Political uncertainty and institutional herding[†]

Konstantinos Gavriilidis[a], Vasileios Kallinterakis[b,*], Maurizio Montone[c]

[a] *University of Stirling*
[b] *Durham University*
[c] *Utrecht University*

Abstract

Political uncertainty represents a key determinant of corporate investment decisions. In this paper, we study the relation between political uncertainty and investment from the perspective of institutional investors. Using U.S. equity holdings data from 13F filings, we find that institutional investors herd during politically uncertain times. This trading behavior is stronger when U.S. presidents are unpopular, due to their proclivity for controversial policies, and among riskier stocks. We also find that this mechanism, despite generating some excess trading, helps incorporate a risk premium into stock prices. Overall, the findings unveil a new channel through which political uncertainty affects financial markets.

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*Corresponding author. Address: Durham University Business School, Mill Hill Lane, Durham DH1 3LB, United Kingdom. Email address: vasileios.kallinterakis@durham.ac.uk.

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1. Introduction

Political uncertainty is a key determinant of corporate investment decisions, both at the micro and the macro level (Rodrik, 1991; Hasset and Mecalf, 1999). Companies decrease their investment when political uncertainty is high (Julio and Yook, 2012; Jens 2017), because they find it optimal to defer investment until uncertainty has been resolved (Bernanke, 1983; Bloom, Bond, and Van Reenen, 2007). Investor beliefs become more dispersed as a result (Pástor and Veronesi, 2012, 2013), thus increasing volatility in international financial markets (Boutchkova et al., 2012). Correspondingly, asset prices command a risk premium during politically uncertain times (Pástor and Veronesi, 2013; Brogaard and Detzel, 2015; Kelly, Pástor, and Veronesi, 2016; Montone, 2022).

In this paper, we study the relation between political uncertainty and investment from the perspective of institutional investors. Using the Sias (2004) herding measure, we analyze whether institutional investors herd, i.e., mimic each other's trades, in response to political uncertainty. Our conjecture builds on two well-known mechanisms. First, noisier signals constitute an incentive for institutional investors to herd more (Wermers, 1999; Sias, 2004).[1] Second, institutional investors face reputational and litigation costs when their behavior deviates from the herd (Scharfstein and Stein, 1990; Trueman, 1994), especially in the presence of negative stock information (Brown, Wei, and Wermers, 2014).[2] Since political uncertainty makes investor beliefs noisier and more pessimistic (Pástor and Veronesi, 2013), we expect both drivers of herding to be operational during politically uncertain times.

Using U.S. institutional investors' quarterly holdings data from 1985 through 2019, we find evidence consistent with this prediction. We find a positive association between institutional herding and political uncertainty, controlling for a number of financial, economic, and political indicators. For brevity, we denote this relation as "politically-motivated herding." The estimates are of higher magnitude in times of low presidential popularity, which supports the view that unpopular administrations have a proclivity for riskier policies, as a form of gambling for resurrection, when a president's political capital is low (see, e.g., Downs and Rocke, 1994; Pástor and Veronesi, 2013).

We also find that politically-motivated herding affects stock prices. Previous research shows that political uncertainty commands a risk premium (see, e.g., Pástor and Veronesi, 2013). In this paper, we find that institutional investors' herd behavior helps impound this premium into stock prices, consistent with the view that herding can improve market efficiency by gradually incorporating information (Wermers, 1999; Sias, 2004). Although we also find some evidence for subsequent price reversals, indicating excess trading behavior (Dasgupta, Prat, and Verardo, 2011; Brown, Wei, and Wermers, 2014), the short-run effect is dominant overall. Correspondingly, companies that are more exposed to political uncertainty face a higher

[1] For more on how informational ambiguity can motivate herding, see the analytical studies by Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992), and the herding review by Hirshleifer and Teoh (2003a).

[2] For example, bank trust departments engage in herd behavior to defend the prudence of their investments, thereby minimizing litigation risk (Sias, 2004).

cost of capital, particularly during periods in which political uncertainty is high. These findings unveil a novel channel through which political uncertainty affects financial markets.

Pástor and Veronesi (2012) identify two types of political uncertainty that affect investor behavior. These are the uncertainty about whether the current government policy will change, and about the impact that government policy will have on the profitability of the private sector. The overall effect of these two types of uncertainty is to make beliefs noisier and depress stock prices (Pástor and Veronesi, 2013). This mechanism should be especially important for fund managers, due to their uncertainty avoidance and reputational concerns (Brown, Wei, and Wermers, 2014). In times of high political uncertainty, they should herd more in an attempt to infer information from each other's trades. As in Pástor and Veronesi (2013), in our empirical analysis we proxy political uncertainty with the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016).[3]

Consistent with our theoretical predictions, we find that a one-standard-deviation increase in either specification of the EPU index is associated with an increase between one-fifth and one-third of a standard deviation in institutional herding within the same quarter. Although the estimates are economically not large, especially when compared with the results from our subsample analysis below, they are nonetheless statistically significant and robust accounting for a number of financial, political, and economic controls, such as the level and volatility of stock returns, presidential term-years and political affiliation, the rate of growth of consumption, industrial production, and employment, and the NBER recession indicator.

Pástor and Veronesi (2013) show that government has an incentive to look for reform when the current policy does not yield the expected results, which increases uncertainty about its future actions. Specifically, new potential policies are likely to be riskier when popularity falls below a given threshold, because the contract between the executive and the constituency makes it optimal to engage in some form of gambling for resurrection (see Downs and Rocke (1994) for an excellent discussion). In light of these considerations, we expect the relation between political uncertainty and institutional herding to be particularly strong in times of low political sentiment. The intuition is that for a given level of uncertainty, the choice set from which new policies will be picked includes a wider range of options when the president is unpopular.

To test this hypothesis, we acknowledge that net disapproval, defined as the difference between disapproval and approval ratings, represents a key measure of popularity of the U.S. president (Abramowitz, 2004, 2008). When net disapproval is high, the group of presidential opponents becomes relatively large vis-à-vis the supporters' group. In turn, this implies that the overall level of political sentiment in the country is low. Consistent with our conjecture, we find that the relation between institutional herding and political uncertainty is significantly stronger in times of large net disapproval. A one-standard-deviation increase in the EPU index is associated with an increase between one-half and two-thirds of a standard deviation in

[3]The index provides a continuous and comprehensive measure of political uncertainty. Attesting to its validity, it spikes around consequential presidential elections and major political shocks (e.g., the Gulf Wars, 9/11, the Eurozone crisis, and the U.S. debt-ceiling dispute). At the time of writing, there is no obvious alternative proxy.

institutional herding within the same quarter. We also find similar estimates when excluding Congress or presidential election years, which addresses the concern that the results may partly reflect cyclical changes of approval ratings around elections (see, e.g., Mueller, 1970; Montone, 2022).

Since stocks characterized by higher risk are also harder to evaluate (see, e.g., Baker and Wurgler, 2006), we expect them to generate a comparatively stronger herding response. Our results lend support to this conjecture. We find that politically-motivated herding is more pronounced among stocks characterized by small market capitalization and weak political connections. We also find a stronger herding response for politically-sensitive stocks, but only under Republican presidencies, which supports the extant evidence that these administrations are characterized by higher risk (Blinder and Watson, 2016; Pástor and Veronesi, 2020). More generally, these stock-level patterns are consistent with the idea that institutional herding partly reflects similar investment styles (Choi and Sias, 2009; Celiker, Chowdhury, and Sonaer, 2015).

We finally study the effect of herding on stock returns. Previous research finds mixed results. Herd behavior can either drive prices closer to fundamentals by gradually impounding information (Wermers, 1999; Sias, 2004), or away from fundamentals if it produces excess trading (Dasgupta, Prat, and Verardo, 2011; Brown, Wei, and Wermers, 2014). The discrepancy between these findings mostly seems to reflect differences in the time horizon under consideration (Edelen, Ince, and Kadlec, 2016). The two effects can in fact occur sequentially, with price discovery taking place in the short run and reversals over longer time horizons (Gutierrez and Kelley, 2009), consistent with the well-known theoretical mechanism of momentum trading followed by overreaction (Hong and Stein, 1999).

In our analysis, we find evidence in line with these predictions. Using a five-year timeframe as in Jegadeesh and Titman (2001), we find that the relation between politically-motivated institutional demand and future stock returns is positive over a two-year window, but negative over the subsequent three years. However, the positive effect is dominant overall. These results lend support to the theoretical prediction that political uncertainty should command a risk premium (see, e.g., Pástor and Veronesi, 2013), and more generally to the idea that institutional investor demand helps impound information into stock prices (Kacperczyk, Sundaresan, and Wang, 2021), although the efficiency with which this information is impounded is partly hindered by excess trading behavior.

Our findings speak to a large body of literature on herd behavior. Previous studies analyze the relation between herding and financial uncertainty, the latter proxied through periods during which financial markets become more volatile, and finds mixed results (see, e.g., Christie and Huang, 1995; Chang, Cheng, and Khorana, 2000; Chieng and Zheng, 2010; Cui, Gebka, and Kallinterakis, 2019). Our focus on political uncertainty provides two advantages. First, the EPU index is unlikely to be affected by institutional trading, which moderates concerns of reverse causality or spurious correlation that may bias the empirical estimates. Second, this setup allows us to derive a richer set of predictions for stock prices, both in the cross section and in the time series. Overall, then, political uncertainty provides an ideal framework to analyze the effect of uncertainty on herd behavior.

More generally, the paper also contributes to a burgeoning literature on politics and finance. A growing body of evidence shows that political evaluations affect risk taking (Bonaparte, Kumar, and Page, 2017; Meeuwis et al., 2018), analysts' forecasts (Kempf and Tsoutsoura, 2021), asset allocation (Hong and Kostovetsky, 2012; Addoum and Kumar, 2016), and stock returns (Santa-Clara and Valkanov, 2003; Montone, 2022). In this paper, we find that political evaluations also generate substantial herd behavior among institutional investors, which in turn has important consequences for stock market efficiency.

The paper proceeds as follows. Section 2 describes the data and methodology. Section 3 illustrates the main findings. Section 4 presents the analysis of stock returns. Section 5 concludes.

2. Data and methodology

Institutional herding

We consider 13F institutional ownership quarterly data from 1985 through 2019, for a sum total of 34 years (136 quarters, overall), and identify institutional herding as in Sias (2004). The methodology is as follows. We calculate each institutional investor's end-of-quarter position in each security. For each security and quarter, we define buyers (sellers) as institutional investors who increased (decreased) their ownership in the stock quarter-on-quarter. We only include managers that hold at least one security at both the beginning and at the end of the quarter, and common stocks that have the same CUSIP throughout the quarter and at least one institutional trader during the quarter.

