Political Divide and the Composition of Households' Equity Portfolios*

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Abstract

We examine the differences in the stock holdings of wealthy households in different counties of the U.S. with different political preferences over the past 25 years. Although political differences between counties have been increasing since at least 1996, it is not until 2013 when they started to increasingly and significantly contribute to differences in equity portfolio composition. Using the entry of a major conservative media network as a shock to county-level political preferences, we find evidence for a causal effect of political differences. We show that the effect of political differences on portfolio differences operates mainly through diverging political views on social and environmental issues rather than differences in economic expectations. Our study suggests that political polarization could reduce risk sharing and segment U.S. equity markets by political lines and – given the partisan segregation – geographical lines.

Keywords: Political preference, political polarization, equity portfolio composition, ESG **JEL Classification:** G11, G41, G50

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1 Introduction

Increasing political polarization in the U.S. is not only hindering political compromise on many important policy issues, but also affecting an ever larger number of choices – whether to wear a mask during the Covid-19 pandemic, what food to consume, what car to drive, as well as where to live. Indeed, partisan location choices contribute to pronounced regional clustering of households with similar political views (Bishop (2008)).¹ Could regional differences in political preferences also lead to differences in individuals' demand for financial assets and thereby possibly to a divergence in the composition of households' equity portfolios across the U.S.?

To answer this question, we examine the relationship — over the past 25 years — between differences in county-level equity portfolios of wealthy households and differences in political preferences between these counties. The geographic lens of our approach is motivated by the increasing partian segregation in the U.S., where neighborhoods and counties increasingly associate with one or the other party (Brown and Enos (2021); McCartney, Orellana-Li, and Zhang (2021)) as well as by the influence of local norms and local social interactions on households' financial decisions (Brown et al. (2008)).

Our empirical analysis is derived from a simple conceptual framework. We assume that political preferences of investors can affect individual stocks' portfolio weights, tilting them away from market weights, as Democratic- or Republican-leaning investors over- or underweigh certain stocks. We show that the average degree of partian disagreement across all stocks can be recovered from a regression of differences in county-level portfolio composition on differences in county-level political preferences.

In order to implement our empirical approach, we collect the direct equity holdings from the 13F filings of local independent investment advisers that predominantly cater to individual as opposed to institutional investors. We then derive county-year portfolio weights for all stocks as the equal-weighted average portfolio weights of all advisers in a given county and year. While investment advisers may offer one or a few "house portfolios" to all clients, they usually accommodate clients' preferences, often expressed via investment restrictions and mandates. Thus, the average portfolio weight for a stock in a given county could reflect the average partian deviation from the market due to local clients' political preferences.

¹Bishop (2008) argues that over several decades Americans have sorted themselves into extremely homogeneous communities. "We have been choosing the neighborhoods, news shows, and places of worship that most closely reflect our individual values. As people in like-minded communities grow more extreme and firm in their beliefs, we are left with a country of neighborhoods and towns that are so polarized ...that people don't know and can't understand those who live just a few miles away."

For each year, we measure the difference in portfolio composition between two counties as the county-pair *Portfolio Distance*, which is the sum of the absolute differences between the county-level portfolio weights across all investable out-of-state stocks.² Our full sample consists of 39,517 unique county-pairs with non-missing data between 1997 and 2019, representing 309 U.S. counties that house 55% of the U.S. population. As the number of investment advisers and therefore the number of counties with non-missing data increases over time, we also consider a balanced sample of unique 4,371 county-pairs, representing 94 relatively large counties housing 30% of the U.S. population.

We proxy for the political preferences of investors in a county using county-level voting outcomes in U.S. presidential elections. To measure differences in political preferences between two counties, we construct *Political Distance* as the sum of the absolute differences in two counties' fractions of votes for the Republican, Democratic, and Independent candidates in the US presidential elections between 1996 and 2020. Figure 1a shows that the average political distance between all possible U.S. county-pairs has been steadily increasing over the past 25 years, leading to a 40% higher political distance in 2020 compared to 1996.

Our conceptual framework suggests that a regression of *Portfolio Distance* on *Political Distance* can recover the average degree of partian disagreement across all stocks in the form of the estimated coefficient on *Political Distance*. Taking advantage of our long time series, we find that the estimated partian disagreement in wealthy households' equity portfolios was small and statistically insignificant before 2013, but has become increasingly large and significant since 2013 (see Figure 2).

Our finding is robust to the inclusion of a large number of controls, related to county-pair differences with respect to industry composition, income, education, religious affiliations as well as the number of advisers. It holds when we construct portfolio differences simply as the fraction of stocks that are held in one county but not in the other as well as when we use the self-reported political leanings of local high-income (i.e., above county median) households as opposed to presidential election results to measure political distance.

To strengthen the causal interpretation of the documented impact of political distance, we exploit the staggered entry of Sinclair Broadcast Group, a large conservative TV network, into different local media markets during our sample period. Sinclair's entry has been shown to increase the voting share for the Republican party (Martin and Yurukoglu (2017), Levendusky (2022)). Using a difference-in-differences approach, we confirm that Sinclair's

²See Cronqvist and Siegel (2014) and Aiken, Ellis, and Kang (2020) for similar approaches to compare portfolio compositions. To minimize the effect of investors' home bias on the bilateral portfolio distance, we exclude stocks of firms headquartered in the state of either of the two counties in a county pair.

entry into a media market does not correlate with any pre-existing trend in local political preferences, yet it increases the local Republican vote share in presidential elections postentry, leading to a change in political distance between counties with and without Sinclair entry. Importantly, we also find a consistent change in the portfolio distance of treated county-pairs, whose political distance changes due to Sinclair's entry, relative to control county-pairs without a Sinclair entry.

Our results suggest that political preferences shape investors' portfolio choice and that since 2013 political differences between counties translate into portfolio differences. In the last part of the study, we analyze several possible mechanisms underlying these effects. On the one hand, investors' political preferences may be correlated with their perception of economic conditions or regulatory risks for certain industries and firms, which can influence households' financial investment decisions (e.g., Meeuwis et al. (2022); Goldman, Gupta, and Israelsen (2022)). We call this mechanism *the expectations channel*. On the other hand, political preferences may be correlated with investors' social and environmental preferences, which may influence their stock portfolios, as suggested by the rise of values-based investing. Political preferences may also affect portfolio choice if they shape attitudes towards firms based on the political affiliation of firms' leaders. We call both of these mechanisms *the preference channel*.

Using Gallup survey data on high-income households' macroeconomic expectations, we find that differences in expectations across counties contribute to differences in their equity portfolios, but it appears to explain only a small part of the political distance effect on portfolio distance. To examine the preference channel, we use the Gallup survey data to confirm the widening gap between self-identified Democrats and Republicans in their attitudes towards environmental protection, labor protection, and gun control. Given that investment advisers cater to clients' preferences mainly by excluding certain investment as requested by their clients, we focus on "under-weighting" in our analysis. We show that relative to more Republican-leaning counties, more Democratic-leaning counties invest significantly less in firms associated with environmental concerns, labor-related concerns, and the production of civilian firearms, particularly in the later part of the sample period.

However, Democrats and Republicans could have different perceptions of regulatory risks related to these environmental and social issues. For example, compared to Republicans, Democrats expect weaker environmental regulations during a Republican presidency relative to a Democratic presidency. Therefore, under the economic expectations channel, Democratic-leaning investors should hold more stocks with environmental or social concerns during a Republican presidency relative to a Democratic presidency. However, we find the opposite. Consistent with the preference but not the expectations channel, Democraticleaning investors seem to underweight environmentally or socially problematic firms even more under a Republican presidency, presumably because they expect those firms to pose more harm to the environment or the society when regulation is lax.

Finally, we examine whether political preferences affect allocation decisions based on firms' perceived political affiliation. Using data for political campaign contributions of executives in S&P 1500 firms (Fos, Kempf, and Tsoutsoura (2021)), we show that investors in more Republican-leaning counties underweight firms with Democratic-leaning CEOs relative to those in more Democratic-leaning counties, especially in recent years, consistent with the increasingly unfavorable views of the other party.

Our study is related to an emerging literature on the impact of political views on financial decisions and the consequences of political divisions. While some studies examine the recommendations or investment decisions of Democratic versus Republican analysts (Kempf and Tsoutsoura (2021)), portfolio managers (Hong and Kostovetsky (2012); Wintoki and Xi (2020)) or politicians (Aiken, Ellis, and Kang (2020)), others document a negative impact of political divide within teams of mutual fund managers on fund performance (Vorsatz (2021); Evans et al. (2022)). Our focus is on the relationship between increasing partian segregation in the U.S. and differences in households' equity portfolio compositions. The long time series of our sample allows us to study the evolution of this relationship and to identify an important shift around 2013.

Furthermore, several recent papers show that Democratic-leaning and Republican-leaning investors take different amounts of equity risk due to different economic beliefs following the 2016 presidential election (Meeuwis et al. (2022)) or during the Covid-19 pandemic (Cookson, Engelberg, and Mullins (2020); Sheng, Sun, and Wang (2021)).Our study highlights the role of politically shaped environmental and social preferences in explaining differences in households' equity portfolio composition. Our study thereby also provides support for the importance of investors' non-financial preferences in determining portfolio composition and asset demand (see, for example, Riedl and Smeets (2017); Hartzmark and Sussman (2019); Krueger, Sautner, and Starks (2020); Barber, Morse, and Yasuda (2021); Pan et al. (2022)).

Finally, previous studies have highlighted that geographic differences in investment choices can arise due to home bias (Pool, Stoffman, and Yonker (2012)), differences in the religious make-up (Kumar, Page, and Spalt (2011)), or exposure to different social interactions (Brown et al. (2008); Pool, Stoffman, and Yonker (2015)) or media networks (Burt (2019)). We show that geographic political divisions can also induce variation in households' portfolio composition. Politically induced differences in equity portfolios could reduce risk sharing and segment the U.S. equity markets along the partian lines and — given partian segregation — geographical lines.

The remainder of the paper is organized as follows. Section 2 describes our conceptual framework of the relationship between political and portfolio distance as well as data used to construct both distances. Section 3 explores the effect of political differences on portfolio differences across the U.S. counties over time. Section 4 examines the role of partian differences in economic expectations and in environmental and social values in explaining the effect of political distance on portfolio distance. Section 5 concludes.

2 Political Distance and Portfolio Distance: Conceptual Framework and Data

2.1 Conceptual Framework

We introduce the concepts of political distance and portfolio distance between two geographical locations (e.g., counties) and, under a few simplifying assumptions, derive the relation between these two distances.

We assume that investors are homogeneous except for their political preferences and their likelihood of living in a given county. Thus, there are three types of investors, Republicanleaning, Democratic-leaning, and Independent, whose relative distribution varies across counties. Politically independent investors hold a given stock *i* using its politically-neutral benchmark weight such as the market weight (w_o^i) . In contrast, Democratic-leaning and Republican-leaning investors might deviate from the benchmark weight, by over- or underweighting a given stock by factor δ^i for Democratic-leaning investors and ρ^i for Republicanleaning investors, such that, the portfolio weight for stock *i* for a Democratic-leaning investor is $w_d^i = \delta^i w_o^i$ and $w_r^i = \rho^i w_o^i$ for a Republican-leaning investor. We assume that investors do not short-sell stocks and all weights are non-negative. The weight of stock *i* in county A (w_A^i) therefore depends only on the fraction of Democratic-leaning (d_A) , Republican-leaning (r_A) , and Independent $(o_A \equiv 1 - d_A - r_A)$ investors, such that $w_A^i = d_A w_d^i + r_A w_r^i + o_A w_o^i$. Similarly, the weight of stock *i* in county B's portfolio is $w_B^i = d_B w_d^i + r_B w_r^i + o_B w_o^i$.

We summarize the differences in portfolio composition across all stocks between counties A and B as the sum of the absolute differences between the stock portfolio weights (i.e., the L1 norm of the two vectors of portfolio weights), which we call *portfolio distance*:

$$Portfolio \ Distance_{AB} = \sum_{i=1}^{N} |w_A^i - w_B^i|, \tag{1}$$

where N is the set of all investable stocks.

