Racial Integration and Active Investing*

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Abstract

This paper studies how racial residential integration (RRI) influences information diffusion in the stock market. We find that firms headquartered in states with high RRI tend to have lower information asymmetry, as reflected in lower analyst earnings forecast dispersion and a narrower adverse selection component of the bid-ask spread. Their stock prices tend to be more informative, comoving more strongly with fundamentals. We also find that active mutual fund managers exhibit stronger abilities to pick local stocks in states with lower RRI, which points to a neglected channel through which active investing improves firms' information environment.

JEL Classification: G11, G14, G23, G41
Keywords: stock selection; information flow; mutual fund; racial integration

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Abstract

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Introduction

Recent studies have begun to explore the impact of racial and ethnic backgrounds, as well as their diversity, on various outcomes for mutual fund managers, financial analysts, and corporate directors (Kumar, Niessen-Ruenzi, and Spalt, 2015; Bernile, Bhagwat, and Yonker, 2018; Han, Huang, Kadan, and Wu, 2021; Chhaochharia, Kumar, and Zhang, 2022). One aspect of racial diversity that has been studied extensively in the sociology literature is racial residential integration (RRI), the degree to which individuals of different races and ethnicities reside in close geographic proximity.[1] According to contact theory, RRI attenuates interracial prejudices through exposure to other groups and promotes social interactions and friendships between groups (Allport, 1954; Pettigrew and Tropp, 2006). Increased social interactions lead to more diverse individual social networks (Hofstra, Corten, van Tubergen, and Ellison, 2017) and less fragmented social networks overall (Henry, Pralat, and Zhang, 2011). These more connected social networks enhance the diffusion of information (Watts and Strogatz, 1998), thus suggesting that RRI can increase the social transmission of information, resulting in a better information environment. In this study, we build on these findings and posit that RRI facilitates the social dissemination of local firm-specific information to the market, decreasing information acquisition costs and increasing the quality of the firm's information environment. Given that corporate headquarters play a central role in information exchange (Davis and Henderson, 2008), we expect firms headquartered in states with higher (lower) RRI to have lower (higher) information asymmetry and higher (lower) stock price informativeness.

Studies have shown that mutual funds have an informational advantage for local stocks and can benefit from the information asymmetry of local firms (e.g., Coval and Moskowitz, 2001). In

[1] Consistent with US Census guidelines, we categorize White, Black, Asian, and American Indian as racial groups, and recognize Hispanic as an ethnicity. In doing so, we conform to the traditional distinction between the terms "race," which is associated with physical traits, and "ethnicity," which includes elements such as origin, culture, language, or religious beliefs. For ease of reference, we will subsequently use the term "race" to refer to both race and ethnicity in the paper.

an environment with higher RRI and lower information asymmetry, mutual fund managers will subsequently lose their local information advantage, resulting in lower local stock-picking performance, which relies heavily on firm-specific information (Kacperczyk, Nieuwerburgh, and Veldkamp, 2014). Thus, at the mutual-fund level, we expect funds in states with higher (lower) RRI to have weaker (stronger) stock-picking performance for local firms. By establishing the links between RRI, the information environment, and active mutual fund managers' stock-picking ability, we hope to shed light on how RRI affects information diffusion for sophisticated investors like mutual funds.

To test the above predictions, we construct RRI measures common in the sociology literature to quantify two primary dimensions of residential integration (Massey and Denton, 1988). First, the *evenness* dimension captures the extent to which members of the minority and majority groups are evenly distributed among geographical units in a region.[2] Second, the *exposure* dimension of residential integration refers to the probability that minority and majority members share the same neighborhood and have the potential for contact. It is intended to measure the experience of segregation or integration felt by the average minority or majority member. We construct state-level RRI measures using census tract data on racial composition from three waves (2000, 2010, and 2020) of the US Decennial Census and interpolate them to construct a state-by-year panel of RRI measures from 2000 to 2020.[3]

To examine the effect of state-level RRI on the local firm-level information environment and mutual fund stock-picking performance, we must identify the historical headquarters of both firms and mutual funds. The CRSP/COMPUSTAT Merged Database provides historical firm

[2] Consistent with the sociology literature, we designate non-Hispanic whites as the majority group, while Hispanics, Blacks, Asians, and American Indians are together classified as the minority group. Instead of comparing all minorities to a white majority, we replicate all our findings using RRI measures that incorporate specific minorities via three sets of racial pairs (i.e., “African American-white”, “Asian-white”, and “Hispanic-white”) in the Appendix and find similar results.

[3] For robustness, we confirm our results are unchanged when using annual data from the American Community Survey which provides racial compositions by Public Use Microdata Area, as defined by the US Census Bureau, from 2005 to 2019.

headquarters starting in 2007. Prior to 2007, we rely on textual analysis to extract firm headquarter zip codes from SEC online filings (10Q/10K). Data on historical mutual fund headquarters are directly available from the CRSP mutual fund database starting in 2000. Using this geographical information, we link both stock-level data using the state of firm headquarters and mutual-fund-level data using the state of fund headquarter to state-level RRI data.

At the firm level, we find that RRI is negatively associated with both earnings forecast dispersion and the adverse selection component of the bid-ask spread. Consistent with expectations, this suggests that firms headquartered in states with high (low) RRI tend to have lower (higher) information asymmetry. To evaluate the role of RRI in determining stock price informativeness, we test whether RRI enhances the comovement between firms' stock prices and future cash flows (Sundaresan and Wang, 2021). We find that firms located in higher (lower) RRI states have more (less) informative stock prices and that this relationship is particularly pronounced for firms with low active institutional ownership, suggesting that active ownership may mitigate the adverse effect of low RRI on stock price informativeness.

Second, at the mutual-fund level, we find that mutual funds headquartered in high (low) RRI states exhibit weaker (stronger) stock-picking performance for local stocks headquartered in the same state. This decline in stock-picking performance for local stocks leads to a decrease in the overall stock-picking performance of the fund. Next, we examine the heterogeneity in this relationship along two dimensions, the strength of the economy and the race of the mutual fund manager. We find that the relationship between RRI and stock-picking performance is more pronounced during economic expansions, when mutual funds are more actively engaged in stock-picking (Kacperczyk et al., 2014). We also find that the RRI-local-stock-picking relationship is only significant for white fund managers and does not exist for minority managers. This suggests that minority managers do not benefit from the same local information asymmetries that white managers do, consistent with findings in the sociology literature that white male networks offer greater social capital resources (McDonald, Lin, and Ao, 2009; McDonald and Day, 2010;

McDonald, 2011).

To ensure the robustness of our mutual fund-level results, we perform several additional tests. First, we examine the validity of alternative explanations that may drive our results. It is possible that the relationship between RRI and local stock-picking ability is due to passive exposure to firms headquartered in states with low RRI, which may have positive risk premiums to compensate for unidentified risks associated with segregation. However, our placebo test reveals that pure index funds do not exhibit the same relationship between RRI and local stock-picking ability as actively managed funds do. Second, lower social trust has been shown to increase institutional investment in local firms (Wei and Zhang, 2020). If RRI is merely a proxy for social trust, it is possible that low (high) RRI states have lower (higher) social trust, leading to more (less) investment in local stocks. We control social trust and find that it cannot explain our findings. Third, we construct our RRI measures using the annual American Community Survey (ACS) to avoid the need for inter-year interpolation and find that the relationship between RRI and local stock-picking performance persists. Fourth, we show that our results remain unchanged when excluding mutual funds from fund-clustered states (i.e., CA, NY, MA). Lastly, in the Appendix[4] we show that our findings hold using two additional measures of local-stock-picking ability, as well as using various additional model specifications that include controls for past performance, fund-fixed effects, and the omission of all control variables.

We make three primary contributions to literature. First, we contribute to the literature on firm-level information asymmetry and stock price informativeness and show that RRI plays an important role in price discovery efficiency through information diffusion. Prior studies generally find that increases in firm-level disclosures reduce information asymmetry (e.g., Gul, Srinidhi, and Ng, 2011), although some studies show that new information or unusual firm-level news may

[4] Internet Appendix can be download via this link:
https://drive.google.com/drive/folders/1QjgtYncd07SfmCHTV1M1guN8eMoPc9Vx?usp=sharing

instead increase investor disagreement (Harris and Raviv, 1993; Bali, Bodnaruk, Scherbina, and Tang, 2018). Institutional investment can also enhance stock price informativeness via either new information (e.g., Kacperczyk et al., 2021) or better monitoring (Boone and White, 2015), though in some cases, institutional investor short-termism may drive prices away from fundamentals (Bushee, 2001). We contribute to this literature by showing that, beyond information and monitoring, the social transmission of information via race-based integration can also lead to lower information asymmetry for local firms. Along these lines, recent papers have begun to study the role of social information transmission for retail investors and find that, in general, a higher intensity of social interactions leads to poorer stock price informativeness. Campbell, Drake, Thornock, and Twedt (2023) find that viral earnings announcements result in higher retail investor recognition, ownership, and trading, but lead to overall lower market liquidity and slower price formation. Bali, Hirshleifer, Peng, and Tang (2021) observe that intense social interactions can increase retail investors' attraction to lottery stocks, which results in their overvaluation. We contribute to this line of work by showing that the social transmission of information can affect not only retail investors, but also the performance of local institutional investors. Furthermore, we identify the moderating role of active investor ownership in the RRI-stock price informativeness relationship, which enriches existing studies on the pricing impact of institutional investors (e.g., Boone and White, 2015).

Second, we contribute to the growing literature exploring the role of social networks on institutional investor outcomes. Prior research has explored the impact of education connections (Cohen, Frazzini, and Malloy, 2008), neighbor interactions (Hong, Kubik, and Stein, 2005; Pool, Stoffman, and Yonker, 2015), and social networks (Ahern, 2017; Hirshleifer, Peng, and Wang, 2021; Kuchler, Li, Peng, Stroebel, and Zhou, 2022) on institutional investor portfolio decisions and performance. Further, studies have found that the geographic proximity of mutual funds to firm headquarters can generate a local informational advantage manifesting in higher abnormal returns from nearby investment (Coval and Moskowitz 1999, 2001; Baik, Kang, and Kim 2010; Bernile, Kumar, and Sulaeman 2015). Drawing on insights from the sociology literature, we consider the role of race in networks for institutional investor outcomes. Specifically, we examine how racial integration within networks impacts the social spread of information, shaping the local information advantage for institutional investors. Studies have shown that social network resources (i.e., social capital) differ along racial lines (Pedulla and Pager, 2019; Fernandez and Fernandez-Mateo, 2006) and that information flows differently among ethnic networks (Bertrand, Luttmer, and Mullainathan, 2000; Agarwal, Choi, He, and Sing, 2019). We build on these studies by showing that race-based residential patterns can affect investors' local informational advantage, and that this relationship can vary as a function of the fund manager's race.