For each quarter, we calculate the fraction of institutional investors that are net buyers of security k in quarter t:

$$Raw\Delta_{k,t} = \frac{\text{No. of institutions buying}_{k,t}}{\text{No. of institutions buying}_{k,t} + \text{No. of institutions selling}_{k,t}}. \tag{1}$$

To allow for aggregation over time and comparisons across specifications, we standardize this ratio. Specifically, we subtract the cross-sectional average fraction of net buyers in quarter t from the raw ratio for a given stock in the same quarter, and divide by the cross-sectional standard deviation (across securities) of the fraction of net buyers in quarter t:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})}. \tag{2}$$

For each quarter, we estimate a cross-sectional regression of the standardized fraction of institutions buying security k in quarter t over the fraction from the previous quarter:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \epsilon_{k,t}, \tag{3}$$

where $\Delta_{k,t}$ is the standardized fraction of institutions buying security k in the current quarter (t), and β_t measures institutional demand's cross-sectional correlation between the current quarter (t) and the previous one ($t-1$). We expect $\beta_t > 0$ for two reasons. First, institutional investors may follow their own trades over time, i.e., continue trading in the same direction, for example when following a momentum strategy. Second, and importantly for our purposes, such investors may follow each other into and out of the same securities (herding). To tease out the latter mechanism from the former, we respectively partition β_t into these two components:

$$
\begin{aligned}
\beta_t &= \rho(\Delta_{k,t}, \Delta_{k,t-1}) \\
&= \left[\frac{1}{(K-1)\sigma(Raw\Delta_k)\sigma(Raw\Delta_{k,t-1})}\right] \\
&\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t}-\overline{Raw\Delta_t})(D_{n,k,t-1}-\overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right] \\
&+ \left[\frac{1}{(K-1)\sigma(Raw\Delta_k)\sigma(Raw\Delta_{k,t-1})}\right] \\
&\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \sum_{m=1,m\neq n}^{N_{k,t-1}} \frac{(D_{n,k,t}-\overline{Raw\Delta_t})(D_{m,k,t-1}-\overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right],
\end{aligned} \tag{4}
$$

where $N_{k,t}$ is the number of active funds trading security k on quarter t; $N_{k,t-1}$ is the number of active funds trading security k on quarter $t-1$; $D_{n,k,t}$ is a dummy variable that takes the value of one if fund n increases its position in security k on quarter t, and zero otherwise; $D_{m,k,t-1}$ is a dummy variable that takes the value of one if fund m ($m \neq n$) increases its position in security k in quarter $t-1$, and zero otherwise. The second addend on the right-hand side represents our estimate of herding. We re-estimate this coefficient using stocks held by at least 1, 5, 10, and 20 institutional traders at the beginning of each quarter, which generates four herding measures overall.

In Table 1, Panel A, we provide time-series averages for each of the four institutional herding measures. We find that herding is positive and significant for all four thresholds of active funds per stock we consider. Specifically, stocks with at least 1, 5, 10, or 20 institutional traders respectively exhibit a herding coefficient of 0.11, 0.28, 0.35, and 0.40 (p-value < 0.01 for all four, computed from the time-series standard errors). The magnitude increases with the number of institutional traders active in a stock. These stocks are indeed more popular among institutions due for example benchmarking or regulatory nudging, and therefore receive more attention.

Political uncertainty

To empirically identify political uncertainty, we follow Pástor and Veronesi (2013) and use the U.S. EPU index from Baker, Bloom, and Davis (2016), measured using the latest available value at the end of each quarter for consistency with the institutional holdings data. The main version of the index has three components. The first component is an index of search results from 10 large newspapers. The newspapers included are the USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal. From these papers, the authors construct a normalized index of the volume of news articles discussing economic policy uncertainty.

The second component draws on reports by the Congressional Budget Office (CBO) that compile lists of temporary federal tax-code provisions. The authors create annual dollar-weighted numbers of tax-code provisions scheduled to expire over the next 10 years, giving a measure of the level of uncertainty regarding the path that the federal tax code will take in the future.

The third and last component draws on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. Specifically, the authors utilize the dispersion among individual forecasters' predictions about future levels of the Consumer Price Index, Federal Expenditures, and State and Local Expenditures to construct indices of uncertainty about policy-related macroeconomic variables.

We also consider a second version of the EPU index, which is exclusively news-based. This index draws on newspaper archives from Access World News' NewsBank service. The original database contains the archives of thousands of news sources from all over the world, ranging from newspapers to magazines to newswire services. The index focuses on more than a thousand newspapers in the United States, including both national and local ones.

The primary measure for this index is the number of articles that contain at least one term from each of three sets of terms. The first set is "economic" or "economy." The second is "uncertain" or "uncertainty." The third set includes "legislation," "deficit," "regulation," "Congress," "Federal Reserve," and "White House." The number of newspapers that NewsBank covers over time has increased substantially, from 18 in 1985 to over 1,800 by 2008. To correct for this growth, the authors normalize the index by relating the number of economic policy uncertainty articles to the total number of newspaper articles.

Other papers have tried to identify political uncertainty using presidential elections (e.g., Julio and Yook, 2012), or gubernatorial elections (e.g., Jens, 2017). However, neither approach provides a comprehensive (and continuous) measure of political uncertainty. Attesting to its validity, the EPU index "spikes near tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the failure of Lehman Brothers, the 2011 debt-ceiling dispute and other major battles over fiscal policy" (see Baker, Bloom, and Davis (2016)). As noted by Pástor and Veronesi (2013), no obvious alternative proxy for political uncertainty existed at the time of their writing. To the best of our knowledge, this is still the case today.

The summary statistics in Table 1, Panel B, show that the EPU index has a relatively symmetric distribution, with a sample mean of 109.9 and a median of 104.4. The standard deviation is 32.9, and the interquartile range is between 84.3 and 126.4. For the news-based version of the index, the sample mean and the median are 114.4 and 105.1, respectively. The standard deviation is 42.8, and the interquartile range is between 84.4 and 134.2. As can be seen in Figure 1, the EPU index exhibits a similar empirical pattern to that of our herding measures.[4]

The positive association between political uncertainty and the propensity of fund managers to herd likely reflects two established herding drivers. First, investment professionals herd intentionally as a response to informational uncertainty (Devenow and Welch, 1996; Avery and Zemsky, 1998). When information signals become noisy, fund managers may choose to mimic the trades of their peers – either because their processing

[4]For reasons of space, the figure only reports the graph for herding over stocks with at least five institutional traders. We obtain similar graphs with the other herding measures.

skills are inadequate or because they perceive that their peers are better-informed. In the process, they may sideline their private signals which could give rise to informational cascades (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992).

Second, this uncertainty may bear a professional connotation. In view of the periodic performance evaluation of investment professionals, low-quality fund managers may resort to tracking the trades of their high-quality peers in order to emit an image of competence and safeguard their career prospects (Scharfstein and Stein, 1990; Jiang and Verardo, 2018). This is expected to be more so in the presence of negative news' arrival, since this is associated with a greater potential for losses – and then reputational/litigation risk (Brown, Wei, and Wermers, 2014).[5]

Previous research shows that a high degree of uncertainty makes economic outcomes harder to assess, which in turn translates into greater differences of opinion (see, e.g., Bloom, 2014). Consistent with this view, and thereby attesting to the economic relevance of the EPU index, we find a positive and highly significant correlation of 0.53 between economic policy uncertainty and dispersion of macroeconomic evaluations (p-value < 0.001).[6]

Political sentiment

We also construct a measure of nationwide political sentiment. To that end, we consider the U.S. president's approval rating polls from Gallup. The data is collected nationwide via telephone interviews. The number of respondents per poll is approximately 1,500 adults, and the typical question asked is "Do you approve or disapprove of the way the president is handling his job?" The answer can be positive, negative, or neutral. The overall proportion of positive (negative) answers is commonly referred to as presidential approval (disapproval) ratings. To the extent that political beliefs affect expectations, the president's supporters and opponents can be thought of as optimists and pessimists, respectively.

We define political sentiment as the difference between disapproval and approval ratings (Abramowitz, 2004, 2008), measured using the latest available poll at the end of each quarter. When net disapproval is positive, presidential opponents outnumber the president's supporters, which implies that the overall level of political sentiment in the country is low. In our sample, we find that 45 quarters fall into positive net disapproval periods, and 90 under negative net disapproval, where the latter represent the instance in which approval ratings are above disapproval ratings. In the analysis that follows, we use net disapproval both for

[5] Intent aside, fund managers may also exhibit correlation in their trades without imitation mediating the process ("spurious herding"); the latter may hold when they follow similar investment styles (Celiker, Chowdhury, and Sonaer, 2015; Frijns, Gilbert, and Zwinkels, 2016), or when their information sets are correlated ("investigative herding" – see Froot, Scharfstein, and Stein, 1992 and Hirshleifer, Subrahmanyam, and Titman, 1994).

[6] In the spirit of Li and Li (2014), we identify the latter as the 12-month business conditions forecast (BEXP) from the Thomson Reuters/University of Michigan Surveys of Consumers. We also acknowledge that the data only includes qualitative responses, therefore we transform the series following Li and Li (2014). The survey question is: "(...) About a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?" The answers are "Better," "About the same," "Worse," "I don't know," and "N/A." We delete "N/A" and "I don't know" responses, and impose a $(-1, 1)$ domain for the answers (positive = 1, neutral = 0, negative = -1). To calculate the standard deviation of beliefs, we construct a negative Herfindahl index, so that higher values indicate greater dispersion of opinion.

a sample breakdown and as a moderating variable in the relation between institutional herding and political uncertainty.

Controls

The analysis also includes a number of financial, economic, and political controls. The financial variables are excess returns on the market portfolio over the quarter, along with average excess returns over the previous year, and the standard deviation of excess returns over the previous year.[7] The market portfolio is defined as the set of all stocks traded on the NYSE, AMEX, and NASDAQ, and is retrieved from Kenneth French's website. The average quarterly excess return on the stock market portfolio is 1.26%, with a median of 2.84%, and a standard deviation of 11.98%.

The economic variables are the six macroeconomic indicators from Baker and Wurgler (2006). The list includes the growth in the industrial production index, growth in personal consumption expenditures on durables, nondurables, and services, growth in employment, and a dummy variable that assumes the value of one for NBER recessions. All variables are retrieved from the Bureau of Economic Analysis. The average growth rate is equal to 0.49% for the industrial production index, 1.04% for consumption of durable goods, 1.01% for consumption of nondurable goods, 1.01% for consumption of services, and 0.33% for employment. Of all the quarters in the sample, about 8% fall under recession periods.

