Political Divide and Partisan Portfolio Disagreement

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Abstract

In this paper, we propose a novel approach for estimating partisan portfolio disagreement in equity portfolios, defined as a weighted average disagreement in the portfolio weighting between Democratic-leaning and Republican-leaning investors across all stocks. We document that partisan portfolio disagreement among wealthy households in the United States was small and insignificant in the 2000s but has since become increasingly prevalent and significant. Exploring a shock to local political attitudes due to the staggered entry of Sinclair, a conservative television network, we provide evidence of a causal effect of political preference on portfolio choices. Further evidence suggests that the rising partisan portfolio disagreement is driven by an increase in the number of stocks, particularly large-cap stocks, that become partisan stocks over time. Ideological and affective polarization has likely fueled the partisan portfolio disagreement. Our study suggests that the growing political divide can lead to segmentation of U.S. equity markets along political lines.

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

1 Introduction

Increasing political polarization in the U.S. is not only hindering political compromise on many important policy issues but is also affecting an ever larger number of individual 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.[1] Could increasing political divide among households lead to a divergence in their financial portfolios?

To answer this question, we propose a novel approach for estimating partisan portfolio disagreement, defined as a weighted average disagreement in the portfolio weighting between Democratic-leaning and Republican-leaning investors across all stocks. In a simple conceptual framework in which investors' political preferences can tilt their portfolio weights of individual stocks away from politically neutral weights, we show that a regression of differences in county-level equity portfolio composition on differences in county-level political preferences can uncover partisan portfolio disagreement.

Our approach has several advantages. First, using a simple regression coefficient to summarize the influence of political preferences on portfolio compositions, we can uncover the time-series evolution of partisan portfolio disagreement. Second, our approach allows us to estimate the partisan nature of any stock at any point in time, which is crucial for detecting the time-varying partisan patterns in stocks. We let the data tell us whether a stock is nonpartisan, a Democratic stock, or a Republican stock at any point of time.

To implement our empirical analysis, 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 between 2001 and 2019. The individual clients of these local investment advisors tend to be high-net-worth households, an important yet understudied group of equity investors. We then derive county-year portfolio weights for each stock as the equal-weighted average portfolio weights of all advisers in a given county and year. While some investment advisers may offer one or a few "house portfolios" to all clients, we find

[1] Bishop (2008) argues that over several decades Americans have sorted themselves into more 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." See also Brown and Enos (2021); McCartney, Orellana-Li, and Zhang (2021).

that they often allow clients to express their non-financial preferences through investment restrictions and mandates. Thus, our county-level portfolio weights should reflect county-level differences in preferences and beliefs.

We measure the difference in equity portfolio composition between two counties, the county-pair *Portfolio Distance*, as the sum of the absolute differences between the county-level portfolio weights across all investable out-of-state stocks, in each year.[2] Our full sample consists of approximately 40,000 unique county pairs, 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 between 2001 and 2019, we also consider a balanced sample of over 4,000 unique county-pairs, representing 94 relatively large counties housing 30% of the U.S. population.

To measure differences in political preferences between two counties, we construct county-pair *Political Distance* as the sum of the absolute differences in the two counties' fractions of votes for the Republican, Democratic, and unaffiliated candidates in the U.S. presidential elections. Figure 1 shows that the average political distance between all U.S. county pairs has increased by about 30% over the past 20 years. We also use self-reported political preferences in Gallup surveys to construct an alternative political distance measure.

Taking advantage of our long time series and following the insights of our conceptual framework, we run annual regressions of *Portfolio Distance* on *Political Distance* to recover for each year in our sample the average degree of partisan portfolio disagreement, that is, the relative partisan over- and under-weighting of all stocks in the county pairs' equity portfolios. We find a substantial increase in the average partisan disagreement in the past decade, amounting to a more than doubled increase relative to the level in the earlier part of the sample period. Counter-factual analyses confirm that the main driver of this time trend is the increase in partisan portfolio disagreement rather than the increase in political distance itself.

To further strengthen the causal interpretation of the documented political distance effect, we exploit the staggered entry of Sinclair Broadcast Group, a large conservative TV network, into different local media markets. Sinclair's entry has been shown to increase the voting share for the Republican party (Martin and Yurukoglu (2017), Levendusky (2022)).

[2]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.

Our analysis based on county-pairs provides a unique advantage for using the Sinclair entry for identification purposes. The direction of the treatment effect on county-pair political distance depends on whether Sinclair enters the relatively more Republican county in a pair, while other potential effects associated with Sinclair's entry do not. If Sinclair enters the relatively more (less) Republican county in a pair, then we predict an increase (a decrease) in the county-pair political distance. We find that changes in political distance due to Sinclair's entry leads to changes in portfolio distance in the expected direction, thus providing causal evidence for the effect of political distance on portfolio distance.

In the last part of our study, we provide stock-level insights into the nature of the rising partisan portfolio disagreement. We estimate political tilts for each stock individually and over time. We call stocks with statistically significant political tilts "partisan stocks." Our estimates suggest that more and more stocks, particularly large-cap stocks, have become partisan stocks over time, with the fraction of partisan stocks growing from 4% to 10%, and the fraction of total market capitalization associated with partisan stocks growing from 10% to 29% during our sample period. This trend prevails across industries, with the largest increases in political tilts happening in consumer goods industries and industries with significant environmental footprints. Evidence based on the stock-level political tilts also suggests that ideological polarization, such as polarized policy positions with respect to environmental and social issues, and affective polarization, as reflected in dislike or distrust in political out-groups, have likely fueled the partisan portfolio disagreement.

Finally, we examine the role of investment advisers in explaining our findings. We capture an adviser's political leaning through the political donations by its employees. We then relate an adviser's portfolio tilts for stocks with environmental or labor concerns to the adviser's political leaning as well as the investors's political preferences as captured by the county's vote share. We find that an adviser's political preferences not only cannot explain the effect of the county-level political preferences, but also have little effect on their portfolios' political tilts, suggesting that our findings are unlikely driven by advisers' political preferences.

Our study is related to an emerging literature on the impact of political views on financial decisions and the consequences of political divisions. Several studies have examined stock 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)). Two recent studies document a negative impact of the political divide within teams of mutual fund managers on fund performance (Vorsatz (2021); Evans, Prado, Rizzo, and Zambrana (2022)). Our study is different both in terms of methodology and goals. None of these papers aims to study the partisan nature of stocks, its evolution, or the underlying mechanisms driving portfolio disagreements. By providing a new framework for studying partisan tilts in individual stocks or equity portfolios, our study is the first to provide systematic evidence on the time-series evolution of partisan portfolio disagreement in the U.S. and provide causal evidence for the effect of political differences on portfolio differences.

Previous studies have shown 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)), exposure to different social interactions (Brown, Ivković, Smith, and Weisbenner (2008); Pool, Stoffman, and Yonker (2015)) or media networks (Burt (2018)). 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 partisan lines and—given partisan segregation—geographical lines.

2 Conceptual Framework, Data, and Measurement

2.1 Conceptual Framework

We first introduce our definition of *Partisan Portfolio Disagreement* and then show how to recover it from the relationship between *Portfolio Distance* on *Political Distance*, under a few simplifying assumptions.

We distinguish between three types of investors: Republican-leaning, Democratic-leaning, and Unaffiliated, each differing in their portfolio allocations. Unaffiliated investors' allocation for stock i serves as a politically neutral benchmark weight, w_u^i (e.g., the market weight). By contrast, Democratic- and Republican-leaning investors may deviate from this benchmark, overweighting or underweighting the stock by factors δ^i and ρ^i, respectively. Their portfolio weights are thus given by:

$$w_d^i = \delta^i w_u^i, \quad w_r^i = \rho^i w_u^i.$$

We assume no short-selling so that all weights remain non-negative, thus, $\delta^i, \rho^i \leq \frac{1}{w_u^i}$. We define *Partisan Portfolio Disagreement* (*PPD*) as:

$$PPD = \frac{1}{2} \sum_{i=1}^{N} w_u^i |\delta^i - \rho^i|, \tag{1}$$

where N is the set of all investable stocks and $|\delta^i - \rho^i|$ captures the relative partisan tilt for stock i. The *PPD* is thus the weighted average of these tilts across all stocks and ranges from 0 to 1, where 0 corresponds to no disagreement and 1 corresponds to entirely non-overlapping portfolios between Republican- and Democratic-leaning investors (see Section IA1 for the proof). Thus, *PPD* provides a succinct yet informative gauge of how strongly partisan identities shape portfolio choices.

Next, we show how *PPD* can be estimated from political and portfolio distances across geographical locations (i.e., counties), even in the absence of data on individual households' portfolios and political preferences.

Assume that, within a given county, investors are homogeneous except for their political preferences. The weight of stock i in county A's equity portfolio is therefore: $w_A^i = d_A\, w_d^i + r_A\, w_r^i + u_A\, w_u^i$, where d_A, r_A, and $u_A = 1 - d_A - r_A$ are the fractions of Democratic-leaning, Republican-leaning, and Unaffiliated investors in county A, respectively.

We define *Portfolio Distance* between counties A and B as the sum of the absolute differences between all stocks' portfolio weights (i.e., the L1 norm of the two vectors of portfolio weights):

$$\textit{Portfolio Distance}_{AB} = \sum_{i=1}^{N} |w_A^i - w_B^i|. \tag{2}$$

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

$$\textit{Political Distance}_{AB} \;=\; |d_A - d_B| + |r_A - r_B| + |u_A - u_B|. \tag{3}$$

If in counties A and B the fractions of Unaffiliated investors are approximately the same ($u_A \approx u_B$ or equivalently $d_A - d_B \approx -(r_A - r_B)$), then $\textit{Political Distance}_{AB} \approx 2|d_A - d_B|$. We use this approximation to rewrite the absolute difference in equity portfolio weights between counties A and B for stock i as: $|w_A^i - w_B^i| = |d_A w_d^i + r_A w_r^i + u_A w_u^i - d_B w_d^i - r_B w_r^i - u_B w_u^i| \approx w_u^i \times |d_A \delta^i + r_A \rho^i - d_B \delta^i - r_B \rho^i| = w_u^i \times |\delta^i (d_A - d_B) + \rho^i (r_A - r_B)| = |d_A - d_B| \times w_u^i |\delta^i - \rho^i| = \textit{Political Distance}_{AB} \times \frac{1}{2} w_u^i |\delta^i - \rho^i|$. Therefore, Eq. (2) becomes:

$$\textit{Portfolio Distance}_{AB} \approx \textit{Political Distance}_{AB} \times PPD. \tag{4}$$

Equation (4) shows that *Portfolio Distance* is proportional to *Political Distance*, with the proportionality factor being the overall *Partisan Portfolio Disagreement* (*PPD*). If we regress *Portfolio Distance* on *Political Distance* using cross-sectional data across county pairs, the slope coefficient provides an estimate of *PPD*. A significant and positive slope indicates significant partisan disagreement in equity holdings, and changes in this coefficient over time capture trends in that disagreement.

2.2 Measuring Portfolio Distance

To capture equity portfolios of investors across U.S. counties over time, we construct a novel stock holding dataset from the 13F filings of local independent investment advisers that primarily serve individual as opposed to institutional investors. We aggregate stock-level portfolio weights by county and year to compare equity portfolios across counties over time.

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, including high-net-worth individuals, in a given year to be no less than 50% of the adviser's client base.[3] From 2012 onwards, advisers reported the AUM by type of client, which allows us to verify that the fraction of individual clients based on client counts and on AUM exhibit a high correlation of 83%. To focus on advisers who serve *local* households, we exclude adviser-year observations when an adviser reports office locations in

[3]We 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.

more than one MSA. We retain about 53% of the initial observations that satisfy the above two criteria and belong to local retail advisers.

Finally, we combine the local adviser data with holdings data from Thomson Reuters Global Ownership database for 2001-2019. The database includes data from 13F filings for advisers with more than $100 million in Section 13F securities, such as domestic stocks, ADRs, and exchange-traded funds (ETFs). We identify holding records for about 17% of advisers in our sample. 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.[4]

Our final sample of local advisers consists of 11,382 adviser-year observations between 2001 and 2019, representing 1,652 unique advisers in 309 counties. The average (median) fraction of individual clients is 87% (93%) based on client counts and 83% (81%) based on AUM, suggesting that we successfully select retail-focused local advisers. Based on the summary statistics in Table IA1, the average (median) number of accounts is 1,606 (446), and the average (median) AUM is $1.56 ($0.40) billion. Dividing each adviser's AUM by the adviser's number of accounts, we obtain an average (median) account size of $4.57 ($0.98) million. For comparison purposes, 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, with an average account size of $0.40 million.[5]

While a typical investment adviser in our sample serves a relatively small number of wealthy households, these advisers combined managed about 300,000 accounts in 2001 and 2.6 million accounts in 2019. Their combined equity holdings, on average, capture 3.5% of the U.S. equity market over our sample period, 2.3% in 2001 and 3.0% in 2019. That is, our data set not only covers a long time period but also compares well to other data sets in terms

[4]We 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 exceed 110% of their total AUM.

[5]Similarly, the average account size is $0.50 million for individual investors with brokerage and retirement accounts at Vanguard between 2017 and 2020 (Giglio, Maggiori, Stroebel, and Utkus (2021)).

of the fraction of the U.S. equity market that it includes. For example, the combined holdings of about 65,000 households in Barber and Odean (2000) on average represent 0.04% of the U.S. market capitalization, while the mutual fund holdings in Hong and Kostovetsky (2012) cover between 0.6% and 0.9% of the U.S. market capitalization. The total equity value held by households in our sample, close to one trillion dollars in 2019, is also comparable to the total assets held by millions of U.S. households studied by Meeuwis et al. (2022).