Lastly, we contribute to the literature exploring the role of race in the mutual fund and hedge fund industries. Studies reveal the disadvantages that fund managers of racial and ethnic minorities face as a result of name-induced stereotypes or in-group bias (Kumar, Niessen-Ruenzi, and Spalt, 2015; Han et al., 2021; Lu, Naik, and Teo, 2022). More recently, Agarwal, Jiang, Luo, and Zuo (2023) show that increased racial hate toward East Asians in 2020 and 2021 resulted in lower mutual fund performance and worsened stock-picking ability for funds with East Asian female managers. We contribute to this literature by showing that a sociological aspect of race, racial integration, can also have implications for mutual fund stock-picking ability and performance. In addition, we find that minority managers do not realize the same local stock-picking advantages that white managers do when RRI is low. Therefore, we identify a further disadvantage that minority managers face in the mutual fund industry.

The remainder of this paper is organized as follows. Section 2 describes the data and key measures used. Section 3 presents firm-level results on the relationship between RRI and the firm's information environment, and Section 4 presents mutual fund-level results on the RRI-stock-picking relationship. We present our conclusions in Section 5.

2 Data and Variables

2.1 Racial residential integration measures

Most generally, RRI is the degree to which two or more racial groups live amongst each other throughout an urban environment.[5] Massey and Denton (1988) identify five dimensions of RRI that correspond to five distinct aspects of spatial variation: evenness, exposure, clustering concentration, and centralization. In our analysis, we focus on quantifying the *evenness* and *exposure* dimensions. Based on a principal component analysis, *evenness* has been identified as the most important dimension in characterizing racial integration (Massey and Denton, 1988). To measure evenness, which captures the extent to which minority group members are overrepresented in some areas and underrepresented in others, we construct the widely used dissimilarity index (Jahn, Schmid, and Schrag, 1947; Derenoncourt, 2022) and transform it to a measure of RRI (i.e., a similarity index) by multiplying by -1. Thus, our first RRI measure, the state-level similarity index, is constructed as follows:

$$RRI\ Similarity_j = -\frac{1}{2} \times \sum_i \left| \frac{m_i}{M_j} - \frac{w_i}{W_j} \right|, \quad (1)$$

[5] The sociology and economics literatures have identified four main factors that shape patterns of RRI (Charles, 2003; Lichter, Parisi, and Taquino, 2015; Ambrose, Conklin, and Lopez, 2021; Derenoncourt, 2022). First, labor market discrimination, as measured by income inequality, results in lower income for minorities, limiting their neighborhood choice. Second, race-based in-group bias may encourage people to choose neighborhoods inhabited by individuals of the same race. Third, institutionalized discrimination embedded in the zoning practices of local governments coupled with racially disparate pricing and recommendations from real estate agents contribute to low racial integration. Lastly, exogenous shocks, including the Great Migration, industrialization, and urbanization also impact RRI.

where m_i and w_i denote the number of racial minorities and white people, respectively, in census tract i in state j. M_j and W_j are the total number of racial minorities and white people, respectively, in state j.[6] This results in a state-level similarity index that ranges from -1 to 0; a value of -1 indicates a state with complete segregation where all minority members reside in entirely different census tracts than majority members, and a value of 0 indicates a perfectly integrated state with equal distribution of both minority and majority members across all census tracts in a state.[7] For robustness, we construct an additional measure of *evenness* using Theil's (1972) entropy index for robustness. Entropy is a concept commonly used to characterize a state of disorder, randomness, or uncertainty and is used here to capture the diversity in race of a residential area. Entropy (i.e., the level of diversity) for census tract i is constructed as follows:

$$E_i = P_i^m \times log(P_i^m) + P_i^w \times log(P_i^w), \quad (2)$$

where P_i^m and P_i^w denote the proportion of racial minorities and of white people, respectively, in census tract i, such that $P_i^m + P_i^w = 1$. When both groups are equally represented ($P_i^m = P_i^w = 0.5$), E_i reaches a maximum value of 0.69 indicating maximum diversity. Conversely, when only one group is present, E_i reaches a minimum of zero. Based on this measure of entropy at the census-tract level, we construct Theil's (1972) entropy index which we multiply by -1 to produce a state-level measure of racial integration:

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[6] For simplicity, we aggregate all racial minorities in the construction of our RRI indices, but verify in robustness tests that our findings remain unchanged when employing RRI measures constructed using the population-weighted average of three minority-majority pairs (African American-white, Hispanic-white, and Asian-white).

[7] To illustrate the intuition behind the similarity index, consider a state j, with two census tracts ($i = 1, 2$) and two racial groups: majority and minority. If state j is perfectly segregated, all minority members reside in the first tract ($\frac{m_1}{M_j} = 1$ and $\frac{w_1}{W_j} = 0$) while all majority members are in the second ($\frac{m_2}{M_j} = 0$ and $\frac{w_2}{W_j} = 1$), yielding a similarity index of -1 (*RRI Similarity* $= -1$). Conversely, in a perfectly integrated state with equal distribution of both groups across tracts ($\frac{m_i}{M_j} = \frac{w_i}{W_j} = 0.5, i = 1, 2$), the similarity index takes on a value of 0 (*RRI Similarity* $= 0$). This example represents the two extreme cases. In reality, no census tract is perfectly integrated or segregated and therefore: *RRI Similarity* $\in (-1, 0)$.

$$RRI\ NegTheil_j = -1 \times \sum_i \frac{N_i}{N_j} \times \frac{E_j - E_i}{E_j}, \tag{3}$$

where N_i and N_j are the total populations in census tract *i* and state *j*, respectively. This index is nearly identical in interpretation to the similarity index (White, 1983) and also ranges from -1 to 0, with a higher value indicating a more integrated state.

Exposure, the second dimension of RRI we measure, refers to the probability that minority and majority members share the same neighborhood and have the potential for contact. This dimension is of particular interest given its ability to capture interracial interactions (Echenique and Fryer, 2007), which is crucial when examining how RRI can impact the social dissemination of information. To measure exposure, we construct the Massey and Denton (1988) exposure index, also known the interaction index, at the state level as follows:

$$RRI\ Exposure_j = \sum_i \frac{m_i}{M_j} \times \frac{w_i}{N_i}, \tag{4}$$

where m_i and w_i denote the number of racial minorities and white people, respectively, in census tract *i* which is located in state *j*. M_j is the total number of racial minorities in state *j* and N_i is the total population in census tract *i*, such that $m_i + w_i = N_i$. $\frac{m_i}{M_j}$ represents the minority proportion in census tract *i* relative to its state's (*j*) white population, and $\frac{w_i}{N_i}$ is the proportion of white people in tract *i*. Consequently, *RRI Exposure* is the minority-weighted average of each census tract's white proportion, depicting the minority's exposure to white people within tracts, with values ranging from 0 to 1. A higher value indicates increased interracial interactions and greater racial integration, under the assumption of constant relative group sizes.[8]

[8] As an example, consider a state *j*, with two census tracts ($i = 1, 2$) and two racial groups: majority and minority. If state *j* is perfectly segregated, all minority members reside in the first tract ($\frac{m_1}{M_j} = 1$ and $\frac{w_1}{N_1} = 0$) while all majority members reside in the second tract ($\frac{m_2}{M_j} = 0$ and $\frac{w_2}{W_j} = 1$), yielding an exposure index of 0 indicating complete segregation and no potential for contact between the two groups. When minority residents move from the first tract

We use data from the US Decennial Census of Population and Housing from the 2000, 2010, and 2020 waves to construct state-level RRI indices at these three points in time. We then use linear interpolation to construct annual RRI measures for each state from 2000 to 2020. For illustrative purposes, we show heat maps indicating state-level similarity index levels in Figure 1. These heat maps demonstrate that on average, racial integration increased from 2000 to 2020, however, consistent with other studies (e.g., Lichter, Parisi, and Taquino, 2015), there is a persistent lack of racial integration in some states (e.g., New York). Appendix B1 shows that these patterns are similar for our two other RRI measures, $RRI\ NegTheil$ and $RRI\ Exposure$.

Insert Figure 1 Here

Previous research has shown relationships between racial residential patterns and demographic and socioeconomic variables (Lichter et al., 2015). Relative racial group sizes are correlated with RRI measures, particularly measures of exposure (Massey and Denton, 1988). To verify if this is an issue in our sample, we examine the correlations between RRI and various state-level variables including the proportions of the white, Asian, Hispanic, Black, senior, and female populations; the natural logarithm of median age, median housing value, median income, and state population; poverty rate; and zoning behavior in Appendix B2 and find significant correlations.[9] To ensure that we are purely measuring the effect of RRI and not capturing the effects of these state-level demographic and socioeconomic characteristics, we orthogonalize each RRI measure by regressing each on this set of state-level variables and using the error term to measure RRI in our subsequent analyses, as detailed in Appendix B2.[10]

to another, exchanging places with an incoming majority, *RRI Exposure* becomes non-zero. This exposure increases with more exchanges until it reaches a maximum, determined by the relative proportions of the two groups. Because the exposure index explicitly considers the relative sizes of the minority and majority groups in gauging residential integration (Massey and Denton, 1988), if the minority population is extremely small, *RRI Exposure* approaches 1, regardless of regional evenness. We address this issue via orthogonalization, as described below.

[9] We describe these variables in more detail in section 2.4 below.

[10] We verify that our results are similar when using the raw RRI measures in the Appendix.

2.2 Firm-level variables

To identify historical firm headquarters, which is crucial for determining the level of RRI surrounding a firm, we use data from the CRSP/Compustat Merged Database starting in 2007. From 2000 to 2006, we rely on textual analysis of 10Q and 10K files with the SEC to extract the zip codes of the firm headquarters. And for other records missing geographic locations of their headquarters, we resort to Compustat which provides the location of current headquarters, and not historical headquarters (Pirinsky and Wang, 2006; Parsons, Sabbatucci, and Titman, 2020).[11]

We construct two proxies for stock-level information asymmetry. First, we use the dispersion of analysts' forecasts, which measures differences in investor opinions, as a gauge in the degree of asymmetric beliefs and opinions among investors. (Diether et al. 2002). We obtain earnings forecast data from I/B/E/S and construct a quarterly measure of earnings forecast dispersion as the standard deviation of earnings forecasts divided by the mean earnings forecasts for each firm in each quarter. Our second information asymmetry proxy is the adverse selection component of the bid-ask spread, or more specifically, the bid-ask spread component required by the market maker as compensation for the existence of informed traders (George, Kaul, and Nimalendran, 1991). Higher adverse selection thus suggests more information asymmetry between informed investors and other investors. We construct this measure by removing the effect of order-processing costs from the overall bid-ask spread (George, Kaul, and Nimalendran, 1991; Jiang and Sun, 2014).[12] Both information asymmetry proxies are winsorized at the 1% and 99% levels.

We start with the universe of publicly-listed US firms from CRSP and exclude financial

[11] We rely on Compustat headquarter data for only 162 of our final sample of 4,460 firms. These firms that do not disclose their 10Q/10K filings and are not covered by CRSP/Compustat Merged Database tend to be small and thus account for a smaller portion of a mutual fund's portfolio. Smaller firms are also less likely to move their headquarters because of the costs associated with this.