Similarly, we define the political distance between counties A and B as the sum of the absolute differences between the fractions of Democratic-leaning, Republican-leaning, and Independent investors (i.e., the L1 norm of the two vectors of political preferences):

$$Political \ Distance_{AB} = |d_A - d_B| + |r_A - r_B| + |o_A - o_B|.$$
(2)

If in counties A and B the fractions of Independent investors are approximately the same $(o_A \approx o_B \text{ or equivalently } d_A - d_B \approx -(r_A - r_B))$, then *Political Distance*_{AB} $\approx 2|d_A - d_B|$. We can use this approximation and rewrite the absolute difference in equity portfolio weights between counties A and B for a stock *i* as:

$$\begin{split} |w_A^i - w_B^i| = & |d_A w_d^i + r_A w_r^i + o_A w_o^i - d_B w_d^i - r_B w_r^i - o_B w_o^i \\ \approx & w_o^i \times |d_A \delta^i + r_A \rho^i - d_B \delta^i - r_B \rho^i| \\ = & w_o^i \times |\delta^i (d_A - d_B) + \rho^i (r_A - r_B)| \\ = & |d_A - d_B| \times w_o^i |\delta^i - \rho^i| \\ = & \frac{1}{2} Political \ Distance_{AB} \times w_o^i |\delta^i - \rho^i|. \end{split}$$

Therefore, we can rewrite Equation (1) as:

$$Portfolio \ Distance_{AB} = \frac{1}{2} Political \ Distance_{AB} \sum_{i=1}^{N} w_o^i |\delta^i - \rho^i|.$$
(3)

For a given stock *i*, the partisan portfolio disagreement between Democratic- and Republicanleaning investors is captured by $|\delta^i - \rho^i|$. Equation (3) implies that *Portfolio Distance* is a product of *Political Distance* and the weighted-average of the partisan portfolio disagreement across all stocks in the two counties' equity portfolios. Therefore, if we regress *Portfolio Distance* on *Political Distance*, the regression coefficient would capture the importance of partisan portfolio disagreement. A significant regression coefficient estimate would suggest significant portfolio disagreement between Democratic- and Republican-leaning counties, and the magnitude of the coefficient estimate and its evolution over time would indicate the degree and the trend of partisan portfolio disagreement.

2.2 Measuring Portfolio Distance

To capture equity portfolios of investors across counties in the U.S. over a long period of time, we construct a novel stock holding data set from the 13F filings of local independent investment advisers that predominantly cater to individual as opposed to institutional investors. We aggregate the stock-level portfolio weights across all local retail investment advisers in a given county-year and use the county-year-level data to compare equity portfolio compositions between different counties over time. While the clients of investment advisers are likely wealthier than the median investor in a given county, they provide us with the opportunity to observe the portfolio composition of at least one, arguably important set of individual investors in the U.S. over a time period that is longer than that of any other generally available data set of U.S. investors' portfolio composition.

2.2.1 Local Investment Advisers

Since 2001, all U.S. investment advisers file Form ADV with the SEC and provide information about the number of their individual and institutional clients, their total assets under management (AUM), and their office locations (see Appendix A for details). We collect data from Form ADV filings for all U.S. advisers directly from the SEC between 2001 and 2019.

We identify advisers that primarily cater to individuals by requiring that the fraction of individual clients and high-net-worth individuals in a given year is no less than 50% of the adviser's client base.³ From 2012 onward, advisers report the AUM by type of client, which allows us to verify that the fraction of individual clients based on client counts and that based on AUM exhibit a high correlation of 91%. To focus on advisers who serve local households, we exclude adviser-year observations when an adviser reports office locations in more than one MSA and retain about 53% of the observations that belong to local retail advisers.

Finally, we combine the local adviser data with holdings data from Thomson Reuters Global Ownership database for 1997-2019.⁴ The database includes data from 13F filings for those advisers with more than \$100 million in Section 13F securities, such as domestic stocks, ADRs, and exchange-traded funds (ETFs). We can identify holding records for about

³We also retain up to two consecutive adviser-years that do not meet these criteria as long as the adviser is included in the sample immediately before and after those years.

⁴For years 1997-2000, we backfill Form ADV data from 2001 as adviser characteristics are time persistent.

17% of our sample of local advisers. Thus, the investment advisers in our sample serve predominantly local individual clients, but they are large enough to report their holdings with the SEC.

Section 13F filings exclude fixed income securities, mutual funds, as well as private securities. To ensure that the 13F holdings provide a meaningful description of an adviser's portfolio composition, we restrict our sample advisers to those whose 13F holdings are at least 50% of their total AUM reported in Form ADV.⁵

Our final sample of local investment advisers consists of 12,411 adviser-year observations between 1997 and 2019, representing 1,654 unique advisers in 309 counties. Based on the summary statistics in Appendix Table C1, their average (median) number of accounts is 1,576 (435) and the average (median) AUM is \$1.6 (\$0.4) billion.⁶ For comparison, Edward Jones, a nationally operating retail investment adviser that is not in our sample, reports about 533,000 accounts and an average AUM of \$75 trillion between 2000 and 2019. Dividing the AUM of the advisers in our sample by the number of accounts, we obtain an average (median) account size of \$4.8 (1.0) million. For comparison, the average account size for the same time period reported by Edward Jones is \$0.4 million. Overall, a typical investment adviser in our sample serves a relatively small number of relatively wealthy local households.

2.2.2 Portfolio Composition

On average, we observe about 73% of advisers' assets under management through their 13F filings (see Appendix Table C1). For purposes of characterizing investors' portfolios and detecting differences shaped by political preferences, we focus on equities, i.e., domestic stocks and ADRs, among the 13F securities. Equities make up the largest fraction of advisers' portfolios, accounting for approximately 60% of total (ADV) AUM and 85% of 13F assets.⁷

The average adviser portfolio contains about 122 equities. While investment advisers likely affect the selection of stocks, often by providing one or a limited number of "house" portfolios, advisers also cater to their clients' preferences. Indeed, many advisers explicitly

⁵We use values for a given reporting year as well as the rolling 3-year median. In a few cases, we again retain up to two consecutive adviser-years that do not meet these criteria as long as the adviser is included in the sample immediately before and after those years. The value of 13F holdings can exceed the total AUM reported in Form ADV in case of large short positions. Given that such advisers are unlikely to serve individual clients, we exclude from the sample advisers whose 13F holdings exceeds 110% of their total AUM.

⁶Given our selection criteria, the average (median) fraction of individual clients is 85% (93%) based on client counts and 81% (81%) based on AUM. All variable definitions are provided in Appendix B.

 $^{^{7}}$ ETFs, which have been increasing over time to about 20% in 2019 on average, comprise about 8% of total AUM. Other securities, such as mutual funds and fixed-income securities, make up remaining 32% of total AUM. However, these holdings are not included in the 13F filings and thus not observable to researchers.

acknowledge clients' input through investment restrictions and exclusions in Item 16 of Part 2 of their ADV filings. For example, Tieton Capital Management, an independent adviser in Yakima, WA with \$110 millions in AUM, states that their "services are tailored to each individual client's requirements. This is done by allowing clients to identify individual security restrictions, or other requested restrictions. The most common restrictions prohibit us from buying specific companies or social restrictions." Similarly, Robinson Value Management in San Antonio, TX, with \$120 million in AUM says that their "clients may impose restrictions on investing in certain securities or types of securities." In conversations with several other advisers in our sample, advisers have confirmed the increasing importance of recognizing clients non-financial preferences. Thus, stock-level portfolio weights in advised portfolios should provide insights into local investors' beliefs and preferences.

To summarize the revealed preferences of investors in a given county, we average portfolio weights for all stocks across all investment advisers headquartered in given county. Specifically, stock k's weight in county A is computed as:

$$w_{A,t}^{k} = \frac{1}{I_{A,t}} \sum_{i=1}^{I_{A,t}} w_{A,t,i}^{k},$$

where $I_{A,t}$ is the number of investment advisers in county A in year t in our sample.

We obtain a "full sample" of 3,848 county-year observations with 309 unique counties between 1997 and 2019. To maintain comparability over time, in some of our analyses we rely on a "balanced sample" of 94 counties that consistently appear in our sample from 2001 to 2019.⁸ On average, there are 3.2 (4.6) investment advisers per county in the full (balanced) sample and the median number of advisers is 2 in both samples.

While the 309 counties in the full sample represent only 10% of all U.S. counties,⁹ Appendix Table C2 Panel A shows that, based on U.S. Census data from 1990, 2000, and 2010, they account for 54.7% of the U.S. population, 61.5% of the income, and 60.4% of college graduates. Similarly, the 94 counties in the balanced sample account for 29.1% of the population, 33.9% of the income, and 32.3% of college graduates. That is, the counties in our samples are of economic importance, but also represent meaningful geographic dispersion. Panel B of Appendix Table C2 shows that in comparison to the population of all U.S. counties, the Democratic vote share in presidential elections between 1996 and 2016 is larger in our sample, especially in the case of the balanced sample. However, our sample displays

⁸Most but not all 94 counties are consistently present between 1997 and 2000.

⁹See Appendix Table C3 for the average number of counties per year for each U.S. state with at least one county-year in the full sample.

about the same level of variation as do all U.S. counties.

2.2.3 County-pair Portfolio Distance

To compare the portfolio composition between counties A and B, we construct the distance between their out-of-state equity portfolio weights according to Equation (1), i.e., the L1 norm:

$$Portfolio \ Distance_{AB,t} = \sum_{k=1}^{N_{AB,t}} |w_{A,t}^k - w_{B,t}^k|,$$

where $N_{AB,t}$ is the set of out-of-state stocks held by households in either county A or B. For example, when we compute the distance between Orange County, CA and El Paso County, CO, we exclude their stock holdings of firms headquartered in California and Colorado, and $N_{AB,t}$ includes all the out-of-state stocks observed in the advised portfolios in Orange County, CA and El Paso County, CO.¹⁰ The weight of out-of-state stock k in the portfolio of county A(B) in year t is $w_{A,t}^k(w_{B,t}^k)$. Then, all weights are rescaled such that they add up to one.

To alleviate potential concerns that portfolios could be dominated by large stocks, for robustness purposes we employ an alternative distance measure, the L0 norm, defined as follows:

$$Portfolio \ Distance_{AB,t}^{Alt} = 2 \cdot \frac{1}{N_{AB,t}} \sum_{k=1}^{N_{AB,t}} |\mathbb{1}_{A,t}^k - \mathbb{1}_{B,t}^k|,$$

where $\mathbb{1}_{A,t}^k$ ($\mathbb{1}_{B,t}^k$) is an indicator variable that equals 1 if stock k is in the portfolio of county A(B) in year t and 0 otherwise, for all out-of-state stocks held by households in counties A and B. In essence, the alternative portfolio distance measure is based on whether stocks are present in a given portfolio, while our main portfolio distance measure is based on stock weights. We rescale *Portfolio Distance*^{Alt} such that it is bounded between 0 and 2.

Table 1 provides summary statistics for the two portfolio distance measures at the countypair-year level for the full and balanced samples. Figure 3 shows the evolution of the portfolio distances over the entire sample period from 1997 to 2019, for the two samples. We observe a declining trend in county-pair portfolio distances over time in both the full and balanced samples, suggesting convergence in households' advised equity portfolios across different

¹⁰We exclude stocks of firms with headquarters in the same state for two reasons. First, home bias in households' portfolio choices has been well documented (Coval and Moskowitz (1999); Karlsson and Nordén (2007)). Second, in-state equity holdings are often related to employee stock compensation. Since we are interested in examining the impact of local political preferences on portfolio choices, we want to mitigate the impact of factors that are not driven by political preferences.

geographic areas. For example, according to our *Portfolio Distance* measure the average county-pair distance drops from 1.65 to 1.35 (from 1.70 to 1.50) in the balanced (full) sample over the sample period, which is equivalent to an 18.2% (11.8%) decrease. The decline in the count-based portfolio distance measure (*Portfolio Distance^{Alt}*) is more moderate, 9.0% (5.2%) in the balanced (full) sample.

2.3 Measuring Political Distance

For each county-pair A and B, we construct their political distance according to Equation (2). To capture d, r, and o in a county-year, we use the county-level voting shares for the Democratic, the Republican, and other candidates in presidential elections from 1996 to 2016. The voting data is from the MIT Election Lab. The voting outcomes reflect the political climate in a county, which should reflect local households' political preferences on average. Panels (a), (b) and (c) of Figure 1 plot the time trend of the average *Political Distance* for all county-pairs in the U.S. as well as for the county-pairs in the full and balanced samples.¹¹ Consistent with what has been documented in the political science literature (e.g., Boxell, Gentzkow, and Shapiro (2017)), we observe a clear upward trend in *Political Distance*, especially in more recent presidential election cycles.