Finally, the political indicators include a set of dummy variables for each of the presidential term-years, and a dummy variable that takes on the value of one for Democratic presidents. The political affiliation of the presidency is almost equally split between Democrats and Republicans over the sample period, where the former occupied the White House 47% of the time.

3. Main findings

We present our main findings as follows. First, we estimate our baseline regressions of institutional herding on economic policy uncertainty. Second, we study how this relation is moderated by political sentiment. Third, we address some endogeneity concerns. Finally, we carry out additional tests for some specific stock categories.

3.1. Baseline regressions

We begin the empirical analysis by estimating the relation between institutional herding and economic policy uncertainty. Our test equation is as follows:

$$y_t = \beta_0 + \beta_1 EPU_t + \gamma' X_t + \epsilon_t, \tag{5}$$

[7] The results that follow are similar when replacing this measure with the Chicago Board Options Exchange implied volatility index (VIX). The advantage of our baseline specification is that it is available for a longer time series than the VIX, thus increasing the statistical power of our tests.

where y_t is institutional herding, EPU_t is the index of economic policy uncertainty, standardized to ease the interpretation of the results, and X_t is a vector that includes the economic, financial, and political controls introduced above. Given the persistent nature of both the dependent and the main independent variables, we use Newey-West standard errors and implement the non-parametric automatic lag selection in covariance matrix estimation from Newey and West (1994).[8] Following our theoretical arguments, we expect $\beta_1 > 0$.

In Table 2, we consider the primary specification of the EPU index. Consistent with our expectations, the coefficient of the index is positive and significant across all specifications, and its magnitude is largely unaffected by the inclusion of controls. For the herding measures over stocks with at least 1, 5, 10, or 20 institutional traders, respectively, a one-standard-deviation increase in economic policy uncertainty prompts an increase in institutional herding of 20%, 29%, 29%, and 24% of a standard deviation. Although the magnitude is not economically large, especially when compared with the results from our subsample analysis below, it is nonetheless statistically strong.

In additional tests, we find similar results when expressing either version of the EPU index in logs, which addresses the concern that the results may be partly driven by outliers (Table A1), and when we consider the news-based specification of the EPU index (Table A2). Overall, the findings suggest that political uncertainty exerts a positive and robust second-order effect over herding. To the extent that beliefs become more dispersed, it is plausible that managers might become less confident in their own signals during politically uncertain times, and thus more willing to herd.

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) show that herding decreases during recessions. We find some mixed evidence for this prediction and, more generally, we find no evidence that economic variation subsumes the relation between herding and EPU. Among the other coefficients of interest, we find that herding increases significantly during the last year of the presidential term, i.e., the one with presidential elections. This is in line with the idea that the political scenario becomes more uncertain in pre-election years, thus affecting investment strategies (see, e.g., Julio and Yook, 2012). We also find evidence that herding is inversely related to (excess) returns on the market portfolio, which seems to reflect the fact that managers herd more in the presence of negative stock information (Brown, Wei, and Wermers, 2014). Overall, adding controls does not really impact the time-series relation between herding and EPU.

3.2. Presidential popularity

Next, we test our conjecture that the effect of economic policy uncertainty on institutional herd behavior should be more pronounced in times of low political sentiment. To this end, we define periods of low (high) political sentiment as those in which net disapproval is positive (negative). Then, we re-estimate the test equation separately in each of these subsamples. The results are in Table 3, Panels A and B. We find that the effect of economic policy uncertainty on institutional herding is confined in times of low political sentiment,

[8] The autocorrelation coefficients are respectively 0.39, 0.69, 0.70, and 0.68 for the herding measures over stocks with at least 1, 5, 10, or 20 institutional traders (p-value < 0.01). For the two measures of economic policy uncertainty, the autocorrelation coefficients are respectively equal to 0.63 and 0.41 (p-value < 0.01). None of these variables contain a unit root.

and the estimates substantially increase in magnitude.

To test whether the coefficients are significantly different across periods of high and low political sentiment, we estimate an additional specification in which we include an interaction term between economic policy uncertainty and net disapproval, and also net disapproval as a standalone variable as a control. The results are in Table 3, Panel C. The coefficient of the interaction term is positive and significant, indicating that the effect of economic policy uncertainty on institutional herding is significantly larger in times of low sentiment. For each of the four herding measures, a one-standard-deviation increase in economic policy uncertainty prompts an increase in institutional herding of respectively 50%, 73%, 76%, and 71% of a standard deviation in the low-sentiment subsample. The effect then becomes economically strong. We find again similar estimates for the news-based EPU index in the political sentiment breakdown (Table A3).

One potential concern is that approval ratings follow a cyclical pattern over the presidential cycle, decreasing sharply towards the end of the term (see, e.g., Mueller, 1970; Montone, 2022). Hence, these results may simply reflect a more general increase in uncertainty that surrounds elections rather than presidential popularity in and of itself. To address this point, we repeat the analysis excluding presidential election years (Table A4, Panel A), defined as term-year 4, and Congress election years (Table A4, Panel B), defined as term-years 2 and 4. Reassuringly, the estimates are largely unchanged.

In addition to net disapproval, there are also other potential channels that may contribute to a president's political capital, such as the stock market and presidential affiliation. To test this conjecture, we perform additional tests by introducing alternative two-way interaction terms between EPU and the investor sentiment index from Baker and Wurgler (2006, 2007), excess returns on the stock market portfolio, and the Democratic dummy. None of these coefficients, however, are significant (see Table A5). The results suggest that the degree of presidential popularity embedded in approval ratings seems to provide the best identification for the mechanism we hypothesize.

Overall, we find that U.S. institutional investors herd more when political uncertainty is high, and this pattern amplifies during periods of adverse political sentiment toward the president in office. These results suggest that political uncertainty can motivate herding among fund managers, in line with our theoretical predictions.

3.3. Addressing endogeneity concerns

Despite the large battery of controls, the EPU index may still partly capture the state of the economy. For example, the index is inversely and significantly correlated with our macroeconomic indicators from Table 1.[9] It is then possible, in principle, that the empirical relation between herding and political uncertainty may reflect a more general relation between herding and the state of the economy.

To address this issue, we proceed with three sets of additional tests. First, we repeat our analysis by

[9]Specifically, the pairwise correlation coefficients are -0.28 for IPI growth (p-value < 0.05), -0.14 for PCED growth, although not significant, -0.19 for PCEND growth (p-value < 0.05), -0.42 for PCES growth (p-value < 0.01), -0.37 for employment growth (p-value < 0.01), and 0.25 with the NBER recession indicator (p-value < 0.05).

excluding economic downturns, defined as periods of NBER recessions, the subprime crisis, and the tech bubble burst. Reassuringly, we find that the relation between herding and political uncertainty becomes even stronger, both in magnitude and significance, without the confounding effect of economic downturns (Table A6, Panel A). The robustness of the findings to the exclusion of crisis periods also moderates the potential concern that fire sales may have an impact on our estimates. In unreported tests, we find similar results when excluding net disapproval from the test equation.

The fact that the results become stronger when excluding recession periods deserves further attention, because it might merely be an artifact of the higher baseline herding that takes place away from recession periods (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014). If so, the point estimate as a percentage of the sample mean may not be larger. Reassuringly, however, we find that herding means are rather similar across recession and expansion periods.[10]

Second, we re-estimate our test equation using an alternative version of the EPU index orthogonalized to macroeconomic indicators. To build this measure, we run an auxiliary regression of the index on the economic controls introduced above, with heteroskedasticity- and autocorrelation-consistent standard errors, and define the residuals from this regression as the orthogonalized version of the index. We find that the results become again stronger, which suggests that the effect of political uncertainty on herding documented in our previous tests seems largely unrelated to the state of the economy (Table A6, Panel B).

Third, we follow an instrumental variable approach considering U.S. mass shootings. The intuition is as follows. These attacks have nationwide political and economic resonance, although their root causes are typically individual- and county-specific (Brodeur and Yousaf, 2019; Kwon and Cabrera, 2018, 2019).[11] Therefore, mass shootings constitute a source of exogenous variation in sentiment among economic agents (Brodeur and Yousaf, 2019; Lagerborg, Pappa, and Ravn, 2020), and disapproval over the U.S. president's job (Smith, 2002; Wosniak, 2015; Montone, 2022).

We retrieve data from the Stanford Mass Shootings of America (MSA) data project. For each shooting incident, we consider the following variables: the number of fatalities, the number of shooters, and a dummy variable that takes on the value of one if the perpetrator(s) had a known history of mental illness, and zero otherwise. The inclusion of the latter variable is important because mass shootings routinely prompt calls to address untreated mental illness, which increases the public outrage that surrounds these events (Hirschtritt and Binder, 2018). All three variables exhibit positive and significant correlation with net disapproval (Montone, 2022). The sample period for this data set ends in the fourth quarter of 2015.

Then we estimate two-stage IV regressions. In the first stage, we regress net disapproval on the aforementioned variables (with HAC standard errors), and define the predicted values from this regression as the

[10] During recessions, the herding means are 0.12, 0.24, 0.32, and 0.39 for each of the four measures under consideration, respectively. During expansions, the estimates are 0.11, 0.28, 0.35, and 0.41, respectively.

[11] For example, contributing factors are personal financial distress (Brodeur and Yousaf, 2019), or county-level economic inequality (Kwon and Cabrera, 2018, 2019). These factors constitute triggers because they generate anger and resentment (Merton, 1968), which in turn is more conducive to acts of violence (Daly, 2016).

instrument.[12] To ease the interpretation of the subsequent tests, we also standardize this variable. In the second stage, we repeat the analysis of the conditional effect of political uncertainty on herding replacing net disapproval with its instrument. We find that the results are again robust (Table A6, Panel C).

Taken together, these additional tests allay the concern that our estimates might be spuriously driven by macroeconomic conditions.

3.4. Additional tests

In the last part of this section, we carry out some additional tests for some specific stock categories. First, we repeat our baseline regressions among stocks that are harder to evaluate. Then, we explore the role of presidential affiliation for politically-sensitive stocks.

Risky stocks

Since stocks characterized by higher risk are also harder to evaluate (see, e.g., Baker and Wurgler, 2006), they should generate a stronger herding response. We test this conjecture by identifying two categories of risky stocks. First, we consider small stocks (see, e.g., Fama and French, 1992, 1993), defined as stocks with below-median market capitalization and held by at least 5 institutional investors.[13] We re-estimate our baseline regressions in separate subsamples of small and large stocks, and then directly compare the coefficients of interest in the full sample.