[12] We construct adverse selection using the following formula: Adverse selection = $S - 2 \times \sqrt{-cov(RD_t, RD_{t-1})}$, where S is the proportional quoted spread, and RD_t is the difference between returns computed using last-trade transaction prices and the midpoint of bid-ask prices at close on day t. Further details on the construction of this variable is available in Jiang and Sun (2014).

and utility firms, as well as observations with any missing variables (Amiram, Owens, and Rozenbaum, 2016; Cui, Jo, and Na, 2018). We also drop firms with less than four records in our sample. This results in a final sample of 122,760 stock-quarter observations for 4,460 distinct stocks from 2000 Q1 to 2020 Q1. The adverse selection measure is only available for 20,543 stock-quarter observations and 3,715 distinct stocks due to insufficient day-to-day transaction records for a subset of stocks, an issue common in the literature (Jiang and Sun, 2014; Gong et al., 2021). Panel A of Table 1 reports summary statistics for firm-level information asymmetry measures, which are comparable to those in prior studies (e.g., Cui, Jo, and Na, 2018; Gong et al., 2021).

Insert Table 1 Here

2.3 Mutual fund-level variables

To examine mutual-fund level stock-picking performance, we merge mutual fund attributes from the CRSP mutual fund database with portfolio holdings data from the Thomson Reuters Institutional (13F) Holdings database (Jiang and Zheng, 2018).[13] We include only active mutual funds, as classified by the fund investment objectives in the CRSP mutual fund database. Additionally, we exclude fund observations with an annual turnover ratio of less than 5%, with either fewer than $5 million total net assets or 10 stocks (Kacperczyk et al., 2014), and observations with any missing variables.[14] We also exclude funds with less than eight records in our sample.

[13] Data in the Thomson Reuters Holding database is reported at the fund-portfolio level, while information on fund characteristics from the CRSP mutual fund database is reported at the share-class level. As a result, we aggregate CRSP fund characteristics to the fund-portfolio level for portfolios with multiple share classes based on the asset weight of different share classes, as detailed by Kacperczyk, Nieuwerburgh, and Veldkamp (2014). To construct quarterly excess returns, we use aggregated monthly returns from CRSP and monthly risk factor data from the Fama-French Portfolios and Factors database.

[14] Removing fund observations with either fewer than $5 million total net assets or 10 stocks mitigates the incubation bias, when fund families incubate private funds, which tend to be small, and then only make public the track record of the surviving incubated funds, not the terminated funds (Kacperczyk, Nieuwerburgh, and Veldkamp, 2014).

Given that identifying the location of fund headquarters is necessary for our analysis, we limit our sample to the period from Q1 2000, when historical fund headquarter location data becomes available, to Q1 2020. This results in a panel of 85,802 quarterly-fund observations for 2,293 distinct mutual funds. Panel B of Table 1 reports summary statistics for the mutual funds in our sample, which are comparable to that in the existing literature (e.g., Wardlaw, 2020). Figure 2 shows the geographic dispersion of mutual funds in our sample, in which a deeper shade indicates a higher density of funds.

Our key dependent variable of interest is mutual fund stock-selection performance, which captures a mutual fund's ability to predict future stock alphas and how it weights these opportunities in their portfolio relative to the market (Kacperczyk, et al., 2014). The measure is defined as follows:

$$SP_t^j = \sum_{i=1}^{N^j} \left(w_{i,t}^j - w_{i,t}^m\right)\left(R_{t+1}^i - \beta_{i,t} R_{t+1}^m\right), \tag{5}$$

where SP_t^j is the stock-picking ability of mutual fund *j* in quarter *t*. $w_{i,t}^j$ is the portfolio weight mutual fund *j* has invested in stock *i* in quarter *t*. $w_{i,t}^m$ is the weight of stock *i* in the market portfolio. R_{t+1}^i denotes the excess return for stock *i* in quarter *t+1*, which unknown at time *t*. R_{t+1}^m denotes the excess return for the market portfolio in quarter *t+1*. $\beta_{i,t}$ is stock *i*'s CAPM beta in quarter *t*, calculated using past quarterly returns from *t-20* to *t-1*.[15]

We decompose this measure of stock-picking ability into its local and non-local components based on the state of the fund's headquarters relative to the state of the firm's headquarters. To construct local stock-picking ability, we construct the measure in equation (5) using only stocks headquartered in the same state as the mutual fund. Non-local stock picking is

[15] Unlike Kacperczyk et al. (2014), who compute CAPM betas using the past 12-month returns, we instead use 20 data points (quarters) because the Fama-French three-factor and Carhart four-factor models estimated in robustness tests have additional regressors relative to the CAPM model. We retain 96% of the 12,659 stocks in our holdings data sample by requiring at least 20 quarters of data.

constructed analogously using only stocks that are *not* headquartered in the same state as the mutual fund, such that local stock-picking ability plus non-local stock-picking ability is equal to overall stock picking ability. Panel B of Table 1 shows that average quarterly stock-picking ability is 15.4 basis points, similar to that of other studies (e.g., Chuprinin and Sosyura, (2018). However, average *local* stock-picking ability is close to zero. While the local advantages of mutual funds have been well documented (e.g., Coval and Moskowitz, 2001), Bernile et al. (2019) find that the local advantage largely disappeared for institutional investors after 2000, which is when our sample starts.

2.4 State-level variables

In our regression analyses, we must control a number of time-varying state-level factors to isolate the effect of RRI on both firm-level information asymmetry and mutual fund-level stock-picking ability. First, we control for state-level demographic and socioeconomic variables including the natural logarithm of the median housing value state population (Christoffersen and Sarkissian, 2009), poverty rate, senior citizen ratio (≥65 years old), and the female ratio (Wei and Zhang, 2020) using data from the US Census Bureau and the Federal Housing Finance Agency.

Second, we control for regional racial patterns that are related to but different from RRI including population-weighted average census tract diversity using the Herfindahl index (Pinto-Coelho and Zuberi, 2015), as well as indicator variables for whether any racial group accounts for more than 95% of the population (i.e., fully segregated) and whether white people account for less than 50% of the total population (i.e., a white minority) using data from the US Census Bureau.

Next, we control for institutionalized discrimination which may be correlated with RRI, but is unrelated to the social transmission channel through which we propose RRI can affect information asymmetry and local stock-picking ability. We proxy for institutionalized discrimination using discrimination in zoning behavior, which is constructed as the number of census tracts times 5000 (the average population of a census tract) divided by the total population in a given state using data from the US Census Bureau (Lichter, Parisi, and Taquino, 2015). Zoning behavior has been identified as one source of racial segregation (Lichter et al., 2015) whereby governments set up redundant census tracts with the purpose of imposing seemingly legitimate land-use regulations or pricing policies that, in reality, are intended to steer immigrants and minorities towards certain areas.

Fourth, we use data from CRSP and Compustat to control for local stock market conditions that may impact investment opportunities, including state-level market capitalization, the number of publicly traded stocks in each state, the state-level ratio of dividend-paying firms, the weighted average return for firms headquarters in each state, and state-level Amihud illiquidity (Bernile et al., 2015; Bernile, Bhagwat, and Yonker, 2018). Lastly, since institutional ownership can increase firms' information production resulting in a positive effect of institutional investor clustering on the local stock market (Kacperczyk et al., 2021; Kim, Wang, and Wang, 2022), we control for state-level institutional ownership to accounting for the possibility that funds may select headquarters in states with low RRI.

We control for these state-level factors for firm-level tests for information asymmetry and mutual fund-level tests because these factors can affect both the quality of the firm's information environment as well as mutual fund stock-picking ability. We provide summary statistics for these control variables in Panel D of Table 1. A more detailed description of these variables is available in Appendix A.

3 Firm-Level Results

3.1 RRI and information asymmetry

To test our prediction that RRI is negatively associated with firm-level information asymmetry, we estimate the following model:

$$DV_{i,t} = \beta_0 + \beta_1 RRI_{i,t} + \boldsymbol{\beta X_{i,t}} + Q_t + Y_t + I_i + S_i + \epsilon_{i,t}. \qquad (6)$$

The dependent variables, $DV_{i,t}$, are proxies for information asymmetry (i.e., earnings forecast dispersion and the adverse selection component of the bid-ask spread) for firm *i* in quarter *t*. $RRI_{i,t}$ is the state-level RRI in firm *i*'s headquarter state in quarter *t*. To mitigate the potential for omitted variable bias, $\boldsymbol{X_{i,t}}$ is a vector of control variables that includes common predictors of firm-level information asymmetry (i.e., R&D disclosure dummy, advertisement disclosure dummy, leverage, intangible assets, market capitalization, sales-to-total assets, book-to-market, cash holdings, payout ratio, proportion of institutional blockholder ownership, number of covering analysts (Boone and White, 2015)); firm-level market attributes (i.e., lagged returns, lagged price level, lagged dollar volume, lagged market cap (Amiram, Owens, and Rozenbaum, 2016; Cui, Jo, and Na, 2018)); and state-level characteristics described in section 2.4 (i.e., median housing value, state population, poverty rate, senior citizen ratio, female ratio, population-weighted average census tract diversity, zoning behavior, the number of publicly traded firms, the state-level ratio of dividend-paying firms, the weighted average return for firms headquartered in each state, state-level market liquidity, and state-level institutional ownership).[16] All control variables are winsorized at the 1% and 99% levels (Amiram, Owens, and Rozenbaum, 2016). Additionally, we include quarter (Q_t) and year (Y_t) fixed effects to control for unobserved macroeconomic variables that may vary over time and influence firm-level information asymmetry. We also include two-digit SIC code (I_i) and state (S_i) to control for unobserved differences in information asymmetry that can vary by industry and by state, such as regulatory policies. Standard errors are clustered at the firm level. In all tables, we report coefficient estimates only for variables of interest and exclude estimates for control variables for brevity. Estimates for all regression variables are available in the Appendix.

The results in Table 2 show that RRI is negatively associated with firm-level information asymmetry. Economically, the coefficient in column 1 (-0.698) indicates that a one standard

[16] Appendix A contains a more detailed description of all control variables.

deviation increase in the similarity index (0.07) is associated with a 23.95% reduction in earnings forecast dispersion relative to its mean (0.204). Similarly, the coefficient in column 4 (-0.011) indicates that a one standard deviation increase in the similarity index is associated with a 38.5% reduction in adverse selection relative to its mean (0.002). The coefficient estimates for the negative Theil index and the exposure index suggest effects of similar magnitudes.[17] These findings suggest that stocks headquartered in high RRI states have lower analyst forecast dispersion and lower adverse selection, and thus lower information asymmetry, relative to stocks headquartered in low RRI states.

