Factors, and Reversal Factors**										
	α	*RMRF*	*SMB*	*HML*	*UMD*	*IND1*	*IND2*	*IND3*	*STR*	*LTR*	*Adj R^2*
Long	0.442	0.928	0.051	-0.427	0.068	0.099	0.008	0.014	-0.025	-0.099	0.806
	2.59	21.58	0.83	-6.17	1.77	3.42	0.28	0.51	-0.51	-1.24	
Others	-0.179	0.962	0.372	0.296	-0.003	-0.133	0.020	-0.116	0.081	0.029	0.598
	-1.77	15.93	4.37	3.05	-0.05	-3.28	0.50	-3.02	1.17	0.26	
Short	-0.374	1.027	0.261	0.079	-0.050	-0.067	-0.145	-0.056	-0.013	0.073	0.809
	-2.39	26.01	4.68	1.25	-1.42	-2.52	-5.54	-2.20	-0.28	0.99	
Long - Short	0.816	-0.099	-0.210	-0.506	0.117	0.166	0.153	0.070	-0.012	-0.171	0.268
	3.50	-1.68	-2.54	-5.36	2.25	4.20	3.92	1.86	-0.18	-1.57	

Table 6

Performance of Trading Strategies: Estimates from Robustness Tests

The table reports the risk-adjusted performance estimates (alphas) of trading strategies from the nine-factor model in Panel D of Table 5. The evaluation period is from 1984 to 2004. The alpha estimates are in large font and t-statistics are in smaller font beneath them. Table 5 defines the three portfolios and provides details on the construction of the trading strategies. Also, see Section IV.A. **Panel A.** The ranking of states is based on various approaches: **(1)** one-quarter-ahead prediction model (see Table 3, specification (5)); **(2)** historical average of past characteristic adjusted returns ("naive" trading strategy); **(3)** qualitative approach that uses an index of state-level macroeconomic conditions (see Section III.B); **(4)** and **(5)** one-quarter-ahead prediction model (see Table 3, specification (5)) in which state-level variables are replaced with their regional averages; **(6)** one-quarter-ahead prediction model (see Table 3), excluding from the model the state-level macroeconomic variables. **Panel B**. We use the results in specification (5) in Table 3 to rank states. The trading strategy portfolios exclude stocks with certain characteristics: stocks with price less than $5, stocks with low local institutional ownership, small stocks (size in the bottom one third), growth stocks (BM in the bottom one third), and less visible firms (visibility measure in the bottom one third).

$N_s = 3$	**Panel A: Different Prediction Models**					
	(1) *Avg. State Portfolio Return*	**(2)** *Naïve Trading Strategy*	**(3)** *Qualitative Prediction Model*	**(4)** *8 Census Divisions*	**(5)** *4 Census Divisions*	**(6)** *Exclude State Macro Variables*
Long	0.313	0.035	0.252	0.189	0.050	0.075
	2.40	0.77	2.20	1.82	0.31	1.04
Short	-0.284	-0.063	-0.412	-0.325	-0.181	-0.256
	-2.26	-0.92	-2.91	-2.22	-1.01	-1.81
Long - Short	0.597	0.098	0.664	0.515	0.231	0.331
	2.96	0.50	3.21	2.51	1.63	2.02

$N_s = 3$	**Panel B: Stock Characteristics**				
	(1) *Exclude Stocks with Price < $5*	**(2)** *Exclude Low IO Stocks*	**(3)** *Exclude Small Stocks*	**(4)** *Exclude Growth Stocks*	**(5)** *Exclude Less Visible Firms*
Long	0.433	0.344	0.281	0.259	0.270
	2.44	2.60	1.99	1.91	1.86
Short	-0.339	-0.279	-0.261	-0.264	-0.271
	-2.14	-2.42	-2.36	-2.26	-1.95
Long - Short	0.772	0.623	0.542	0.523	0.541
	3.35	3.03	2.78	2.31	2.39