Our assumption is that the distribution of political preferences among the investors who are clients of local investment advisers is similar to that of the voters in the county. However, the households in our sample tend to be wealthier than an average household in a county. If wealthier households tend to lean towards one party (e.g., the Republican Party), then the political distance between the wealthier people in two counties could be smaller than that between all voters.

To assess the validity of our assumption with respect to using the voting data and for robustness purposes, we also use data from Gallup U.S. Daily surveys. Gallup U.S. Daily surveys were introduced in 2008 and conduct daily surveys on a large representative sample of individuals across the U.S. counties every year, with an average number of respondents of more than 331,000 per year. Each Gallup survey asks respondents about their political affiliation: "In politics, as of today, do you consider yourself a Republican, a Democrat, or an Independent?" The Gallup surveys also have self-reported information about family income (in income brackets), which allows us to compare the distribution of political prefer-

¹¹Note that in the full sample, the political distance may not be identical within a presidential election cycle because the number of counties and thus county-pairs can vary from year to year.

ences between all respondents and high-income respondents.¹² We define respondents with family income above (below) the county median as high-income (low-income) individuals. Information about county-year median family income comes from the U.S. Census Bureau.

As reported in Panel B of Table 1, in the balanced sample, the political distance measures based on the voting data and that based on Gallup survey data (all respondents, PD Gallup All) have similar distributions. The political distance between high-income people in a county-pair (PD Gallup High Income) is actually slightly larger, rather than smaller, compared to that between all respondents. The three political distance measures are also highly correlated. The correlation between Political Distance and PD Gallup All in a three-year window around a presidential election year (the average political distance from the year before until the year after) is 0.90. If we use PD Gallup High Income, then the correlation becomes 0.81. Thus, the political distance measure based on the voting data is consistent with alternative measures of political preferences, including preferences of high-income households.

3 The Effect of Political Distance on Portfolio Distance

3.1 Main Results

In our baseline specification, we relate the portfolio distance between counties A and B in year t to their political distance as captured by the most recent presidential election voting outcome before year t. Recall that based on our model, the coefficient estimate for political distance is directly proportional to the weighted average portfolio disagreement between Democrats and Republicans (see equation (3)). Specifically, we estimate:

$$Portfolio \ Distance_{AB,t} = a + bPolitical \ Distance_{AB,t-1} + cFE_t + dFE_{AB} + e_{AB,t}$$
(4)

Year fixed effects, FE_t , are included to absorb time trends in both political and portfolio distances. County-pair fixed effects, FE_{AB} , absorb persistent cross-county differences, so that we capture the effect of time-varying political distance on portfolio distance. Standard errors are double clustered by each county in a county pair.¹³

¹²Although the Gallup Poll Social Series, which started in 2001, also provide information about respondents' political preferences and family income, they are conducted monthly with a much smaller number of respondents (about 1,000 individuals) and thus do not provide good representation at the county level.

¹³We find similar results when using dyadic clustering.

Table 2 Panel A reports the results for the full sample (columns (1) and (2)) and the balanced sample (columns (3) and (4)). The estimated coefficients on *Political Distance* are positive and significant in all specifications, suggesting that county-pairs with a larger difference in political preferences tend to have a larger difference in households' equity portfolios. The economic magnitude is the largest in column (4), when we focus on the balanced sample and the time-varying component in political distance. A one-standard-deviation increase in the county-pair political distance is associated with a 0.028 (= 0.130×0.212) increase (or a 12% standard-deviation increase) in the county-pair equity portfolio distance.

To examine the time-series trend in the relation between political distances and portfolio distances, we estimate the specification in column (3) yearly for each year between 1997 and 2019, using the balanced sample. We then plot the estimated coefficients on *Political Distance* over time in Figure 2. Visual inspection reveals an interesting pattern. Before 2013, the estimated impact of political distance on portfolio distance is small and statistically insignificant. In 2013, it exhibits a clear jump and then becomes increasingly larger and statistically significant after 2013. The average coefficient estimate is 0.005 before 2013, while it is 0.198 in 2019, suggesting a 40-fold increase in partian portfolio distance adjusted for the effect of political distance.¹⁴ It suggests that the convergence of the compositions of equity portfolios across the U.S. is increasingly countered by diverging political attitudes.

In Table 2, Panel B, we formally test the differential effect of political distance on portfolio distance in the earlier versus the later part of our sample period. We construct an indicator variable *Recent*, which equals one from 2013 onward and zero before. We then add an interaction term between this indicator and *Political Distance* to the baseline specification and estimate it using the balanced sample. The results are reported in columns (1) and (2) of Panel B. Consistent with the time trend in Figure 2, the positive correlation between portfolio distance and political distance is not significantly different from zero in the early years but becomes larger and significant in the later part of the sample period. In recent years, a one-standard-deviation increase in the county-pair political distance is associated with a 0.037 (= $(0.065 + 0.111) \times 0.212$) increase (or a 16% standard-deviation increase) in the county-pair equity portfolio distance.

Unlike Portfolio Distance, which varies by year, Political Distance is measured at the

¹⁴Portfolio Distance_{Hyp, t} = Portfolio Distance_t - \hat{b}_t Political Distance_{t-1}, where \hat{b}_t are the cross-sectional coefficient estimates reported in Figure 2.

level of presidential election cycles. In columns (3) and (4), we collapse the observations to the election cycle level, by averaging *Portfolio Distance* within an election cycle and repeat the exercise. Standard errors are again double clustered by each county in a county-pair. Results are very similar to those in the first two columns.

3.2 Robustness

3.2.1 Omitted Variables

Our baseline empirical model controls for time fixed effects and county-pair fixed effect. It is, however, possible that *Political Distance* is correlated with other time-varying differences between counties that affect portfolio differences, such as, for example, differences in the religious composition (Shu, Sulaeman, and Yeung (2012); Kumar, Page, and Spalt (2011)).

In Appendix Table C4, we explore possible determinants of *Political Distance*, using the balanced sample. In column (1), we show the association between *Political Distance* and county-pair distances in per-capita income, population, and education introduced in Section 2.2.2. In column (2), we add *Geographic Distance*, *Industry Distance*, and *Religious Distance*.¹⁵ However, column (3) shows that county-pair fixed effects absorb most associations, with only the effect of *Religious Distance* remaining statistically significant.

The results in Panel A of Table 3 suggest that none of these additional controls has a significant impact on *Portfolio Distance* in recent years and the inclusion of them leads to only a small reduction in the recent effect of *Political Distance* on *Portfolio Distance*.

In addition to the above county characteristics, we also explore the role of the number of advisors per county and a county's use of ETFs in recent years. A larger number of advisers in a county may allow us to measure portfolio composition in the county better, thereby reducing possible measurement error that affects *Portfolio Distance*. The difference in the number of advisors between counties may also be related to differences in economic conditions or political preferences. The rising trend in ETFs could affect *Portfolio Distance*, which reflects portfolio differences with respect to individual stocks only. ETF adoption could also differ across counties, even though it is unclear that the share of ETFs in a county's portfolio has to correlate with its political attitudes. The results in Panel B of Table 3 suggest that these county characteristics do have a significant impact on *Portfolio*

¹⁵Industry Distance is constructed in the same way as other distance measures, using county-level vectors of (2-digit NAICS) industry-shares of local employment. Similarly, *Religious Distance* is constructed using county-level fractions of Protestants, Catholics, Orthodox Christians, Mormons, Jews, Others, as well as non-religious individuals. See Table 1 Panel B for summary statistics.

Distance, but they do not explain the effect of Political Distance on Portfolio Distance.

Overall, our results suggest that while political distance is correlated with some potentially confounding factors, its estimated effect on portfolio distance is robust to the inclusion of these factors.

3.2.2 Alternative Measures of Political Distance and Portfolio Distance

So far, we have used presidential election voting data to characterize the geographic polarization of political views in the U.S. over time. One concern is that county-level voting results are an imperfect proxy for the political views of investors whose portfolio composition we observe. In Table 4, we therefore repeat our analysis for the balanced sample using political distance measures based on the Gallup U.S. Daily survey data between 2008 and 2019. The data allows us to differentiate between respondents with different income levels. We use political distance measures based on responses of all respondents (column (1)) and high-income respondents only (column (2)) and find results similar to those in our baseline specifications. Interestingly, we find no significant association between portfolio distances and political distances based on responses by low-income respondents only (columns (3)), suggesting that the differentiation by income is meaningful and that the effect of political distance based on all voters is mainly driven by the political preferences of high income voters. In column (4), we again find that the effect of political distance is concentrated in the latter part of our sample period.

Finally, in Appendix Table C5, we show that our results are qualitatively unchanged when we use the alternative count-based measure of portfolio distance and thus less likely to be just driven by changes in the market capitalization of any particular set of firms.

3.3 Sinclair Entry as a Shock to Political Distance

It is, of course, impossible to control for all potential time-varying omitted variables. Therefore, to further strengthen the identification of a political preference effect on portfolio allocations, we explore a shock to the political attitudes in a county that we argue is largely unrelated to other economic determinants of portfolio choice. Specifically, we explore the staggered entry of a conservative TV network, Sinclair Broadcast Group, into different media markets during our sample period.

As of 2020, Sinclair is the second-largest television station operator in the U.S., with about 200 stations in close to 100 (out of 210) designated media markets (DMAs) covering approximately 40% of U.S. households. Sinclair's business model is to achieve economies of scale by acquiring television stations in a large number of DMAs and replacing more costly local news with national news that is shared across DMAs. Importantly, stations acquired by Sinclair shift towards more right leaning slant as captured by textual analysis of TV transcripts (Martin and McCrain (2019)). Similar to prior research about the entry of conservative FOX news (DellaVigna and Kaplan (2007); Martin and Yurukoglu (2017)), Miho (2020) and Levendusky (2022) show that Sinclair's entry seems also to shift political attitudes of the local population to the right, resulting in an increase in the local Republican vote share in the subsequent presidential elections.

We collect data on DMAs in which Sinclair operates from Sinclair's annual reports for the period of 1996-2017. During this period, Sinclair's expansions are concentrated in an earlier period of 1997-1999 (19 new DMAs) and a later period of 2011-2017 (54 DMAs).

Sinclair's acquisitions are, of course, not random. One possible concern is that Sinclair targets more conservative DMAs, which may exhibit a different trend in the evolution of political preferences relative to DMAs without Sinclair's entry. This concern is mitigated in our setting for several reasons. First, Sinclair's expansion is achieved by a growth-by-acquisition strategy. As Mastrorocco and Ornaghi (2020) point out, Sinclair mostly acquires other broadcast companies, which usually operate in multiple DMAs. That is, Sinclair enters into new DMAs typically in bundles. It is therefore unlikely that Sinclair's entry is driven by the characteristics of any specific DMA in a bundle. Second, just like in any mergers and acquisitions (M&A) deals, the timing of Sinclair's acquisitions also depends on the sellers' decisions.¹⁶

Econometrically, the exogeneity of Sinclair's entry with respect to local political preferences implies that the parallel trend assumption should hold in a difference-in-differences (DiD) analysis, which we examine in Table 5, Panel A. We collect voting outcomes for each county in all presidential elections between 1988 and 2020. The dependent variable *Republican Share* is the fraction of votes for the Republican candidate in a county in a presidential election. Since the elections occur in 4-year cycles, we aggregate Sinclair's entries with each political cycle and conduct the analysis at the presidential election cycle level. *Treated* is a dummy variable that equals one (zero) for counties in DMAs with (without) Sinclair's entry between 1996 and 2017. For a given treated county, the event cycle 0 corresponds to the election in the year of Sinclair's entry or the most recent election before entry. For example,

¹⁶For example, in 2011 Sinclair acquired eight stations in seven DMAs from Freedom Communications, which had to initiated the disinvestment in order to reduce its debt (see PR Newswire and TVNewsCheck for details).

for counties with Sinclair's entry in years between 2000 and 2003, event cycle 0 corresponds to the 2000 presidential election, and the 2004 presidential election is event cycle 1. *Post* is a dummy variable that equals one for event cycles 1-3, and equals zero for event cycles -2 to 0. We identify 29 out of the 94 counties in our balanced as treated counties. Following Cengiz et al. (2019), we use a stacked-by-event approach to calculate the average treatment effect across all events by including Event×County fixed effects and Event×Time fixed effects.