Insert Table 2 Here

3.2 RRI and stock price informativeness

In this section, we investigate the relationship between RRI and stock price informativeness as an alternative way to examine the effect of racial integration on the quality of the firm's information environment. We employ the stock price informativeness methodology developed by Kacperczyk et al. (2021) that tests the strength of the correlation between future cash flow, as proxied by future EBIT in year *t+1*, and the natural logarithm of current market capitalization in year *t*. Following Kacperczyk et al. (2021), we exclude firms headquartered in states with fewer than 20 publicly listed stocks in year *t*, firms with less than $1 million in market capitalization in year *t*, financial firms (SIC codes starting with 60-69), and records with any missing variables. Furthermore, we retain only firms with eight annual observations, resulting in a final sample of 25,224 firm-year records for 1,798 unique firms.

To examine the impact of RRI on firm-level stock-price informativeness, we estimate the

[17] In robustness tests shown in Appendix B4, we verify that we observe quantitatively similar results when using raw, unorthogonalized RRI measures, as well as RRI indices constructed using three minority-majority pairs (African American-white, Hispanic-white, and Asian-white), weighted by their state-level populations.

following model:

$$\frac{E_{i,t+1}}{A_{i,t}} = \alpha + \beta_1 \log\left(\frac{M}{A}\right)_{i,t} + \beta_2 RRI_{i,t} + \beta_3 \log\left(\frac{M}{A}\right)_{i,t} \times RRI_{i,t}$$
$$+ \boldsymbol{\beta_4 X_{i,t}} + \boldsymbol{\beta_5} \log\left(\frac{M}{A}\right)_{i,t} \boldsymbol{X_{i,t}} + \boldsymbol{\beta_6 X_{s,t}} + F_i + Y_t + \epsilon_{i,t+1}, \qquad (7)$$

where $\frac{E_{i,t+1}}{A_{i,t}}$ is the ratio of firm *i*'s EBIT in year *t+1* to total assets in year *t*. $RRI_{i,t}$ is the state-level RRI in firm *i*'s headquarter state in quarter *t* and $\log\left(\frac{M}{A}\right)_{i,t}$ is the market valuation for firm *i* in year *t*, measured as the natural logarithm of firm *i*'s market capitalization divided by its total assets in year *t*. $\boldsymbol{X_{i,t}}$ is a vector of controls that are associated with firms' future cash flows including the EBIT-to-asset ratio, leverage, invest, intangible assets, total assets, cash holdings, sales-to-asset ratio, trading dollar volume, and illiquidity (Kacperczyk et al., 2021) for firm *i* in year *t*. $\boldsymbol{X_{s,t}}$ is a vector of state-level controls (i.e., state population, female ratio, senior citizen ratio, zoning behavior, state-level economic condition index developed by the Federal Reserve Bank of Philadelphia (SC Index), number of publicly traded firms, market capitalization, weighted average return for firms headquartered in the state) for firm *i* headquartered in state *s* in year *t*.[18] We winsorize all control variables at the 1% and 99% levels. We include year fixed effects (Y_t) to control for the influence of unobserved time-varying macroeconomic factors on firms' future cash flows. We also include firm fixed effects (F_i) to control for unobservable firm characteristics that may affect future cash flows. Standard errors are clustered at the firm level.

We are interested in the coefficient estimate (β_3) on the interaction between the market valuation, $\log\left(\frac{M}{A}\right)$, and RRI. This coefficient measures the explanatory power of current market valuation on future cash flows, conditional on RRI. A positive β_3 means higher RRI is associated

[18] The state-level economic condition index is developed by the Federal Reserve Bank of Philadelphia based on a national coincident index method developed by Stock and Watson (1989). The amalgamation of the following four state-level metrics is employed to encapsulate prevailing economic circumstances into a singular statistical measure: nonfarm payroll employment, average hours worked in manufacturing, unemployment rate, and wage and salary disbursements adjusted for inflation using the Consumer Price Index (U.S. city average).

with increased comovement between a firm's future cash flow and its stock price, indicating improved price efficiency and more informative stock prices. In Table 3, we find that the coefficients on the interaction between market valuation RRI are indeed positive and statistically significant for all RRI measures and specifications. Consistent with our results on firm-level information asymmetry, this suggests that higher RRI is associated with improved stock price informativeness.

Insert Table 3 Here

3.2.1 Heterogeneity by active ownership

Prior research indicates that a higher proportion of ownership by active institutional investors is associated with higher stock price informativeness (Kacperczyk et al., 2021). Motivated by this finding, we expect that firms with higher active ownership will have a higher quality information environment and will thus benefit less from the improved social dissemination of firm-level information when RRI is higher. However, we continue to expect that firms with low active ownership, which have lower-quality information environments and are thus more likely to benefit from the social dissemination of firm-level information, to have stronger comovement between market valuation and future cash flows.

We use data from the Thomson Reuters 13F database and define active traders to include hedge funds, investment advisors, and mutual funds with transient or dedicated investment styles (Bushee, 2001).[19] We construct active ownership, IOR_{active}, as the proportion of equity owned by active investors divided by total shares outstanding (Kacperczyk et al., 2021) and, in each year, sort firms into quintiles based on their level of active ownership. In Table 4, we estimate the stock price informativeness results for stocks in the highest and lowest quintiles of active ownership. As expected, the coefficient estimates on the interaction between market valuation and RRI are

[19] This data is available on Dr. Bushee's personal website: https://accounting-faculty.wharton.upenn.edu/bushee/.

insignificant for firms in the highest active ownership quintile (columns 1-3) and are significantly positive for firms in the lowest active ownership quintile (columns4-6). These results point to a stronger positive association between RRI and stock price informativeness for firms with lower active institutional ownership compared to those with higher ownership, suggesting that higher active institutional ownership can ameliorate the adverse effects of low RRI on stock price informativeness.

Insert Table 4 Here

4 Mutual Fund-Level Results

4.1 RRI and local stock picking ability

Given the association between RRI and the quality of a firm's information environment, a natural question is whether RRI can affect the ability of local institutional investors to exploit the local information advantage (Coval and Moskowitz, 2001). To examine this, we construct a quarterly measure of fund stock-picking performance based on funds' ability to predict individual stocks' alphas. We also decompose it into its local and non-local components based on the state of the fund's headquarters relative to the state of the firm's headquarters, as described in section 2.4, in order to examine the effect of RRI on funds' local information advantage. We evaluate the relationship between RRI and stock-picking performance using the following model:

$$DV_{j,t} = \beta_0 + \beta_1 RRI_{j,t} + \boldsymbol{\beta X_{j,t}} + Q_t + Y_t + S_j + \epsilon_{j,t}, \quad (8)$$

where $DV_{j,t}$ is a measure of stock-picking performance for fund j in quarter *t* and $RRI_{j,t}$ is the state-level RRI in fund *j*'s headquarter state in quarter *t*. $\boldsymbol{X_{j,t}}$ is a vector of controls that includes common predictors of mutual fund performance (i.e., trading style, net flow, turnover ratio, fund load, fund age, expense ratio, total net assets, number of managers, an indicator for funds with more than four managers, number of share classes in the fund family, and total net assets of the fund family) (Coval and Moskowitz, 2001; Cohen et al., 2008; Kacperczyk et al., 2014; Chuprinin and Sosyura, 2018), as well as state-level characteristics described in section 2.4 that may affect stock-picking performance (i.e., median housing value, state population, poverty rate, senior citizen ratio, female ratio, population-weighted average census tract diversity, zoning behavior, the number of publicly traded firms, the state-level ratio of dividend-paying firms, the weighted average return for firms headquartered in each state, state-level market liquidity, and state-level institutional ownership).[20] Additionally, we include quarter (Q_t) and year (Y_t) fixed effects to control for unobserved time-varying factors that may influence funds' stock-picking performance, such as the seasonality in active fund performance (Brown, Sotes-Paladino, Wang, and Yao, 2014). We also include state (S_j) fixed effects to control for unobserved differences in fund-level stock-picking abilities that can vary by state. All standard errors are clustered at the fund level.

Columns 1-3 and 7-9 in Table 5 reveal that our three measures of RRI, *RRI Similarity*, *RRI Exposure*, and *RRI NegTheil*, are significantly negatively associated with local and overall stock-picking abilities, but are unrelated to non-local stock-picking ability (columns 4-6).

performance reduction in local investments. In terms of economic magnitude, the coefficient estimate for *RRI Similarity* in column 1 (-0.065) indicates that a one standard-deviation increase in the similarity index (0.07) is associated with a 45.5 basis point decrease in local stock-picking performance, which comprises more than half of its standard deviation (74.8 bps). In terms of overall stock-picking performance, the coefficient estimate on the similarity index in column 7 (-0.086) indicates a one standard-deviation increase in the similarity index is associated with a 60.2 basis point decrease in overall stock-picking performance, which constitutes 17.6% of its standard deviation (343 bps). The economic magnitudes of the coefficient estimates for the other RRI

[20] We determine a mutual fund's trading style by sorting funds into four categories according to their portfolio-level size and book-to-market factor loadings estimated using the Fama and French (1993) three-factor model. We describe the construction of other variables in detail in the Appendix. We also winsorize net flow and turnover ratio at the 1% and 99% levels to mitigate the impact of outliers (Kacperczyk et al., 2014).

indices are comparable. Given the substantial size of mutual funds' net assets, these findings are economically meaningful (Chuprinin and Sosyura, 2018) and suggest that funds headquartered in states with higher RRI tend to have lower overall stock-picking performance, driven by the decrease in local stock-picking performance. This is consistent with contact theory, which posits that higher RRI fosters increased social interactions among groups, resulting in more connected social networks. This, in turn, can bolster the diffusion of information, thereby decreasing the local informational advantage of mutual funds.

Insert Table 5 Here

4.2 Heterogeneity analysis

4.2.1 RRI, stock-picking performance, and economic conditions

Economic conditions can impact mutual funds' stock-picking abilities (e.g., Kacperczyk et al., 2014). In expansion years, characterized by economic growth and increased investment opportunities, mutual funds tend to focus more on stock-picking. In contrast, in recession years with limited investment opportunities, funds are more likely to focus on market timing. Thus, we anticipate a stronger negative relationship between state-level RRI and stock-picking performance in expansion years.

Table 6 presents the relationships between RRI stock-picking ability for expansion years in Panel A and for recession years in Panel B. We define recession years as those with at least six recession months, as identified by the NBER recession indicator. The remaining years are considered expansion years.[21] In Panel A, we continue to find a significantly negative relationship between RRI and both local and overall stock-picking ability in expansion years with coefficients that are

[21] Based on our definition, expansion years are 2000, 2002–2007, and 2010–2019, while recession years are 2001 (the Dotcom Crash and the September 11th attacks), 2008-2009 (the Global Financial Crisis and collapse of the housing bubble), and 2020 (the COVID-19 recession).

slightly larger in magnitude relative to our baseline results in Table 5. In recession years in Panel B, we continue to find a significantly negative relationship between RRI and local stock-picking ability, but we do not find a relationship between RRI and overall stock-picking ability. This suggests that in recession years, funds still benefit from a local information advantage when RRI is low. However, this local portion of their portfolio does not appear substantial enough to affect overall stock-picking ability consistent with funds underweighting the local active stock-picking portion of their portfolio to focus more on market timing.