Finally, while the wealthy households in our study do not represent the average U.S. household, they are, of course, an important subset of households that remain understudied as many data sets have limited coverage of households in the top 10% of the wealth distribution. Given their substantial financial asset ownership and higher political activity (Cook, Page, and Moskowitz (2013); Nadeau, Lewis-Beck, and Foucault (2019)), wealthy households are particularly relevant when studying the relationship between political views and investment choices.

Overall, we believe that the 13F holdings of local retail-focused investment advisers can be a valuable data source that can provide new insights into the portfolio choices of wealthy households across the U.S. and over an extended period of time.

2.2.2 Portfolio Composition

On average, we observe about 73% of advisers' assets under management through their 13F filings (see Table IA1). To characterize investors' portfolios and detect 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.[6]

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 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

[6]ETFs, which have been increasing over time to about 20% in 2019 on average, comprise about 9% of total AUM. Other securities, such as mutual funds and fixed-income securities, make up the remaining 32% of total AUM. However, these holdings are not included in the 13F filings and thus not observable to researchers.

in Yakima, WA with \$110 millions in AUM, states that their "services are tailored to each individual client's requirements [...] 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." A 2020 survey of 872 investors by Hartford Funds Management Group found that 57% of investors consider political alignment with their financial advisor important, and 44% would switch advisors over a mismatch. It is, therefore, reasonable to assume that stock-level portfolio weights in advised portfolios reflect local investors' beliefs and preferences. However, we explicitly examine the role of advisers' political views in Section 4.3.

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

$$w^i_{A,t} = \frac{1}{I_{A,t}} \sum_{i=1}^{I_{A,t}} w^i_{A,t,i}, \tag{5}$$

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 3,420 county-year observations with 309 unique counties between 2001 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. On average, there are 3.3 (4.9) investment advisers per county in the full (balanced) sample, and the median number of advisers is 2 in both samples.

The counties in our full and balanced samples represent meaningful geographic dispersion across the U.S. (see Table IA2). Although the 309 counties in the full sample represent only 10% of all U.S. counties, they account for 54.8% of the U.S. population, 61.2% of the income, and 59.7% of college graduates (based on 2000 and 2010 Census data, see Table IA3, Panel A). Similarly, the 94 counties in the balanced sample account for 28.6% of the population, 33.1% of the income, and 31.4% of college graduates. That is, the counties in our samples are of economic importance. While the Democratic vote share in presidential elections between 2000 and 2016 is higher in our sample compared to all U.S. counties, especially in the balanced sample, our sample displays about the same level of variation as all U.S. counties (see Table IA3, Panel B).

2.2.3 County-pair Portfolio Distance

For each county-pair A and B, we construct the distance between their out-of-state equity portfolio weights according to Equation (2):

$$Portfolio\ Distance_{AB,t} = \sum_{i=1}^{N_{AB,t}} |w^i_{A,t} - w^i_{B,t}|, \tag{6}$$

where $N_{AB,t}$ is the set of all out-of-state stocks held by households in either county A or B.[7] 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. We 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 that are not driven by political preferences. Thus, the weight of out-of-state stock i in the portfolio of county A (B) in year t is $w^i_{A,t}$ ($w^i_{B,t}$), where all weights are re-scaled such that they add up to one.

2.3 Measuring Political Distance

For each county-pair A and B, we construct the political distance as in Equation (3). To capture d, r, and u in a county-year, we use the county-level voting shares for the Democratic, Republican, and other candidates in presidential elections from 2000 to 2016. The voting data is from the MIT Election Lab. 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.[8] Consistent with 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.

[7] See Cronqvist and Siegel (2014) and Aiken, Ellis, and Kang (2020) for similar approaches to compare portfolio compositions.

[8] Note 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.

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 county's voters. However, the investors in our sample are likely wealthier than an average household in a county. For robustness purposes, we use data from Gallup U.S. Daily surveys that provide income groups' political affiliations. Gallup U.S. Daily surveys were introduced in 2008 and are daily surveys on a large representative sample of individuals across the U.S., 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). 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.

Focusing on the balanced sample, we note that the county-level Democratic and Republican shares in the Gallup survey data are highly correlated with the corresponding shares in the presidential election data. The correlation of the Democratic (Republican) share in a three-year window around a presidential election year (the average share from the year before until the year after) based on Gallup with the voting share is 0.92 (0.94). We also observe that, on average, at the county level, high-income individuals have a lower (higher) Democratic (Republican) share than low-income individuals: the high-income Democratic share is 0.51, and the Republican share is 0.43; the low-income Democratic share is 0.56, and the Republican share is 0.34.

As reported in Panel B of Table 1, the political distance measures based on the voting data and that based on Gallup survey data (all respondents, $PolitDistGallup_{All}$) have similar distributions. The political distance between high-income people in a county-pair, $PolitDistGallup_{HighInc}$ is 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 $PolitDistGallup_{All}$ in the three-year window around a presidential election year is 0.90. If we use $PolitDistGallup_{HighInc}$, 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 Rising Partisan Portfolio Disagreement

We begin our empirical analysis by estimating the average degree of partisan portfolio disagreement (*PPD*) from a regression of *Portfolio Distance* on *Political Distance*. Taking advantage of the long time-series of our data set, we then examine the evolution of partisan portfolio disagreement over time. Then, the Gallup survey data allows us to separate economic expectations from political preferences. Finally, we exploit exogenous shocks to *Political Distance* to establish a causal effect on *Portfolio Distance*.

3.1 Baseline

Using data across all years in our sample, we estimate the average *PPD* by relating 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, indicated by subscript $t-k$, where k takes on the values 1 through 4. Specifically, we estimate:

$$\text{Portfolio Distance}_{AB,t} = \alpha + \beta \cdot \text{Political Distance}_{AB,t-k} + \tau_t + \lambda_{AB} + \epsilon_{AB,t} \qquad (7)$$

We include year as well as county-pair fixed effects, represented by τ_t and λ_{AB}, to absorb time trends and persistent county-pair differences. Standard errors are double clustered by each county in a county pair.[9]

Table 2 Panel A reports the results for the full sample (columns (1) and (2)) and the balanced sample (columns (3) and (4)) of 4,371 county-pairs between 2001 and 2019. The estimated coefficients, $\widehat{\beta}$, are consistently positive and significant.

According to Equation (4), the coefficient estimate $\widehat{\beta}$ directly captures *Partisan Portfolio Disagreement*, $\frac{1}{2}\sum_{i=1}^{N} w_u^i |\delta^i - \rho^i|$. Its magnitude corresponds to the minimum total market capitalization of all stocks with partisan tilts ($i : \delta^i \neq 1$ or $\rho^i \neq 1$; see Section IA1 for proof). A coefficient estimate of 0.144 (in column (4)) suggests that investors collectively disagree over approximately 14% of the total market capitalization due to differences in political preferences. This partisan disagreement could take two forms: (i) a complete partisan split, where Democratic-leaning investors entirely avoid some stocks ($\delta^i = 0$) while overweighting others ($\delta^i > 1$), with Republican-leaning investors doing the opposite, or (ii) a more diffuse

[9] We find similar results when using dyadic clustering.

disagreement, where smaller partisan tilts, $|\delta^i - \rho^i|$, affect a larger portion of the market. We will examine the roles of these two possibilities in shaping our results in Section 4.

Our data allows us to examine how the partisan portfolio disagreement has evolved over time. To do so, we use the balanced sample and estimate the specification in column (3) yearly for each year t between 2001 and 2019:

$$\text{Portfolio Distance}_{AB,t} = \alpha_t + \beta_t \cdot \text{Political Distance}_{AB,t-k} + \epsilon_{AB,t} \tag{8}$$

We then plot the estimated coefficients, $\hat{\beta}_t$, for $t = 2001, ...2019$, in Panel (a) of Figure 2. Visual inspection reveals an interesting pattern. The estimated partisan portfolio disagreement is small and statistically insignificant in the first three presidential cycles in our sample period but becomes significant and increasingly larger in the last two presidential cycles (2013-2019). The average coefficient estimate is 0.013 before 2013, and is 0.198 in 2019.

Given the rise in partisan portfolio disagreement over time, in Table 2, Panel B, column (1) we explicitly account for a differential effect of political distance on portfolio distance in each presidential election cycle. 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. Although the increase has been gradual, for ease of exposition we construct an indicator variable *Recent*, which equals one for the period of 2013-2019 and zero before. In column (2), we then estimate an interaction effect between this indicator and *Political Distance* using the balanced sample. Based on the reported estimates, *PPD* has increased by about 0.11 to a total of 0.185. In columns (3) and (4), we collapse the observations to the election cycle level by averaging *Portfolio Distance* within an election cycle and find results similar to those in the first two columns.

While the rise in the *PPD* contributes to a significant increase in portfolio distance, this trend coincides with a notable increase in average political distance over time (see Figure 1). To disentangle these effects, we compare the actual portfolio distance with two counterfactual measures. The first measure, $\textit{Portfolio Distance}_{Hyp|PolitDist2001,t}$ isolates the effect of raising partisan portfolio disagreement (i.e., the raising $\hat{\beta}_t$ coefficients) by keeping the political distance constant at its 2001 level. It is defined as $\textit{Portfolio Distance}_t$ minus $\hat{\beta}_t \times$ $\textit{Political Distance}_{2001}$, where $\hat{\beta}_t$ represents the cross-sectional coefficient estimates reported in Figure 2. This measure is depicted as dark gray hollow diamonds in Figure 3. The second measure, *Portfolio* $Distance_{Hyp,t}$ accounts for changes in both political distance and partisan portfolio disagreement. It is defined as *Portfolio* $Distance_t$ minus $\widehat{\beta}_t$ × *Political* $Distance_{t\text{-}1}$. It is depicted using light gray hollow squares. Figure 3 shows a declining trend in county-pair portfolio distances over time (solid green squares), suggesting convergence in households' advised equity portfolios across different geographic areas. Most importantly, Figure 3 clearly shows that the main driver of the increasing political distance effect is the increase in *PPD* rather than in political distance itself, because the two gray lines are close to each other. Moreover, both counterfactual measures are substantially lower than the realized average *Portfolio Distance* (depicted using solid green squares) in the later part of our sample. In other words, the convergence in the composition of equity portfolios across the U.S. is increasingly countered by the increasing partisan portfolio disagreement.

3.1.1 Robustness: Omitted County-Pair Differences

While the county-pair fixed effects in Table 2 help to control for persistent county-pair differences such as geographic distance, it is possible that *Political Distance* is correlated with other time-varying differences between counties that affect portfolio differences. In Table 3, Panel A, we include county-pair differences with respect to population size, per-capita income, and education. Furthermore, we include the county-pair differences in local industry composition (*Industry Distance*).[10] Finally, we include *Religious Distance* as a proxy for differences in counties' religious make-up (Shu, Sulaeman, and Yeung (2012) and Kumar, Page, and Spalt (2011)). Table 1, Panel B reports summary statistics for all these variables and Appendix Table B provides detailed definitions. We find that none of these county-pair differences increasingly contribute to *Portfolio Distance* in the later part of our sample, and their inclusion leads to only a small reduction in the estimated *PPD*.

In Table 3, Panel B, we control for the size and growth of household wealth managed by local independent advisors and differences in ETF adoption in a county-pair. During our sample period, the average number of advisors and the average number of accounts per capita in a county-pair tend to increase over time. The size and growth of local wealth management may be correlated with local economic conditions. The change in the number

[10] We note that the negative coefficient on this variable is due to the county-pair fixed effect, and becomes positive and insignificant if we drop it or replace it with county fixed effects.

of advisers or accounts could also indicate potential shifts in the composition of adviser's clienteles and portfolio choices. In addition, a larger number of advisers (accounts) in a county may allow us to better measurement of portfolio composition in the county (e.g., by averaging out adviser-specific, idiosyncratic tilts), potentially reducing measurement error in *Portfolio Distance* in the later part of our sample period. Finally, 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. Although it is unclear how these county-pair characteristics correlate with political distance, they could affect portfolio distance over time. However, the results in Table 3, Panel B suggest that controlling for these characteristics does not affect our estimates of the *PPD*. This means that our baseline results are unlikely to be driven by changes in the composition or growth of local wealth management, or the choice between holding individual stocks versus ETFs.

3.2 Evidence Based on Gallup Survey Data

Next, we use the Gallup U.S. Daily survey data between 2008 and 2019, described in Section 2.3, which provides rich information on respondents' political attitudes, income, and economic expectation. The survey data allows us to construct alternative measures of political distance that do not rely on election voting data, to distinguish between the political preferences of high- and low-income households, and to control for variations in macroeconomic outlooks that might influence portfolio choices.