Column (1) shows a positive effect of Sinclair's entry on *Republican Share* in treated counties relative to control counties. Column (2) reports the results of a dynamic DiD estimation. There is no significant difference in the trend of *Republican Share* between treated and control counties before Sinclair's entry, consistent with the parallel trend assumption. Following Sinclair's entry, treated counties experience a gradual but significant increase in *Republican Share* relative to control counties in the subsequent three presidential election cycles. In columns (3) and (4), we further examine whether the treatment effect differs across pro-Republican counties and pro-Democratic counties before Sinclair's entry. A pro-Republican (pro-Democratic) county is a county with the Republican vote share greater (smaller) than the Democratic vote share in event cycle 0. The results suggest that the treatment effect exists in both pro-Republican and pro-Democratic counties, but is stronger in pro-Republican counties. In addition, in Appendix Table C6, we show that Sinclair's entry has no significant treatment effect on county-level economic expectations, religiosity, or median household income,¹⁷ suggesting that Sinclair's entry affects local political preferences but not other factors that may affect portfolio choices.

Next, we examine the treatment effect of Sinclair's entry on portfolio distance. We exclude county-pairs with both counties experiencing Sinclair's entry less than six years apart to have a clean event window for each entry event.¹⁸ We recognize that the effect of Sinclair's entry on a county-pair political distance depends on which of the two counties in a pair experiences the Sinclair entry. Sinclair's entry is more likely to decrease (increase) the political distance between a county pair if the county with the entry is more Democratic (Republican) than the county without an entry. We thus construct a new treatment indicator for county-pairs, *Treatment Direction* that equals plus one if Sinclair enters the county with a larger Republican share in a county-pair, minus one if Sinclair enters the more Democratic county, and zero if Sinclair does not enter either of the counties in the pair.

Since the effect of political distance on portfolio distance is only significant after 2012

¹⁷Here we use the annual Small Area Income and Poverty Estimates from Census.

¹⁸For county-pairs with sequential entries over a long period so that the event windows for the two entries do not overlap, we include only the first event.

and Sinclair has no entries between 2000 and 2010, we focus on the time period of 2013-2019 in this analysis. In our balanced sample, we identify 594 county-pairs as treated, and 1,798 county-pairs as controls, during this sample period. Since portfolio distance is constructed annually, the analysis is also conducted at the annual level. The year Sinclair enters a county in a county-pair is event year 0 for the pair. *Post* is a dummy variable that equals one for event years 1-3, and equals zero for event years -2 to 0. Among 594 county-pairs treated during this sample period, 392 experience a positive treatment in political distance (*Treatment Direction* = +1), and 202 experience a negative treatment (*Treatment Direction* = -1).

The results using a stacked-by-event approach are reported in Table 5, Panel B. Column (1) shows that the portfolio distances of county-pairs with positive (negative) Sinclair treatment tend to increase (decrease) relative to those of control county-pairs or county-pairs with negative (positive) Sinclair treatment. Column (2) reports the results from a dynamic DiD estimation. The treated county-pairs do not exhibit any significant difference in the trend of portfolio distance before Sinclair's entry, suggesting that Sinclair's entry is relatively exogenous to local portfolio choices. In the three years after Sinclair's entry, county-pairs that experience an increase (decrease) in political distance tend to experience an increase (increase) in political distance and control county-pairs.

Overall, the results in Section 3 suggest that geographic differences in political views have increasingly contributed to geographic differences in households' equity portfolios over time. The effect of political distance on portfolio distance does not seem to be driven by cross-county differences in potentially confounding factors, and the analysis using Sinclair's entry as a shock to county-pair political distance supports a causal interpretation of the political distance effect.

4 Mechanism

In this section, we investigate the mechanism(s) behind the impact of political distance on households' equity portfolio distance. First, differences in political views could lead to different expectations about the economy as a whole or the economic outlook of certain industries or firms, which in turn could lead to differences in portfolio allocations between more Democratic counties and more Republican counties. We call this *the expectations channel*. For example, Meeuwis et al. (2022) find that during the Trump presidency, Republicans become more optimistic, while Democrats more pessimistic about the future of the U.S. economy. They show that such differences lead to differences in the equity share of individuals' portfolios. A second channel is related to diverging values and priorities between Democrats and Republicans with respect to a range of political, social, and environmental issues. We refer to the effect of such differences in values and preferences on portfolio choice as *the preference channel*. Both channels are not mutually exclusive, but we will try to distinguish between them in our analysis.

4.1 The Role of Economic Expectations

We begin by asking whether different stock choices by counties with different political leanings are driven by differences in economic expectations.

To measure a county's economic expectations, we use the Gallup surveys (see Section 2.3 for details) about perceived macroeconomic conditions and expectations. Specifically, we use answers to the question "How would you rate economic conditions in this country today – as excellent, good, only fair, or poor?" and construct *EconCondition Distance* for each county-pair-year in the balanced sample. We focus on high-income respondents in this analysis as they better represent investors in our sample.¹⁹ We also construct *EconOutlook Distance* using responses ("better", "worse", or "the same") to the question "Right now, do you think that economic conditions in the country as a whole are getting better or getting worse?" The correlation between the two economic expectations distances is 0.48.

In Table 6, we contrast the impact of political distance and that of economic expectations in explaining county-pair portfolio distance. The effect of political distance remains statistically significant and relatively large when differences in economic expectations are controlled for. The distance in economic expectations matters more than that in perceived economic conditions for portfolio distance. In column (4), when we simultaneously control for distances in economic expectations and the factors examined in Table 3, the effect of political distance on portfolio distance remains robust. Relative to the result in column (4) of Table 4, the results in Table 6 suggests that the marginal effect of political distance in the recent political cycles declines by 16-21%. Thus, some part but not all of the effect of political distance on portfolio distance may operate through differences in economic expectations.

¹⁹Specifically, for each county-year we construct a vector containing the fractions of high-income survey respondents that choose "excellent", "good", "only fair", or "poor". We then calculate the county-pair-year level distance in the same way as political distance.

4.2 The Role of Preferences

4.2.1 Politically Shaped Social and Economic Values

Desmet and Wacziarg (2021) study the evolution of cultural divides in the U.S. between 1972 and 2018 using responses to 76 questions in the General Social Surveys. Their study presents a striking pattern: The cultural divide by political affiliation has substantially increased since 2005, while the cultural divides by income, race, gender and urbanicity have remained largely flat or even declined.

The increase in the partian value gap in the second half of the 2000s precedes the rise of political preferences as a determinant of households' equity portfolios that we document in Figure 2. The late 2000s also mark the rise of the so-called values-based investing, including but not limited to ESG investing, that advocates for financial investment to align with personal values (see, for example, Eccles and Fisch (2022)). Around the same time, impact investing started to gain institutional support, for example, in form of the release of the United Nations Principles for Responsible Investment (UN PRI) in 2006 and the establishment of the Sustainability Accounting Standards Board (SASB) in 2011. The direction and timing of these trends are consistent with the conjecture that the increase in partian values gap may have generated an increase in the demand and supply for values-based investing.

We use several examples to illustrate that views and preferences of Democrats and Republicans have been diverging over time and that these differences predictably affect the equity portfolio composition of households residing in Democratic-leaning counties versus in Republican-leaning counties. Specifically, we first use Gallup survey data to identify political, environmental, and social values that exhibit a widening partian gap over our sample period. Then, for each specific issue, we test whether portfolios in Democratic-leaning versus Republican-leaning counties differ in their allocation to stocks that have negative or positive exposure to a given issue in a way consistent with the observed partian gap.

Besides preferences, Democrats and Republicans may have different economic expectations regarding stocks sensitive to certain environmental or social issues. For example, Democrats and Republicans could have different perceptions of environmental regulation risk and the cash flow consequences for stocks exposed to this risk, leading to different portfolio choices on those stocks. We will explicitly address this alternative interpretation in our analysis.

Attitudes towards Environmental Protection. To examine how Democrats and Republicans increasingly differ in their views about environmental issues and the tradeoff with economic outcomes (McCright and Dunlap (2011), Painter and Qiu (2020)), we examine the following Gallup survey question: "With which one of these statements about the environment and the economy do you most agree: Protection of the environment should be given priority, even at the risk of curbing economic growth (or) economic growth should be given priority, even if the environment suffers to some extent?" The answers are coded as +1 (protect environment), -1 (economic growth priority), and 0 (equal priority). For each Gallup survey year, we compute Political Gap_{Env} as the difference between the average response of self-reported Democrats and that of self-reported Republicans.

Figure 4a shows the time-series pattern in *Political* Gap_{Env} . In all years between 2000 and 2019 the gap is positive, suggesting that Democrats tend to put more emphasis on environmental protection over economic growth relative to Republicans. Importantly, the difference has grown substantially over time, from a little over 0.2 to about 1.0. We observe similar patterns in the responses to questions specific to water pollution, air pollution, global warming, and biodiversity. Overall, the evidence suggests that Democrats tend to become increasingly more willing to favor the environment over economic output compared to Republicans.

We next examine whether the increasing difference in environmental consciousness is reflected in investments in stocks of environmentally harmful businesses. Since Democrats have a preference against environmentally harmful businesses while Republicans do not necessarily favor them, we expect that counties with a larger Democratic vote share (*Democratic Share* (%)) have lower allocations to these stocks. We further expect that the effect to be more pronounced in recent years as the preference gap widens.

We use the MSCI ESG KLD ratings to identify environmentally harmful businesses as ones with a history of hazardous waste spills and exceptionally high greenhouse gas (GHG) emissions (see Appendix B for more details). Then for each county's portfolio, we compute the average fraction of portfolio value invested in stocks with environmental concerns, *Portfolio Fraction*_{Env. Concerns}, and relate it to the county's *Democratic Share* (%). The results in columns (1) and (2) of Table 7 Panel A suggest that *Democratic Share* (%) is negatively related to investment in stocks with environmental concerns, but only in the later period of the sample.²⁰

Although the results are consistent with Democratic investors disliking stocks with environmental concerns in recent years, they are also consistent with an alternative interpretation that Democratic investors view those stocks as less profitable or riskier because they are more

²⁰The specifications in Table 7 include time fixed effect but not county fixed effects. In Appendix Table C7 we include county fixed effects and obtain similar results.

subject to environmental regulations and litigation. To distinguish between these two interpretations, we compare Democratic investors' attitude towards stocks with environmental concerns under a Republican presidency versus a Democratic presidency. The expected environmental regulatory risk tends to be lower under the former. Survey evidence suggests that this is particularly true from the perspectives of Democrats.²¹

If economic expectations drive Democratic investors' portfolio allocations in stocks of environmentally harmful firms, then we expect them to hold more of these stocks during a Republican presidency than during a Democratic presidency. But if environmental preferences drive their portfolio choices, we expect them to hold the same amount or even less during a Republican presidency. The perceived weakening of environmental regulations by Democrats could lead them to believe that environmentally harmful firms would pollute more during a Republican presidency, which could strengthen their unfavorable preferences against those firms, leading to a reduction of portfolio weights on those stocks. To distinguish between the two possibilities, in columns (3) and (4) of Table 7 Panel A, we separately examine the portfolio decisions in Democratic-leaning (*Democratic Share* ≥ 0.5 , column (3)) and Republican-leaning (*Republican Share* ≥ 0.5 ; column (4)) counties during recent years (Recent = 1). The results suggest that Democratic-leaning counties significantly reduce holdings of stocks with environmental concerns during a Republican president (i.e., Trump) compared to a Democratic president (i.e., Obama), while Republican-leaning counties do not invest differently across the two presidencies. These results are consistent with the role of preferences rather than economic expectations shaping our findings.

Attitudes towards Labor Protection. The Gallup survey has the following question related to attitude towards labor union: "Would you, personally, like to see labor unions in the United States have more influence than they have today, the same amount as today, or less influence than they have today?" The answers are coded as +1 (more influence than they have today), -1 (less influence than they have today), and 0 (same amount as today). Figure 4b shows that Democrats are generally friendlier to labor unions relative to Republicans, and increasingly so over time.