Table 7
Mispricing and Cash Flow Panel Regression Estimates

The table reports the results from mispricing (Panels A and B) and cash flow (Panel C) regressions of the form: $\overline{Y}_{j,t,h} = \alpha_{j,h} + X_{j,t-2}\delta_{1,h} + X_{USA,t-1}\delta_{2,h} + \log(1 + D/P)_{j,t-1}\delta_{3,h} + \varepsilon_{j,t,h}$. **Panel A**. $\overline{Y}_{j,t,h}$ is the h-quarter cumulative return. **Panel B**. $\overline{Y}_{j,t,h}$ is the hth quarter return $Y_{j,t+h-1}$. $Y_{j,t}$ represents characteristic adjusted returns. **Panel C**. The dependent variable, $\overline{Y}_{j,t,h}$, is the hth quarter cash flow growth rate divided by a hundred, i.e., $(Y_{j,t+h-1} - Y_{j,t+h-2})/Y_{j,t+h-2}$. The regressions are estimated with OLS. The t-statistics reported beneath the estimates use Driscoll and Kraay (1998) standard errors and the number within square brackets are their bootstrapped critical values (Mark (1995)). The estimation period is from 1980(Q3) to 2004(Q4). Table 3 provides the sources and definitions of all independent variables.

	Panel A: h-Quarter Cumulative R^{loc}				
	(1)	(2)	(3)	(4)	(5)
	h = 1	h = 4	h = 8	h = 12	h = 24
State-Level Predictors					
Inc Gr	0.029	0.014	-0.219	-0.237	-0.316
	0.35	0.09	-0.69	-0.64	-0.75
	[1.11]	[1.25]	[-2.27]	[-2.82]	[-1.56]
Rel Un	0.012	0.038	0.055	0.078	0.115
	3.99	3.16	3.03	3.15	4.54
	[2.71]	[2.71]	[2.89]	[3.13]	[3.45]
hy	-0.031	-0.121	-0.199	-0.247	-0.384
	-2.98	-2.34	-2.15	-1.96	-8.08
	[-2.21]	[-2.17]	[-2.09]	[-2.23]	[-3.32]
Adj R^2	0.009	0.035	0.057	0.091	0.155

	Panel B: h-Quarter Ahead R^{loc}					Panel C: h-Quarter Ahead CF Gr		
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)
	h = 1	h = 4	h = 8	h = 12	h = 24	h = 1	h = 8	h = 24
State-Level Predictors								
Inc Gr	0.029	0.037	0.054	0.017	-0.025	-0.729	-0.089	0.082
	0.35	0.60	0.95	0.17	-0.31	-1.56	-0.90	0.24
	[1.11]	[1.18]	[2.04]	[1.43]	[-1.83]	[-1.41]	[-2.03]	[1.36]
Rel Un	0.012	0.008	0.008	0.010	-0.004	-0.033	0.029	0.022
	3.99	2.48	2.49	3.33	-0.57	-1.28	1.18	0.72
	[2.71]	[2.92]	[3.26]	[3.21]	[-0.83]	[-1.31]	[1.48]	[1.37]
hy	-0.031	-0.019	-0.012	-0.006	0.010	0.050	0.029	0.003
	-2.98	-1.59	-0.84	-0.48	0.93	1.21	0.70	0.07
	[-2.21]	[-1.55]	[-1.31]	[-1.86]	[1.68]	[1.18]	[1.01]	[1.35]
Adj R^2	0.009	0.006	0.007	0.011	0.006	0.002	0.001	0.000

[*Coefficient estimates of U.S. macro variables and other control variables are suppressed.*]