First, we construct alternative measures of a county's political preference based on self-reported political preferences of all respondents, high-income respondents (income above the median level in a county-year), and low-income respondents in a county in the Gallup surveys. The result in column (1) of Table 4, Panel A suggests that our baseline estimates of *PPD* are robust to using the survey-based county-pair political distance. In column (2), we contrast the political distance among high-income individuals and that among low-income individuals in a county pair. The political preference of wealthy investors in our sample should be more correlated with that of high-income individuals. Indeed, we find that only the county-pair political distance among high-income individuals are positively associated with county-pair portfolio distance, suggesting that the differentiation by income is meaningful and that the effect of political distance based on all voters is likely driven by the political preferences of high-income voters. In columns (3)-(4) we show that the positive effect of political distance on portfolio distance is concentrated in the last two election cycles in our sample, consistent with our baseline results in Table 2. In column (5) we further control for other county-pair differences in Table 3, and the results are still robust. We also estimate the effect of political distance on portfolio distance (i.e., the average partisan portfolio disagreement) annually from 2009 to 2019 using $PolitDistGallup_{HighInc}$. The results displayed in Panel (b) of Figure 2 reveal a similar but more gradual increase in the *PPD* over time compared to the pattern based on the voting-based political distance measure in Panel (a).

Second, political preferences could be correlated with differences in views and expectations about the economy, which in turn could lead to differences in portfolio allocations. The Gallup survey data allows us to construct county-pair differences in macroeconomic expectations. Specifically, we analyze answers to the following survey questions: a) "How would you rate economic conditions in this country today – as excellent (1), good (0.5), only fair (-0.5) or poor (-1)?" and (b) "Right now, do you think economic conditions in the country as a whole are getting better (1) or getting worse (-1) or the same (0)?" Using responses from high-income respondents to these two survey questions, we construct *EconCondition Distance* and *EconOutlook Distance* for each county-pair-year in the balanced sample.

The results in Table 4, Panel B show that although *EconCondition Distance* also increasingly contributes to portfolio distance in the later part of our sample, controlling for distances in economic expectations decreases the *PPD* estimate only by 6% compared to the result in column (5) of Table 4, Panel A. Thus, differences in macroeconomic expectations seem to increasingly explain differences in portfolio distance through a largely separate channel from political preferences.

3.3 Sinclair Entry as a Shock to Political Distance

Our conceptual framework assumes that *Political Distance* causes *Portfolio Distance*. While we have shown that the political distance effect is robust to controlling for many county-pair differences, and not explained by differences in macro-economic expectations, in this section, we provide evidence consistent with a causal effect by using an exogenous shock to the political distance of a county pair. Specifically, we explore the staggered entry of the Sinclair Broadcast Group, a conservative TV network, into different media markets during our sample period.

3.3.1 Background about Sinclair's Expansion

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. Notably, stations acquired by Sinclair shift toward a more right-leaning slant, as evidenced 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 to also 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 our balanced sample of 94 counties during our sample period of 2000-2019. During this period, Sinclair's expansions were concentrated in 2011-2017 (13 counties). A potential concern is that Sinclair's entry timing and location are endogenously determined by local characteristics correlated with political trends. However, several factors mitigate this issue in our setting. First, Sinclair's expansion is achieved by a growth-by-acquisition strategy. Mastrorocco and Ornaghi (2020) point out that Sinclair mostly acquires other broadcast companies, which usually operate in multiple DMAs. That is, Sinclair enters 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.[11]

3.3.2 Sinclair's Entry and Changes in Portfolio Distance

We match treated counties in our sample with Sinclair entries to control counties based on the pre-entry local demographics (*Population*, *Income*, and *Education*) as well as a county's

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

Republican vote share, *RepShare*, and its change in the latest election cycle before Sinclair's entry.[12] Panel A in Table IA4 provides summary statistics and comparisons of the 13 treated and 13 matched control counties in our sample. Panel B reports the results from a difference-in-differences (DiD) analysis, where the dependent variable is *RepShare*. These results are largely in line with those of the prior literature using the entire U.S. sample (e.g., Miho (2020)). In Panel C, we show that Sinclair's entry has no significant treatment effect on county-level median household income, economic expectations, and religiosity,[13] suggesting that Sinclair's entry affects local political preferences but not other factors that may affect portfolio choices.

We analyze the effect of Sinclair's entry on portfolio distance in Table 5, Panel A. In our county-pair setting, the impact on political distance depends on whether Sinclair enters the more Republican county (potentially increasing distance, a *positive* treatment) or the more Democratic county (potentially decreasing distance, a *negative* treatment). To capture this, we define *Treatment Direction*, which equals +1 if Sinclair enters the more Republican county and -1 if it enters the more Democratic county.[14] Based on the 13 entry events, we identify 566 treated county-pairs: 375 with positive treatment (*Treatment Direction* = +1) and 191 with negative treatment (*Treatment Direction* = -1).[15]

The 566 control county-pairs are constructed by using the 13 control counties from above to replace the treated county in the treated county-pairs. For example, if county A is a treated county and county B is its closest match, then the control county-pair for the treated pair (A,C) is (B,C).[16] *Treatment Direction* equals 0 for all control county-pairs.

Since portfolio distance is measured annually, our analysis is at the annual level. The year Sinclair enters a county-pair is event year 0. *Post* is an indicator variable equal to one for event years 1 to 3 and zero for years -2 to 0. Table 5, Panel A, column (1) shows that the direction of the political preference treatment is positively related to portfolio

[12] We use the nearest neighbor matching approach and compute similarity between counties using the Mahalanobis distance (that weighs the co-variates based on the inverse of their variance–covariance matrix).

[13] Here we use the annual Small Area Income and Poverty Estimates from Census.

[14] In this test, we exclude pairs where both counties experience entry to ensure a clean event window.

[15] The event county-pairs have an average political distance of 0.29 with a standard deviation of 0.21. It is thus very rare that a Sinclair entry to the more Democratic county in a pair would increase, not decrease, the political distance after the event.

[16] An exception would be if C is the nearest neighbor match for A: then we choose the second-best match, say D, and use (D, C) as the matched control pair for treated pair (A, C).

distance. Relative to the control county-pairs, county-pairs with positive treatments see a 14% (=0.028/0.196) standard-deviation increase in portfolio distance in the three years after Sinclair's entry.

Next, we further address the concern that Sinclair's entry leads to other changes in the local counties besides political preferences, leading to portfolio changes. For example, since Sinclair is a media company, its entry may affect local households' portfolio choices through information provision, such as shifting coverage from local to national news (Kaviani, Li, Maleki, and Savor (2023)). Unlike the political preference effect, this information effect should not systematically depend on whether Sinclair enters the more or less Republican county in a pair, allowing us to distinguish between the two. We thus define an indicator variable *Sinclair Entry* that equals +1 after Sinclair enters a county in a county-pair and 0 otherwise. We use this variable to help control for other, non-political effects related to Sinclair's entry. In Table 5, Panel A, column (2), the coefficient for *Sinclair Entry* $\times$ *Post* is insignificant and an order of magnitude smaller than that for *Treatment Direction* $\times$ *Post*. At the same time, the estimated political preference effect is not impacted at all. These results suggest that the treatment effect is unlikely driven by other effects that come with Sinclair's entry.

Column (3) reports the results from a dynamic DiD estimation. The treated and control county-pairs do not exhibit any significantly different trend in portfolio distance before Sinclair's entry, suggesting that the entry is likely exogenous to local portfolio choices. However, in the three years after Sinclair's entry, treated county-pairs that experience an increase in political distance tend to experience an increase in portfolio distance relative to control county-pairs that experience no Sinclair's entry as well as treated county-pairs that experience a decrease in political distance.

3.3.3 Further Evidence on Political Preference Effect vs. Information Effect

The test in column (2) of Table 5, Panel A, does not have a clear prediction on how Sinclair's entry may affect the information distance of a county pair. To further distinguish between the political preference and information effects of Sinclair's entry, we analyze a complementary setting in Panel B of Table 5, in which we can have a clear prediction of whether the information distance increases or decreases following a Sinclair's entry. Specifically, we examine county-pairs where Sinclair was already present in one county and assess the impact of its entry into the second county on the portfolio distance.[17] We define *Sinclair Second Entry* as an indicator variable equal to +1 after Sinclair enters the second county in the pair and 0 before. To capture the political preference effect, we again construct *Treatment Direction*, which takes the value of +1 (-1) if Sinclair entered the more Republican (Democratic) county in the pair.

The information effect predicts that Sinclair's second entry would make the information sets of two counties more similar, leading to a decline in the information distance and thus portfolio distance in a county pair. That is, we expect a negative coefficient on *Sinclair Second Entry* . The political preference effect predicts that Sinclair's entry would lead to a decline (an increase) in portfolio distance if it leads to a decrease (an increase) in the two counties' political distance. That is, we expect a positive coefficient on *Treatment Direction.* As in Panel A, the event window is years [-2, +3], and we control for year-fixed effects and county-pair fixed effects. The results reported in Table 5, Panel B suggest that the information effect of Sinclair's entry is statistically insignificant, and the political preference effect remains strong and is largely independent of the information effect.

Overall, the results in Section 3 suggest that political differences have increasingly contributed to differences in wealthy households' equity portfolios over time. The effect of political distance on portfolio distance is not driven by county-pair differences in potentially confounding factors, or differences in macro-economic expectations. The analysis using Sinclair's entry as a shock to county-pair political distance further supports a causal interpretation of the political distance effect.

4 Stock-level Evidence

In this last section, we further investigate the nature of the rising partisan portfolio disagreement by analyzing the stock-level partisan tilts over time. We also show how partisan portfolio disagreement arises with increased willingness to align financial decisions with personal values and views, both accompanied by increasing ideological as well as affective polarization, i.e. differences in policy positions and emotional dislike or distrust of political out-groups. Finally, we examine the role of investment advisers and their political views in

[17]We use the full sample to maximize the sample size for this analysis. Also, all county-pairs are treated in this test.

explaining our findings.

4.1 Partisan Tilts over Time

Our baseline evidence suggests that the weighted average political tilt of stocks in the portfolio of wealthy households was small in earlier years but has become sizable in recent years. This could be due to an increase in the number of stocks that exhibit a significant partisan tilt (i.e., *partisan stocks*), an increase in the market capitalization of partisan stocks, an increase in the average absolute magnitude of partisan tilts, or a combination of these elements.

To identify partisan stocks, we relate the tilt in a stock's weight in a given county to the county's political preferences using our conceptual framework in Section 2.1. Specifically, for each stock i and each presidential cycle T, we estimate the following regression:

$$w^i_{A,t}/w^{mkt_i}_{A,t} = \alpha^i + \gamma^i_T \cdot \text{DemShare}_{A,T} + \tau_t + \epsilon^i_{A,t}, \tag{9}$$

where $w^i_{A,t}$ is the weight of stock i in the out-of-state equity portfolio of county A in year t,[18] and $w^{mkt_i}_{A,t}$ is the market weight of stock i in a market portfolio that excludes in-state stocks of county A. $DemShare_{A,T}$ is the fraction of voters in county A who support the Democratic candidate in the presidential elections during election cycle T. We assume that $DemShare_{A,T} = 1 - RepShare_{A,T}$, such that $\gamma^i_T = (\delta - \rho)^i_T$ and γ^i_T captures the relative over- or underweighting of stocks by Democratic-leaning investors compared to Republican-leaning investors. τ_t indicates year fixed effects. For each stock, we pool annual observations by election cycle to reduce noise in stock-level analysis, using portfolio data from 2001–2004 for the 2000 election, 2005–2008 for the 2004 election, and so on. Standard errors are clustered at the county level.

For each stock and each presidential cycle, we classify a stock as partisan if the coefficient estimate $\widehat{(\delta - \rho)}^i_T$ is statistically different from zero (p-value $\leq$ 10%). Panel A of Table 6 lists the 10 largest stocks with significant Democratic and Republican tilts during the 2016 presidential cycle as well as the year since when each stock has had a significant partisan tilt. We acknowledge the difficulty of assigning partisan tilts to individual stocks based on a

[18] As before, we remove in-state stocks from a county's portfolio to negate home bias, and then re-weight the weights of the remaining stocks such that they add up to one.

limited number of observations, and we therefore leave it to the readers to verify the extent to which the results in Panel A of Table 6 align with their priors. In the next subsection, we will investigate the relationship between partisan tilt and several stock characteristics that are known to be related to political preferences.

In Panel B of Table 6, we take a look at the components behind the increasing partisan portfolio tilt. Rows (1)-(3) list the number of partisan stocks, the fraction of such stocks among all stocks, and the fraction of market capitalization associated with partisan stocks, by presidential cycle. The number and fraction of partisan stocks start to increase after the 2012 presidential election and more strongly so after the 2016 presidential election. This trend is even more pronounced when considering the fraction of partisan stocks by market capitalization (MCap). Our estimates show that this fraction increases from 10.3% in 2001-2004 to 29.3% in 2017-2019. The divergence between the count- and the Mcap-based trend further suggests that large-cap stocks are an important part of the increase in political tilt documented in Section 3.1. This could be due to the salience of their political positions and the attention and possibly liquidity that large-cap stocks enjoy. In row (4), we report the growth in market capitalization of partisan stocks from one presidential cycle to the next. We find that the growth in market capitalization of already partisan stocks accounts for only a small fraction of the overall growth in the market capitalization associated with partisan stocks. In other words, the trend documented in row (3) is not driven by the market capitalization of a few partisan stocks growing faster than that of the rest of the market.

Rows (5)-(7) of Panel B report the average size of partisan portfolio disagreement for partisan stocks ($\widehat{|\delta - \rho|}$) over time. Empirically, it is the average absolute value of statistically significant estimates of $\widehat{|\delta - \rho|}^i$ by presidential cycle, equally weighted in row (5) and MCap weighted in row (6). These statistics suggest that while political tilts have become increasingly prevalent among stocks, the tilts themselves have not increased. In row (7), we report the MCap weighted average of $\widehat{|\delta - \rho|}^i$ of all stocks but assign $\widehat{|\delta - \rho|}^i = 0$ to the non-partisan stocks (i.e., stocks with insignificant coefficient estimates). According to this measure, the disagreement has increased by 0.21 ($= \frac{1}{2}(0.45 + 0.54) - \frac{1}{3}(0.26 + 0.24 + 0.36)$) between the earlier and more recent part of our sample period. This value is comparable to the one implied by our results in Panel B of Table 2, where we estimate that the weighted average partisan portfolio disagreement has increased by about 0.22 ($= 2 \times 0.11$).