Insert Table 6 Here

4.2.2 RRI and mutual fund manager race

Social capital refers to the resources accessed through social connections that are crucial for individuals and groups to achieve their objectives (Lin, 2002). Given existing findings that social networks tend to be segregated by race and gender, with white male networks offering more resources and higher status connections (McDonald, Lin, and Ao, 2009; McDonald and Day, 2010; McDonald, 2011), we examine whether the relationship between RRI and fund stock-picking performance is contingent on fund manager race. Specifically, under the assumption that white mutual fund managers benefit more from their social capital when investing locally, leading to a more pronounced local information advantage, we expect higher RRI to have a stronger impact on stock-picking ability for white-managed mutual funds, since it lowers local information asymmetries from which white fund managers benefit.

To test this, we examine a subsample of funds with only one manager to mitigate organizational structure impacts (Csaszar, 2012) and also exclude influential managers in charge of four or more funds simultaneously. To identify manager race and ethnicity, we use the NamePrism application that is increasingly popular among finance and economics papers to identify one's race based on their race (e.g., Pool et al., 2015; Diamond, McQuade, and Qian, 2019).[22] For each fund manager name, NamePrism indicates the probability that the name comes from one of six racial and ethnic groups according to the US Census Bureau (i.e., Hispanic; non-Hispanic white; non-Hispanic African American; non-Hispanic Asian/Pacific Islander; non-Hispanic Native American and Alaska Native; and non-Hispanic multiracial). We classify a manager as part of a particular race when the corresponding racial probability is over 50%. We exclude manager from the sample if none of the six racial probabilities is over 50%. This process results in 16,893 fund manager-quarter records for 1,284 mutual fund managers in the sample period. The majority of these fund-quarter observations (15,959) and managers (1,264) are white, while we have only 934 fund-quarter observations for 76 non-white managers.

In Table 7, we report the relationships between RRI stock-picking ability for funds with white managers in Panel A and for funds with non-white managers in Panel B. We additionally include controls for gender and manager experience, which are both associated stock-picking performance.[23] Panel A of Table 7 shows that the relationship between RRI and local and overall stock-picking performance is significantly negative for white mutual fund managers; the coefficients appear larger in magnitude relative to the baseline results in Table 5 using the full sample. In Panel B, we observe a negative but insignificant relationship between RRI and local and overall stock-picking ability for non-white managers. However, since the sample for non-white managers is substantially smaller, these insignificant relationships may be due to lack of statistical power in our estimates. Thus, we tentatively conclude that RRI tends to have a stronger impact on stock-picking ability for white-managed mutual funds by lowering local information

[22] More details regarding the develop of NamePrism can be found in Diamond, McQuade, and Qian (2019). The NamePrism app can be found here: https://www.name-prism.com/.

[23] We determine manager gender by the pronouns used in SEC documents (i.e., he/she or Mr./Ms./Mrs.). If pronouns are missing, we use their name to identify their gender with the help of NamePrism. The number of years of work experience is based on a fund manager's working history from their LinkedIn homepage, the biography provided by their affiliated mutual fund's website, or their working history disclosed through fund-level SEC documents (i.e., how many years they have been working in the money management industry). We do not include these controls in our main analyses because their availability, along with the availability of the race variable, considerably reduces the sample size.

asymmetries that white fund managers tend to benefit more from.

Insert Table 7 Here

4.3 Alternative explanations

4.3.1 Passive exposure to the premium caused by the lack of racial integration

A potential alternative explanation for our findings may be that the superior local stock-picking performance of mutual funds in low RRI states reflects a premium compensating investors for an unidentified risk associated with regional RRI. To mitigate this concern, we employ a placebo test using pure index funds, which passively follow market indices and do not engage in active stock selection. If the impact of RRI on the stock-selection ability of index funds is similar to that of actively managed mutual funds, our findings may be attributed to passive exposure to a premium for firms in states with low RRI.

In this placebo test, we identify pure index funds using the fund investment objectives in the CRSP mutual fund database. Table 8 reports that we do not find the same relationship between RRI and stock-picking ability for index funds that we do for active funds. This suggests that our findings cannot be explained by passive exposure to firms that may carry a premium because they are headquartered in states with low (or high) RRI, and can only be observed when there is active stock selection.

Insert Table 8 Here

4.3.2 Racial integration as a proxy for social trust

RRI has been associated with increased social trust (Uslaner, 2010; Alesina and Zhuravskaya, 2011; Rothwell, 2012). Wei and Zhang (2020) observe that institutional investors in low-trust regions tend to favor and direct more attention and resources to local stocks, resulting in a local informational advantage. Conversely, they find that institutional investors in high-trust regions exhibit lower local bias and no informational advantage in local holdings. Thus, if RRI is simply a proxy for social trust, our finding that funds in high-RRI states exhibit lower local stock-picking ability may be driven by the relationship between trust and the local informational advantage.

To address this concern, we use data from the World Values Survey to construct the social trust index developed by Wei and Zhang (2020) and include it as a control variable our baseline regressions.[24] We also control for state-level violent crime and property crime rates, obtained from the Federal Bureau of Investigation's Uniform Crime Reports, since they are associated with social trust (Wei and Zhang, 2020). The results in Table 9 reveal that trust itself cannot explain the relationship between RRI is negatively associated with local stock-picking ability. The coefficient estimates for RRI are comparable in magnitude and statistical significance to our baseline results in Table 5, which suggests that our results are not driven by trust.

Insert Table 9 Here

5 Robustness

[24] The social trust index (Wei and Zhang, 2020) is based on responses to the following question from the World Values Survey: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?". The World Values Survey only provides data for 10 geographical regions. They are: *New England* (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, and Connecticut), *Middle Atlantic* (New York, Pennsylvania, and New Jersey), *East North Central* (Wisconsin, Michigan, Illinois, Indiana, and Ohio), *West North Central* (Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota, and Iowa), *South Atlantic* (Delaware, Maryland, Washington, D.C., Virginia, West Virginia, North Carolina, South Carolina, Georgia, and Florida), *East South Central* (Kentucky, Tennessee, Mississippi, and Alabama), *West South Central* (Oklahoma, Texas, Arkansas, and Louisiana), *Rocky Mountain* (Montana, Wyoming, Nevada, Utah, Colorado, Arizona, and New Mexico), *Northwest* (Oregon, Washington, and Idaho), and *California*. Each state in our sample is assigned the social trust index for the geographical region it belongs to.

5.1 Alternative measures of RRI

In this section, we construct alternative variations of our RRI measures to ensure that certain features of the RRI measures used in our main analysis are not driving our findings. Using each variation of the RRI measures detailed below, we verify that we find similar results and conclusions for both our firm-level tests as well as our mutual fund-level tests.

5.1.1 RRI measures using annual data

One limitation of using US Census data is that it provides data only once every ten years, meaning we rely heavily on interpolation to construct annual measures of RRI. While this approach is consistent with studies that use variables related to culture (e.g., Kumar, Page, and Spalt, 2011), it introduces a forward-looking bias since the interpolated values partially rely on future RRI values. To mitigate this concern, we use annual data from the American Community Survey (ACS) which is available annually starting in 2005. The ACS provides data on race by Public Use Microdata Area (PUMA), a geographic unit defined by the US Census Bureau that contains at least 100,000 people.[25] For comparison, in 2020, there were 74,001 census tracts and 2,378 PUMAs (US Census Bureau, 2021). On average, this implies that each PUMA contains approximately 31 census tracts. Since we construct state-level RRI by capturing variation in the distribution of populations across subunits, smaller subunits allow more granularity in measurement across subunits, resulting in a more reliable measure of RRI. The larger size of PUMAs relative to census tracts reduces the reliability of our RRI measures by making variations across subunits less observable. In particular, this has the greatest effect on the exposure index which is only reliable when each subunit is small enough for each individual to potentially interact with others in that subunit. This assumption is less plausible when using PUMAs, instead of census tracts, as subunits.

Using ACS data, we compute annual state-level RRI measures that incorporate specific

[25] ACS data on race is also available by county, which is smaller than a PUMA, however county-level data is only available for counties with at least 65,000 people which results in a substantial portion of missing values for our sample.

minorities via three sets of racial pairs (i.e., “African American-white”, “Asian-white”, and “Hispanic-white”).[26] Further, we lag the RRI measures constructed using ACS data by one year such that firm data as well as mutual fund data in year *t* is merged with RRI measures in year *t-1*. We report firm-level results on information asymmetry and stock price informativeness in Appendix D1 and D2, respectively. These results are comparable to our baseline firm-level estimates, with the exception the RRI-forecast dispersion relationship which is no longer significant. Next, in Table 10, we report mutual-fund level results on the relationship between RRI and stock-picking performance. We continue to find a negative relationship between racial integration and local and overall stock-picking performance across all RRI measures. Overall, the magnitudes of the estimates tend to be smaller relative to our baseline results, and the relationship between the exposure index and overall stock-picking ability is no longer significant. This is not surprising considering that RRI measures constructed using data from much larger subunits (i.e., PUMAs) tends to be less reliable, particularly for the exposure index.

Insert Table 10 Here

5.1.2 Unorthogonalized RRI measures

To ensure that the orthogonalization process that we use for the RRI measures in our main tests is not driving our findings, orthogonalized RRI measures. For robustness, in this section we instead employ the raw RRI measures in the testing of our fund-level results. Although the statistical significance of the RRI-SP coefficient decreases, it remains significant. The higher

[26] Using the similarity index as an example, we calculate three $RRI\ Similarity_j^k$ with formula (1), considering each of the three minority racial groups (African American, Asian, and Hispanic) in conjunction with the majority group (white). Subsequently, we aggregate these race-specific similarity indices for state j based on the relative sizes of the three racial minority groups, employing the formula: $RRI\ Similarity_j = \sum_k P_k \times\ RRI\ Similarity_j^k$, where *k* denotes *minority k*, including African American, Asian, and Hispanic populations, and P_k is the proportion of *minority k* relative to the combined African American, Asian, and Hispanic populations.

variances of raw measures do not alter the economic significance, and our main conclusions persist. See Appendix D3 and D4 for detailed results.

5.2 Mutual fund-level robustness tests

In this section, we perform additional tests to ensure the robustness of our mutual fund-level findings regarding the impact of RRI on both local and overall stock-picking performance.

5.2.1 Geographical clustering of mutual funds

Over 50% of the mutual funds in our sample are concentrated in three states: New York, California, and Massachusetts, a trend observed in prior studies (e.g., Pool, Stoffman, and Yonker, 2012; Wei and Zhang, 2020). Thus, to ensure that our results are not driven by funds in these three states, we report our results when excluding all funds headquartered in New York, California, and Massachusetts in Table 11. While this reduces our sample by approximately half, we continue to find a significantly negative similar relationship between RRI and local and overall stock-picking performance.