Table 8

Consumption Growth and Risk Aversion Regression Estimates

This table reports estimation results from risk aversion motivated tests. In **Panels A and B,** we report the estimation results from contemporaneous regressions of the form: $Y_{j,t} = \alpha_j + X_{j,t}\delta_1 + X_{USA,t}\delta_2 + Y_{j,t-1}\delta_4 + \varepsilon_{j,t}$. **Panel A.** In **regression (1)**, $Y_{j,t}$ is the beta from a univariate regression of the state portfolio return on the corresponding state consumption growth. The quarterly state consumption growth rate is proxied as one-fourth of the annual growth of state retail sales. This consumption growth series is the dependent variable in **regression (2)**. In **regression (3)**, $Y_{j,t}$ is the quarterly risk aversion for state j. The risk aversion series is from Korniotis (2008). **Panel B.** The dependent variable $Y_{j,t}$ is a trading measure of stocks of local firms (i.e., local stocks) by either institutional investors or retail investors. For each investor category, we consider an equal-weighted (EW) and value-weighted (VW) local trading measure. We measure the trading behavior using the buy-sell imbalance measure, which is the ratio of the buy-sell volume differential and the total trading volume. We use quarterly trading measure for the institutions and monthly measures for the retail investors. The institutional (retail) investor data cover the 1980 to 2004 (1991 to 1996) period. **Panel C** reports the results from one-quarter ahead forecasting regressions as in Table 3. The dependent variable is: **(1)** the CAPM residual, **(2)** the four-factor residual, **(3)** the conditional-on-risk-aversion CAPM residual **(4)** the conditional-on-risk-aversion four-factor residual, **(5)** the difference between the residuals in (1) and (3), and **(6)** the difference between the residuals in 2 and 4. To obtain the conditional-on-risk-aversion residuals in quarter q of year t, the risk aversion in the previous year $(t-1)$ is added as an additional factor in the CAPM and four-factor model. The risk aversion is defined in the same manner as in regression (3) in Panel A. The estimation period is from 1980(Q3) to 1998(Q4). For more details on the estimation methodology see Table 3. **Panel D**. Like Panel D in Table 5, this panel reports the nine-factor alpha estimates for trading strategies. To form the long and short portfolios held in quarter q year t, we rank states using the risk aversion level in the previous year $(t-1)$. The exception is column **(3)** in which the state ranking are based on the one-quarter-ahead prediction model (see Table 3, specification (5)). In columns **(1)** and **(2)** the evaluation periods are from 1980 to 1999 and 1966 to 1999, respectively. In **(3)**, we exclude months in which the U.S. economy was in recession according to the National Bureau of Economic Research. The evaluation period is from 1980 to 2004.

	Panel A: Contemp. Regressions			Panel B: Contemp. Trading Regressions			
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
				Institutional Investors		Retail Investors	
	$\beta_{Con\ Gr}$	*Con Gr*	*RA*	*EW*	*VW*	*EW*	*VW*
State-Level Predictors							
Inc Gr	-7.962	0.421	-15.771	-0.922	-0.609	0.022	0.055
	-1.66	2.18	-2.68	-0.67	-0.50	0.89	1.45
Rel Un	1.200	-0.124	1.982	-0.138	-0.018	-0.006	-0.006
	1.76	-8.63	5.36	-2.19	-0.23	-2.56	-2.48
hy	1.983	0.121	-15.194	0.210	-0.106	0.005	0.007
	1.44	2.56	-6.53	1.82	-0.84	1.31	1.40
Adj R^2	0.227	0.146	0.154	0.021	0.001	0.063	0.043

	Panel C: Predictability Regressions					
	(1)	(2)	(3)	(4)	(5)	(6)
	CAPM	*4 Factor*	*CAPM + RA*	*4 Factor + RA*	*(1) - (3)*	*(2) - (4)*
State-Level Predictors						
Inc Gr	-0.002	0.030	-0.030	0.023	0.027	0.007
	-0.02	0.27	-0.32	0.21	1.18	0.42
Rel Un	0.019	0.017	0.017	0.015	0.003	0.002
	5.09	5.26	3.99	4.43	4.18	3.17
hy	-0.040	-0.040	-0.022	-0.026	-0.018	-0.014
	-4.46	-4.06	-2.08	-2.41	-3.43	-2.77
Adj R^2	0.033	0.030	0.027	0.022	0.036	0.054

[In Panels A to C coefficient estimates of U.S. macro and other control variables are suppressed.]