The results are in Table 4, Panel A, columns (1) to (3). We find a positive and significant association between economic policy uncertainty and institutional herding for both small and large stocks. The effect, however, is more pronounced among the former. A one-standard-deviation increase in the EPU index is associated with an increase in institutional herding equal to 38% of a standard deviation for small stocks, and 22% of a standard deviation for large stocks. The difference is also statistically significant.

In columns (4) to (6), we introduce net disapproval ratings. Consistent with our expectation, we find that politically-motivated herding is more pronounced for small stocks in times of low political sentiment, whereas the effect does not vary with sentiment among large stocks. The difference between these two coefficients is also statistically significant. Overall, these results lend support to our prediction that small stocks are more sensitive to political uncertainty, especially so when political sentiment is low.

In the second group of tests, we study the effect of political connections. To identify politically-connected companies in the universe of U.S. stocks, we proceed as follows. Building on the methodology from Bonaparte, Kumar, and Page (2017), we match the zip code of company headquarters with state-level voting data in presidential elections. Then we define companies as politically connected if they are located in states that

[12] The coefficient is positive and highly significant for the variable measuring the number of shooters (0.0572, t-stat 2.93), whereas it is close to zero and not significant for the number of fatalities (-0.0024, t-stat -0.59) and the mental illness history dummy (-0.0004, t-stat -0.01).

[13] This choice reflects the trade-off between minimizing the effect of common styles across funds, and avoiding stocks whose coverage is too sparse.

exhibit the same political affiliation as the White House. This choice incorporates the idea that politically-affiliated governors may provide firms access to the office of the presidency.[14]

Companies that lack this connection, on the other hand, are at a political disadvantage compared with politically-connected firms. Since companies with less political connections have more uncertain prospects (see, e.g., Fisman, 2001; Faccio, Masulis, and McConnell, 2006), we hypothesize that unconnected companies face greater political uncertainty, and should then be the target of greater politically-motivated herding.

We test this hypothesis in Table 4, Panel B, columns (1) to (3). We find that the coefficient of economic policy uncertainty is positive and significant among both connected and unconnected companies (columns 1 and 2).[15] However, a one-standard-deviation increase in economic policy uncertainty is associated with an increase in institutional herding of 44% of a standard deviation for unconnected firms, and 31% of a standard deviation for connected ones, and the difference is not only economically but also statistically significant (column 3). Consistent with our conjecture, then, the relation between institutional herding and economic policy uncertainty is significantly stronger for companies located in states that are not politically aligned with the White House.

Next, we study how this relation varies with political sentiment. The results are in columns (4) to (6). We find that the results from the unconditional tests only hold in times of high political sentiment. When political sentiment is low, instead, politically-motivated herding actually becomes stronger for connected companies. The results suggest that there is a dark side to political connections, as being linked to an unpopular administration can make the company's prospects more uncertain. This mechanism provides a new kind of confirmation to the idea that politically-connected firms suffer disproportionately more from negative shocks to the politicians they support (see, e.g., Fisman, 2001).

Presidential affiliation

Recent research shows that Republican administrations have been historically associated with a number of tough and controversial issues in the postwar era, such as adverse oil shocks, lower total factor productivity performance, a generally less favorable international environment, lower consumer optimism, and an overall less predictable economy. Pástor and Veronesi (2020) argue that this association might not be random, because it is theoretically optimal for electors to choose Republican presidential candidates when they prefer less insurance from government and more business risk.

Drawing on these insights, we expect economic policy uncertainty to have a stronger effect on institutional herding under Republican administrations. The intuition is that higher risk makes it comparatively harder to assess the impact of current policies, and/or make predictions on future alternative policies. If risk is positively associated with Republican presidencies, then we expect the latter to represent a moderating

[14]The intuition is that a state governor who is from the same political party as the president may grant local companies (directly or indirectly) preferential access to the office of the presidency, with potential advantages ranging from information acquisition to favorable policy-making. This is the reason we consider the political color of the state, rather than the county, because this mechanism is unlikely to be operational for lower-level political representatives.

[15]Unfortunately, there is one missing observation for the herding measure of unconnected companies.

variable in the relation between economic policy uncertainty and institutional herding.

To test this hypothesis, we augment our baseline regressions with an interaction term between economic policy uncertainty and the Democratic dummy, and identify a number of specific stock categories that are more sensitive to the political affiliation of the presidency. Santa-Clara and Valkanov (2003) show that U.S. stock returns earn a substantial premium under Democratic presidencies, and that the effect is particularly pronounced among small stocks. The intuition is that small stocks are particularly sensitive to systematic risk (Cooley and Quadrini, 1997; Perez-Quiros and Timmermann, 2000). In light of this, we expect politically-motivated herding to be more pronounced among small stocks under Republican presidencies.

The results are in Table 5, column (1). We find again that the coefficient of economic policy uncertainty as a standalone variable is positive and significant. Specifically, the effect of a one-standard-deviation increase in the EPU index on institutional herding is 31% (of a standard deviation) stronger for small stocks when compared with large stocks. Interestingly, however, the effect is entirely concentrated under Republican presidencies. Under Democratic administrations, politically-motivated herding does not differ across small and large stocks.

Hong and Kostovetsky (2012) identify a number of stock categories that are particularly divisive across party lines, and define them as politically sensitive.[16] They argue that Republicans tend to be more lenient on issues such as environmental damage, smoking, and guns. For these industries, then, shifts in the political affiliation of the presidency have an important bearing on their future economic prospects.

The mechanism we propose is as follows. As Republicans introduce more favorable legislation on politically-sensitive industries, they also make these stocks riskier because most of the provisions will likely be modified or reversed under future Democratic administrations. In light of this, we expect politically-motivated herding to be more pronounced on politically-sensitive stocks relative to non-sensitive stocks under Republican presidencies.

The results are in Table 5, column (2). We find evidence in support of our conjecture. While the coefficient of economic policy uncertainty as a standalone variable is positive and (marginally) significant, the coefficient of its interaction term with the Democratic dummy is negative and significant. Politically sensitive stocks attract indeed greater politically-motivated herding, but only under Republican presidencies.

In the last group of tests, we consider the measure of firm-level political risk from Hassan et al. (2019), and divide again stocks into those with above- and below-median risk.[17] Given their higher sensitivity to the political environment, we expect stocks labeled as politically risky to have particularly uncertain prospects under Republican presidencies. To test this hypothesis, we directly compare politically-motivated herding on stocks with an above- and below-median level of political risk, and study how this relation varies with presidential affiliation.

[16] Such stocks are from the following industries (SIC codes in parentheses): tobacco (2100-2199); guns and defense (3760-3769, 3795, 3480-3489); natural resources, including forestry (0800-0899) and mining (1000-1119, 1400-1499); and alcohol (2080, 2082-2085).

[17] Unfortunately, this measure is only available from 2002q2.

The results are in Table 5, column (3). We find that politically-risky (i.e., above-median) stocks do indeed attract greater politically-motivated herding than less risky (i.e., below-median) ones, but only under Republican presidencies. Under Democratic administrations, the effect disappears. In additional tests, we find that none of these results are driven by correlation between institutional herding and the president's political affiliation, or between political affiliation and economic policy uncertainty. Rather, there seems to be a genuine structural break in politically-motivated herding. Overall, the empirical evidence lends support to the idea that Republican presidencies are associated with greater risk.

4. Stock returns

In the last part of the paper, we analyze whether the herding response to political uncertainty is beneficial or detrimental to the stock market's efficiency. First, we outline the two competing hypotheses introduced in previous literature. Second, we describe our methodology. Third, we analyze stock returns over a two-year horizon as in Dasgupta, Prat, and Verardo (2011). Fourth, we consider longer time horizons as in Jegadeesh and Titman (2001). Finally, we assess the robustness of our results by using an alternative estimation method.

4.1. Competing hypotheses

There are two competing hypotheses on the relation between herding and market efficiency. First, herd behavior can drive prices closer to fundamentals by gradually impounding information (Wermers, 1999; Sias, 2004). In this case, subsequent stock returns should be consistently positive (negative) if the price is initially below (above) the fundamental value. Second, herding can create mispricing if it produces excess trading (Dasgupta, Prat, and Verardo, 2011; Brown, Wei, and Wermers, 2014). Under this scenario, subsequent stock returns should "overshoot" in the short run, and exhibit reversals afterwards.

To tease out these two competing stories, we carry out an analysis of returns over a multi-year period. A long-run perspective is important for at least three reasons. First, the discrepancy between studies that respectively find a positive or a negative relation between institutional holdings and future stock returns likely reflects differences in time horizon (see, e.g., Edelen, Ince, and Kadlec, 2016). Second, sensitivity to political uncertainty likely represents a stable characteristic of a stock, and therefore should be related to long-run returns. Third, the effect of policy changes can be mostly seen in the long run.

Following Sias (2004), we identify the fraction of institutional buyers for a given stock as a stock-level component of the herding measure, as the former constitutes the key building block for the latter (see Section 2), and study the relation between stock-level institutional demand and stock returns. However, we introduce an important element of novelty. We decompose institutional demand into a component that is attributable to a stock's sensitivity to economic policy uncertainty, and a residual component that captures any other factors that affect stock-level institutional demand. In so doing, we are able to separately estimate the relation between institutional demand and returns for each of these two components of institutional demand. Next, we describe our methodology in detail.

4.2. Methodology

Our methodology consists of two auxiliary regressions and a Fama-MacBeth regression. In the first auxiliary regression, we estimate time-varying EPU betas for each of the stocks in our sample. In the spirit of Akey and Lewellen (2017) and Caldara and Iacoviello (2022), we run rolling time-series regressions of individual stock returns on the EPU index controlling for the market portfolio, defined as the set of all stocks traded on the NYSE, AMEX, and NASDAQ (see, e.g., Fama and French, 1993).[18] Following Hong and Kacperczyk (2009), the regressions are monthly and use a 36-month rolling window.

The distribution of our EPU betas is roughly centered on zero, with standardized values varying from -2.42 to 2.24. For comparison, we obtain a similar distribution for standardized betas on canonical risk factors. For example, the beta range is between -2.28 and 4.17 for the market factor (MKT), between -2.56 and 3.97 for the size factor (SMB), and between -3.36 and 3.28 for the book-to-market factor (HML). More generally, this distribution is consistent with the presence of cross-sectional differences that make some stocks more exposed to political uncertainty, whereas other stocks provide insurance against it (see, e.g., Belo, Gala, and Li, 2013).