 $^{^{21}}$ For example, the Gallup Surveys had the following question from 2003 to 2008: "When it comes to environmental protection, which of these do you think is happening under the Bush administration – the nation's environmental protection policies are being strengthened, the nation's environmental policies are being kept about the same, or the nation's environmental protection policies are being weakened?" While the majority (72.4%) of the Republican-leaning survey respondents believe that the policies are kept about the same and only 16.5% believe that the policies are being weakened. A similar survey conducted by the Pew Research Center in 2017 yields similar responses under the Trump administration.

The MSCI ESG KLD data set provides indicators on whether a company had laborrelated concerns in the past. For each county's portfolio, we compute the fraction of portfolio value invested in stocks with labor concerns, *Portfolio Fraction*_{Labor Concerns}, and relate it to the county's political leaning. The results in Table 7 Panel B show a similar pattern as in Panel A. Democratic-leaning counties tend to invest less in stocks with labor concerns than Republican-leaning counties, but only in recent years. Consistent with the preferences interpretation, we find that Democratic-leaning counties reduce rather than increase their holdings of stocks with labor concerns during a Republican presidency.

Attitudes towards Gun Control. Gun control has long been a controversial and dividing issue in the U.S. (Miller (2019)). The Gallup survey has the following question: "In general, do you feel that the laws covering the sale of firearms should be made more strict, less strict, or kept as they are now?" The answers are coded as +1 (more strict), -1 (less strict), and 0 (kept as they are now). We compute Political Gap_{Firearms} as the difference between the average response of self-reported Democrats and that of self-reported Republicans each year. Figure 4c shows that in all years between 2001 and 2019, Democrats preferred stricter gun control than Republicans, and the partisan gap grew substantially from 0.25 to 0.80.

We then examine whether the difference in the attitudes towards gun control is reflected in investments in stocks of firearm manufacturers. Again, we use the MSCI ESG KLD indicators to identify companies involved in firearm-related businesses. Then for each county's portfolio, we compute the average fraction of portfolio value invested in the firearm-related stocks, *Portfolio Fraction_{Guns}*, and relate it to the county's political leaning. The results in Table 7 Panel C suggest that more Democratic-leaning counties tend to invest less in firearmrelated stocks relative to more Republican-leaning ones, but only in recent years. However, different from the pattern in the previous two panels, the holdings of firearm stocks by Democratic-leaning counties do not significantly differ between a Republican presidency and a Democratic presidency. This result can be consistent with the preference interpretation, if a Republican presidency does not make Democrats dislike firearm stocks more. Under the economic expectations interpretation, this result implies that investors do not expect any real tightening of gun control laws during a Democratic presidency relative to a Republican presidency, which seems plausible. But in this case, cash flow expectations related to perceived gun control regulations are also unlikely to drive investors' portfolio decisions.

4.2.2 Attitudes towards the Other Party

Political scientists have pointed out that political polarization is reflected not only in ideological polarization, i.e., differences in policy positions as explored above, but also in affective polarization, i.e., an emotional dislike and distrust of political out-groups (Iyengar et al. (2019)). Increasing affective polarization is again evident in the survey data. The Gallup surveys have the following questions: "Please tell me whether you have a favorable or unfavorable opinion of each of the following parties. How about Republican Party (Democratic Party)?" The answers are coded as +1 (favorable), -1 (unfavorable), and 0 (no opinion).

For each year, we construct the fraction of self-reported Democrats having unfavorable views of the Republican Party as well as the fraction of self-reported Republicans having unfavorable views of the Democratic Party. Figure 5 shows that the fraction of respondents having unfavorable views of the other party has been increasing since 2001 for both self-identified Democratic and Republican respondents.

We hypothesize that the increasing affective polarization could impact investors' willingness to invest in firms affiliated with the other political party. To test this prediction, we classify firms based on the political leaning of their CEO as captured by the CEO's political campaign contributions. In particular, using data for executives in S&P 1500 firms between 1992 and 2018 from Fos, Kempf, and Tsoutsoura (2021), we label a CEO as a Democratic-(Republican-) leaning CEO if she has made the majority of the contributions to the Democratic (Republican) Party in the most recent 5 years and if she has never been classified as a Republican (Democratic) CEO since 1992. This filter allows us to exclude CEOs who make political donations mostly for strategic rather than ideological reasons.

Out of all identifiable CEOs associated with public firms in our sample, about 18% are classified as Republican-leaning, while only 7% of the CEOs are classified as Democraticleaning. We then compute the county-level portfolio fraction invested in stocks with Democratic (Republican) CEOs by averaging across all the investment advisers in a county-year. The results in Table 8 suggest that a county with a higher Republican share tends to have lower portfolio weights in stocks with Democratic CEOs, particularly in the last two presidential election cycles (columns (1) and (2)). However, Republican-leaning counties do not underweight stocks with Republican CEOs (columns (3) and (4)), suggesting that they do not shun CEOs with well-identified political preferences in general but rather CEOs with opposing political views.

Overall, the results in Section 4 suggest that investors' portfolio choices are related to their political values in predictable ways, and the relation between the two becomes more pronounced in the last two presidential election cycles. These results are consistent with the increasing partial values gap and cannot be explained solely by differences in economic expectations or different expectations about regulatory risks on certain stocks or industries.

5 Conclusion

We examine the effect of political differences across the U.S. on the differences of wealthy households' equity portfolios between 1997 and 2019. Political differences between the U.S. counties have been increasing over the last 25 years, but they seem to have little effect on differences in households' portfolio composition until 2013, after which political differences have exhibited an increasingly large and significant effect on differences in stock portfolio composition. Exploring a shock to local political attitudes due to a staggered entry of Sinclair, a conservative television network in local media markets, we provide evidence of a causal effect of political distance on portfolio distance.

To shed light on the mechanism through which political distance impacts portfolio distance, we examine the effect of politically shaped expectations and of politically shaped values. We find that while differences in economic expectations correlate with our measure of portfolio distance, expectations seem to explain only a small part of the effect of political differences. To examine the effect of politically shaped values, we identify several social and environmental dimensions that exhibit a widening partian gap over our sample period. Consistent with politically shaped values-investing, we find that Democratic-leaning counties invest less in stocks incongruent with democratic values, such as stocks of firms with environmental or labor concerns as well as small firearms manufacturers and distributors. Republican-leaning counties seem to underweight firms led by a Democratic CEO.

Our results are consistent with the increasing importance of values-based investing. As political identity and preferences increasingly reflect and shape social and environmental preferences, they ultimately influence investment decisions. Political divide therefore seems to cause divergence in households' portfolios across the U.S. While our results are based on portfolios of relatively small investment advisers that work directly with their local clients, recently the largest investment advisers started embracing portfolio tilts to serve their clients preferences. For example, Fidelity Solo FidFolios allow investors to create their own custom indexes and then purchase them with one click. Vanguard now offers personalized indexing solutions to its clients that among others deliver an increased level of precision in screening or tilting individual stocks. Over time, such trends could significantly reduce risk sharing, segment U.S. equity markets, and pose challenges for firms which have to deal with nonfinancial and possibly opposing preferences of their shareholders.

Finally, to the extent that voters vote based on their economic interests, politically induced differences in portfolios could reinforce the political divide.

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Figure 1: Political distance between all the U.S. counties and between ounties in the full and balanced samples.

Panel (a) plots the evolution of the average *Political Distance* from 1996 to 2020, between all counties in the United States. Panels (b) and (c) plot the evolution of the average *Political Distance* from 1996 to 2018, for the full sample and the balanced sample.



Figure 2: Effect of political distance on portfolio distance over time

The figure plots the regression coefficients and their standard errors for the annual cross-sectional regressions of *Portfolio Distance* on *Political Distance* lagged by one year in the balanced sample.



(b) Balanced sample

Figure 3: Portfolio distance in the full and balanced samples.

The figure plots the evolution of the average *Portfolio Distance* (green squares) and *Portfolio Distance*^{Alt} (orange triangles) during the sample period, from 1997 to 2019, for the full sample (panel (a)) and the balanced sample (panel (b)). Panel (b) also depicts the average *Portfolio Distance*_{Hyp} and *Portfolio Distance*^{Alt}_{Hyp} (green and orange dashed lines), defined as *Portfolio Distance*^{Alt} adjusted for the effect of *Political Distance*. The adjustment is based on annual cross-sectional regressions.



(c) Gun control

Figure 4: Political gap in attitudes towards environmental protection, labor protection, and gun control.

The figure plots the evolution of the differences in attitudes towards environmental protection (a), labor protection (b), and (c) gun control laws between self-identified Democratic and Republican respondents in the Gallup survey over time. *Political Gap_X* is the difference between the average answers of self-identified Democrats and self-identified Republicans, where X = Env, *Labor*, *Firearms* for the following questions. (a) The respondents are asked whether the protection of the environment should be given priority, even at the risk of curbing economic growth (answer = 1), economic growth should be given priority, even if the environment suffers to some extent (-1), or both should be given equal priority (0). (b) The respondents are asked whether labor unions in the U.S. should have more influence than today (answer= 1), less influence (-1), or the same amount (0). (c) The respondents are asked whether the laws covering the sale of firearms should be made more strict (answer = 1), less strict (-1), or kept the same (0)).



(a) Fraction of Democrats with an unfavorable opinion of the Republican Party



(b) Fraction of Republicans with an unfavorable opinion of the Democratic Party

Figure 5: Views of the other party.

The figure plots the evolution of the Gallup respondents' opinion of the other party. Figure (a) plots the fraction of self-identified Democratic respondents having an unfavorable opinion of the Republican Party. Figure (b) plots the fraction of self-identified Republican respondents having an unfavorable opinion of the Democratic Party.

Table 1: County-Pair Distances

This table presents summary statistics for various county pair distance measures, for the full sample (Panel A) and balanced sample (Panel B). All variables are defined in Appendix B.

Panel A. County-pair Distances, Full Sample						
Variable	Ν	Mean	S.D.	P25	Median	P75
Portfolio Distance Portfolio Distance_{Alt}	$343,626 \\ 343,626$	$1.577 \\ 1.708$	$0.240 \\ 0.173$	$1.408 \\ 1.582$	$1.580 \\ 1.721$	$1.759 \\ 1.846$
Political Distance	343,626	0.315	0.223	0.138	0.270	0.446

Panel B.	County-pair	Distances.	Balanced	Sample
I and D.	County pair	Distances,	Datancea	Sampie

Variable	Ν	Mean	S.D.	P25	Median	P75
Portfolio Distance	96,008	1.511	0.239	1.338	1.511	1.683
Portfolio $\operatorname{Distance}_{\operatorname{Alt}}$	96,008	1.672	0.174	1.545	1.680	1.810
Political Distance	96,008	0.303	0.212	0.135	0.260	0.429
PD Gallup All	47,802	0.296	0.203	0.135	0.254	0.417
PD Gallup High Income	47,802	0.333	0.233	0.148	0.284	0.471
PD Gallup Low Income	$47,\!802$	0.299	0.205	0.144	0.256	0.408
Population Difference	96,008	0.936	1.477	0.212	0.473	0.936
Income Difference	96,008	7.231	6.521	2.300	5.290	10.36
Education Difference	96,008	0.100	0.077	0.039	0.086	0.143
Geographical Distance	96,008	1.019	0.729	0.437	0.828	1.508
Industry Distance	96,008	0.379	0.153	0.271	0.349	0.455
Religious Distance	96,008	0.555	0.332	0.291	0.498	0.765
# of Advisers	96,008	9.302	9.689	3.000	6.000	11.00
Diff. in $\#$ of Advisers	96,008	4.991	7.807	1.000	2.000	6.000
ETF Difference	96,008	0.085	0.118	0.003	0.031	0.125

Table 2: Effect of Political Distance on Portfolio Distance

This table presents the effects of *Political Distance* on *Portfolio Distance*. Panel A reports the baseline effect (annual level). Panel B reports the change in the effect over time, in particular in the recent years of the (balanced) sample, both at the annual level and election cycle level. *Recent* is an indicator variable equal to one for year 2013 and after. Standard errors are double-clustered by county A and county B. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

	Panel A	A. Baseline Results	3			
	Portfolio Distance					
	Full S	Sample	Balanced Sample			
	(1)	(2)	(3)	(4)		
Political Distance	0.040*	0.071**	0.066	0.130***		
	(0.024)	(0.032)	(0.042)	(0.046)		
Observations	343,626	343,626	96,008	96,008		
Adjusted \mathbb{R}^2	0.033	0.686	0.088	0.669		
Time FE	Yes	Yes	Yes	Yes		
County Pair FE	No	Yes	No	Yes		