$N_s = 3$	Panel D: 9-Factor Alphas based on RA		
	(1)	(2)	(3)
	1980 - 99	*1966 - 99*	*No U.S. Recessions*
Long	0.216	0.210	0.381
	2.01	1.96	2.21
Short	-0.146	-0.133	-0.291
	-1.52	-1.61	-2.18
Long - Short	0.362	0.342	0.671
	2.56	2.32	2.77

Table 9

Performance of Trading Strategies Conditional on Local Bias Proxies

This table reports the nine-factor alpha estimates for local bias motivated trading strategies. In Panels A to D, we rank states using specification (5) in Table 3. **Panel A**. The trading strategies use stocks with *low* (bottom one third) or *high* (top one third) visibility (Hong, Kubik and Stein (2008)). **Panel B**. The trading strategies use stocks with *low* (bottom one third) or *high* (top one third) local betas (i.e. exposure to the local stock market index). The evaluation period in Panels A and B is from 1984 to 2004. **Panel C**. The trading strategies use stocks with *low* (bottom one third) or *high* (top one third) retail investor local bias (LB) or portfolio concentration. The evaluation period is from 1991 to 2004. **Panel D**. We rank states using the average ratio (ratio = state book equity to state personal income) and average change in the ratio measure of Hong, Kubik and Stein (2008). The trading strategies use stocks from states with *low* (bottom one third) or *high* (top one third) average ratio level and average change in the ratio measure. The evaluation period for this exercise is from 1984 to 2004. **Panel E**. To form the long and short portfolios held in quarter q year t, we rank states using the risk aversion (RA) estimate in the previous year $(t-1)$. See Panel D of Table 8. The trading strategies include stocks with *high* (top one third) or *low* (bottom one third) local bias. The evaluation period is from 1991 to 1999.

$N_s = 3$	**Panel A: Visibility**		**Panel B: Local Beta**		**Panel C: Local Bias Proxies**			
					Distance-based		**Portfolio Conc.**	
	Low	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Long	0.512	0.249	0.197	0.522	0.057	0.547	0.028	0.655
	2.87	1.92	1.90	2.54	0.53	2.85	0.23	3.03
Short	-0.395	-0.188	-0.296	-0.390	-0.002	-0.385	0.036	-0.443
	-2.19	-1.88	-2.24	-1.89	-0.05	-2.69	0.11	-2.85
L - S	0.907	0.437	0.493	0.912	0.059	0.932	-0.008	1.098
	3.52	2.47	2.17	2.98	0.32	2.96	-0.17	3.16

	Panel D: Ratio				**Panel E: Risk Aversion**	
	Level		**Change**			
	Low	*High*	*Low*	*High*	*Low LB Firms*	*High LB Firms*
Long	0.072	0.544	0.112	0.520	0.044	0.222
	0.41	2.80	0.56	2.14	0.38	1.77
Short	-0.149	-0.435	-0.075	-0.475	-0.100	-0.195
	-0.65	-2.54	-0.62	-2.22	-0.52	-1.46
L - S	0.220	0.979	0.187	0.995	0.143	0.417
	1.99	2.95	1.72	3.06	1.25	2.17