The interpretation of EPU betas, however, differs from the betas for canonical risk factors. The reason is as follows. Both the EPU index and stock returns are measured at the end of every month in the auxiliary regression, but the former is expressed in levels whereas the latter in (log-) changes in closing prices across consecutive months. Therefore, stocks that are more sensitive to EPU exhibit a low (in fact, negative) EPU beta, as these are stocks whose prices tend to decrease the most when the EPU index is high. This is in contrast with canonical risk factors because the latter are measured in returns rather than levels, so that a higher beta implies higher sensitivity to a factor (see, e.g., Frazzini and Pedersen, 2014).

Consistent with this interpretation, we find that EPU betas in our sample exhibit negative and highly significant correlation with stock-level betas for the market, size, and book-to-market factors, indicating that stocks with low EPU betas are more sensitive to market fluctuations, of smaller size, and with higher book-to-market ratios. These characteristics indeed identify riskier stocks (see, e.g., Fama and French, 1993). The presence of such correlations further validates our interpretation of EPU betas as a measure of firm-level sensitivity to political uncertainty.

Having identified EPU betas, we go on to estimate their relation with stock-level institutional demand in our second auxiliary regression. Our goal is to estimate the component of institutional demand that is explained by a stock's sensitivity to EPU. To this end, we carry out panel regressions of the standardized buy ratio from Eq. (2) on a stock's EPU beta, aggregated from the original monthly frequency into quarterly averages for consistency with the asset holdings data set. We run these regressions separately for each of the

[18] The EPU index is expressed in levels as in the rest of our analysis.

four stock categories under consideration (i.e., stocks with at least 1, 5, 10, and 20 institutional investors, respectively), thereby estimating four separate slope coefficients.[19]

These coefficients are negative and equal to -0.31, -0.38, -0.31, and -0.15, respectively. Since low EPU-beta stocks identify greater sensitivity to political uncertainty, the results indicate that institutions tend to prefer stocks that load up on EPU risk, consistent with the well-known "search for yield" (see, e.g., Becker and Ivashina, 2015).[20] Each of these coefficients represents an estimate of the structural relation between institutional demand and EPU betas, across both stocks and time, within a given stock category. The proportion of stock-level institutional demand explained by EPU betas is then defined as the product between the category-specific slope coefficient and the stock's time-varying EPU betas. Therefore, this proportion is also time-varying.

Finally, we run a modified version of the Fama-MacBeth regressions of stock returns from Sias (2004), where we replace institutional demand from Eq. (2) with our proposed decomposition:

$$R_{i,t+s} = \beta_0 + \beta_1 \Delta^E_{i,t} + \beta_2 \Delta^U_{i,t} + \gamma' F_t + \epsilon_{i,t+s}, \tag{6}$$

where $R_{i,t+s}$ is excess returns on stock i over future time window s; $\Delta^E_{i,t}$ and $\Delta^U_{i,t}$ are respectively the fraction of institutional buyers for stock i in quarter t explained and unexplained by EPU betas, both standardized to ease the interpretation of the results; and F_t is a vector of controls including the three Fama-French factors (market, size, and book-to-market), the momentum factor from Carhart (1997), and the liquidity factor from Pástor and Stambaugh (2003). The inclusion of these risk factors is important because they represent primary drivers of stock returns. We also introduce a number of return-based explanatory variables to better capture potential confounding effects related to momentum or reversals unrelated to EPU betas. In particular, we consider the average past excess returns measured over the period that spans years -4 through -1 (Dasgupta, Prat, and Verardo, 2011), the average excess return over year -1 (Brown, Wei, and Wermers, 2014), and excess returns in the current quarter (Gutierrez and Kelley 2009; Brown, Wei, and Wermers, 2014).[21]

Sias (2004) argues that institutional demand can be related to future returns in two ways. If institutions trade for non-informational reasons, they exert an upward pressure on stock prices and therefore institutional demand should be a negative predictor of future stock returns. If institutional trades are based on information, institutional demand should be a positive predictor instead. Sias (2004) finds evidence for the

[19]A panel estimation of these slope coefficients reflects the following trade-off. Although using the full sample may introduce a potential look-ahead bias, it allows us to substantially increase the number of observations and therefore average out measurement errors across stocks and time.

[20]In light of the pronounced heterogeneity that characterizes investors in terms of sophistication and risk preferences (Chen, Hong, and Stein, 2002; Hirshleifer and Teoh, 2003b; Hong and Sraer, 2013, 2016), these results suggest that, on average, low EPU-beta stocks are held by relatively more informed or less risk-averse institutional investors.

[21]Past returns have high explanatory power over current returns (see, e.g., Carhart, 1997), thereby increasing the goodness of fit of the regressions that follow. More generally, the high R-squared reflects the fact that we consider lower-frequency returns (quarterly rather than monthly) and calculate them cumulatively over a long time window (up to five years). As a result, the noise and potential outliers associated with short-term data are largely smoothed out by arbitrage forces (Greenwood, 2005), thereby enhancing the performance of our empirical models. Consistent with this interpretation, the R-squared increases with the time window over which we calculate our cumulative returns.

latter hypothesis. In our setup, we split institutional demand into two components to study how each of them is related to future stock returns. Our component of interest is the one based on EPU betas, because it allows us to analyze the impact of institutional demand on the pricing of EPU risk.

The main coefficient of interest is then β_1 and our priors are as follows. If EPU-related institutional demand has a beneficial effect on market efficiency, then the coefficient should be positive in the long run. Conversely, a detrimental effect implies an overall negative coefficient.

4.3. Two-year horizon

Following Dasgupta, Prat, and Verardo (2011), we primarily define long-run returns as (excess) stock returns over a two-year horizon. The estimates are in Table 6, Panel A. We find that the coefficient of explained institutional demand is positive and highly significant, indicating that stocks with a larger component of EPU-related institutional demand (i.e., those with lower EPU betas) yield higher future stock returns. This result is therefore consistent with the informational trading argument from Sias (2004), and more generally with the view that political uncertainty commands a risk premium (Pástor and Veronesi, 2013).

To get a sense of the magnitude, a one-standard-deviation increase in explained institutional demand is associated with an increase in two-year-ahead stock returns of 2.22%, 2.37%, 4.09%, and 5.22%, respectively, for each of the four stock categories (related to the number of institutional traders) under consideration. The increasing magnitude is consistent with the idea that larger herds have a bigger impact on stock prices (Wermers, 1999). Overall, then, the results seem to point to a stabilizing effect of institutional investor demand over a two-year horizon.

To shed further light on our results, we separately re-estimate our test equation into periods in which the EPU index respectively takes on low (below-median) and high (above-median) values. The intuition is as follows. If institutional investors help impound a premium for EPU risk into stock prices, then the positive relation between explained institutional demand and stock returns should be more pronounced during periods in which EPU risk is high – that is, when the EPU index takes on above-median values. The results, reported in Table 6, Panels B and C, support this prediction, as they are confined in the latter subsample.

To dig deeper on the underlying mechanism, we also analyze the relation between the two components of institutional demand and contemporaneous stock returns (i.e., measured within the same quarter), both in the full sample and into subsamples of low and high EPU, respectively. Our estimates, reported in Table 7, indicate that the EPU-beta component of institutional demand is negatively related to contemporaneous stock returns during periods of high EPU, indicating selling pressure for low-EPU beta stocks when EPU risk is high.[22] The corresponding downward impact on stock prices at the end of the quarter then seems to generate higher expected returns in subsequent quarters, consistent with the findings from Table 6.

In additional tests, we re-estimate our test equation in two periods of roughly equal length (see, e.g.,

[22]For example, less informed (or more risk-averse) institutions may sell high EPU-beta stocks to their more informed (or less risk-averse) counterparts.

Wermers, 1999; Dasgupta, Prat, and Verardo, 2011; Brown, Wei, and Wermers, 2014). This analysis is interesting because institutional investors have become increasingly important in setting stock prices over time (see, e.g., Brown, Wei, and Wermers, 2014), so we would expect our results to be especially strong in the more recent subsample. Consistent with this prediction, we find that our results are concentrated in modern times (Table A7). The coefficient of interest is large, positive, and significant in the more recent subsample (2000-2019), whereas it is largely outside of the rejection region in the early subsample (1985-1999). It is also interesting to note that EPU is about 20% higher on average in the more recent sample period, so the two mechanisms highlighted in these subsample analyses likely reinforce each other.

4.4. Five-year horizon

Gutierrez and Kelley (2009) show that the relationship between institutional investor demand and future stock returns depends on the time horizon under consideration. They find evidence that institutional herding promotes price discovery in the short run, but is followed by reversals in the long run, consistent with the theoretical predictions of Hong and Stein (1999). Next, we analyze whether there is a similar empirical pattern in our sample.

Following Jegadeesh and Titman (2001), we consider an overall five-year horizon. This timeframe is especially appropriate also in light of the consideration that EPU risk has potential effects in the (very) long run. We propose two sets of tests. First, we analyze the relation between institutional investor demand and future stock returns calculated between three and five years ahead, which complements the analysis of two-year-ahead returns from our baseline regressions. Second, we analyze returns over the full five-year horizon to determine the overall effect of institutional investor demand on stock returns.

Our findings can be summarized as follows. In the first set of tests, in Table 8, we find evidence consistent with return reversals in a similar manner to Gutierrez and Kelley (2009). The coefficient of interest again monotonically increases (in absolute value) across our specifications – i.e., when considering stocks with a progressively larger minimum number of institutional investors. The results are also mostly confined to the subsample period in which the EPU index takes on above-median values. Therefore, the effect of explained institutional demand on stock returns from the two-year return analysis partly vanishes in subsequent years. Overall, our results identify a price discovery effect (in years 1 and 2) followed by a subsequent price pressure effect (in years 3 to 5).

In the second group of tests, we analyze which of the two effects prevails. The results are in Table 9. We find that the price discovery effect ultimately wins out, as we uncover an overall positive and significant relation between explained institutional demand and five-year stock returns. The results are again confined to the high-EPU subsample, indicating that institutional trading seems to improve overall market efficiency by impounding a premium for EPU risk in the long run.

The results provide support to well-known theoretical mechanisms of herd behavior. The relatively slow speed of information acquisition is in line with models of sequential trading, where investors who observe a signal trade ahead of the others (Froot, Scharfstein, and Stein, 1992; Hirshleifer, Subrahmanyam, and

Titman, 1994; Hong and Stein, 1999).[23] Herding then seems to facilitate the incorporation of information, where less informed investors infer signals from earlier trades (Wermers, 1999; Sias, 2004).