Table 7 presents the fractions of market capitalization of partisan stocks for each of the thirty Fama-French industries in the earliest (2001 to 2004) and the latest (2017 to 2019) parts of our sample period, sorted by the overall change. Several interesting observations emerge. First, among the 30 industries, all but eight experience an increase in the fraction of partisan stocks. Second, industries with a significant environmental footprint, such as Precious Metals Mining, Aircraft, Ships, Railroad Equipment, Construction and Construction Materials, and Petroleum and Natural Gas industries, experience a particularly large increase in the fraction of market capitalization of stocks with a significant partisan portfolio disagreement. Third, consumer-oriented industries like Beer & Liquor, Consumer Goods, Retail, Automobiles and Trucks show some of the largest increases in the fraction (MCap) of partisan stocks, consistent with both the high visibility—stemming from investors' exposure to their products—and the broader political attention these industries attract amid rising consumer activism.[19]

Overall, the stock-level analysis provides us with a detailed understanding of the increasing average partisan portfolio disagreement. The evidence suggests that over the past 20 years, more and more stocks, large-cap stocks in particular, across different industries have become partisan in the sense that portfolio holdings of these stocks have become increasingly sensitive to investors' political preferences.

4.2 Ideological and Affective Polarization

The political science literature has conceptualized two forms of political polarization: ideological polarization and affective polarization. The former refers to partisan differences in policy positions, while the latter refers to an emotional dislike and distrust of political out-groups (Iyengar et al. (2019)). In this section, we examine partisan portfolio disagreement on stocks with specific characteristics that we believe are likely reflective of increasing polarization in both forms.

4.2.1 Ideological Polarization: Environmental and Labor Protections

Various survey data have robustly shown that Democrats and Republicans differ significantly on their policy positions with respect to important environmental and social issues

[19]See, for example, "Are your jeans red or blue?" by the WSJ, November 19, 2019 and "Can You Guess Which Brands Republicans and Democrats Love?" by the WSJ, September 4, 2024.

and increasingly so over time. For example, using survey questions from the Gallup Poll Social Series, we show in Figures 4a and 4b that partisan gaps in the importance of environmental protection and labor protection have increased substantially between 2000 and 2019. Democrats increasingly place more emphasis on environmental and labor protection compared to Republicans.

At the same time, ESG investing has grown substantially in the past 10 years, with the amount of institutionally managed assets with ESG considerations having increased sharply from about USD 2 trillion in 2012 to about USD 15 trillion in 2020.[20] In addition, when examining the investment approach of advisers, including those in our sample, we find that the fraction of ADV forms mentioning ESG-related investment restrictions has doubled since 2011 (see Figure IA1). This suggests that independent investment advisers have increasingly accommodated their clients' views on environmental and social issues via investment restrictions.

Given the prominence of ESG considerations, we use environmental and labor protection as examples to illustrate that firms' environmental and labor concerns are predictably associated with partisan tilts. Specifically, counties with higher Democratic vote shares tilt their portfolios away from stocks with environmentally harmful business practices and labor-related concerns, particularly in the later part of our sample period. We use the MSCI ESG KLD ratings and identify firms with a history of such concerns (see Appendix B for more details). For each firm and year, we form indicators variables, $\mathbb{1}(\text{Concerns}_t)$, that equal to one if a firm has at least one environmental (labor) concern in the past 5 years according to the MSCI ESG KLD, and zero otherwise.

We first confirm that partisan stocks with Democratic tilts are less likely to have environmental concerns ($\mathbb{1}(EnvConcerns) = 1$) or labor concerns ($\mathbb{1}(LaborConcerns) = 1$) than partisan stocks with Republican tilts. Panel A of Table 8 reports the average values of these indicators for partisan stocks across two sub-periods (2001-2012 and 2013-2019), comparing stocks with estimated Republican and Democratic tilts based on Equation (9). Our results indicate that partisan disagreement over environmental concerns was already present before 2013 but intensified over time. The gap between stocks with Democratic and Republican tilts was 12.1 percentage points in 2001-2012 but widened to 39.5 percentage points in 2013-2019, a statistically significant change of 27.4 percentage points ($p<0.01$).

[20]See the Executive Summary of the US SIF Trends Report 2020.

For labor concerns, the initial partisan gap was small and statistically insignificant in 2001-2012 (4.3 pp) but became large and significant in 2013-2019, expanding to 41.8 percentage points. This represents a statistically significant change of 37.5 percentage points ($p<0.01$), driven by a decline in labor concerns among Democratic-tilted stocks and an increase among Republican-tilted stocks.

We then test whether Democratic-leaning counties tilt their portfolios away from stocks with environmental or labor concerns in a panel regression analysis, which allows us to control for time-varying stock and county characteristics. That is, we regress a scaled stock's weight in a given county's portfolio, $\mathit{ScaledWeight}_{County}$, $w^i_{A,t}/w^{mkt_i}_{A,t}$, on the interaction between the firm-specific concern indicator and the Democratic vote share ($\mathit{DemShare}_{A,t-k}$) of the county in the most recent presidential election before year t, indicated by subscript $t-k$, where k takes on the values 1 through 4. The coefficient estimate of the interaction term captures our estimate of partisan tilt on stocks with specific concerns. Since we are particularly interested in the change in partisan tilts in recent years, we focus on the triple interaction with Recent_t. Specifically, using stock-county-year (i, A, t) observations, we estimate the following model:

$$\begin{aligned} w^i_{A,t}/w^{mkt_i}_{A,t} = \alpha &+ \beta_1 \cdot \mathbb{1}(\text{Concerns})^i_t \times \text{DemShare}_{A,t-k} \times \text{Recent}_t \\ &+ \beta_2 \cdot \mathbb{1}(\text{Concerns})^i_t \times \text{DemShare}_{A,t-k} + \beta_{XR} \cdot \text{X}^i_t \times \text{DemShare}_{A,t-k} \times \text{Recent}_t \\ &+ \beta_X \cdot \text{X}^i_t \times \text{DemShare}_{A,t-k} + \tau^i_t + \lambda_{A,t} + \eta^i_A + \epsilon^i_{A,t} \end{aligned} \tag{10}$$

To account for the potential correlation between environmental or labor concerns and other stock characteristics, we include interaction terms between *DemShare* and firm size as well as book-to-market and the corresponding triple interactions with *Recent*. We also include stock-by-year (τ^i_t), county-by-year ($\lambda_{A,t}$), and stock-by-county fixed effects (η^i_A) to absorb the impact of stock price changes and other time-varying stock or county characteristics as well as time-invariant factors that might contribute to the selection of a given stock by a given county. Finally, given the important role large-cap stocks play for our baseline results, we estimate the above equation using a value-weighted model.

Panel B of Table 8 reports the results. Columns (1)-(2) reveal that in recent years more Democratic-leaning counties underweight their exposure to stocks with environmental concerns and labor concerns. These results offer concrete examples of increasing partisan portfolio disagreement over environmental and social issues, consistent with increasing ideological polarization over these issues.

4.2.2 Affective Polarization: Attitudes towards the Other Party

While politically shaped attitudes towards environmental and social issues combined with the rise of ESG investing likely play an important role in the rise of partisan portfolio disagreement, political polarization extends beyond policy questions and also affects attitudes towards the other party. Again, using survey questions from the Gallup Poll Social Series, we show in Figure 5 that the fraction of respondents having unfavorable views of the other party has been increasing for both self-identified Democratic and Republican respondents. We therefore test whether affective polarization could be another reason for rising partisan portfolio disagreement.

We hypothesize that affective polarization could impact investors' willingness to invest in firms affiliated with the other political party (Wintoki and Xi (2020)). To test this prediction, we classify firms based on the political leaning of their CEOs as indicated by the CEOs' 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 Democratic-leaning (Republican-leaning) if they have predominantly (more than 50%) contributed to the Democratic (Republican) Party in both the most recent year and the past five years (based on cumulative donations). 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 28% are classified as Republican, while only 14% are classified as Democratic.

We test whether in recent years Republican-leaning counties tilt their portfolios away from stocks with Democratic CEOs and towards Republican CEOs. To do so, we run essentially the same regression as in Equation (10). The result in column (1) of Table 9 suggests that a county with a higher Republican vote share tends to have lower portfolio weights in stocks with Democratic CEOs during the last two presidential election cycles. However, more Republican-leaning counties do not significantly underweight stocks with Republican CEOs (column (2)), suggesting that they do not shun CEOs with well-identified political preferences in general but rather CEOs with opposing political views.

4.3 The Role of Advisers

Given the delegated nature of the equity portfolios in our sample, a key question arises: Could our findings be driven by advisers' political preferences rather than those of their clients?

To explicitly distinguish between the effect of advisers' and clients' political preferences on portfolio choices, we construct a measure of advisers' political preferences using their employees' individual political donation data from the Federal Election Commission (FEC). We match individuals making contributions to federally registered political committees with the advisers in our sample using the individuals' employer names. We identify relevant employees for 22.6% (373 out of 1,654) of the advisers in our full sample.[21]

An adviser's employee is categorized as Democratic if the employee's total donations to Democratic political committees over the past five years exceed those to Republican political committees, and as Republican if the opposite is true. We categorize an adviser as Democratic-leaning, $AdvDem = 1$, (Republican-leaning) if all its employees with identifiable political preferences are Democratic-leaning (Republican-leaning). In the adviser sample with political donation data, 26% (52%) of the firm-year observations advisers are Democratic-leaning (Republican-leaning). Thus, advisers in our sample with identifiable political preferences lean more towards the Republican Party, while the counties in our sample lean more towards the Democratic Party. In the cross-section, the advisers' political preferences (measured by *DemAdv*) and local households' political preferences (measured by *DemShare*) are moderately correlated at 12%.

Next, we revisit our tests of scaled stock weights as a function of a stock's environmental or social concerns as well as the county-level political preference, *DemShare*. However, differently from equation (10), we perform the analysis at the stock-adviser-year level (the depended variable is $ScaledWeight_{Adv}$) such that we can explicitly account for the adviser's political preference, *AdvDem* as well as stock time-varying characteristics. We again weight observations by the market weight of each stock.

The results are presented in Table 10. As before, we find that in recent years more Democratic-leaning counties significantly underweight stocks with environmental concerns (column (1)). Importantly, accounting for advisors' political leaning in column (2) does not

[21] We exclude employees with occupations unrelated to finance, e.g., IT or maintenance.

change this finding, while the effect of advisers' own political preferences is small and has not changed in recent years. When examining stocks with labor concerns in columns (3) and (4), we again find that accounting for advisors' political leaning does not change our findings.

Overall, the results in Table 10 suggest that financial advisers' political preferences alone are unlikely to drive our findings. Since advisers' preferences are only moderately correlated with those of local households, our results suggest that independent advisers tailor portfolio decisions to cater to their clients' preferences. This contrasts with mutual fund managers in Hong and Kostovetsky (2012), who serve many anonymous investors and may have more influence over portfolio decisions based on their own preferences.

5 Conclusion

In this paper, we propose a novel approach for estimating partisan portfolio disagreement in equity portfolios. We conceptually show that the weighted average partisan portfolio disagreement over all stocks can be uncovered in a regression of county-pair portfolio distances on political distances. Using this framework, we document that partisan portfolio disagreement among wealthy households in the United States was small and insignificant in the 2000s but has since become increasingly prevalent and significant. Further evidence at the stock level suggests that the rising partisan portfolio disagreement is driven by an increase in the number of stocks, particularly large-cap stocks, that become partisan over time. That is, the portfolio weights of more and more stocks become sensitivity to investors' political preferences. Exploring a shock to local political attitudes due to the staggered entries of Sinclair, a conservative television network, we provide evidence of a causal effect of political distance on portfolio distance.

Our study suggests that wealthy investors in the U.S. are increasingly willing to invest based on their political values, using their financial investments as a means of expressing their political preferences. Recently, even the largest national retail investment advisers have started to embracing portfolio tilts to serve their clients' preferences. For example, Fidelity Solo FidFolios allows investors to create their own custom indices and then purchase them with one click. Vanguard now offers personalized indexing solutions to enable its clients to over- and underweight individual stocks. This trend suggests that the phenomenon documented in our study is not unique to investors in our sample.

Although such political values-investing could be consistent with investors' utility maximization, its impact on portfolio performance is unclear and deserves future research. A 2025 Wall Street Journal article suggests that political-value-fueled ETFs have underperformed relative to the market.[22]

Finally, our study also calls for future research into the drivers and consequences of the increasing partisan nature of stocks for corporations. What makes a stock obtain partisan tilts? Will increasing partisan tilts on stocks distort corporate policies? Recent theoretical development (Wu and Zechner (2024)) provides insights on how partisan portfolio disagreement could arise due to the matching between investors and firms based on their political preferences. Since firms' political stances could emerge endogenously in equilibrium, catering to polarized investor political preferences could reinforce polarized corporate policies, affecting stock returns and welfare.