Panel B	Time	Trend
I and D	• I IIII	TIONG

	Portfolio Distance			
	Annual Level		Presidential Cycle Lev	
	(1)	(2)	(3)	(4)
Political Distance	$0.008 \\ (0.044)$	$0.065 \\ (0.055)$	$\begin{array}{c} 0.010 \\ (0.045) \end{array}$	$0.069 \\ (0.056)$
Political Distance \times Recent	$\begin{array}{c} 0.161^{***} \\ (0.040) \end{array}$	$\begin{array}{c} 0.111^{***} \\ (0.040) \end{array}$	$0.164^{***} \\ (0.041)$	$\begin{array}{c} 0.110^{***} \\ (0.041) \end{array}$
Observations $Adjusted R^2$	96,008 0.093	$96,008 \\ 0.672$	$25,\!848$ 0.105	$25,\!848$ 0.690
Time FE County Pair FE	Yes No	Yes Yes	Yes No	Yes Yes
Table 3: Effect of Differences in County and Adviser Characteristics on PortfolioDistance

This table shows that the effect of *Political Distance* on *Portfolio Distance* is robust to controlling for the differences in the time-varying county and adviser characteristics. The sample is our balanced sample that covers years 1997 to 2019. *Recent* is an indicator variable equal to one for year 2013 and after. Standard errors are double-clustered by county A and county B. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

Panel A. County Characteristics					
		Portfolic	Distance		
	(1)	(2)	(3)	(4)	(5)
Political Distance	0.069	0.069	0.074	0.074	0.077
	(0.054)	(0.054)	(0.053)	(0.056)	(0.054)
Political Distance \times Recent	0.104**	0.108^{***}	0.084**	0.099^{**}	0.086^{**}
	(0.040)	(0.040)	(0.042)	(0.042)	(0.042)
Population Difference \times Recent	-0.003	-0.002	-0.003	-0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Income Difference \times Recent	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Education Difference \times Recent	0.172	0.173	0.106	0.167	0.108
	(0.146)	(0.144)	(0.123)	(0.138)	(0.121)
Geographical Distance \times Recent		-0.010			-0.010
		(0.014)			(0.014)
Industry Distance \times Recent			0.068		0.060
			(0.103)	0.015	(0.101)
Religious Distance \times Recent				0.015 (0.023)	0.010 (0.021)
Deputation Difference	0.044	0.040	0.046		· · · ·
Population Difference	-0.044 (0.028)	-0.040 (0.028)	-0.046 (0.029)	-0.043 (0.028)	-0.041 (0.029)
Income Difference	(0.020) 0.004^*	0.003*	0.003	(0.020) 0.004^*	0.003
Income Dinerence	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Education Difference	0.084	0.064	0.085	0.090	0.068
	(0.186)	(0.175)	(0.189)	(0.184)	(0.178)
Industry Distance	. ,		-0.250**	. ,	-0.248**
5			(0.096)		(0.098)
Religious Distance				-0.020	-0.019
				(0.026)	(0.026)
Observations	96,008	96,008	96,008	96,008	96,008
Adjusted R^2	90,008 0.673		90,008 0.675	90,008 0.673	90,008 0.675
Time FE	Yes	$\begin{array}{c} 37 \begin{array}{c} 0.674 \\ \text{Yes} \end{array}$	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes	Yes

		Portfolio Distanc	e
	(1)	(2)	(3)
Political Distance	0.065	-0.003	-0.013
	(0.055)	(0.049)	(0.049)
Political Distance \times Recent	0.111^{***}	0.104^{***}	0.106^{***}
	(0.040)	(0.035)	(0.034)
# of Advisers		-0.026***	-0.026***
		(0.003)	(0.003)
$\#$ of Advisers \times Recent		0.007***	0.008^{***}
		(0.002)	(0.002)
Diff. in $\#$ of Advisers		0.023***	0.023***
		(0.003)	(0.003)
Diff. in $\#$ of Advisers \times Recent		-0.007***	-0.008***
		(0.002)	(0.002)
ETF Difference			0.067^{*}
			(0.040)
ETF Difference \times Recent			0.186^{***}
			(0.055)
Observations	96,008	96,008	96,008
Adjusted \mathbb{R}^2	0.672	0.706	0.711
Time FE	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes

Panel B. Number of Advisers and ETF Difference

Table 4: Effect of Survey-based Political Distance on Portfolio Distance

This table presents the effects of *PD Gallup*, political distance based on the Gallup U.S. Daily survey on *Portfolio Distance*. In column (1), the measure *PD Gallup All* is based on all Gallup respondents. In columns (2)-(5) we split the respondents into high- and low-income ones (*PD Gallup High Income* and *PD Gallup Low Income* variables), based on whether their annual household income is above or below the county median household income. The sample is our balanced sample conditional on the availability of the Gallup U.S. Daily Survey data; it covers years 2008 to 2019. *Recent* is an indicator variable equal to one for year 2013 and after. Standard errors are double-clustered by county *A* and county *B*. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

		Portfolio	o Distance	
	(1)	(2)	(3)	(4)
PD Gallup All	0.049^{***} (0.017)			
PD Gallup High Income		0.032^{**} (0.016)	0.032^{**} (0.015)	-0.041 (0.029)
PD Gallup Low Income			-0.005 (0.020)	
PD Gallup High Income \times Recent				$\begin{array}{c} 0.108^{***} \\ (0.032) \end{array}$
Observations	47,802	47,802	47,802	47,802
Adjusted \mathbb{R}^2	0.746	0.746	0.746	0.749
Time FE	Yes	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes

Table 5: Sinclair Shock and its Effect on Portfolio Distance

Panel A presents the effects on Sinclair entry on *Republican Share*, the fraction of votes for the Republican candidate in a county in a presidential election, and Event Time is in presidential cycles. Event Time[0] is the presidential election cycle with Sinclair entry for treated counties. *Treated* equals 1 for counties with a Sinclair entry and 0 otherwise. The sample includes counties from our balanced sample and covers presidential cycles from 1988 to 2020. Standard errors are double-clustered by county and by election cycle. Panel B presents the effects on Sinclair entry on *Portfolio Distance*, and Event Time is in calendar years. Event Time[0] is the year with Sinclair entry for treated county-pairs. *Treatment Direction* equals +1 if Sinclair enters the more Republican county in a county-pair, equals -1 if Sinclair enters the more Democratic county, and equals zero if Sinclair does not enter any of the counties in the pair. The sample includes counties from our balanced sample and covers years 2013 to 2019. Standard errors are double-clustered by county and system 3000 + 1000

Fallel A. St	nclair Entry a	-		
		R	epublican Share	
			Rep. $<$ Dem.	Rep. \geq Dem.
	(1)	(2)	(3)	(4)
Treated \times Post	0.020^{*} (0.009)			
Treated \times Event Time[-2]	~ /	$0.005 \\ (0.008)$	$0.003 \\ (0.009)$	$0.008 \\ (0.009)$
Treated \times Event Time[-1]		-0.002 (0.003)	-0.005 (0.003)	0.003 (0.003)
Treated \times Event Time[+1]		0.013^{**} (0.006)	0.010^{*} (0.006)	0.017^{**} (0.007)
Treated \times Event Time[+2]		0.021^{**} (0.009)	$0.010 \\ (0.008)$	0.037^{**} (0.014)
Treated \times Event Time[+3]		0.033^{**} (0.011)	0.025^{*} (0.011)	0.044^{**} (0.018)
Observations	1,523	1,523	1,456	1,426
Adjusted \mathbb{R}^2	0.948	0.948	0.947	0.951
Event \times County FE	Yes	Yes	Yes	Yes
Event \times Calendar time FE	Yes	Yes	Yes	Yes

Panel A. Sinclair Entry and Republican Share

	Portfoli	io Distance
	(1)	(2)
Treatment Direction \times Post	0.215^{**} (0.067)	
Treatment Direction \times Event Time[-2]		-0.120 (0.072)
Treatment Direction \times Event Time [-1]		-0.088 (0.085)
Treatment Direction \times Event Time[+1]		$\begin{array}{c} 0.143^{***} \\ (0.037) \end{array}$
Treatment Direction \times Event Time[+2]		$0.108 \\ (0.090)$
Treatment Direction \times Event Time[+3]		0.187^{*} (0.092)
Observations	35,928	$35,\!928$
Adjusted \mathbb{R}^2	0.813	0.813
Event \times County-pair FE	Yes	Yes
Event \times Calendar time FE	Yes	Yes

Panel B. Sinclair Entry and Portfolio Distance

Table 6: Economic Expectations

This table presents the effect of the distance in the future economic expectations of high income individuals (*EconOutlook Distance*, column (1)) and of the distance in their beliefs about the current economic conditions (*EconCondition Distance*, column (2)) on *Portfolio Distance*. Column (3) shows that the effect of *Political Distance* on *Portfolio Distance* is robust to inclusion of both of the variables. In column (4) we include other controls: *Population Difference, Income Difference, Education Difference, Geographical Distance, Industry Distance*, and *Religious Distance* as well as their interactions with the *Recent* dummy. *Recent* is an indicator variable equal to one for year 2013 and after. The sample is our balanced sample conditional on the availability of the Gallup U.S. Daily Survey data; it covers years 2008 to 2019. Standard errors are double-clustered by county A and by county B. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

		Portfolio	Distance	
	(1)	(2)	(3)	(4)
PD Gallup High Income	-0.029 (0.026)	-0.024 (0.025)	-0.024 (0.025)	-0.036 (0.031)
PD Gallup High Income \times Recent	$\begin{array}{c} 0.091^{***} \\ (0.029) \end{array}$	$\begin{array}{c} 0.085^{***} \\ (0.029) \end{array}$	$\begin{array}{c} 0.088^{***} \\ (0.029) \end{array}$	0.106^{***} (0.037)
EconOutlook Distance	-0.046^{**} (0.021)		-0.015 (0.021)	-0.023 (0.020)
EconOutlook Distance \times Recent	0.055^{*} (0.032)		-0.003 (0.026)	0.009 (0.028)
EconCondition Distance		-0.060^{**} (0.030)	-0.057^{*} (0.031)	-0.062^{**} (0.030)
EconCondition Distance \times Recent		0.106^{***} (0.030)	$\begin{array}{c} 0.109^{***} \\ (0.033) \end{array}$	$\begin{array}{c} 0.119^{***} \\ (0.035) \end{array}$
Observations Adjusted R ²	$47,802 \\ 0.749$	$47,802 \\ 0.750$	$47,802 \\ 0.750$	$47,802 \\ 0.751$
Other Controls Time FE	No Yes	No Yes	No Yes	Yes Yes
County Pair FE	Yes	Yes	Yes	Yes

Table 7: Attitudes towards Environmental Protection, Labor Protection, GunControl and Portfolio Allocation

This table reports the relation between *Democratic Share* (a proxy for attitudes towards environmental protection, labor protection, and gun control) and (a) *Portfolio Fraction*_{Env.Concerns}, the average portfolio fraction invested in firms engaged in environmentally harmful businesses within a county (Panel A); (b) *Portfolio Fraction*_{Labor Concerns}, the average portfolio fraction invested in firms engaged in environmentally harmful businesses within a county (Panel A); (b) *Portfolio Fraction*_{Labor Concerns}, the average portfolio fraction invested in firms engaged in environmentally harmful businesses within a county (Panel B); (c) *Portfolio Fraction*_{Firearms}, the average portfolio fraction invested in firms involved in small firearms production and distribution within a county (Panel C). The sample is our balanced sample that covers years 1997 to 2019. *Recent* is an indicator variable equal to one for year 2013 and after. In column (3) and (4) we report the results for two subsets of counties, those with *Democratic Share* above 50% and those with *Republican Share* above 50% in the second half of our sample (*Recent* = 1). Standard errors are clustered by county. ***, ***, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