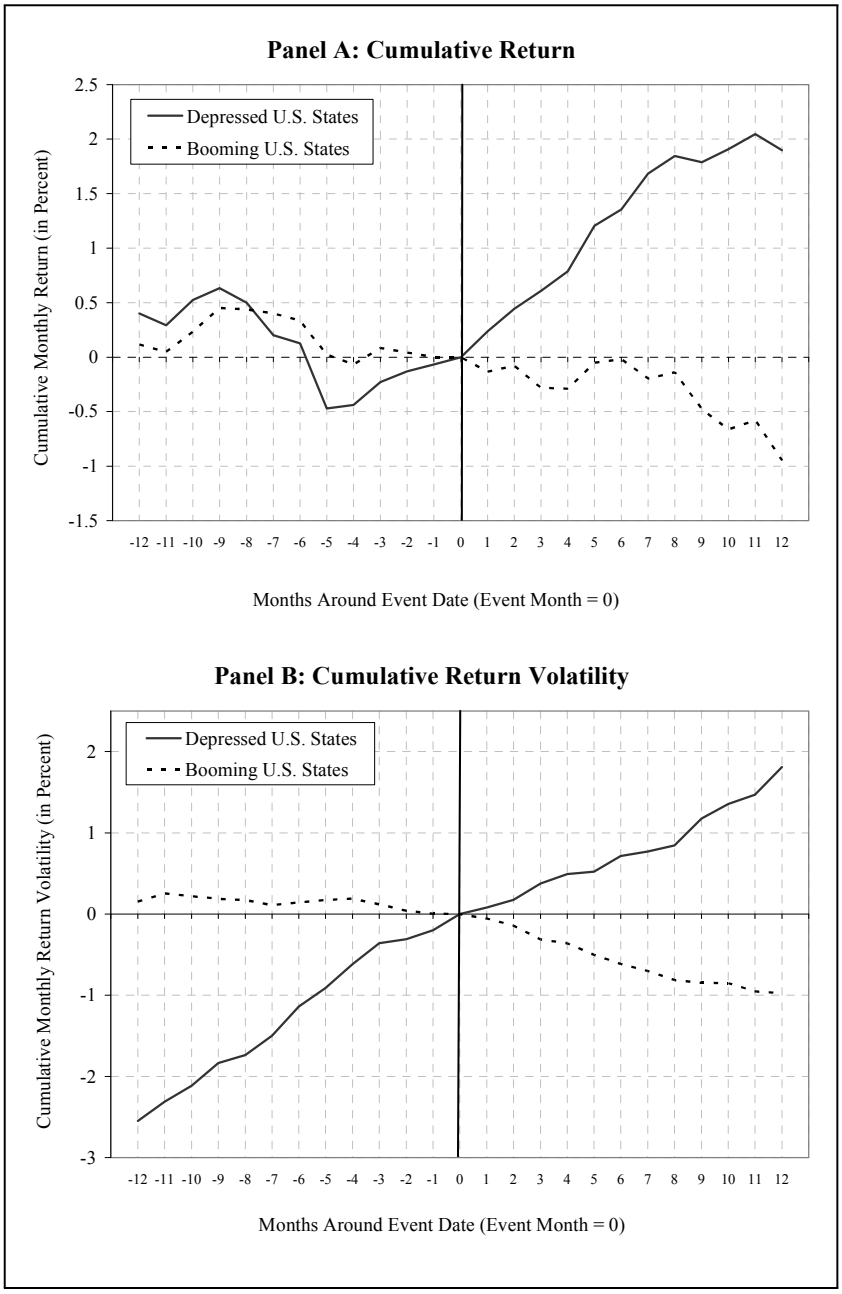

Figure 1: Risk and Return Patterns Around State-Level Booms and Busts. The figure presents the performance differential between firms located in expanding and contracting U.S. states. The state-level economic condition is measured using the signed average of normalized state income growth rate, relative state unemployment rate, and state-level housing collateral (see Section III.B). We rank all states quarterly using the strength of their economic conditions. States with the highest (top third) and lowest (bottom third) values of the economic index are assumed to expanding and contracting, respectively. **Panel A** reports the equal-weighted cumulative monthly returns. **Panel B** reports the equal-weighted cumulative return volatility, where volatility is measured as the standard deviation of daily returns within a certain month.