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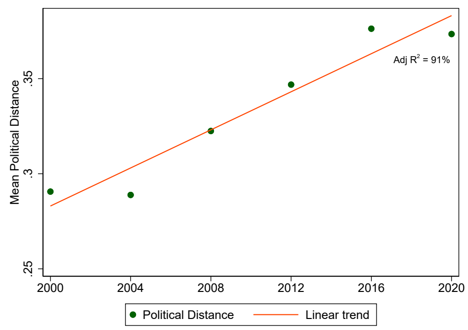
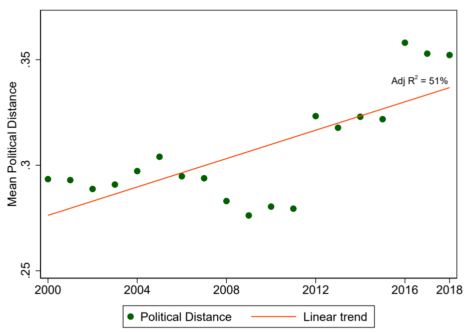
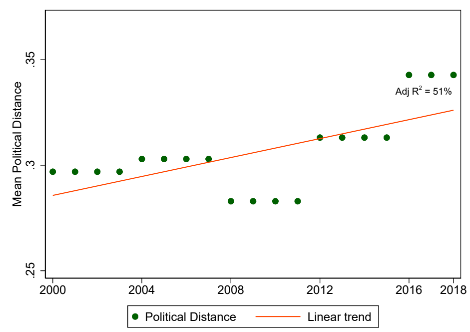


(a) All U.S. counties



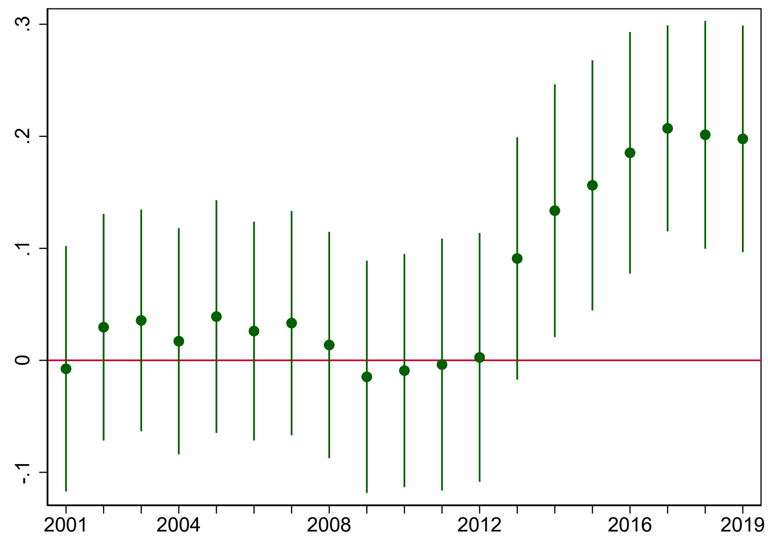
(b) Full sample



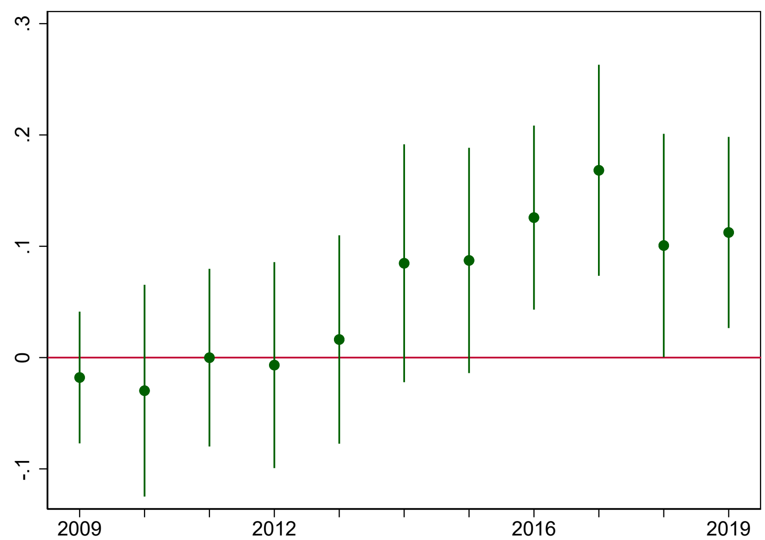
(c) Balanced sample

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

Panel (a) plots the evolution of the average *Political Distance* from 2000 to 2020, between all counties in the United States. Panels (b) and (c) plot the evolution of the average *Political Distance* from 2000 to 2018, for the full sample and the balanced sample.



(a) Vote-based *Political Distance*



(b) Survey-based $PolitDistGallup_{HighInc}$

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* (Panel (a)) and $PolitDistGallup_{HighInc}$ (Panel (b)) lagged by one year in the balanced sample.

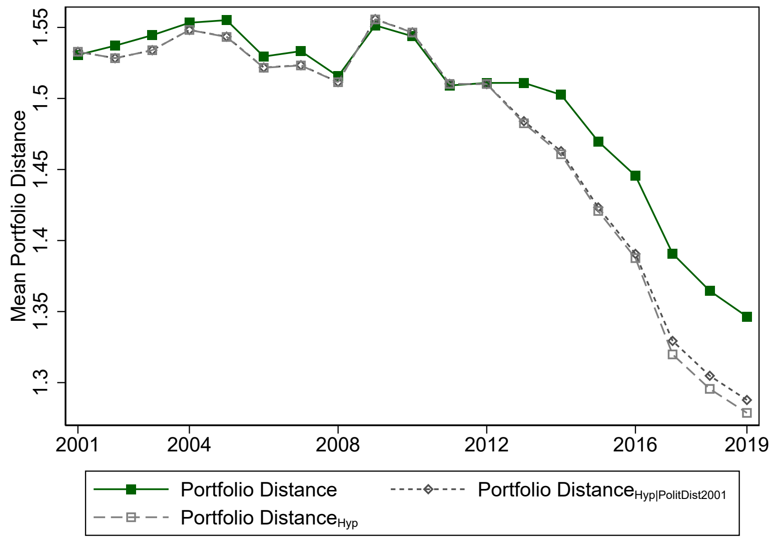
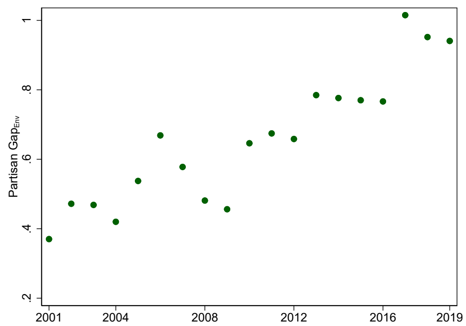
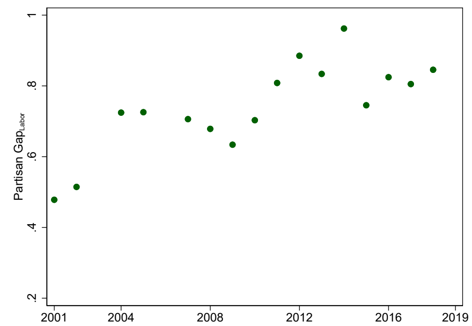


Figure 3: **Contribution of *Political Distance* to the evolution of *Portfolio Distance* over time.**

The figure plots the evolution of the average *Portfolio Distance* (solid green squares) in the balanced sample from 2001 to 2019. It also depicts the average *Portfolio Distance*$_{Hyp}$ (light gray hollow squares) defined as *Portfolio Distance* adjusted for the effect of *Political Distance* and *Portfolio Distance*$_{Hyp|PolitDist2001}$ (dark gray hollow diamonds) defined as *Portfolio Distance* adjusted for the effect of *Political Distance*$_{2001}$. In both cases, the adjustment is based on annual cross-sectional regressions.

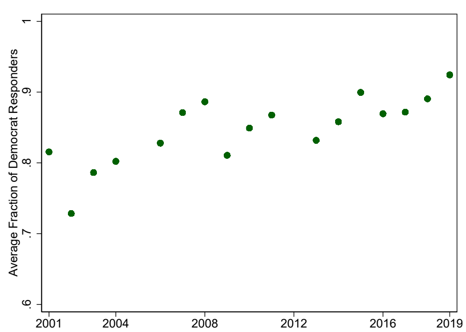


(a) Environmental protection

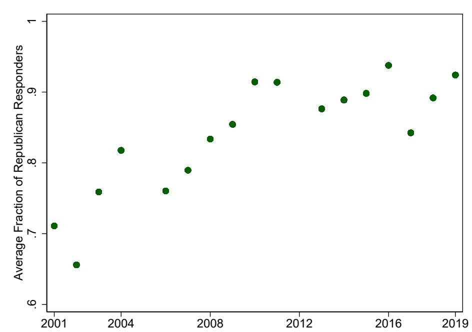


(b) Labor protection

Figure 4: **Partisan gap in attitudes towards environmental and labor protection.**
The figure plots the evolution of the differences in attitudes towards (a) environmental and (b) labor protection between self-identified Democratic and Republican respondents in the Gallup Poll Social Series. *Partisan* Gap_X is the difference between the average answers of Democratic and Republican respondents, where $X =$ *Env, Labor* for questions: (a) Should the protection of the environment 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) Should labor unions in the U.S. have more influence than today (answer$= 1$), less influence (-1), or the same amount (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 Poll Social Series respondents' opinion of the other party for (a) self-identified Democratic respondents and (b) self-identified Republican respondents. The measures are created using the following question: "Do 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).

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). Panels C and D present the summary statistics for county- and adviser-level (for advisers with the donations data) characteristics. All variables are defined in Appendix B.

Panel A. County-pair Distances, Full Sample

Variable	N	Mean	S.D.	P25	Median	P75
Portfolio Distance	320,568	1.572	0.239	1.405	1.575	1.752
Political Distance	320,568	0.318	0.225	0.138	0.273	0.452

Panel B. County-pair Characteristics, Balanced Sample

Variable	N	Mean	S.D.	P25	Median	P75
Portfolio Distance	83,049	1.497	0.234	1.329	1.500	1.664
Political Distance	83,049	0.306	0.215	0.135	0.264	0.434
$\text{PolitDistGallup}_{\text{All}}$	47,802	0.296	0.203	0.135	0.254	0.417
$\text{PolitDistGallup}_{\text{HighInc}}$	47,802	0.333	0.233	0.148	0.284	0.471
$\text{PolitDistGallup}_{\text{LowInc}}$	47,802	0.299	0.205	0.144	0.256	0.408
EconOutlook Distance	47,802	0.220	0.177	0.095	0.178	0.294
EconCondition Distance	47,802	0.240	0.173	0.130	0.204	0.305
Population Difference	83,049	0.942	1.486	0.214	0.476	0.932
Income Difference	83,049	7.599	6.724	2.446	5.600	10.90
Education Difference	83,049	0.099	0.076	0.039	0.086	0.141
Geographical Distance	83,049	1.018	0.729	0.436	0.827	1.506
Industry Distance	83,049	0.374	0.146	0.269	0.346	0.450
Religious Distance	83,049	0.556	0.332	0.293	0.500	0.764
# of Advisers	78,678	5.048	4.997	2.000	3.500	6.000
# Accounts	78,678	0.014	0.030	0.002	0.004	0.010
# of Advisers Growth	78,678	1.071	0.026	1.000	1.000	1.143
# of Accounts Growth	78,678	1.177	0.982	0.984	1.065	1.215
ETF Difference	78,678	0.103	0.123	0.012	0.054	0.154

Panel C. County-stock-year level Characteristics, Balanced Sample

Variable	N	Mean	S.D.	P25	Median	P75
ScaledWeight$_{\text{County}}$, $w^i_{A,t}/w^{mkt_i}_{A,t}$	5,196,528	0.913	10.32	0.000	0.000	0.000
DemShare	5,196,528	0.552	0.128	0.456	0.544	0.634
RepShare	5,196,528	0.421	0.131	0.338	0.425	0.519
$\mathbb{1}$(EnvConcerns)	5,196,528	0.093	0.290	0.000	0.000	0.000
$\mathbb{1}$(LaborConcerns)	5,196,528	0.252	0.434	0.000	0.000	1.000
$\mathbb{1}$(Dem CEO)	5,196,528	0.051	0.219	0.000	0.000	0.000
$\mathbb{1}$(Rep CEO)	5,196,528	0.104	0.305	0.000	0.000	0.000
ln(MktCap)	5,196,528	20.47	1.95	19.17	20.44	21.72
B/M	5,196,528	0.637	0.576	0.282	0.500	0.795

Panel D. Adviser–stock-level Characteristics, for Advisers with Donation Data

Variable	N	Mean	S.D.	P25	Median	P75
ScaledWeight$_{\text{Adv}}$, $w^i_{j,t}/w^{mkt_i}_{A,t}$	6,110,271	1.094	21.91	0.000	0.000	0.000
DemShare	6,110,271	0.642	0.143	0.540	0.641	0.762
AdvDemShare	6,110,271	0.113	0.261	0.000	0.000	0.000
$\mathbb{1}$(EnvConcerns)	6,110,271	0.103	0.304	0.000	0.000	0.000
$\mathbb{1}$(LaborConcerns)	6,110,271	0.268	0.443	0.000	0.000	1.000
ln(MktCap)	6,110,271	20.73	1.85	19.47	20.66	21.91
B/M	6,110,271	0.622	0.556	0.277	0.494	0.785