In recent research, Kacperczyk, Sundaresan, and Wang (2021) show that institutional investors help incorporate information into stock prices, as their demand positively predicts subsequent changes in stock returns. Our findings suggest that this mechanism may partly work through herd behavior, as institutional herding helps impound a risk premium for political uncertainty.

4.5. Fixed-effects regressions

One potential concern with our results is that Fama-MacBeth regressions of persistent variables, such as institutional demand and its components, may generate biased standard errors (see, e.g., Petersen, 2009). To address this issue, we repeat our main analyses by replacing the Fama-MacBeth methodology with panel regressions with firm and time fixed-effects. This specification also addresses the concern that the estimates may be driven by time-invariant stock characteristics or common time trends across institutional trades.

The results, reported in Table A8, are qualitatively similar to those from the Fama-MacBeth regressions. Over a two-year horizon (Panel A), we find a strong positive relation between the EPU-beta component of institutional demand and future stock returns. The magnitude is slightly weaker compared with the coefficients from the Fama-MacBeth regressions, indicating that the explanatory power of our variables of interest is partly absorbed by the battery of fixed effects, but the results become statistically stronger, reflecting the increase in statistical power associated with a panel setup compared with Fama-MacBeth regressions. Also, the coefficient of interest increases again in magnitude with the number of institutional traders, thereby providing further support to the idea that the impact of larger herds on stock prices is more pronounced (Wermers, 1999). Conversely, the coefficient of unexplained institutional demand is negative and significant, consistent with the findings on excess trading from Dasgupta, Prat, and Verardo (2011).

Over years three to five (Panel B), we find again some evidence that EPU-related institutional trading leads to subsequent reversals, although the coefficient is only statistically significant for the first two stock categories under consideration. We find a similar result, although with the opposite sign, for unexplained institutional demand. Over a five-year horizon (Panel C), the impact of the two components of institutional demand on stock returns largely reflects the empirical patterns from the two-year-horizon regressions, indicating that the short-term effect of institutional demand on stock returns is again dominant. Overall, then, our results are robust to this alternative panel specification with fixed effects.

Our findings are consistent with previous research on institutional investor behavior (see, e.g., Gutierrez and Kelley, 2009), and more generally with extant asset pricing models with heterogeneous investor types. Hong and Stein (1999) show that in a model with investors who exhibit different degrees of sophistication, a gradual diffusion of information creates overreaction in the long run. This prediction seems particularly

[23] Recent studies provide empirical evidence for this setup, and correspondingly show that herding funds underperform with respect to their anti-herding peers due to delayed trading (Wei, Wermers, and Yao, 2015; Jiang and Verardo, 2018).

fitting for our framework due to the presence of investor heterogeneity and the gradual resolution of political uncertainty over time. Consistent with this mechanism, the return patterns associated with the EPU-beta component of institutional demand partially revert at longer horizons, indicating price overshooting.

5. Conclusion

In this paper, we show that political uncertainty generates substantial herd behavior among institutional investors. Our analysis builds on two well-known mechanisms. First, noisier signals constitute an incentive for institutional investors to mimic each other's trades. Second, institutional investors face reputational and litigation costs when their behavior deviates from the "herd," and especially so in the presence of negative stock information. In light of the fact that political uncertainty makes investor beliefs noisier and depresses stock prices, we expect both channels to be operational.

Our empirical findings lend support to this conjecture. The results are particularly pronounced in times of high presidential disapproval, which is in line with the idea that unpopular administrations steer towards riskier policies to try and win back the electorate. The estimates are also stronger for stocks that are commonly thought of as riskier or politically sensitive. While a growing body of literature unveils a link between political evaluations and a number of financial outcomes, we show that such evaluations also generate herd behavior among institutional investors.

We also find that this mechanism has important consequences for market efficiency. Despite generating some excess trading with partial reversals, institutional herding ultimately helps impound a risk premium into stock prices, especially during times in which political uncertainty is high. To the best of our knowledge, this is the first paper to identify herding as a channel through which financial markets incorporate political uncertainty. This is consistent with the view that herd behavior can improve market efficiency by facilitating price discovery, and more generally with the theoretical prediction that political uncertainty should be associated with higher stock returns.

This mechanism also has important implications for firms. When political uncertainty is high, companies find it optimal to delay investment until uncertainty is resolved. Our findings suggest that the trading behavior of institutional investors during politically uncertain times can exacerbate this issue. Politically-motivated herding generates a higher cost of capital for companies that are more exposed to political uncertainty, thus creating an even stronger incentive to put off investment.

Finally, our findings are of interest to the investment community as well. As far as regulators and policymakers are concerned, the political sensitivities we uncover could be included in the curriculum of financial education initiatives, in order to enhance investors' awareness of this issue. Our findings can also constitute useful input for investors with a U.S. market outlook. To the extent that U.S. quarterly institutional investors' holdings constitute public information, an investor could extrapolate from them to predict future returns conditional on the stock's sensitivity to political uncertainty.

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Figure 1. Herding and political uncertainty over time

Graph of the Sias (2004) herding measure calculated using stocks with at least five institutional traders (H5), and the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), both standardized to exhibit zero mean and a unit standard deviation. The sample period is from the first quarter of 1985 through the fourth quarter of 2019.

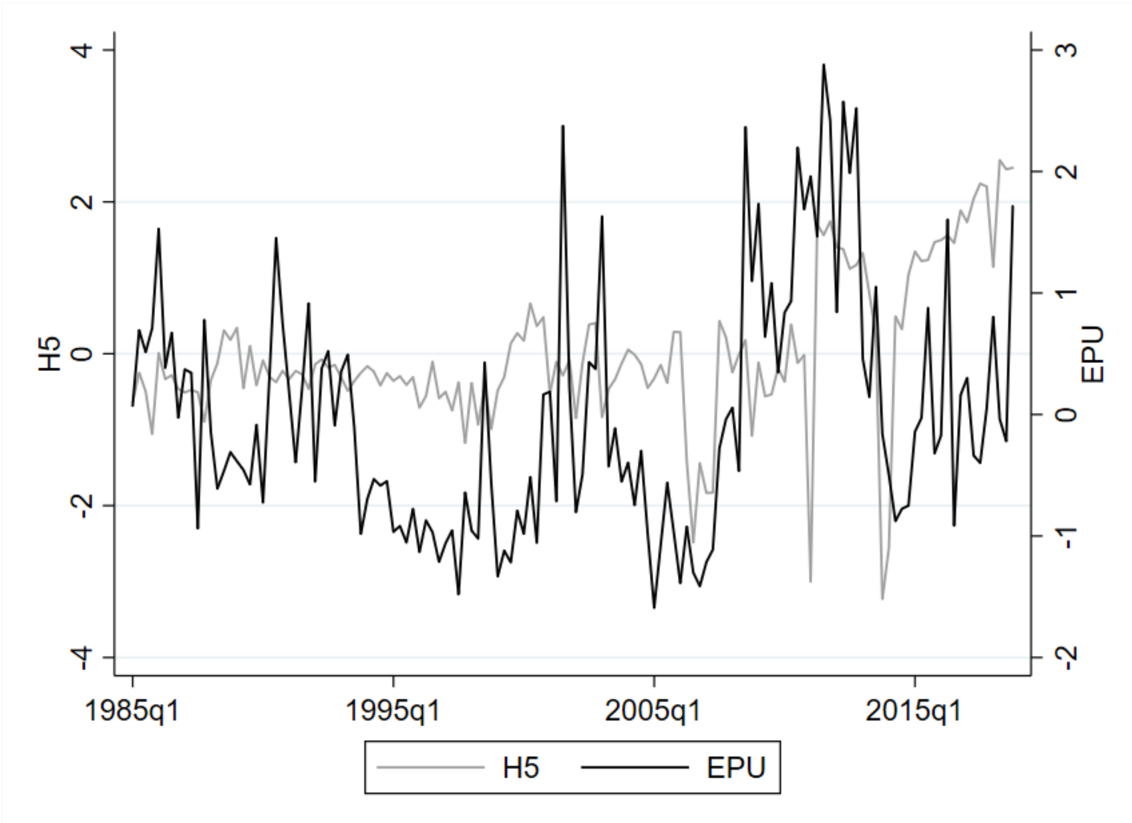

Table 1. Summary statistics

Summary statistics for the main variables used in our analysis. The variables are: herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004); the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), along with a news-based version of the index; net disapproval ratings, defined as the difference between Gallup's disapproval and approval ratings over the U.S. president's job; a dummy variable that takes on the value of one of the U.S. president is a Democrat, and zero otherwise; excess stock returns on the market portfolio over the quarter (RmRf), retrieved from Kenneth French's website, along with average excess returns over the previous year (RmRf, 1y-mean), and the standard deviation of excess returns over the previous year (RmRf, 1y-SD); growth in the industrial production (IPI) index, growth in personal consumption expenditures on durables (PCED), nondurables (PCEND), and services (PCES), growth in employment, and a dummy variable that takes on one for NBER recessions, all retrieved from the Bureau of Economic Analysis. The sample period is from the first quarter of 1985 through the fourth quarter of 2019.