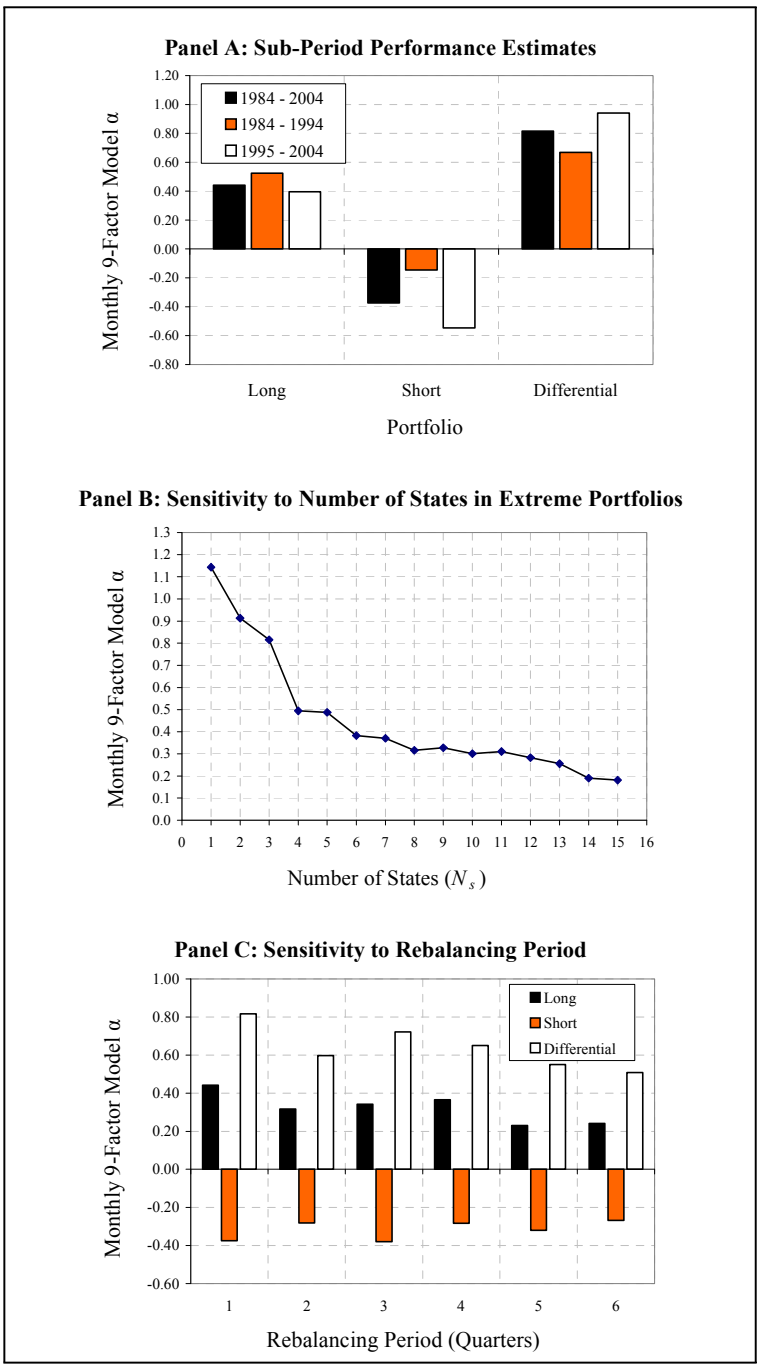

Figure 2: Performance of Trading Strategies: Estimates from Robustness Tests. The figure presents nine-factor alpha estimates for the "Long", "Short", and "Long − Short" portfolios described in Table 5. To rank states, we use the one-quarter-ahead prediction model (see Table 3, specification (5)). **Panel A**. N_s is 3 and we consider three evaluation periods: 1984 to 2004, 1984 to 1994, and 1995 to 2004. **Panel B** reports the alpha of the Long − Short portfolio over the 1984 to 2004 period when N_s varies from 1 to 15. **Panel C** considers various rebalancing periods ranging from one to six quarters. The evaluation period is from 1984 to 2004 and N_s is 3.