Insert Table 11 Here

5.2.2 Alternative estimation of stock-picking ability

To construct the stock-picking ability measure from Kacperczyk et al. (2014), we estimate alpha using the CAPM in our main analysis. Here, we ensure that our results are robust to using measures of stock-picking ability based on alphas estimated using the Fama-French (1993) three-factor and the Carhart (1997) four-factor models. Results in Appendix D5 show that despite lower magnitudes, the estimated coefficients for local stock picking remain statistically significant but with lower magnitudes. These lower magnitudes may explain why we no longer find a relationship between RRI and overall stock-picking ability.

5.2.3 Autocorrelation

To mitigate the potential for autocorrelation and the possibility that our findings are due to the persistent holdings of well-performing funds, we include controls for lagged stock-picking ability. For local stock-picking performance tests, we additionally include a control for contemporaneous non-local stock-picking performance to proxy for omitted variables characterizing the mutual fund management team. The results in Appendix D6 indicate that we continue to find a significantly negative relationship between RRI and stock-picking performance, suggesting that our results are largely unaffected by autocorrelation issues or previously unobservable fund attributes captured by non-local stock-picking performance.

5.2.4 Fund fixed effects

We do not include fund fixed effects in our main tests because local bias and local stock-picking ability are thought to be driven by fund-level factors such that including fund fixed effects would absorb some of the variation we are trying to observe. However, to ensure that unobservable fund attributes are not driving our results, we include fund fixed effects to ensure that our results are robust to this very conservative test. In Appendix D7, we still observe a negative relationship between RRI and both local and overall stock-picking ability, but not surprisingly, the estimates for RRI tend to be smaller in magnitude.

5.2.5 Overspecification

While we include a large number of control variables to account for time-varying state-level characteristics that may influence the relationship between RRI and stock-picking ability, including too many control variables may result in overspecification. In Appendix D8, we estimate simplified models without any control variables or fixed effects, except for state, year, and quarter fixed effects, and find results consistent with our baseline tests.

6 Conclusions

We find that firms headquartered in more racially integrated states tend to have a higher quality information environment, characterized by lower earnings forecast dispersion and a narrower adverse selection component of the bid-ask spread. Additionally, in these more racially integrated states, firms tend to have stock prices that comove more strongly with fundamentals and are thus more informative. These findings highlight the role that racial integration plays in price discovery efficiency, particularly in less racially integrated states, and may have policy implications for governments and regulators interested in fostering market efficiency.

Given the lower quality information environment in less racially integrated states, we find that active fund managers benefit more from a local information advantage, resulting in a stronger local-stock picking ability. By doing so, we identify race as a new dimension important to the social dissemination of information that can influence affect institutional investor stock-picking ability. Lastly, we find heterogeneity in the relationship between racial integration and the local stock-picking ability. White fund managers can benefit from the local information advantage in less racially integrated states, whereas non-white managers do not enjoy the same benefit. This points to an additional source of disadvantage that minority fund managers face in the active fund management industry.

In conclusion, we introduce racial integration as a novel dimension important in the study of how information transmission impacts both the firm-level information environment, as well as institutional investor outcomes. These findings not only provide valuable insights for practitioners and policymakers with an interest in cultivating more inclusive and efficient financial markets, bust also emphasizes the need for a more comprehensive understanding of the role of race and racial integration in shaping investment.

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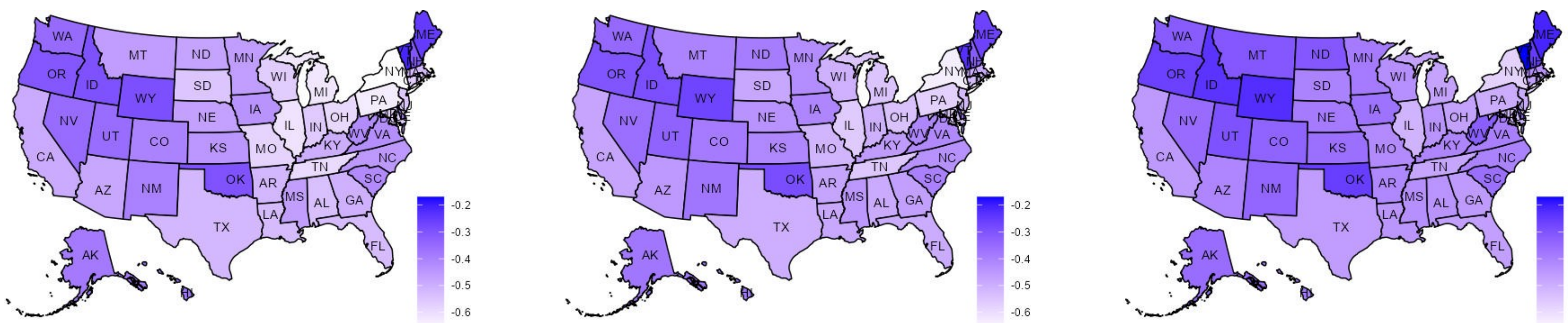
Figure 1: Heat map of similarity index across different states from 2000 to 2020

In the following graphs, the deeper shade of color means the state is more racially integrated (i.e., it has a higher similarity index). Graphs (a)-(c) are based on the raw similarity index. Graphs share the same legend and "shade-value" manifestation. The calculation of the similarity index is based on the formula detailed in Section 2. Detailed statistics can be found in Appendix B1. Time trends of *RRI Exposure* and *RRI NegTheil* are present in Appendix B1.



(a) Map of RRI Similarity in 2000

(b) Map of RRI Similarity in 2010

(c) Map of RRI Similarity in 2020

Figure 2: Density of mutual funds in the US

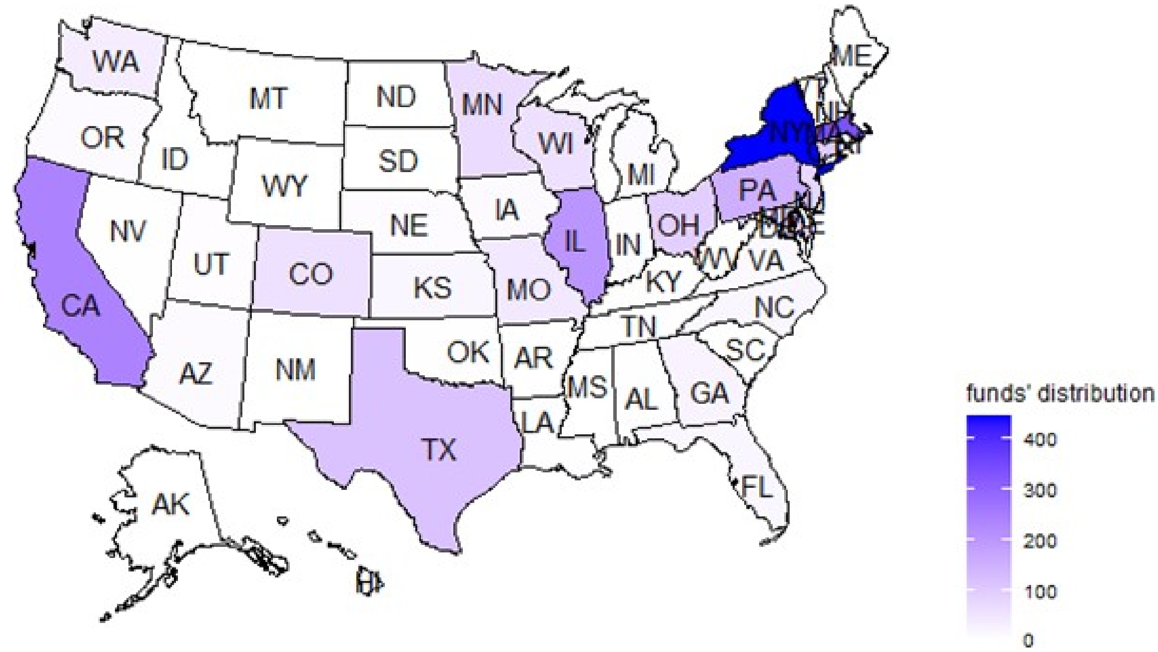


Table 1: Summary statistics

Table 1 provides descriptive statistics of variables used in this study. ***For the stock-level variables:*** The construction of Adverse selection follows Jiang and Sun (2014). Earnings forecasts dispersion is the standard deviation of earnings forecasts modified by the average earnings forecast. IOR denotes the institutional ownership rate based on investors at least holding 5% shares of the firm. *Prc(t-1)* denotes the natural logarithm of the lagged stock price. The original trading volume (*Vol(t-1)*) and market cap (*Market Cap (t-1)*) are denominated in $1,000. Sale to total asset (*Sale*), intangible asset to total asset (*Intangibility*), book to market ratio (*B/M*), leverage, cash holdings to total asset (Cash Holding), and payout ratio (*Payout*), and investment to total asset (*Invest*) come from the last fiscal year, updated annually. *R&D* (0/1) and *Advertising* (0/1) are dummy variables and equal to 1 when the firm disclosed their R&D expenditure and advertising cost in the fiscal year *t-1*, respectively. Other firm-level variables are quarterly variables. According to the literature, all controls are winsorized at 1 % and 99% levels. ***For the fund-level variables:*** Net flow, turnover, expense ratio, and total load are all annualized data. *Fund age* is achieved based on the initial date of that mutual fund measured by years. *Local investment* is defined as the fraction of the portfolio of mutual funds invested in local stocks (stocks headquartered in the same state as the mutual fund). *TNA* denotes the total net assets. The team managed is a 0/1 variable. If the mutual fund is managed by a team, then the number of managers will be set as one. In this paper, "*managed by a team*" means there are at least four different managers for a mutual fund. Factor loading is a portfolio-level variable used to sort mutual funds into four categories. The *fund family size* is the number of shares of funds belonging to the same asset management firm. According to the literature, *Net Flow* and *Turnover* are winsorized at 1 % and 99% levels. ***For the State-level variables:*** We exclude Washington DC and Puerto Rico. The orthogonalization of raw RRI measures results in orthogonalized RRI measures and detailed processes see Appendix B. Senior rate means the rate of population older than 65. Fully Seg means one single race makes up more than 95% of the population of a state. Less White means the fraction of non-Hispanic white people are lower than 50%. The calculation of *Trust Index* is based on Wei and Zhang (2020), and *SC Index* is the state-level economic condition index developed by the Federal Reserve Bank of Philadelphia. All non-ratio state-level capital market variables are achieved in a market capitalization weighted manner, expect for the total market capitalization, which is the summation of individual stocks' market cap. *State Ret* is the value weighted return; *State Illiq* is the Amihud's (2002) illiquidity measure $\times 10^6$; *State Fpd* is the ratio of firms paying dividends; *State IO* is the state-level ownership. The definitions of all variables can be found in Appendix A.