Panel A. Herding

Variable	Mean	SD	P25	Median	P75
H1	0.1109	0.0657	0.0789	0.1049	0.1536
H5	0.2773	0.1360	0.2150	0.2521	0.3253
H10	0.3471	0.1609	0.2864	0.3202	0.4054
H20	0.4034	0.1769	0.3392	0.3975	0.4752

Panel B. Politics

Variable	Mean	SD	P25	Median	P75
EPU (primary)	109.8661	32.8975	84.3421	104.3965	126.4087
EPU (news-based)	114.4105	42.8059	84.4045	105.1156	134.2322
Net disapproval	-0.1113	0.2436	-0.2750	-0.0850	0.0500
Democrat	0.4706	0.5010	0.0000	0.0000	1.0000

Panel C. Stock market

Variable	Mean	SD	P25	Median	P75
RmRf	0.0126	0.1198	-0.0498	0.0284	0.0875
RmRf (1y-mean)	0.0181	0.0407	0.0005	0.0261	0.0449
RmRf (1y-SD)	0.0402	0.0180	0.0264	0.0383	0.0509

Panel D. Economic growth

Variable	Mean	SD	P25	Median	P75
IPI growth	0.0049	0.0132	0.0010	0.0069	0.0111
PCED growth	0.0104	0.0318	-0.0039	0.0124	0.0252
PCEND growth	0.0101	0.0149	0.0029	0.0113	0.0180
PCES growth	0.0139	0.0057	0.0105	0.0139	0.0173
Employment growth	0.0033	0.0043	0.0021	0.0041	0.0062
NBER	0.0809	0.2737	0.0000	0.0000	0.0000

Table 2. Herding and economic policy uncertainty

Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and the vector of financial, economic, and political controls from Eq. (5). In Panel A, we report estimates without controls. In Panel B, we include all controls. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. No controls

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0136**	0.0351***	0.0452***	0.0418**
	(2.28)	(3.41)	(3.22)	(2.29)
Constant	0.0656***	0.1602***	0.1962***	0.2637***
	(3.64)	(4.54)	(3.70)	(3.64)
Adj. R-squared	0.0354	0.0595	0.0720	0.0489
Observations	136	136	136	136

Panel B. Full model

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0140**	0.0388***	0.0479**	0.0443**
	(2.31)	(2.65)	(2.48)	(2.02)
IPI growth	-0.1974	-1.1937	-1.0816	-0.7353
	(-0.39)	(-1.09)	(-0.96)	(-0.66)
PCED growth	0.0344	-0.0104	-0.1211	0.0149
	(0.35)	(-0.06)	(-0.64)	(0.08)
PCEND growth	0.0585	-0.1057	-0.3322	-0.9142
	(0.14)	(-0.14)	(-0.44)	(-1.10)
PCES growth	-1.7095	-4.8528	-4.6318	-3.2771
	(-0.91)	(-1.21)	(-1.04)	(-0.72)
Employment growth	1.8626	6.5732*	7.9898*	8.0958*
	(0.99)	(1.84)	(1.87)	(1.96)
NBER	-0.0133	-0.1080*	-0.0879	-0.0492
	(-0.49)	(-1.81)	(-1.32)	(-0.72)
Term-year 2	0.0042	-0.0155	-0.0359	-0.0386
	(0.28)	(-0.53)	(-0.93)	(-0.87)
Term-year 3	0.001	-0.0077	-0.016	-0.0206
	(0.05)	(-0.19)	(-0.36)	(-0.41)
Term-year 4	0.0297**	0.0510*	0.0512*	0.0586**
	(2.24)	(1.85)	(1.83)	(2.02)
Democrat	-0.0016	-0.0034	0.0134	0.0486
	(-0.09)	(-0.08)	(0.27)	(0.91)
RmRf	-0.0087	-0.0970*	-0.1905**	-0.2279**
	(-0.17)	(-1.75)	(-2.48)	(-2.50)
RmRf (1y-mean)	-0.1391	-0.2274	-0.0663	-0.1447
	(-0.79)	(-0.56)	(-0.14)	(-0.27)
RmRf (1y-SD)	-0.4997	-1.0365	-0.6549	-0.8013
	(-1.64)	(-1.17)	(-0.60)	(-0.67)
Constant	0.0982**	0.2520*	0.2676	0.3074*
	(2.09)	(1.89)	(1.62)	(1.68)
Adj. R-squared	0.0056	0.1069	0.1077	0.0981
Observations	135	135	135	135

Table 3. Herding and economic policy uncertainty: Presidential popularity breakdown

Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and the vector of financial, economic, and political controls from Eq. (5). In Panels A and B, we only include subperiods in which Gallup's presidential net disapproval ratings (ND) are positive and negative, respectively. In Panel C, we include the full sample and add an interaction term between the EPU index and net disapproval ratings, as well as standalone net disapproval ratings as a control. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. ND > 0

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0332*	0.0976***	0.1203***	0.1235***
	(1.89)	(2.66)	(2.78)	(3.06)
Adj. R-squared	-0.0153	0.1109	0.1059	0.0630
Observations	45	45	45	45

Panel B. ND $<$ 0

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0048	0.012	0.0103	0.002
	(0.98)	(0.91)	(0.80)	(0.14)
Adj. R-squared	0.0706	0.2449	0.2060	0.2002
Observations	90	90	90	90

Panel C. Full sample

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0191***	0.0462***	0.0573***	0.0564**
	(2.97)	(3.09)	(2.92)	(2.42)
EPU $\times$ ND	0.0522***	0.0784**	0.1042**	0.1320**
	(2.58)	(2.03)	(2.14)	(2.30)
ND	-0.1395*	-0.2573**	-0.4197**	-0.5231**
	(-1.85)	(-1.99)	(-2.39)	(-2.40)
Adj. R-squared	0.0505	0.1125	0.1212	0.1194
Observations	135	135	135	135

Table 4. Herding and economic policy uncertainty: Risky stocks

Time-series regressions of a herding measure (H) over stocks held by at least 5 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), on the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and the vector of financial, economic, and political controls from Eq. (5). In columns (4) to (6), the specifications also include an interaction term between the EPU index and Gallup's presidential net disapproval ratings (ND), as well as standalone net disapproval ratings as a control. In Panel A, the herding measure includes stocks with below-median ("Small") market capitalization in columns (1) and (4), stocks with above-median ("Big") market capitalization in columns (2) and (5), and the difference in herding between small and large stocks in columns (3) and (6). In Panel B, the herding measure includes stocks from companies whose headquarters are located in states that exhibit a different political affiliation from the White House ("Unconnected") in columns (1) and (4), and states aligned with the political affiliation of the presidency ("Connected") in columns (2) and (5). In columns (3) and (6), the dependent variable is the difference in herding between unconnected and connected stocks. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Size

Dep. Var.: H5	(1) Small	(2) Big	(3) S−B	(4) Small	(5) Big	(6) S−B
EPU	0.0521***	0.0294**	0.0227***	0.0596***	0.0336**	0.0259***
	(3.63)	(2.03)	(2.88)	(3.77)	(2.25)	(3.62)
EPU × ND				0.0782*	0.0417	0.0366**
				(1.74)	(1.11)	(2.47)
Adj. R-squared	0.140	0.205	0.234	0.147	0.207	0.246
Observations	135	135	135	135	135	135

Panel B. Political connections

Dep. Var.: H5	(1) Unconnected	(2) Connected	(3) U−C	(4) Unconnected	(5) Connected	(6) U−C
EPU	0.0596***	0.0422***	0.0174**	0.0667***	0.0520***	0.0146
	(3.58)	(2.62)	(1.98)	(3.98)	(2.95)	(1.53)
EPU × ND				0.0734	0.1033**	-0.0327**
				(1.59)	(2.17)	(-2.21)
Adj. R-squared	0.172	0.126	0.118	0.174	0.137	0.127
Observations	134	135	134	134	135	134

Table 5. Herding and economic policy uncertainty: Presidential affiliation

Time-series regressions of a herding measure (H) over stocks held by at least 5 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), on the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), an interaction term between the EPU index and a dummy variable that takes on the value of one if the U.S. president is a Democrat, and the vector of financial, economic, and political controls from Eq. (5). The dependent variable is the difference in herding between below- and above-median market capitalization in column (1), between politically sensitive and insensitive stocks in column (2), and between stocks with above- and below-median firm-level political risk in column (3). Politically sensitive stocks are defined as in Hong and Kostovetsky (2012), and firm-level political risk as in Hassan et al. (2019). The sample period starts in the first quarter of 1985 in columns (1) and (2), and in the second quarter of 2002 in column (3), and ends in the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Dep. Var.: H5	(1) Size	(2) Political Sensitivity	(3) Political Risk
EPU	0.0441***	0.0247**	0.0425**
	(3.82)	(2.02)	(2.15)
EPU × Democrat	-0.0334**	-0.0584***	-0.0345*
	(-2.11)	(-3.62)	(-1.71)
Adj. R-squared	0.257	0.076	0.045
Observations	135	135	67

Table 6. Two-year future stock returns

Fama-MacBeth regressions of quarterly future excess returns on stock i, calculated over a two-year period, on the fraction of institutional buyers for stock i ($\Delta_{i,t}$), calculated over stocks held respectively by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data, and applying the methodology from Sias (2004), further divided into a component that is explained by stock-level economic policy uncertainty (EPU) betas, calculated using the U.S. EPU index from Baker, Bloom, and Davis (2016), and an unexplained (residual) component. All regressions include the vector of controls from Eq. (6). In Panel A, we consider the full sample. In Panels B and C, we respectively consider periods of low and high EPU. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Full sample

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0222***	0.0237***	0.0409***	0.0522***
	(3.55)	(3.48)	(5.63)	(7.41)
Unexplained $\Delta_{i,t}$	0.0032	-0.0272	0.0010	0.0115*
	(0.23)	(-1.14)	(0.17)	(1.72)
Adj. R-squared	0.6404	0.6463	0.6447	0.6401
Average number of stocks	3,152	2,619	2,203	1,766
Number of time periods	136	136	136	136

Panel B. Low EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0037	0.0073	0.0152*	0.0322***
	(0.61)	(1.04)	(1.90)	(4.33)
Unexplained $\Delta_{i,t}$	0.0231	0.0088	0.0205*	0.0230*
	(1.37)	(0.97)	(1.83)	(1.72)
Adj. R-squared	0.6996	0.7047	0.7014	0.6934
Average number of stocks	3,608	2,972	2,472	1,957
Number of time periods	65	65	65	65

Panel C. High EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0461***	0.0484***	0.0628***	0.0666***
	(6.04)	(5.72)	(6.78)	(7.90)
Unexplained $\Delta_{i,t}$	-0.0170	-0.0294***	-0.0142	-0.0060
	(-0.83)	(-3.61)	(-0.78)	(-0.55)
Adj. R-squared	0.7400	0.7347	0.7289	0.7150
Average number of stocks	2,726	2,296	1,953	1,591
Number of time periods	71	71	71	71

Table 7. Contemporaneous stock returns

Fama-MacBeth regressions of quarterly excess returns on stock i on the fraction of institutional buyers for stock i ($\Delta_{i,t}$), calculated over stocks held respectively by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data, and applying the methodology from Sias (2004), further divided into a component that is explained by stock-level economic policy uncertainty (EPU) betas, calculated using the U.S. EPU index from Baker, Bloom, and Davis (2016), and an unexplained (residual) component. All regressions include the vector of controls from Eq. (6). In Panel A, we consider the full sample. In Panels B and C, we respectively consider periods of low and high EPU. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Full sample

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	-0.0034	-0.0008	0.0007	-0.0041
	(-1.20)	(-0.24)	(0.19)	(-1.52)
Unexplained $\Delta_{i,t}$	0.0495	0.0454**	0.0305***	0.0165**
	(0.71)	(2.28)	(3.01)	(2.04)
Adj. R-squared	0.4663	0.4874	0.5025	0.5032
Average number of stocks	3,152	2,619	2,203	1,766
Number of time periods	136	136	136	136