Panel	A. Environ	mental Cor	ncerns	
		Portfo	lio Fraction _{Env.Cor}	ncerns
			Dem.Sh. > 0.5	Rep.Sh. > 0.5
	(1)	(2)	(3)	(4)
Democratic Share	0.0015	0.0529		
	(0.073)	(0.078)		
Democratic Share \times Recent		-0.1423*		
		(0.073)		
Republican President			-0.0431***	0.0140
			(0.008)	(0.020)
Observations	2,109	2,109	439	154
Adjusted \mathbb{R}^2	0.216	0.220	0.054	-0.005
Time FE	Yes	Yes	No	No
Pa	anel B. Lab	or Concern	IS	
		Portfoli	io $\operatorname{Fraction}_{\operatorname{Labor} \operatorname{Cc}}$	oncerns
			Dem.Sh. > 0.5	Rep.Sh. > 0.5
	(1)	(2)	(3)	(4)
Democratic Share	-0.0102	0.0265		
	(0.042)	(0.036)		
Democratic Share \times Recent		-0.1016*		
		(0.058)		
Republican President			-0.0178**	0.0342
			(0.008)	(0.031)
Observations	$2,109^{43}$	3^{3} 2,109	439	154
Adjusted R^2	0.825	0.826	0.006	0.008
Time FE	Yes	Yes	No	No

Panel A. Environmental Concerns

	Portfolio Fraction _{Firearms}			
			Dem.Sh. > 0.5	Rep.Sh. > 0.5
	(1)	(2)	(3)	(4)
Democratic Share	-0.0038	0.0008		
	(0.003)	(0.002)		
Democratic Share \times Recent		-0.0127**		
		(0.006)		
Republican President			-0.0004	-0.0044
			(0.001)	(0.003)
Observations	$2,\!109$	2,109	439	154
Adjusted \mathbb{R}^2	0.158	0.167	-0.002	0.021
Time FE	Yes	Yes	No	No

 \mathbf{D}_{i} ntrol a a \mathbf{C} 1

Table 8: Attitudes towards the Other Party and Portfolio Allocations

This table reports the relation between *Republican Share* and *Portfolio Fraction*_{Dem CEO} (*Portfolio Fraction*_{Rep CEO}), the average portfolio fraction invested in firms with a Democratic-leaning (Republican-leaning) CEO within a county. The sample is our balanced sample that covers years 1997 to 2019. *Recent* is an indicator variable equal to one for year 2013 and after. Standard errors are clustered by county. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

	Portfolio Fr (1)	$\begin{array}{c} \operatorname{action}_{\operatorname{Dem}\operatorname{CEO}}\\ (2) \end{array}$	Portfolio I (3)	$\frac{\text{Fraction}_{\text{Rep CEO}}}{(4)}$
Republican Share	-0.0227^{***}	-0.0107	0.0271	0.0253
	(0.008)	(0.011)	(0.022)	(0.029)
Republican Share \times Recent		-0.0336^{*} (0.017)		$\begin{array}{c} 0.0052 \\ (0.029) \end{array}$
Observations	2,109	2,109	2,109	2,109
Adjusted ²	0.195	0.198	0.199	0.199
Time FE	Yes	Yes	Yes	Yes

Appendix

A ADV Forms

Investment advisers file Form ADV to register with the SEC and/or the states and thereafter file an Annual Updating Amendment 90 days after the end of each fiscal year. Only investment advisers that *solely* advise venture capital funds or private equity funds do not have to register with the SEC or the states ("exempt reporting advisers"). They nonetheless complete some of the questions in Form ADV for purposes of reporting to the SEC and/or the states.

Form ADV is divided into three parts. Part 1 contains information about the investment adviser's business, ownership, clients, employees, practices, affiliations, and any disciplinary events. This information is organized in a check-the-box, fill-in-the-blank format and is available to the public on the SEC's Investment Adviser Public Disclosure (IAPD) website. Parts 2 and 3 require advisers to prepare a plain English summary of their business practices, fees, conflicts of interest, and legal and disciplinary history. These brochures must be delivered to clients but are not available to the public in a research-friendly format. We extracted the following items from Part 1 of Form ADV for all investment advisers that filed with the SEC: legal name (item 1A), number of clients by type and amount of total regulatory assets under management by client type (item 5D), number of accounts and total assets under management (item 5F), and the number of offices and their locations (Schedule D1).

Variable	Definition
Investment adviser character 13F AUM / ADV AUM	eristics, defined at adviser level The ratio between the total value of holdings reported in an adviser's form 13F (from Thomson Reuters Global Ownership data set) and AUM.
Account Size	AUM divided by Number of Accounts.
AUM	Adviser's total assets under management as reported in its form ADV.
Number of Accounts	Total number of accounts as reported in an adviser's form ADV.
Share of individuals, AUM-based	AUM managed for individual clients and high-net-worth individuals divided by AUM .
Share of individuals, count-based	Number of individual clients and high-net-worth individuals divided by the total number of clients.

B Variable Definitions

Portfolio characteristics, defined at county level

All these variables are computed as equal-weighted averages across all investment advisers in a given county-year.

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ETF Fraction	Total ETF holdings from form 13F divided by AUM .
Equity Fraction	Total common equity holdings from form 13F divided by AUM .
Number of Equities	Number of common stock positions in an adviser's portfolio.
Number of Out-of-State Equities	Number of out-of-state stock positions in an adviser's portfolio. Out-of-state equity is defined as common equity issued by firms headquartered in states distinct from the headquarter state of an investment adviser.
Other Fraction	Total holdings other than equities and ETFs divided by AUM .
Out-of-State Equity Fraction	Total out-of-state equity holdings from form 13F divided by AUM . Out-of-state equity is defined as common equity issued by firms headquartered in states distinct from the headquarter state of an investment adviser.
County characteristics, defin	ed at county level
Population	County population computed as a three-year average based on the 1990, 2000, and 2010 Census data.
Income	Average county income per capita computed as a three-year average based on the 1990, 2000, and 2010 Census data.
College Degree	Fraction of county residents with education level equivalent to a college degree or higher computed as a three-year average based on the 1990, 2000, and 2010 Census data.
Dependent Variables	
Portfolio Distance	Sum of absolute differences between two counties' out-of-state equity portfolio weights (L1-norm), $\sum_{k=1}^{N_{AB,t}} w_{A,t}^k - w_{B,t}^k $, where $w_{A,t}^k$ ($w_{B,t}^k$) is the weight of stock k in the portfolio of county A (B) in year t, for all stocks issued by firms that are headquartered in states other than states where counties A and B are located.
Portfolio Distance ^{Alt}	Scaled sum of absolute differences between indicator variables for whether a stock is held in a county (L0-norm), $2 \cdot \frac{1}{N_{AB,t}} \sum_{k=1}^{N_{AB,t}} \mathbb{1}_{A,t}^k - \mathbb{1}_{B,t}^k $, where $\mathbb{1}_{A,t}^k$ ($\mathbb{1}_{B,t}^k$) is an indicator variable equal 1 if stock k is in the portfolio of county A (B) in year t and 0 otherwise, for stocks of firms that are headquartered in states other than states where counties A and B are located.

$\begin{array}{l} Portfolio \\ Fraction_{Dem \ CEO} \\ (Portfolio \\ Fraction_{Rep \ CEO} \end{array}) \end{array}$	County average portfolio fraction invested in firms with a Democratic-leaning (Republican-leaning) CEO across all investment advisers for a county-year. A CEO is a Democratic-leaning (Republican-leaning) if he or she has made the majority of the contributions to the Democratic (Republican) Party in the most recent 5 years and if he or she has never been classified as a Republican (Democratic) CEO since 1992.
Portfolio Fraction _{Env. Concerns}	County average portfolio fraction invested in firms conducting environmentally harmful operations in the prior years as identified by the MSCI ESG KLD indicators from 1991-2018. A firm is identified as conducting environmentally harmful operations if it (i) had significant liabilities for hazardous waste sites (indicator ENV - con - A), (ii) paid a settlement, fine or penalty due to non-compliance with U.S. environmental regulations (ENV - con - B), (iii) had a history of hazardous waste spills and releases (ENV - con - D), or (iv) had been sued and/or publicly criticised for its contribution to climate change and exceptionally high GHGs emissions as well as resistance to change (ENV - con - F).
$\mathbf{Portfolio}$ $\mathbf{Fraction}_{\mathbf{Firearms}}$	County average portfolio fraction invested in firms identified as involved in small firearm-related businesses, by the MSCI ESG KLD indicators from 1991-2018. A firm is identified as involved in small firearm-related businesses if it derives any revenues from manufacturing, distribution (wholesale or retail) of firearms and small arms ammunitions for civilian markets (military, government, and law enforcement markets are excluded) or if it owns or is owned by such a firm (indicator <i>FIR-con-A</i>).
Portfolio Fraction _{Labor Concerns}	County average portfolio fraction invested in firms with labor concerns in the prior years as identified by the MSCI ESG KLD indicators from 1991-2018. A firm is identified as having labor concerns if in the prior years it (i) opposed unionization efforts of its employees, breached union contracts or experienced strikes by non-unionized employees (indicator EMP-con-A), (ii) was involved in controversies related to health and safety of its employees, including job accidents, injuries, and fatalities, (EMP-con-B) or (iii) was involved in controversies related to its labor management practices in its supply chains, including unsafe working conditions, inadequate pay, excessive working hours or overtime, union issues at supplier facilities, the use of forced, prison or child labor by suppliers $(EMP$ -con-F and EMP -con-G).
Main Explanatory Variables Democratic Share (Republican Share)	Fraction of voters supporting a Democratic (Republican) candidate in the U.S. presidential elections.
Political Distance	L1-norm distance between the political preferences vectors for a pair of counties. A political preferences vector consists of the share of voters supporting a Democratic, Republican, and other/independent candidate during the most recent U.S. presidential elections.

PD Gallup All	L1-norm distance between the political preferences vectors based on the Gallup U.S. Daily survey data for a pair of counties. A political preferences vector consists of the share of respondents reporting their party affiliation as Democratic, Republican, and other/independent, based on the question "In politics, as of today, do you consider yourself a Republican, a Democrat, or an Independent?"
PD Gallup High Income	L1-norm distance between the political preferences vectors based on the high-income respondents (annual family income is above the county median) of the Gallup U.S. Daily Survey.
PD Gallup Low Income	L1-norm distance between the political preferences vectors based on the low-income respondents (annual family income is below the county median) of the Gallup U.S. Daily Survey.
Recent	Indicator variable equal to one if year is 2013 or later and zero otherwise.
Control Variables # of Advisers	Total number of investment advisers in a pair of counties.
Diff. in $\#$ of Advisers	Absolute difference in the number of advisers between two counties.
EconCondition Distance	L1-norm distance between two counties' vectors of beliefs about current economic conditions. A county vector consists of county-level fractions of the high-income respondents choosing one of the four answers in the following Gallup U.S. Daily Survey question: "How would you rate economic conditions in this country today? – excellent, good, only fair, or poor?"
EconOutlook Distance	L1-norm distance between two counties' vectors of beliefs about future economic conditions. A county vector consists of county-level fractions of the high-income respondents choosing one of the three answers in the following Gallup U.S. Daily Survey question: "Right now, do you think that economic conditions in the country as a whole are getting better or getting worse? – getting better, getting worse, are about the same."
Education Difference	Absolute difference between two counties' fractions of county residents with education level equivalent to a college degree or higher, as measured in the 1990, 2000, and 2010 Census data.
ETF Difference	Absolute difference between two counties' average ETF fractions.
Geographical Distance	Distance in miles between the internal points of two counties from the NBER County Distance Database for 2010 from https://www.nber.org/research/data/county-distance-database
Income Difference	Absolute difference between two counties' average income per capita, as measured in the 1990, 2000, and 2010 Census data.
Industry Distance	L1-norm distance between two counties' industry composition vectors. A county vector consists of industry (2-digit NAICS) employment shares in a county. Employment data are from the Bureau of Economic Analysis.

Population Difference	Absolute difference between two counties' total county populations, as measured in the 1990, 2000, and 2010 Census data.
Religious Distance	L1-norm distance between two counties' religion composition vectors. A county religion composition vector consists of county-level fractions of Protestants, Catholics, Orthodox Christians, Mormons, Jews, Others, as well as non-religious individuals from the Association of Religion Data Archives (ARDA) for 1990, 2000, and 2010.