Variables	N	MEAN	SD	MIN	P50	MAX
Panel A: Stock-level variables						
Adverse Selection (%)	20,543	0.221	0.409	0.000	0.048	2.363
Earnings Forecasts Dispersion	122,760	0.204	0.426	0.000	0.071	3.000
IOR	122,760	0.226	0.156	0.000	0.219	0.649
Ret(t-1)	122,760	0.039	0.225	−0.526	0.030	0.874
Vol(t-1) (ln)	122,760	11.478	1.466	7.371	11.435	15.016
Prc(t-1) (ln)	122,760	3.303	0.832	1.868	3.228	6.401
Market Cap(t-1) (ln)	122,760	14.147	1.595	10.469	13.989	18.500
Analyst Cover(t-1) (ln)	122,760	2.150	0.628	1.099	2.079	3.466
Sale	122,760	1.006	0.730	0.000	0.842	3.875
Intangibility	122,760	0.206	0.206	0.000	0.144	0.781
B/M	122,760	0.548	0.461	0.035	0.428	2.983
Leverage	122,760	0.863	1.697	0.000	0.391	12.484
Cash Holding	122,760	0.202	0.226	0.001	0.114	0.947
Payout	122,760	0.503	1.428	−5.406	0.157	8.456
R&D (0/1)	122,760	0.640	0.480	0.000	1.000	1.000
Advertising (0/1)	122,760	0.421	0.494	0.000	0.000	1.000
Panel B: Fund-level variables						
Net Flow (%)	85,802	0.814	13.874	−29.008	−1.643	83.106
Turnover (%)	85,802	79.364	65.557	5.000	62.000	384.370
Total Load (%)	85,802	1.596	1.861	0.000	0.976	9.655
Expense Ratio (%)	85,802	1.192	0.405	−0.510	1.152	8.890

Variables	N	MEAN	SD	MIN	P50	MAX
Fund Age	85,802	13.638	10.369	0.000	12.000	85.000
Local Investment (%)	72,655	7.359	6.913	0.000	5.174	84.402
TNA (Billion)	85,802	1.425	5.863	0.005	0.257	201.566
Team Managed (0/1)	85,802	0.304	0.460	0.000	0.000	1.000
Factor Loading Size (%)	85,802	0.113	2.182	−26.953	0.060	20.254
Factor Loading Value (%)	85,802	0.167	2.335	−71.783	0.026	37.092
Number of Stocks in Portfolio	85,802	100.482	141.550	11.000	62.000	2055.000
Fund Family Asset (Billion)	85,802	102.008	335.896	0.000	11.893	5,836.886
Fund Family Size	85,802	50.140	74.815	0.000	24.000	510.000
Stock Picking (%)	85,802	0.154	3.435	−28.387	0.007	45.141
Local Stock Picking (%)	72,655	0.006	0.740	−28.111	-0.002	41.459
Non-Local Stock Picking (%)	85,802	0.148	3.210	−27.388	0.012	26.808
Panel C: State-level demographic variables (annual)						
RRI Similarity (Orthogonalized)	1,050	0.000	0.070	−0.207	0.001	0.204
RRI NegTheil (Orthogonalized)	1,050	0.000	0.066	−0.180	0.002	0.185
RRI Exposure (Orthogonalized)	1,050	0.000	0.062	−0.174	−0.000	0.165
RRI Similarity	1,050	−0.431	0.098	−0.672	−0.439	−0.169
RRI NegTheil	1,050	−0.214	0.091	−0.470	−0.216	−0.027
RRI Exposure	1,050	0.542	0.165	0.183	0.524	0.948
White (%)	1,050	71.020	15.438	21.602	73.525	96.494
Hispanic (%)	1,050	10.431	9.780	0.679	7.348	47.736
African American (%)	1,050	9.999	9.309	0.281	6.721	36.849
Asian (%)	1,050	3.662	5.503	0.506	2.177	40.785
State Population (ln)	1,050	15.156	1.012	13.110	15.292	17.493
Senior Rate	1,050	0.141	0.024	0.053	0.139	0.216
Female Rate	1,050	0.505	0.010	0.457	0.508	0.520
Fully Segregated	1,050	0.015	0.123	0.000	0.000	1.000
Less White	1,050	0.086	0.280	0.000	0.000	1.000
Rate Poverty	1,050	0.131	0.032	0.057	0.127	0.240
Median Housing Value (ln)	1,050	11.913	0.448	10.902	11.859	13.405
Political Fragmentation (ln)	1,050	0.207	0.101	−0.054	0.203	0.529
Violent Crime	1,050	0.004	0.002	0.001	0.004	0.009
Property Crime	1,050	0.029	0.008	0.011	0.028	0.058
Trust Index	1,050	0.393	0.067	0.216	0.393	0.531
SC Index	1,050	103.893	14.921	77.256	100.001	148.606
Panel D: State-level capital market variables (quarterly)						
State Ret (%)	4,183	1.143	5.989	−43.081	1.318	54.431
State Fpd (%)	4,183	22.735	16.860	0.000	20.000	100.000
State Illiq ($\times 10^6$)	4,183	0.0843	0.410	0.000	0.0200	17.061
State MKTCAP (ln)	4,183	18.156	2.144	10.681	18.573	22.847
State Nstocks (ln)	4,183	3.717	1.463	0.000	3.689	7.062
State IO (%)	4,183	32.197	26.285	0.001	24.072	95.993

Table 2: RRI and firm-level information asymmetry

This table presents results regarding the relationship between RRI and the quality of a firms information environment. The dependent variable for columns 1-3 is analyst forecast dispersion, defined as the standard deviation of earnings forecasts divided by the average earnings forecast in a given quarter. The dependent variable for columns 4-6 is adverse selection, constructed as the component of the bid-ask spread that compensates market makers for the obligation to trade with potentially informed traders. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposur*e captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the proportions of the White, Asian, Hispanic, and Black populations, the natural logarithm of median age, median housing value, median income, and state population, poverty rate, senior citizen ratio, female ratio, zoning behavior. Controls are included in all specifications, but with coefficients reported in the Internet Appendix. Controls include firm-level characteristics (i.e., R&D disclosure dummy, advertisement disclosure dummy, leverage, intangible assets, market capitalization, sales-to-total assets, book-to-market, cash holdings, payout ratio, proportion of institutional blockholder ownership, number of covering analysts); firm-level market attributes (i.e., lagged returns, lagged price level, lagged dollar volume, lagged market cap); and state-level characteristics described in Section 2.4 (i.e., median housing value, state population, poverty rate, senior citizen ratio, female ratio, population-weighted average census tract diversity, zoning behavior, the number of publicly traded firms, the state-level ratio of dividend-paying firms, the weighted average return for firms headquartered in each state, state-level market liquidity, and state-level institutional ownership). We include for state, industry (two-digit SIC code), year, and quarter fixed effects. Standard errors are clustered at the firm level and reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	Dependent variable:					
	Analyst Forecast Dispersion			Adverse Selection		
	(1)	(2)	(3)	(4)	(5)	(6)
RRI Similarity	−0.698** (0.331)			−0.011** (0.005)		
RRI NegTheil		−0.600** (0.277)			−0.010** (0.004)	
RRI Exposure			−0.604** (0.275)			−0.010** (0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122,760	122,760	122,760	20,543	20,543	20,543
R^2	0.098	0.098	0.098	0.414	0.414	0.414

Table 3: RRI and stock price informativeness

This table shows results for the relationship between RRI and the comovement between firms' future cash flow and their market valuations. The Dependent variable for columns 1-6 is future cash flow, proxied by the earnings before interest and taxes (EBIT) in year *t+1* modified by the total asset in year *t*. The firm's market valuation, $log(M/A)$, is determined as the natural logarithm of the firm's market capitalization divided by its total assets in year *t*. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the variables listed in Table 2. Specifications in columns 1-3 exclude all controls except for *Cash Flow*, considering the persistence of cash flows over years and the need to control for autocorrelation. Specifications in columns 4-6 include all controls and interactions of firm-level features with market valuation, but coefficients of these terms are reported in the Internet Appendix. In this analysis, controls consist of firm-level features (i.e., EBIT-to-asset ratio (*Cash Flow*), leverage, invest, intangible assets, total assets, cash holdings, sales-to-asset ratio, trading dollar volume, and illiquidity) and state-level controls (i.e., state population, female ratio, senior citizen ratio, zoning behavior, state-level economic condition index developed by the Federal Reserve Bank of Philadelphia (SC Index), number of publicly traded firms, market capitalization, weighted average return for firms headquartered in the state). We control for firm and year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable:					
	Future Cash Flow (in year *t + 1*)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\frac{M}{A}\right)$	0.037*** (0.003)	0.037*** (0.003)	0.037*** (0.003)	−0.031 (0.022)	−0.030 (0.022)	−0.031 (0.022)
RRI Similarity	−0.005 (0.034)			−0.072** (0.036)		
RRI NegTheil		−0.014 (0.034)			−0.078** (0.034)	
RRI Exposure			−0.018 (0.041)			−0.086** (0.040)
$\log\left(\frac{M}{A}\right)\times$ RRI Similarity	0.041* (0.024)			0.046* (0.025)		
$\log\left(\frac{M}{A}\right)\times$ RRI NegTheil		0.042* (0.024)			0.049** (0.024)	
$\log\left(\frac{M}{A}\right)\times$ RRI Exposure			0.051* (0.029)			0.064** (0.029)
Cash Flow	0.615*** (0.027)	0.614*** (0.027)	0.614*** (0.027)	0.544*** (0.028)	0.544*** (0.028)	0.544*** (0.028)
Controls	No	No	No	Yes	Yes	Yes
Firm-level Interactions	No	No	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,224	25,224	25,224	25,224	25,224	25,224
R^2	0.387	0.387	0.388	0.430	0.430	0.430

Table 4: RRI, stock price informativeness, and active traders

The table illustrates the heterogeneity in the relationship between RRI and stock price informativeness based on active ownership. The Dependent variable for columns 1-6 is future cash flow, proxied by the earnings before interest and taxes (EBIT) in year *t+1* modified by the total asset in year *t*. The firm's market valuation, $log(M/A)$, is determined as the natural logarithm of the firm's market capitalization divided by its total assets in year *t*. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the variables listed in Table 2. Active ownership, IOR_{active}, is the proportion of equity owned by active investors divided by total shares outstanding (Kacperczyk et al., 2021). Firms are sorted into quintiles based on their level of active ownership each year, with columns 1-3 including firms from the top quintile and columns 4-6 including firms from the bottom quintile. Controls are included in all specifications, with coefficients reported in the Internet Appendix. These controls encompass the same variables listed in Table 3. Firm and year fixed effects are controlled for, and all standard errors are clustered at the firm level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable: Future Cash Flow (in year *t + 1*)					
	High IOR_{active} (top 20%)			Low IOR_{active} (bottom 20%)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\frac{M}{A}\right)$	−0.002 (0.056)	−0.003 (0.056)	−0.004 (0.055)	−0.022 (0.040)	−0.024 (0.040)	−0.025 (0.040)
RRI Similarity	−0.225** (0.099)			−0.011 (0.112)		
RRI NegTheil		−0.245*** (0.089)			−0.020 (0.102)	
RRI Exposure			−0.257** (0.109)			0.043 (0.114)
$\log\left(\frac{M}{A}\right)\times$ RRI Similarity	0.088 (0.067)			0.127** (0.050)		
$\log\left(\frac{M}{A}\right)\times$ RRI NegTheil		0.085 (0.067)			0.118** (0.052)	
$\log\left(\frac{M}{A}\right)\times$ RRI Exposure			−0.070 (0.079)			0.153** (0.064)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,048	5,048	5,048	5,048	5,048	5,048
R^2	0.348	0.348	0.347	0.371	0.371	0.371