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, particularly in the recent years of the (balanced) sample, both at the annual and election cycle levels. *Election X* is an indicator variable equal to one for four years after the election and zero otherwise. For example, Election 2004 is equal to one for years 2005-2008 and zero otherwise. *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. Baseline Results

	Portfolio Distance			
	Full Sample		Balanced Sample	
	(1)	(2)	(3)	(4)
Political Distance	0.040*	0.071**	0.076*	0.144***
	(0.024)	(0.033)	(0.043)	(0.048)
Observations	320,568	320,568	83,049	83,049
Adjusted R^2	0.027	0.693	0.077	0.678
Time FE	Yes	Yes	Yes	Yes
County-Pair FE	No	Yes	No	Yes

Panel B. Time Trend

	Portfolio Distance			
	Annual Level		Presidential Cycle Level	
	(1)	(2)	(3)	(4)
Political Distance	0.080	0.076	0.074	0.070
	(0.063)	(0.058)	(0.063)	(0.058)
Political Distance × Election 2004	-0.008		-0.009	
	(0.020)		(0.021)	
Political Distance × Election 2008	-0.027		-0.028	
	(0.036)		(0.036)	
Political Distance × Election 2012	0.080*		0.079*	
	(0.046)		(0.046)	
Political Distance × Election 2016	0.118**		0.119**	
	(0.050)		(0.050)	
Political Distance × Recent		0.109***		0.112***
		(0.039)		(0.040)
Observations	83,049	83,049	21,855	21,855
Adjusted R^2	0.680	0.674	0.710	0.710
Time FE	Yes	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes	Yes

Table 3: **The Effect of Differences in Demographic and Economic County Characteristics and Adviser Characteristics**

Panel A shows that the effect of *Political Distance* on *Portfolio Distance* is robust to controlling for the differences in the time-varying county characteristics (*Population Difference*, *Income Difference*, *Eduction Difference*, *Industry Distance*, *Religious Distance*) and *Geographical Distance*, as well as their interactions with *Recent*. Panel B shows that the effect of *Political Distance* on *Portfolio Distance* is robust to controlling for the differences in the time-varying adviser-related county characteristics: *# of Advisers*, *# of Accounts*, *# of Advisers Growth*, *# of Accounts Growth* and *ETF Difference*, their interactions with *Recent* as well as controls from Panel A and their interactions with *Recent*. The sample is our balanced sample that spans 2001-2019. *Recent* is an indicator variable equal to one for years 2013 onward, and zero otherwise. 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.

Panel A. County Characteristics

	Portfolio Distance			
	(1)	(2)	(3)	(4)
Political Distance	0.080	0.090	0.082	0.090
	(0.057)	(0.056)	(0.058)	(0.057)
Political Distance × Recent	0.107***	0.087**	0.105**	0.088**
	(0.039)	(0.043)	(0.041)	(0.044)
Population Difference × Recent	-0.003	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Income Difference × Recent	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Education Difference × Recent	0.170	0.117	0.167	0.117
	(0.153)	(0.127)	(0.145)	(0.125)
Geographical Distance × Recent	-0.008	-0.007	-0.008	-0.007
	(0.014)	(0.014)	(0.014)	(0.014)
Industry Distance × Recent		0.068		0.063
		(0.106)		(0.104)
Religious Distance × Recent			0.017	0.011
			(0.025)	(0.022)
Population Difference	-0.053	-0.058	-0.053	-0.058
	(0.045)	(0.045)	(0.046)	(0.046)
Income Difference	0.004*	0.004	0.004*	0.004
	(0.002)	(0.002)	(0.002)	(0.002)
Education Difference	0.171	0.255	0.183	0.261
	(0.260)	(0.261)	(0.260)	(0.261)
Industry Distance		-0.298**		-0.297**
		(0.119)		(0.120)
Religious Distance			0.014	0.018
			(0.032)	(0.031)
Observations	83,049	83,049	83,049	83,049
Adjusted R^2	0.682	0.684	0.682	0.684
Time FE	Yes	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes	Yes

Panel B. Adviser Characteristics

	Portfolio Distance				
	(1)	(2)	(3)	(4)	(5)
Political Distance	0.084	0.075	0.072	0.059	0.058
	(0.057)	(0.055)	(0.055)	(0.054)	(0.055)
PoliticalDistance × Recent	0.107***	0.096***	0.098***	0.098***	0.100**
	(0.039)	(0.034)	(0.034)	(0.033)	(0.039)
# of Advisers		-0.025***	-0.024***	-0.023***	-0.028***
		(0.004)	(0.004)	(0.004)	(0.005)
# of Advisers × Recent		0.001	0.001	0.002	0.000
		(0.002)	(0.002)	(0.002)	(0.001)
# of Accounts		-0.313	-0.278	-0.290	-0.321
		(0.355)	(0.358)	(0.350)	(0.342)
# of Accounts × Recent		0.208	0.175	0.139	0.238
		(0.230)	(0.227)	(0.189)	(0.223)
# of Advisers Growth			-0.020	-0.022*	-0.021
			(0.013)	(0.013)	(0.013)
# of Advisers Growth × Recent			-0.006	-0.013	- 0.012
			(0.018)	(0.017)	(0.017)
# of Accounts Growth			0.001	0.001	0.000
			(0.002)	(0.002)	(0.002)
# of Accounts Growth × Recent			-0.023**	-0.025***	-0.023**
			(0.009)	(0.009)	(0.009)
ETF Difference				0.050	0.054
				(0.042)	(0.042)
ETF Difference × Recent				0.232***	0.223***
				(0.055)	(0.054)
Observations	78,678	78,678	78,678	78,678	78,678
Adjusted R^2	0.689	0.707	0.708	0.715	0.720
Controls	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes	Yes	Yes

Table 4: **Survey-based Political Distance and Macroeconomic Expectations**

This table presents the effects of political distance based on the Gallup U.S. Daily survey on *Portfolio Distance*. In column (1), the measure $PolitDistGallup_{All}$ is based on all Gallup respondents. In columns (2)-(3), we split the respondents into high- and low-income ones ($PolitDistGallup_{HighInc}$ and $PolitDistGallup_{LowInc}$ variables), based on whether their annual household income is above or below the county median household income. Panel B shows that the effect of $PolitDistGallup_{\text{HighInc}}$ on *Portfolio Distance* is robust to controlling for the time-varying distances in the economic expectations of high-income individuals (*EconOutlook Distance*) and in their beliefs about the current economic conditions (*EconCondition Distance*). In both panels, controls include all the control variables from Panels A and B of Table 3 and their interactions with *Recent*. 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.

Panel A. Survey-based Political Distance, *PD Gallup*

	Portfolio Distance				
	(1)	(2)	(3)	(4)	(5)
$\text{PolitDistGallup}_{\text{All}}$	0.049***				
	(0.017)				
$\text{PolitDistGallup}_{\text{HighInc}}$		0.032**	-0.042	-0.041	-0.042
		(0.015)	(0.029)	(0.029)	(0.029)
$\text{PolitDistGallup}_{\text{LowInc}}$		-0.005			
		(0.020)			
$\text{PolitDistGallup}_{\text{HighInc}}$ × Election 2012			0.086**		
			(0.034)		
$\text{PolitDistGallup}_{\text{HighInc}}$ × Election 2016			0.139***		
			(0.033)		
$\text{PolitDistGallup}_{\text{HighInc}}$ × Recent				0.108***	0.104***
				(0.032)	(0.033)
Observations	47,802	47,802	47,802	47,802	47,802
Adjusted R^2	0.746	0.746	0.749	0.749	0.777
Controls	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes	Yes	Yes

Panel B. Survey-based Macroeconomic Expectations

	Portfolio Distance		
	(1)	(2)	(3)
$\text{PolitDistGallup}_{\text{HighInc}}$	-0.037	-0.037	-0.036
	(0.028)	(0.027)	(0.027)
$\text{PolitDistGallup}_{\text{HighInc}} \times$ Recent	0.098***	0.097***	0.098***
	(0.031)	(0.032)	(0.031)
EconOutlook Distance	-0.024		-0.009
	(0.019)		(0.020)
EconOutlook Distance $\times$ Recent	0.030		0.000
	(0.027)		(0.026)
EconCondition Distance		-0.045	-0.043
		(0.028)	(0.030)
EconCondition Distance $\times$ Recent		0.081**	0.082**
		(0.033)	(0.033)
Observations	47,802	47,802	47,802
Adjusted R^2	0.777	0.777	0.777
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes

Table 5: **Sinclair Shock and its Effect on Portfolio Distance**

This table presents the effects of Sinclair entry on *Portfolio Distance*. Panel A presents the results for a staggered DiD design, where in a treated county pair only one county experiences Sinclair entry. The sample includes county pairs from our balanced sample and covers years from 2009 to 2019, with Sinclair entries from 2011 to 2017. For each treated county (pair), we find a matched control (pair) without Sinclair entry, based on the pre-entry local demographics, *RepShare*, and the change in *RepShare* in the latest election cycle before Sinclair's entry. *Treatment Direction* equals +1 (-1) if Sinclair enters the more Republican (Democratic) county in a county-pair, and zero otherwise. *Post* is an indicator variable equal to one for event years 1 to 3 and zero for years -2 to 0. *Sinclair Entry* equals 1 if Sinclair enters one of the counties in a county pair and 0 otherwise. Event Year[0] is the year with Sinclair entry for treated county pairs. Panel B presents the results for an event study design, where county-pairs with Sinclair already present in one of the counties experience Sinclair entry into the second county. *Sinclair Second Entry* equals to one for event years 1 to 3 and zero for years -2 to 0. *Treatment Direction* equals +1 (-1) if Sinclair enters the more Republican (Democratic) county in a county-pair. In both panels, 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. Sinclair Entry as a Shock to Political Distance

	Portfolio Distance		
	(1)	(2)	(3)
Treatment Direction × Post	0.028***	0.028***	
	(0.005)	(0.005)	
Sinclair Entry × Post		0.003	
		(0.014)	
Treatment Direction × Event Year[-2]			-0.007
			(0.008)
Treatment Direction × Event Year[-1]			-0.005
			(0.003)
Treatment Direction × Event Year[+1]			0.021**
			(0.010)
Treatment Direction × Event Year[+2]			0.022
			(0.014)
Treatment Direction × Event Year[+3]			0.031**
			(0.015)
Observations	9,816	9,816	9,816
Adjusted R^2	0.802	0.802	0.802
Event × County-Pair FE	Yes	Yes	Yes
Event × Calendar-Time FE	Yes	Yes	Yes

Panel B. Political Distance Effect vs. Information Effect

	Portfolio Distance	
	(1)	(2)
Treatment Direction	0.011**	0.012**
	(0.004)	(0.004)
Sinclair Second Entry		-0.022
		(0.021)
Observations	9,745	9,745
Adjusted R^2	0.805	0.805
Event × County-pair FE	Yes	Yes
Event × Calendar time FE	Yes	Yes

Table 6: **Partisan Stocks**

Panel A lists the top 10 largest stocks (as of the end of 2019) with significant Democratic and Republican tilts during the 2016 presidential cycle. We report each company's market capitalization in 2019 (in billions of dollars) and the presidential cycle when it became partisan for the first time. Panel B shows the prevalence of partisan stocks during the presidential cycles from 2000 to 2016. It presents the number of partisan stocks in each presidential cycle, the fraction of partisan stocks relative to all stocks, the fraction of their market capitalization relative to the total market capitalization at the end of the period, and the change in the market capitalization fraction of partisan stocks due to change in market capitalization of the partisan stocks identified in the previous presidential cycle. It also reports the average absolute partisan disagreement, $|\widehat{\delta - \rho}|$, (for significant tilts only) calculated both on an equal-weighted and value-weighted basis for each presidential cycle.

Panel A. Top 10 Stocks with Significant Democratic and Republican Tilts during the 2016 Presidential Cycle, by MCap

Democratic Tilt, $\widehat{\delta - \rho} > 0$			Republican Tilt, $\widehat{\delta - \rho} < 0$		
Company	MCap ($Bn)	Partisan Since	Company	MCap ($Bn)	Partisan Since
Microsoft	1,023.9	2016	Johnson & Johnson	384.0	2008
Amazon.com	920.2	2008	Exxon Mobil	295.4	2016
Bank of America	311.2	2016	Procter & Gamble	274.6	2012
Mastercard	300.7	2008	Coca-Cola	236.9	2008
UnitedHealth Gr.	278.7	2012	Disney (Walt)	234.8	2016
Citigroup	168.8	2008	Chevron	226.8	2000
Adobe	149.3	2008	Pepsico	190.1	2008
Costco	129.6	2000	Abbott Lab.	153.1	2012
Thermo Fischer Sc.	129.5	2016	US Bancorp	91.0	2016
Honeywell Int'l	125.8	2000	Southern Co.	67.1	2012

Panel B. Prevalence of Partisan Stocks

Row		Period				
		2001-04	2005-08	2009-12	2013-16	2017-19
(1)	# of Partisan Stocks	187	197	180	232	384
(2)	Fraction (#) of Partisan Stocks	0.042	0.042	0.043	0.056	0.103
(3)	Fraction (MCap) of Partisan Stocks	0.103	0.109	0.161	0.237	0.293
(4)	Δ Fraction (MCap) of Previously Partisan Stocks	.	-0.003	0.013	0.015	0.025
	Average $\lvert\widehat{\delta - \rho}\rvert$					
(5)	equal-weighted: Partisan Stocks	3.58	5.17	3.69	2.84	2.94
(6)	value-weighted: Partisan Stocks	2.32	2.30	2.21	2.00	2.00
(7)	value-weighted: All Stocks	0.26	0.24	0.36	0.45	0.54

Table 7: **Changes in Fraction of Partisan Market Capitalization, by Industry**

This table shows the fraction of partisan market capitalization for the thirty Fama-French industries during the 2001-2004 and 2017-2019 periods and its change between the two periods (the last column).