C Additional Results

Variable	Ν	Mean	S.D.	P25	Median	P75
AUM, \$ bln	12,411	1.58	7.93	0.22	0.41	0.87
Number of Accounts	12,411	1,576	17,912	200	435	847
Account Size, \$ mln	12,411	4.78	76.62	0.53	1.04	2.14
Share of Individuals, Count-based $(\%)$	12,411	85.4	14.4	76	93	100
Share of Individuals, AUM-based $(\%)$	6,486	80.5	22.7	76	81	100
13F AUM / ADV AUM	12,411	72.9	22.8	58.9	70.2	84.0
Equity Fraction (%)	12,411	59.7	27.4	46.1	59.8	75.7
Out-of-State Equity Fraction (%)	12,411	49.5	23.9	36.4	49.3	63.3
ETF Fraction $(\%)$	12,411	8.46	17.15	0.00	0.53	6.86
Other Fraction $(\%)$	12,411	31.8	21.4	20.6	34.3	45.4
Number of Equities	12,411	122	194	50	82	132
Number of Out-of-State Equities	$12,\!411$	99	141	41	68	109

Table C1: Institutional Characteristics

Table C2: County Characteristics

This table presents summary statistics for county characteristics for three different sets of counties: all the counties in the United States, counties in the full sample, and counties in the balanced sample. Panel A presents the summary statistics for county population characteristics. Panel B presents summary statistics for the voting behavior in the U.S. presidential elections between 1996 and 2016. For each county we compute an average fraction of votes for a Democratic, Republican and other candidates across all the election years between 1996 and 2016. For the counties in the full and balanced samples, we use only those election years that are present in the corresponding samples. All variables are defined in Appendix B.

Variable	Ν	Mean	S.D.	Min	Max	% of U.S. Total
All U.S. counties						
Population	$3,\!137$	89,172	289,431	85	$9,\!400,\!369$	100%
Income (per Capita)	3,137	$17,\!349$	3,921	6,280	44,245	100%
College Degree	$3,\!137$	0.42	0.11	0.17	0.84	100%
Full sample						
Population	309	499,777	760,337	8,445	9,400,369	54.7%
Income (per Capita)) 309	$23,\!057$	5,418	$13,\!170$	44,245	61.5%
College Degree	309	0.56	0.10	0.28	0.84	60.4%
Balanced sample						
Population	94	866,181	$1,\!199,\!534$	8,445	9,400,369	29.1%
Income (per Capita)) 94	24,984	5,871	16,218	44,245	33.9%
College Degree	94	0.57	0.09	0.31	0.78	32.3%

Panel A. County Population Characteristics

	Panel 1	B. County V	oting Beha	vior		
Variable	Ν	Mean	S.D.	P25	Median	P75
All U.S. counties						
Democratic Share $(\%)$	$3,\!115$	39.0	12.4	30.5	38.3	46.4
Republican Share $(\%)$	$3,\!115$	56.9	12.4	49.3	57.7	65.5
Other Share $(\%)$	$3,\!115$	4.08	1.55	2.99	3.90	4.87
Full sample						
Democratic Share $(\%)$	309	49.7	13.2	40.4	50.0	57.5
Republican Share (%)	309	46.0	13.1	38.4	45.4	55.6
Other Share $(\%)$	309	4.30	3.26	2.76	3.76	4.97
Balanced sample						
Democratic Share $(\%)$	94	54.7	12.1	45.1	54.0	63.1
Republican Share $(\%)$	94	41.3	12.3	33.1	42.3	49.9
Other Share (%)	94	3.95	1.30	3.10	3.75	4.71

Panel B. County Voting Behavior

State	Average num	ber of counties	State	Average nun	ber of counties
	Full	Balanced		Full	Balanced
	Sample	Sample		Sample	Sample
AK	1.0	-	MO	2.5	1.0
AL	2.5	1.0	MT	1.4	-
AZ	1.4	1.0	NE	2.0	2.0
CA	13.6	8.8	NH	3.3	3.0
CO	3.3	2.0	NJ	8.3	3.8
CT	3.4	3.0	NM	1.1	1.0
DC	1.0	1.0	NV	1.3	-
DE	1.1	-	NY	10.1	5.9
FL	10.7	6.6	OH	6.3	4.9
GA	5.0	3.0	OK	1.6	-
HI	1.0	-	OR	2.2	1.0
IA	1.5	-	PA	10.0	5.9
ID	1.3	1.0	RI	1.2	1.0
IL	3.2	2.0	\mathbf{SC}	1.9	-
IN	4.4	2.8	SD	1.3	-
KS	2.1	1.0	TN	3.5	2.0
KY	2.5	2.0	ΤХ	6.3	3.0
LA	2.4	-	UT	1.7	-
MA	6.0	1.9	VA	10.5	5.8
MD	2.4	1.9	VT	1.7	-
ME	1.2	1.0	WA	4.0	2.0
MI	5.9	3.0	WI	5.8	5.0
MN	2.3	2.0	WV	1.4	-

Table C3: Geographical Variation in the Sample Coverage

This table reports the average number of counties per year between 1997 and 2019 in the full and balanced samples for each U.S. state with at least one county-year in the full sample.

Table C4: The Effect of County Characteristics on Political Distance

This table presents the effect of the differences in the county characteristics on *Political Distance*. Standard errors are double-clustered by county A and county B. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

	Political Distance				
	(1)	(2)	(3)		
Population Difference	$0.006 \\ (0.005)$	$0.004 \\ (0.005)$	$0.022 \\ (0.016)$		
Income Difference	0.004^{*} (0.002)	$0.002 \\ (0.002)$	$0.001 \\ (0.001)$		
Education Difference	$0.113 \\ (0.123)$	-0.207 (0.158)	-0.176 (0.121)		
Geographical Distance		0.029^{**} (0.014)			
Industry Distance		0.485^{***} (0.127)	-0.013 (0.054)		
Religious Distance		0.063^{**} (0.029)	0.039^{**} (0.015)		
Observations	96,008	96,008	96,008		
Adjusted \mathbb{R}^2	0.003	0.162	0.901		
Time FE	Yes	Yes	Yes		
County Pair FE	No	No	Yes		

$Table \ C5: \ \textbf{Effect of Political Distance on Portfolio Distance}^{Alt}$

This table presents the effects of *Political Distance* on *Portfolio Distance*^{Alt}. Panel A reports the baseline effect (annual level). Panel B reports the change in the effect over time, in particular in the recent years of the (balanced) sample, both at the annual level and election cycle level. *Recent* is an indicator variable equal to one for years after 2012. Standard errors are double-clustered by county A and county B. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

	Panel .	A. Baseline Results	S	
		Portfolio	Distance ^{Alt}	
	Full S	Sample	Balance	d Sample
	(1)	(2)	(3)	(4)
Political Distance	$\begin{array}{c} 0.073^{***} \\ (0.020) \end{array}$	$\begin{array}{c} 0.083^{***} \\ (0.027) \end{array}$	$\begin{array}{c} 0.115^{***} \\ (0.038) \end{array}$	$\begin{array}{c} 0.158^{***} \\ (0.043) \end{array}$
Observations Adjusted R ² Time FE County Pair FE	343,626 0.027 Yes No	343,626 0.635 Yes Yes	96,008 0.077 Yes No	96,008 0.601 Yes Yes

	Panel B.	Time Trend					
	Portfolio Distance ^{Alt}						
	Annua	al Level	Presidentia	al Cycle Level			
	(1)	(2)	(3)	(4)			
Political Distance	0.076^{**} (0.037)	0.120^{***} (0.043)	0.078^{**} (0.037)	$\begin{array}{c} 0.127^{***} \\ (0.044) \end{array}$			
Political Distance \times Recent	$\begin{array}{c} 0.110^{***} \\ (0.024) \end{array}$	0.065^{***} (0.022)	$\begin{array}{c} 0.113^{***} \\ (0.024) \end{array}$	$\begin{array}{c} 0.064^{***} \\ (0.023) \end{array}$			
Observations	96,008	96,008	25,848	25,848			
Adjusted R-squared	0.081	0.603	0.095	0.624			
Time FE	Yes	Yes	Yes	Yes			
County Pair FE	No	Yes	No	Yes			

Table C6: The Effect of Sinclair Entry on County Characteristics

This table presents the effects of Sinclair Entry on several county characteristics. Treated counties are those with Sinclair entries during our sample period. Post is an indicator variable that equals to one after the entry. In column (1), the dependent variable *EconConditions* is a county-year average response to the question from the U.S. Daily Gallup Survey: "How would you rate economic conditions in this country today?", where we code the responses as "poor" = 1, "only fair" = 2, "good" = 3, "excellent" = 4. In column (2), *EconOutlook* is a county-year average response to the question from the U.S. Daily Gallup Survey: "Right now, do you think that economic conditions in the country as a whole are getting better or getting worse?, where we code the responses as "getting worse" = 1, "are the same" = 2, "getting better" = 3. In column (3), *Religiosity* is a fraction of respondents who answer "Yes" to the question from the U.S. Daily Gallup Survey: "Is religion important in your daily life?" where possible answers are "Yes", "No", "Don't Know". In column (4), *Median Income* is county-year median family income from the U.S. Census Bureau. Standard errors are double-clustered by county and by year. ***, **, and *denote significance at 1%, 5%, and 10% level, respectively.

	EconConditions	EconOutlook	Religiosity	Median Income
	(1)	(2)	(3)	(4)
Treated \times Post	0.001 (0.012)	$0.037 \\ (0.044)$	-0.010 (0.015)	-1.060 (0.796)
Observations	1,601	1,601	1,601	1,585
Adjusted \mathbb{R}^2	0.826	0.423	0.791	0.987
Event ID × County FE	Yes	Yes	Yes	Yes
Event ID × Calendar time FE	Yes	Yes	Yes	Yes

Table C7: Attitudes towards Environmental Protection, Labor Protection, GunControl and Portfolio Allocation

This table reports the relation between *Democratic Share* (a proxy for attitudes towards environmental protection, labor protection, and gun control) and (a) *Portfolio Fraction*_{Env.Concerns}, the average portfolio fraction invested in firms engaged in environmentally harmful businesses within a county (Panel A); (b) *Portfolio Fraction*_{Labor Concerns}, the average portfolio fraction invested in firms engaged in environmentally harmful businesses within a county (Panel B); (c) *Portfolio Fraction*_{Firearms}, the average portfolio fraction invested in firms involved in small firearms production and distribution within a county (Panel C). In column (3) and (4) we report the results for two subsets of counties, those with *Democratic Share* above 50% and those with *Republican Share* above 50%. Standard errors are clustered by county. ***, ***, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

Panel A	A. Environm	iental Cor	ncerns	
		Portfo	lio Fraction _{Env.Cor}	ncerns
			Dem.Sh. > 0.5	
	(1)	(2)	(3)	(4)
Democratic Share	-0.2858^{*} (0.159)	-0.2063 (0.169)		
Democratic Share \times Recent		-0.0871 (0.070)		
Republican President			-0.0399^{***} (0.007)	-0.0229 (0.018)
Observations	2,109	2,109	439	154
Adjusted R^2	0.630	0.632	0.708	0.873
Time FE	Yes	Yes	No	No
County FE	Yes	Yes	Yes	Yes

Panel A. Environmental Concerns

		Portfoli	o Fraction _{Labor Co}	ncerns
			Dem.Sh. > 0.5	Rep.Sh. > 0.5
	(1)	(2)	(3)	(4)
Democratic Share	-0.2633^{*} (0.154)	-0.2113 (0.163)		
Democratic Share \times Recent		-0.0568 (0.060)		
Republican President			-0.0158^{**} (0.006)	-0.0007 (0.029)
Observations	2,109	2,109	439	154
Adjusted \mathbb{R}^2	0.893	0.893	0.764	0.694
Time FE	Yes	Yes	No	No
County FE	Yes	Yes	Yes	Yes
	Panel C. Gu		olio Fraction _{Firear} Dem.Sh. > 0.5	$^{\rm ms}$ Rep.Sh. > 0.5
	(1)	(2)	(3)	(4)
Democratic Share	0.0027 (0.010)	0.0169^{*} (0.010)		
Democratic Share \times Recent		-0.0155^{**} (0.006)		
Republican President			-0.0004 (0.001)	-0.0044 (0.004)
Observations	2,109	2,109	439	154
$\begin{array}{l} \text{Observations} \\ \text{Adjusted } \mathbf{R}^2 \end{array}$	$2,109 \\ 0.295$	$2,109 \\ 0.308$	$439 \\ 0.815$	$\begin{array}{c} 154 \\ 0.534 \end{array}$
	,	,		

Panel B. Labor Concerns