Table 5: RRI and stock-picking abilities

This table presents findings on the relationship between RRI and mutual funds' stock-picking performances, categorized into local, non-local, and overall performances. Stock-picking ability, a quarterly portfolio-level measure, assesses funds' predictive capacity for individual stocks' alphas, computed using formula (5) in Section 2.3. Additionally, we decompose it into local and non-local components (i.e., local and non-local stock-picking abilities) based on the state of the fund's headquarters relative to the state of the firm's headquarters. The dependent variables are local stock-picking ability for columns 1-3, non-local stock-picking ability for columns 4-6, and overall stock-picking ability for columns 7-9. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the same variables listed in Table 2. Controls are included in all specifications, with coefficients reported in the Internet Appendix. These controls consist of fund-level controls (i.e., trading style, net flow, turnover ratio, fund load, fund age, expense ratio, total net assets, number of managers, an indicator for funds with more than four managers, number of share classes in the fund family, and total net assets of the fund family) and the same state-level controls as listed in Table 2. State, year, and quarter fixed effects are controlled for, and all standard errors are clustered at the fund level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variables:								
	Local Stock-picking Ability			Non-local Stock-picking Ability			Stock-picking Ability		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RRI Similarity	−0.065***			−0.021			−0.086***		
	(0.006)			(0.030)			(0.032)		
RRI NegTheil		−0.067***			−0.012			− 0.078***	
		(0.006)			(0.024)			(0.026)	
RRI Exposure			−0.061***			−0.012			− 0.073***
			(0.006)			(0.024)			(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,655	72,655	72,655	72,655	72,655	72,655	72,655	72,655	72,655
R^2	0.035	0.036	0.035	0.179	0.179	0.179	0.182	0.182	0.182

Table 6: RRI, stock-picking abilities, and business cycles

This table presents results on how the relationships between Racial Residential Integration (RRI) and stock-picking performances vary across different economic conditions. Panel A displays results for economic expansions, while Panel B presents results for recessions. Recession years are identified as those with at least six recession months, as indicated by the NBER recession indicator, and the remaining years are classified as expansion years. Stock-picking ability and local stock-picking ability are defined in the same manner as in Table 5. The dependent variable for columns 1-3 is local stock-picking ability, and for columns 4-6, it is overall stock-picking ability. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the same variables listed in Table 2. All RRI measures are orthogonalized by the same variables listed in Table 2. All specifications include the control variables listed in Table 5, with coefficients reported in the Internet Appendix. State, year, and quarter fixed effects are controlled for, and all standard errors are clustered at the fund level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable:					
	Local Stock-picking Ability			Stock-picking Ability		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Expansion years						
RRI Similarity	−0.075***			−0.136***		
	(0.008)			(0.033)		
RRI NegTheil		−0.076***			−0.121***	
		(0.007)			(0.027)	
RRI Exposure			−0.072***			−0.114***
			(0.007)			(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,646	60,646	60,646	60,646	60,646	60,646
R^2	0.036	0.037	0.036	0.188	0.188	0.188
Panel B: Recessions years						
RRI Similarity	−0.069***			−0.101		
	(0.014)			(0.075)		
RRI NegTheil		−0.078***			−0.049	
		(0.013)			(0.064)	
RRI Exposure			−0.074***			−0.036
			(0.014)			(0.065)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,009	12,009	12,009	12,009	12,009	12,009
R^2	0.088	0.089	0.088	0.209	0.209	0.209

Table 7: Racial backgrounds of mutual fund managers

This table presents results on how relationships between RRI and stock-picking performances vary by the race of fund managers, with Panel A displaying results for white mutual fund managers and Panel B for minority managers. To qualify for inclusion in this table, mutual funds must have only one manager. The race of fund managers is determined using the NamePrism application, which identifies one's race based on their name, as detailed in Section 4.2. Stock-picking ability and local stock-picking ability are defined in the same manner as in Table 5. The dependent variable for columns 1-3 is local stock-picking ability, and for columns 4-6, it is overall stock-picking ability. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the same variables listed in Table 2. All specifications include the control variables listed in Table 5 and additional controls for gender and work experience, with coefficients of all these controls reported in the Internet Appendix. State, year, and quarter fixed effects are controlled for, and all standard errors are clustered at the fund level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable:					
	Local Stock-picking Ability			Stock-picking Ability		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: White mutual fund managers						
RRI Similarity	−0.083*** (0.018)			−0.212*** (0.075)		
RRI NegTheil		−0.094*** (0.016)			−0.178*** (0.021)	
RRI Exposure			−0.085*** (0.017)			−0.143** (0.065)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,959	15,959	15,959	15,959	15,959	15,959
R^2	0.054	0.056	0.055	0.196	0.196	0.195
Panel B: Minority mutual fund managers						
RRI Similarity	−0.053 (0.041)			−0.165 (0.290)		
RRI NegTheil		−0.033 (0.040)			−0.176 (0.238)	
RRI Exposure			−0.029 (0.043)			−0.181 (0.240)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	934	934	934	934	934	934
R^2	0.100	0.099	0.099	0.255	0.255	0.255

Table 8: A placebo test using index funds

This table presents results for the relationship between RRI and stock-picking performances, exclusively focusing on index funds. We identify pure index funds using the fund investment objectives in the CRSP mutual fund database. Stock-picking ability and local stock-picking ability are defined in the same manner as in Table 5. The dependent variable for columns 1-3 is local stock-picking ability, and for columns 4-6, it is overall stock-picking ability. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the same variables listed in Table 2. All specifications include the control variables listed in Table 5, with coefficients reported in the Internet Appendix. State, year, and quarter fixed effects are controlled for, and all standard errors are clustered at the fund level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable:					
	Local Stock-picking Ability			Stock-picking Ability		
	(1)	(2)	(3)	(4)	(5)	(6)
RRI Similarity	−0.009 (0.013)			0.013 (0.107)		
RRI NegTheil		−0.013 (0.009)			0.078 (0.078)	
RRI Exposure			−0.014 (0.008)			0.104 (0.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,645	7,645	7,645	7,645	7,645	7,645
R^2	0.062	0.062	0.062	0.181	0.182	0.182

Table 9: RRI and social trust

This table presents the relationship between RRI and funds' stock-picking performances with an additional control for social trust. The social trust index, developed by Wei and Zhang (2020), is constructed using data from the World Values Survey. Stock-picking ability and local stock-picking ability are defined in the same manner as in Table 5. The dependent variable for columns 1-3 is local stock-picking ability, and for columns 4-6, it is overall stock-picking ability. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All specifications include the control variables listed in Table 5, with coefficients reported in the Internet Appendix. State, year, and quarter fixed effects are controlled for, and all standard errors are clustered at the fund level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable:					
	Local Stock-picking Ability			Stock-picking Ability		
	(1)	(2)	(3)	(4)	(5)	(6)
RRI Similarity	−0.075*** (0.007)			−0.074** (0.032)		
RRI NegTheil		−0.070*** (0.007)			−0.066** (0.026)	
RRI Exposure			−0.062*** (0.006)			−0.067** (0.026)
Trust Index	0.010*** (0.002)	0.008*** (0.001)	0.009*** (0.001)	0.018** (0.006)	0.016** (0.006)	0.016** (0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,655	72,655	72,655	72,655	72,655	72,655
R^2	0.036	0.037	0.036	0.183	0.183	0.183

Table 10: RRI and stock-picking performance using ACS data

This table shows the relationship between RRI and funds' stock picking performances, utilizing data from the ACS-one-year survey available annually since 2005. The ACS-one-year survey provides race data by Public Use Microdata Area (PUMA), a geographic unit significantly larger than census tracts. For context, in 2020, there were 74,001 census tracts and 2,378 PUMAs (US Census Bureau, 2021). The larger size of PUMAs relative to census tracts diminishes the reliability of our RRI measures by making variations across subunits less observable, particularly for the exposure index. Stock-picking ability and local stock-picking ability are defined in the same manner as in Table 5. The dependent variable for columns 1-3 is local stock-picking ability, and for columns 4-6, it is overall stock-picking ability. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. In this table, all RRI measures are population-weighted averages representing aggregated integration based on three racial pairs ("African American-white," "Asian-white," and "Hispanic-white"). These measures are orthogonalized by the same variables listed in Table 2. All specifications include the control variables listed in Table 5, with coefficients reported in the Internet Appendix. State, year, and quarter fixed effects are controlled for, and all standard errors are clustered at the fund level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable:					
	Local Stock-picking Ability			Stock-picking Ability		
	(1)	(2)	(3)	(4)	(5)	(6)
RRI Similarity	−0.024***			−0.037**		
	(0.003)			(0.016)		
RRI NegTheil		−0.026***			−0.034*	
		(0.003)			(0.019)	
RRI Exposure			−0.020***			-0.019
			(0.005)			(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,782	55,782	55,782	55,782	55,782	55,782
R^2	0.033	0.033	0.032	0.132	0.132	0.132

Table 11: Geographical fund-clustering

This table examines the relationship between Racial Residential Integration (RRI) and mutual funds' stock-picking performance, with a sample excluding all mutual funds headquartered in New York, California, and Massachusetts. These three states account for over 50% of the mutual funds in our original sample. Stock-picking ability and local stock-picking ability are defined in the same manner as in Table 5. The dependent variable for columns 1-3 is local stock-picking ability, and for columns 4-6, it is overall stock-picking ability. *RRI Similarity* and *RRI NegTheil* capture the evenness dimension of racial integration. *RRI Exposure* captures the exposure dimension of racial integration. All RRI measures are orthogonalized by the same variables listed in Table 2. All specifications include the control variables listed in Table 5, with coefficients reported in the Internet Appendix. State, year, and quarter fixed effects are controlled for, and all standard errors are clustered at the fund level, reported in parentheses. Note: *p <0.1; **p <0.05; *** p <0.01

	Dependent variable:					
	Local Stock-picking Ability			Stock-picking Ability		
	(1)	(2)	(3)	(4)	(5)	(6)
RRI Similarity	−0.049*** (0.008)			−0.065* (0.037)		
RRI NegTheil		−0.051*** (0.007)			−0.078** (0.035)	
RRI Exposure			−0.047*** (0.006)			−0.078** (0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,277	35,277	35,277	35,277	35,277	35,277
R^2	0.040	0.040	0.040	0.193	0.193	0.193