	Period: 2001-04		Period 2017-19		
	Obs.	Frac.(MCap)	Obs.	Frac.(MCap)	ΔFrac.(MCap)
Precious Metals, Non-Metallic, and Industrial Metal Mining	22	0.000	32	0.622	0.622
Beer & Liquor	11	0.257	13	0.838	0.581
Consumer Goods	53	0.021	34	0.490	0.468
Retail	205	0.076	146	0.484	0.408
Aircraft, ships, and railroad equipment	24	0.026	28	0.403	0.377
Petroleum and Natural Gas	139	0.146	148	0.481	0.336
Automobiles and Trucks	50	0.026	45	0.351	0.324
Banking, Insurance, Real Estate, Trading	1063	0.082	1083	0.339	0.257
Construction and Construction Materials	110	0.073	100	0.305	0.233
Healthcare, Medical Equipment, and Pharmaceuticals	499	0.099	612	0.311	0.212
Recreation	78	0.000	66	0.170	0.170
Personal and Business Services	639	0.156	436	0.304	0.148
Fabricated Products and Machinery	129	0.069	101	0.204	0.136
Steel Works Etc	43	0.000	29	0.128	0.128
Business Equipment	525	0.023	263	0.148	0.125
Business Supplies and Shipping Containers	49	0.058	33	0.182	0.124
Electrical Equipment	55	0.024	42	0.143	0.119
Utilities	102	0.058	86	0.174	0.116
Food Products	69	0.251	63	0.366	0.115
Transportation	88	0.031	73	0.122	0.091
Coal	6	0.000	12	0.066	0.066
Communication	120	0.259	76	0.308	0.049
Tobacco Products	4	0.000	3	0.000	0.000
Textiles	11	0.000	7	0.000	0.000
Wholesale	116	0.109	94	0.105	-0.004
Chemicals	65	0.108	69	0.091	-0.017
Apparel	56	0.043	28	0.018	-0.026
Everything Else	112	0.174	89	0.146	-0.028
Restaurants, Hotels, Motels	64	0.159	61	0.027	-0.132
Printing and Publishing	32	0.367	23	0.100	-0.267

Table 8: **The Effect of Attitudes towards Environmental and Labor Protection on Portfolio Allocation**

Panel A present the average fractions of stocks with environmental concerns ($\mathbb{1}(EnvConcerns) = 1$) and labor concerns ($\mathbb{1}(LaborConcerns) = 1$), among partisan stocks with Republican and Democratic tilts, during the presidential cycles from 2000 and 2016. Rows (3) and (6) present the differences in the fractions of stocks with concerns between the two groups, along with the corresponding t-test significance levels. Panel B shows the differential effect of environmental and labor concerns on portfolio allocations for counties with different political leanings. The observation level is stock-county-year, where the dependent variable is $ScaledWeight_{County}$, $w^{i}_{A,t}/w^{mkt_i}_{A,t}$. The sample is our balanced sample that covers the years 2001 to 2019. *ln(MktCap)* is the logarithm of a stock's market capitalization. *B/M* is a stock's book-to-market. Robust standard errors are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

Panel A. Prevalence of Environmental and Labor Concerns among Partisan Stocks

Row		Period		Difference
		2001-2012	2013-2019	2013-19 − 2001-12
		(1)	(2)	(3)
Fraction with $\mathbb{1}(EnvConcerns) = 1$ among partisan stocks with				
(1)	Dem.Tilt, $\widehat{\delta-\rho} > 0$	0.115	0.085	-0.030*
(2)	Rep.Tilt, $\widehat{\delta-\rho} < 0$	0.235	0.480	0.245**
(3)	Diff: Dem − Rep	-0.121**	-0.395***	-0.274***
Fraction with $\mathbb{1}(LaborConcerns) = 1$ among partisan stocks with				
(4)	Dem.Tilt, $\widehat{\delta-\rho} > 0$	0.339	0.163	-0.176***
(5)	Rep.Tilt, $\widehat{\delta-\rho} < 0$	0.382	0.581	0.199*
(6)	Diff: Dem − Rep	-0.043	-0.418***	-0.375***

Panel B. Role of Environmental and Labor Concerns in Partisan Portfolio Allocation

	ScaledWeight$_{\text{County}}$, $w^{i}_{A,t}/w^{mkt_i}_{A,t}$	
	(1)	(2)
$\mathbb{1}$(EnvConcerns) × DemShare × Recent	-0.488***	
	(0.097)	
$\mathbb{1}$(EnvConcerns) × DemShare	0.117	
	(0.089)	
$\mathbb{1}$(LaborConcerns) × DemShare × Recent		-0.257***
		(0.093)
$\mathbb{1}$(LaborConcerns) × DemShare		0.114
		(0.073)
ln(MktCap) × DemShare × Recent	0.027	0.011
	(0.023)	(0.025)
ln(MktCap) × DemShare	0.202***	0.217***
	(0.044)	(0.044)
B/M × DemShare × Recent	0.400***	0.363***
	(0.124)	(0.125)
B/M × DemShare	0.060	0.077
	(0.091)	(0.091)
Observations	5,196,528	5,196,528
Adjusted R^2	0.386	0.386
Stock × Time FE	Yes	Yes
County × Time FE	Yes	Yes
Stock × County FE	Yes	Yes

Table 9: **The Effect of Affective Polarization on Portfolio Allocation**

This table shows the differential effect of CEO's political affiliation, Democratic-leaning, $\mathbb{1}$*(DemCEO)*, and Republican-leaning, $\mathbb{1}$ *(RepCEO)*, on portfolio allocations for counties with different political leanings. The observation level is stock-county-year, where the dependent variable is $ScaledWeight_{County}$, $w^i_{A,t}/w^{mkt_i}_{A,t}$. The sample is our balanced sample that covers the years 2001 to 2019. *ln(MktCap)* is the logarithm of a stock's market capitalization. *B/M* is a stock's book-to-market. Robust standard errors are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

	$\text{ScaledWeight}_{\text{County}}$, $w^i_{A,t}/w^{mkt_i}_{A,t}$	
	(1)	(2)
$\mathbb{1}$(DemCEO) × RepShare × Recent	-0.354**	
	(0.173)	
$\mathbb{1}$(DemCEO) × RepShare	-0.029	
	(0.109)	
$\mathbb{1}$(RepCEO) × RepShare × Recent		-0.082
		(0.122)
$\mathbb{1}$(RepCEO) × RepShare		-0.073
		(0.086)
ln(MktCap) × RepShare × Recent	-0.006	–0.010
	(0.023)	(0.023)
ln(MktCap) × RepShare	-0.276***	-0.275***
	(0.042)	(0.042)
B/M × RepShare × Recent	-0.367***	-0.370***
	(0.124)	(0.124)
B/M × RepShare	-0.128	-0.123
	(0.090)	(0.090)
Observations	5,196,528	5,196,528
Adjusted R^2	0.386	0.386
Stock × Time FE	Yes	Yes
County × Time FE	Yes	Yes
Stock × County FE	Yes	Yes

Table 10: **The Role of Adviser Political Preferences**

This table shows that the effect of politically-sensitive stock characteristics, such as the presence of environmental concerns, $\mathbb{1}(EnvConcerns)$, or labor concerns, $\mathbb{1}(LaborConcerns)$, on stock weights is mediated by investors' political leanings, *DemShare*, rather than the political leanings of financial advisers, *DemAdv*. The observation level is stock-adviser-year, where the dependent variable is $ScaledWeight_{Adv}$, $w^{i}_{j,t}/w^{mkt_i}_{A,t}$. *Controls* × *DemShare* (*DemAdv*) stands for double and triply interactions of *ln(MktCap)*, *B/M* with *DemShare* (*DemAdv*) and *Recent*, where *ln(MktCap)* is the logarithm of a stock's market capitalization; *B/M* is a stock's book-to-market. The sample includes all advisers with the donations information from 2001 to 2019. Robust standard errors are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively. All variables are defined in Appendix B.

	ScaledWeight$_{\text{Adv}}$, $w^{i}_{j,t}/w^{mkt_i}_{A,t}$			
	(1)	(2)	(3)	(4)
$\mathbb{1}$(EnvConcerns) × DemShare × Recent	-0.816***	-0.817***		
	(0.142)	(0.138)		
$\mathbb{1}$(EnvConcerns) × DemShare	0.232*	0.235**		
	(0.140)	(0.138)		
$\mathbb{1}$(EnvConcerns) × DemAdv × Recent		0.001		
		(0.049)		
$\mathbb{1}$(EnvConcerns) × DemAdv		-0.006		
		(0.039)		
$\mathbb{1}$(LaborConcerns) × DemShare × Recent			-0.275*	-0.327**
			(0.155)	(0.156)
$\mathbb{1}$(LaborConcerns) × DemShare			0.049	0.103
			(0.118)	(0.120)
$\mathbb{1}$(LaborConcerns) × DemAdv × Recent				0.082*
				(0.049)
$\mathbb{1}$(LaborConcerns) × DemAdv				-0.086**
				(0.042)
Observations	6,110,271	6,110,271	6,110,271	6,110,271
Adjusted R^2	0.605	0.605	0.605	0.605
Controls × DemShare	Yes	Yes	Yes	Yes
Controls × DemAdv	No	Yes	No	Yes
Stock × Time FE	Yes	Yes	Yes	Yes
County × Time FE	Yes	Yes	Yes	Yes
County × Stock FE	Yes	Yes	Yes	Yes

Appendix

A ADV Forms

Investment advisers file Form ADV to register with the SEC and/or the states and, after that, 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 still 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 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 publicly available 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).

B Variable Definitions

Variable	Definition
Investment adviser characteristics, defined at adviser level	
13F AUM/ADV AUM	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 individuals 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.

Portfolio characteristics, defined at county level .

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

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 refers to common equity issued by firms headquartered in states different from the 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 refers to common equity issued by firms headquartered in states different from the state of an investment adviser.

Dependent Variables

Portfolio Distance	Sum of absolute differences between two counties' out-of-state equity portfolio weights (L1-norm), $\sum_{k=1}^{N_{AB,t}} \lvert w^k_{A,t} - w^k_{B,t} \rvert$, where $w^k_{A,t}$ ($w^k_{B,t}$) 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.
$\text{ScaledWeight}_{\text{Adv}}$, $w^i_{j,t}/w^{mkt_i}_{A,t}$	Weight of stock i in the out-of-state (with respect to county A) equity portfolio of adviser j divided by weight of stock i in the out-of-state market portfolio.
$\text{ScaledWeight}_{\text{County}}$, $w^i_{A,t}/w^{mkt_i}_{A,t}$	Weight of stock i in the out-of-state (with respect to county A) equity portfolio of county A divided by weight of stock i in the out-of-state market portfolio.

Main Explanatory Variables

DemAdv	An indicator variable equal to one if all of an adviser's employees are Democratic-leaning based on political donations, and zero otherwise. An employee is Democratic-leaning if, over the past five years, their total contributions to Democratic committees exceed those to Republican committees.

DemShare (RepShare)	Fraction of voters supporting a Democratic (Republican) candidate in the U.S. presidential elections in a given county.
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 unaffiliated candidate during the most recent U.S. presidential elections.
$\text{PolitDistGallup}_{\text{All}}$	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 unaffiliated based on the question "In politics, as of today, do you consider yourself a Republican, a Democrat, or an Independent?"
$\text{PolitDistGallup}_{\text{HighInc}}$	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.
$\text{PolitDistGallup}_{\text{LowInc}}$	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 for years 2013 onward, and zero otherwise.
Control Variables	
$\mathbb{1}$(DemCEO) ($\mathbb{1}$(RepCEO))	Indicator variable equal to one if a firm's CEO predominantly (more than 50%) contributed to the Democratic (Republican) Party in both the most recent year and the past five years (based on cumulative donations), and zero otherwise.
$\mathbb{1}$(EnvConcerns)	Indicator variable equal to one if a firm has at least one negative environment performance indicator from the MSCI ESG KLD (*ENV-con-...*) in the most recent five years, and zero otherwise.
$\mathbb{1}$(LaborConcerns)	Indicator variable equal to one if a firm has at least one negative employment performance indicator from the MSCI ESG KLD (*EMP-con-...*) in the previous five years, and zero otherwise. To maintain consistency throughout the sample period, we also include *HUM-com-F* (Labor rights concerns) before 2010 because the same issues are covered by EMP-con-F afterward.
# of Accounts	Average number of investment accounts per capita in a pair of counties.
# of Accounts Growth	Annual growth in the average number of investment accounts per capita in a pair of counties, # of Accounts_t / # of Accounts_{t-1}.
# of Advisers	Average number of investment advisers in a pair of counties.

# of Advisers Growth	Annual growth in the average number of investment advisers in a pair of counties, # of Advisers$_t$ / # of Advisers$_{t-1}$.
EconCondition Distance	L1-norm distance between two counties' vectors of beliefs about current economic conditions. A county vector contains 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 contains 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 an education level equivalent to a college degree or higher, as measured in the 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 2000 and 2010 Census data.
Industry Distance	L1-norm distance between two counties' industry composition vectors. A county vector consists of its industry (2-digit NAICS) employment shares. Employment data are from the Bureau of Economic Analysis.
Population Difference	Absolute difference between two counties' total county populations, as measured in the 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, and non-religious individuals from the Association of Religion Data Archives (ARDA) for 2000 and 2010.

Internet Appendix

IA1 Properties of the Partisan Portfolio Divide Measure

We define the *Partisan Portfolio Disagreement* (*PPD*) as

$$\text{PPD} = \frac{1}{2}\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right|,$$

where $w_d^i = \delta^i\, w_u^i$, $w_r^i = \rho^i\, w_u^i$, and $\sum_{i=1}^{N} w_u^i = 1$. We also impose the no-short selling constraints $\delta^i, \rho^i \geq 0$, that is, w_d^i, w_r^i must be nonnegative. Finally, each party's portfolio sums to 1: $\sum_{i=1}^{N} \delta^i\, w_u^i = 1$, and $\sum_{i=1}^{N} \rho^i\, w_u^i = 1$.

Below we prove that the *PPD* measure has the following properties:

1. *PPD* is bounded between zero and one: $0 \leq \text{PPD} \leq 1$.
2. *PPD* does not exceed the total market capitalization of all partisan stocks: $\text{PPD} \leq \sum_{i \in N_p} w_u^i$, where $N_p = \{\, i : \delta^i \neq 1 \text{ or } \rho^i \neq 1\}$.

First, we show that $0 \leq \text{PPD} \leq 1$. Since $\left|\delta^i - \rho^i\right| \geq 0$ and $w_u^i \geq 0$, each term of $\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right|$ is nonnegative. Thus, $\text{PPD} = \frac{1}{2}\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right| \geq 0$.

Now let's define

$$T_+ = \sum_{i:\,\delta^i > \rho^i} w_u^i\,(\delta^i - \rho^i), \qquad T_- = \sum_{i:\,\delta^i < \rho^i} w_u^i\,(\rho^i - \delta^i).$$

Since $\sum_{i=1}^{N} w_u^i\,(\delta^i - \rho^i) = 1 - 1 = 0$, it follows that $T_+ = T_-$. Therefore,

$$\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right| = T_+ + T_- = 2\,T_+.$$

Hence to show $\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right| \leq 2$, we just need to prove $T_+ \leq 1$.

Note that

$$T_+ = \sum_{i:\,\delta^i > \rho^i} w_u^i\,(\delta^i - \rho^i) \leq \sum_{i:\,\delta^i > \rho^i} w_u^i\,\delta^i \leq \sum_{i=1}^{N} w_u^i\,\delta^i = \sum_{i=1}^{N} w_d^i = 1,$$

where the last equality follows from the fact that the total Democratic portfolio weight must be 1. Thus $T_+ \leq 1$. Since $T_- = T_+$, we get

$$\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right| \;=\; 2\,T_+ \;\leq\; 2 \quad\Longrightarrow\quad \text{PPD} \;=\; \frac{1}{2}\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right| \;\leq\; 1.$$

Hence $0 \leq \text{PPD} \leq 1$. $\square$

Now we show that $\text{PPD} \leq \sum_{i\in N_p} w_u^i$, where $N_p = \{\, i : \delta^i \neq 1 \text{ or } \rho^i \neq 1\}$, is the set of partisan stocks such that

If $i \notin N_p$, then $\delta^i = \rho^i = 1$, which implies $\left|\delta^i - \rho^i\right| = 0$. Therefore, any such non-partisan stock contributes nothing to *PPD*. Consequently,

$$\text{PPD} \;=\; \frac{1}{2}\sum_{i=1}^{N} w_u^i \left|\delta^i - \rho^i\right| \;=\; \frac{1}{2}\sum_{i\in N_p} w_u^i \left|\delta^i - \rho^i\right|.$$

Now we repeat the argument from the previous part, but restricted to $i \in N_p$. Let's define

$$T_+ \;=\; \sum_{i\in N_p:\delta^i>\rho^i} w_u^i\,(\delta^i - \rho^i), \qquad T_- \;=\; \sum_{i\in N_p:\delta^i<\rho^i} w_u^i\,(\rho^i - \delta^i).$$

Again, $T_+ = T_-$. Hence $\sum_{i\in N_p} w_u^i \left|\delta^i - \rho^i\right| \;=\; 2\,T_+$, and it suffices to show $T_+ \leq \sum_{i\in N_p} w_u^i$. We have

$$T_+ \;\leq\; \sum_{i\in N_p} w_u^i\,\delta^i.$$

But since

$$1 \;=\; \sum_{i=1}^{N} \delta^i\,w_u^i \;=\; \sum_{i\in N_p} \delta^i\,w_u^i \;+\; \sum_{i\notin N_p} \delta^i\,w_u^i,$$

and for $i \notin N_p$, we have $\delta^i = 1$, we get

$$\sum_{i\in N_p} \delta^i\,w_u^i \;=\; 1 - \sum_{i\notin N_p} w_u^i \;=\; \sum_{i\in N_p} w_u^i.$$

Hence,

$$T_+ \;\leq\; \sum_{i\in N_p} w_u^i\,\delta^i \;=\; \sum_{i\in N_p} w_u^i.$$

Thus,

$$\sum_{i \in N_p} w_u^i \left|\delta^i - \rho^i\right| \;=\; 2\,T_+ \;\leq\; 2 \sum_{i \in N_p} w_u^i,$$

which implies

$$\text{PPD} \;=\; \frac{1}{2} \sum_{i \in N_p} w_u^i \left|\delta^i - \rho^i\right| \;\leq\; \sum_{i \in N_p} w_u^i. \quad \square$$

IA2 Additional Results

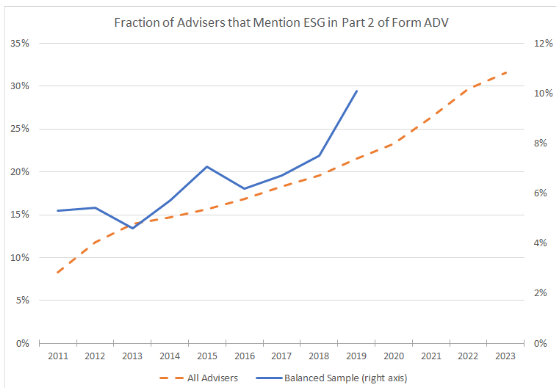


Figure IA1: Fraction of advisers that mention ESG or its components in Part 2 of Form ADV

Table IA1: **Adviser Characteristics (Institution-Year Level)**

Variable	N	Mean	S.D.	P25	Median	P75
AUM, $ bln	11,382	1.563	7.866	0.218	0.395	0.849
Number of Accounts	11,382	1,606	18,642	203	446	866
Account Size, $ mln	11,382	4.57	69.26	0.51	0.98	2.03
Share of Individuals, Count-based (%)	11,382	86.8	15.9	76.0	93.0	100
Share of Individuals, AUM-based (%)	6,486	82.7	24.9	76.0	81.0	100
13F AUM / ADV AUM	11,382	73.2	23.4	59.0	70.6	84.6
Equity Fraction (%)	11,382	59.1	28.2	44.6	59.3	75.7
Out-of-State Equity Fraction (%)	11,382	53.3	26.7	39.0	53.0	68.4
ETF Fraction (%)	11,382	9.39	18.97	0.00	0.88	8.30
Other Fraction (%)	11,382	31.5	22.9	20.1	34.1	45.4
Number of Equities	11,382	122	198	49	81	132
Number of Out-of-State Equities	11,382	98	142	41	67	109

Table IA2: **Geographical Variation in the Sample Coverage**

This table reports the average number of counties per year between 2001 and 2019 in the full and balanced samples for each U.S. state with at least one county-year in the full sample.

State	Average number of counties		State	Average number of counties	
	Full Sample	Balanced Sample		Full Sample	Balanced Sample
AK	1.0	-	MO	2.7	1.0
AL	2.5	1.0	MT	1.4	-
AR	1.9	-	NC	5.8	-
AZ	1.5	1.0	NE	2.0	2.0
CA	14.3	9.0	NH	3.5	3.0
CO	3.6	2.0	NJ	9.1	4.0
CT	3.5	3.0	NM	1.2	1.0
DC	1.0	1.0	NV	1.4	-
DE	1.1	-	NY	10.4	6.0
FL	11.7	7.0	OH	6.5	5.0
GA	5.5	3.0	OK	1.6	.
HI	1.0	-	OR	2.5	1.0
IA	1.5	-	PA	10.8	6.0
ID	1.4	1.0	RI	1.2	1.0
IL	3.4	2.0	SC	2.0	-
IN	4.8	3.0	SD	1.3	-
KS	2.3	1.0	TN	3.8	2.0
KY	2.6	2.0	TX	6.5	3.0
LA	2.4	-	UT	1.7	-
MA	6.5	2.0	VA	11.3	6.0
MD	2.6	2.0	VT	1.7	-
ME	1.2	1.0	WA	4.4	2.0
MI	6.1	3.0	WI	6.0	5.0
MN	2.4	2.0	WV	1.4	-

Table IA3: **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 characteristics, based on the 2000 and 2010 Census data. *Population* is a two-year average of a county's population. *Income* is a two-year average of a county's income per capita. *College Degree* is a two-year average of a county's fraction of residents with an education level equivalent to a college degree or higher. Panel B presents summary statistics for the voting behavior in the U.S. presidential elections between 2000 and 2016. For each county, we compute an average fraction of votes for Democratic, Republican, and other candidates across all the election years between 2000 and 2016. For the counties in the full and balanced samples, we use only those election years in the corresponding samples.

Panel A. County Population Characteristics

Variable	N	Mean	S.D.	Min	Max	% of U.S. Total
All U.S. counties						
Population	3,137	94,051	302,537	75	9,668,972	100.0%
Income (per Capita)	3,137	20,436	4,596	7,711	52,437	100.0%
College Degree	3,137	0.459	0.109	0.191	0.857	100.0%
Full sample						
Population	309	526,220	791,240	9,032	9,668,972	54.8%
Income (per Capita)	309	26,849	6,387	15,764	52,437	61.2%
College Degree	309	0.589	0.093	0.321	0.857	59.7%
Balanced sample						
Population	94	902,459	1,243,641	9,032	9,668,972	28.6%
Income (per Capita)	94	29,059	6,954	18,809	52,437	33.1%
College Degree	94	0.605	0.087	0.321	0.794	31.4%

Panel B. County Voting Behavior

Variable	N	Mean	S.D.	P25	Median	P75
All U.S. counties						
DemShare (%)	3,115	38.0	13.1	29.0	37.0	45.7
RepShare (%)	3,115	59.3	13.2	51.4	60.5	68.7
OthShare (%)	3,115	2.64	1.38	1.65	2.40	3.27
Full Sample						
DemShare (%)	309	49.9	13.4	40.6	50.3	57.7
RepShare (%)	309	46.2	13.2	39.0	45.5	55.6
OthShare (%)	309	3.85	3.31	2.18	3.14	4.50
Balanced Sample						
DemShare (%)	94	55.4	12.5	45.3	54.8	63.4
RepShare (%)	94	41.7	12.7	33.3	42.4	51.2
DemShare (%)	94	2.91	1.18	2.00	2.68	3.51

Table IA4: **The Effect of Sinclair Entry on Republican Share and County Characteristics**

Panel A presents the summary statistics of county level demographic characteristics for the treated and matched control counties. Panel B presents the effects on Sinclair entry on *RepShare*, the fraction of votes for the Republican candidate in a county in a presidential election. *Post* is an indicator variable that equals to one after the entry. *PrCycle*[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 county pairs from our balanced sample and covers presidential election cycles from 2000 to 2020, with Sinclair entries from 2011 to 2017. Standard errors are double-clustered by county and by election cycle. Panel C presents the effects of Sinclair Entry on several county characteristics, using Gallup Daily Survey (aggregated at the annual level) and Census data. In column (1), the dependent variable *EconConditions* is a county-year average response to the question: "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: "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: "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. All variables are defined in Appendix B.

Panel A. Summary Statistics for Treated and Matched Control Counties

Sample	Obs.	RepShare	ΔRepShare	Population	Income	College
Treated	13	0.44	-0.02	618,315	29,029	0.65
Matched Control	13	0.45	-0.03	748,088	32,791	0.67
Difference		-0.01	0.01	-129,773	-3,762	-0.02

Panel B. Sinclair Entry and Republican Share

	RepShare (1)	RepShare (2)
Treated × Post	0.035**	
	(0.017)	
Treated × PrCycle[-2]		-0.004
		(0.009)
Treated × PrCycle[-1]		-0.007
		(0.004)
Treated × PrCycle[+1]		0.021*
		(0.010)
Treated × PrCycle[+2]		0.035*
		(0.016)
Treated × PrCycle[+3]		0.055**
		(0.021)
Observations	148	148
Adjusted R^2	0.934	0.933
Event × County FE	Yes	Yes
Event × Calendar-Time FE	Yes	Yes

Panel C. Sinclair Entry and County Characteristics

	EconConditions (1)	EconOutlook (2)	Religiosity (3)	Median Income (4)
Treated × Post	0.020	0.011	-0.026	1.174
	(0.035)	(0.052)	(0.032)	(1.382)
Observations	166	166	166	223
Adjusted R^2	0.856	0.623	0.852	0.983
Event × County FE	Yes	Yes	Yes	Yes
Event × Calendar-Time FE	Yes	Yes	Yes	Yes