Panel B. Low EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0190***	0.0151***	0.0179***	0.0200***
	(5.97)	(3.64)	(4.98)	(6.61)
Unexplained $\Delta_{i,t}$	0.0307	0.0104	0.0094	-0.0993
	(1.24)	(1.10)	(1.11)	(-0.91)
Adj. R-squared	0.4785	0.4851	0.4949	0.4910
Average number of stocks	3,608	2,972	2,472	1,957
Number of time periods	65	65	65	65

Panel C. High EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	-0.0426***	-0.0476***	-0.0510***	-0.0610***
	(-10.07)	(-8.86)	(-8.35)	(-13.18)
Unexplained $\Delta_{i,t}$	0.0451	0.0392*	0.0184**	0.0283***
	(0.57)	(1.73)	(2.15)	(2.95)
Adj. R-squared	0.6286	0.6408	0.6423	0.6271
Average number of stocks	2,726	2,296	1,953	1,591
Number of time periods	71	71	71	71

Table 8. Future stock returns over years three to five

Fama-MacBeth regressions of future quarterly excess returns on stock i, calculated over years three to five, on the fraction of institutional buyers for stock i ($\Delta_{i,t}$), calculated over stocks held respectively by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data, and applying the methodology from Sias (2004), further divided into a component that is explained by stock-level economic policy uncertainty (EPU) betas, calculated using the U.S. EPU index from Baker, Bloom, and Davis (2016), and an unexplained (residual) component. All regressions include the vector of controls from Eq. (6). In Panel A, we consider the full sample. In Panels B and C, we respectively consider periods of low and high EPU. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Full sample

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	-0.0207***	-0.0260***	-0.0310***	-0.0405***
	(-2.74)	(-2.95)	(-3.23)	(-4.57)
Unexplained $\Delta_{i,t}$	-0.0670*	0.0230	-0.0186	-0.0100
	(-1.65)	(0.62)	(-1.07)	(-1.35)
Adj. R-squared	0.5616	0.5716	0.5671	0.5600
Average number of stocks	3,152	2,619	2,203	1,766
Number of time periods	136	136	136	136

Panel B. Low EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	-0.0099	-0.0063	-0.0105	-0.0260***
	(-1.38)	(-0.75)	(-1.10)	(-2.73)
Unexplained $\Delta_{i,t}$	-0.0500***	-0.0568***	-0.0550***	-0.0256
	(-2.92)	(-3.70)	(-3.22)	(-0.69)
Adj. R-squared	0.6612	0.6684	0.6667	0.6573
Average number of stocks	3,608	2,972	2,472	1,957
Number of time periods	65	65	65	65

Panel C. High EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	-0.0345***	-0.0395***	-0.0466***	-0.0490***
	(-3.76)	(-3.61)	(-4.17)	(-4.58)
Unexplained $\Delta_{i,t}$	-0.0091	0.0272**	-0.0070	0.0121
	(-0.32)	(2.43)	(-0.24)	(1.15)
Adj. R-squared	0.6701	0.6757	0.6685	0.6545
Average number of stocks	2,726	2,296	1,953	1,591
Number of time periods	71	71	71	71

Table 9. Five-year future stock returns

Fama-MacBeth regressions of future quarterly excess returns on stock i, calculated over a five-year period, on the fraction of institutional buyers for stock i ($\Delta_{i,t}$), calculated over stocks held respectively by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data, and applying the methodology from Sias (2004), further divided into a component that is explained by stock-level economic policy uncertainty (EPU) betas, calculated using the U.S. EPU index from Baker, Bloom, and Davis (2016), and an unexplained (residual) component. All regressions include the vector of controls from Eq. (6). In Panel A, we consider the full sample. In Panels B and C, we respectively consider periods of low and high EPU. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Full sample

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0104*	0.0110*	0.0166**	0.0160**
	(1.87)	(1.75)	(2.35)	(2.17)
Unexplained $\Delta_{i,t}$	0.0373	-0.0062	-0.0031	0.0040
	(0.77)	(-0.85)	(-0.56)	(0.79)
Adj. R-squared	0.7278	0.7248	0.7154	0.7054
Average number of stocks	3,152	2,619	2,203	1,766
Number of time periods	136	136	136	136

Panel B. Low EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0002	-0.0014	0.0007	0.0054
	(0.04)	(-0.20)	(0.09)	(0.68)
Unexplained $\Delta_{i,t}$	-0.0188**	-0.0154**	-0.0105	-0.0110
	(-2.05)	(-2.39)	(-1.43)	(-1.26)
Adj. R-squared	0.7666	0.7613	0.7576	0.7479
Average number of stocks	3,608	2,972	2,472	1,957
Number of time periods	65	65	65	65

Panel C. High EPU

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0323***	0.0286***	0.0296***	0.0336***
	(4.06)	(3.06)	(2.99)	(3.28)
Unexplained $\Delta_{i,t}$	-0.0389**	-0.0127	-0.0250***	0.0046
	(-2.57)	(-1.35)	(-2.65)	(0.43)
Adj. R-squared	0.7868	0.7790	0.7690	0.7520
Average number of stocks	2,726	2,296	1,953	1,591
Number of time periods	71	71	71	71

Appendix A. Additional tables

Table A1. Herding and economic policy uncertainty in logs

Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), the natural logarithm of the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and the vector of financial, economic, and political controls from Eq. (5). In Panel A, we report estimates without controls. In Panel B, we include all controls. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. No controls

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0498**	0.1281***	0.1662***	0.1550**
	(2.22)	(3.21)	(3.03)	(2.12)
Constant	-0.1211	-0.3196*	-0.4269*	-0.3187
	(-1.21)	(-1.84)	(-1.69)	(-0.93)
Adj. R-squared	0.0399	0.0658	0.0805	0.0559
Observations	136	136	136	136

Panel B. Full model

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0545**	0.1478***	0.1843**	0.1755**
	(2.41)	(2.73)	(2.49)	(2.05)
IPI growth	-0.1597	-1.0991	-0.9578	-0.6050
	(-0.33)	(-1.02)	(-0.87)	(-0.57)
PCED growth	0.0340	-0.0132	-0.1233	0.0155
	(0.33)	(-0.07)	(-0.61)	(0.08)
PCEND growth	0.0650	-0.0897	-0.3111	-0.8917
	(0.15)	(-0.11)	(-0.35)	(-1.01)
PCES growth	-1.7113	-4.9125	-4.6641	-3.2187
	(-1.00)	(-1.30)	(-1.12)	(-0.73)
Employment growth	1.9552	6.8090*	8.2957**	8.4121**
	(1.06)	(1.95)	(2.09)	(2.08)
NBER	-0.0118	-0.1044*	-0.0831	-0.0439
	(-0.46)	(-1.85)	(-1.31)	(-0.67)
Term-year 2	0.0044	-0.0148	-0.0350	-0.0377
	(0.28)	(-0.49)	(-0.89)	(-0.86)
Term-year 3	0.0019	-0.0053	-0.0130	-0.0176
	(0.10)	(-0.13)	(-0.30)	(-0.36)
Term-year 4	0.0303**	0.0527*	0.0532*	0.0602**
	(2.22)	(1.92)	(1.88)	(2.04)
Democrat	-0.0007	-0.0010	0.0165	0.0517
	(-0.04)	(-0.02)	(0.33)	(0.98)
RmRf	-0.0077	-0.0952	-0.1876**	-0.2236***
	(-0.15)	(-1.60)	(-2.41)	(-2.61)
RmRf (1y-mean)	-0.1483	-0.2497	-0.0962	-0.1778
	(-0.88)	(-0.62)	(-0.21)	(-0.35)
RmRf (1y-SD)	-0.5393	-1.1284	-0.7815	-0.9472
	(-1.62)	(-1.30)	(-0.75)	(-0.83)
Constant	-0.1083	-0.3060	-0.4301	-0.3612
	(-1.01)	(-1.13)	(-1.10)	(-0.78)
Adj. R-squared	0.0150	0.1207	0.1246	0.1134
Observations	135	135	135	135

Table A2. Herding and news-based economic policy uncertainty

Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), on the news-based U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and the vector of financial, economic, and political controls from Eq. (5). In Panel A, we report estimates without controls. In Panel B, we include all controls. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. No controls

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0133	0.0466***	0.0599***	0.0599***
	(1.40)	(2.82)	(3.50)	(3.03)
Constant	0.0754***	0.1527***	0.1871***	0.2433***
	(3.85)	(4.73)	(4.26)	(4.11)
Adj. R-squared	0.0338	0.1108	0.1319	0.1080
Observations	136	136	136	136

Panel B. Full model

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0111	0.0492***	0.0640***	0.0648***
	(1.34)	(2.80)	(3.09)	(2.87)
IPI growth	-0.2075	-0.9972	-0.7986	-0.4058
	(-0.38)	(-0.83)	(-0.61)	(-0.33)
PCED growth	0.0185	-0.0294	-0.1400	0.0050
	(0.21)	(-0.18)	(-0.73)	(0.03)
PCEND growth	0.0556	-0.0724	-0.2837	-0.8568
	(0.15)	(-0.1)	(-0.35)	(-0.97)
PCES growth	-1.8860	-3.9095	-3.2090	-1.5291
	(-0.96)	(-1.15)	(-0.82)	(-0.40)
Employment growth	1.7154	6.4082	7.8306*	8.0208**
	(0.87)	(1.64)	(1.84)	(2.08)
NBER	-0.0116	-0.087	-0.059	-0.0175
	(-0.38)	(-1.53)	(-0.90)	(-0.27)
Term-year 2	0.0038	-0.0169	-0.0377	-0.0403
	(0.28)	(-0.6)	(-0.99)	(-0.92)
Term-year 3	0.0006	-0.0084	-0.0168	-0.0212
	(0.03)	(-0.21)	(-0.38)	(-0.45)
Term-year 4	0.0299**	0.0485*	0.0476	0.0542*
	(2.31)	(1.69)	(1.61)	(1.80)
Democrat	-0.0019	-0.0024	0.0149	0.0506
	(-0.09)	(-0.06)	(0.34)	(1.07)
RmRf	-0.0138	-0.0912*	-0.1798**	-0.2120**
	(-0.31)	(-1.77)	(-2.28)	(-2.32)
RmRf (1y-mean)	-0.0639	0.0171	0.2416	0.1516
	(-0.40)	(0.04)	(0.49)	(0.26)
RmRf (1y-SD)	-0.3290	-0.7709	-0.3653	-0.595
	(-1.12)	(-0.85)	(-0.35)	(-0.50)
Constant	0.1105***	0.2202**	0.2165	0.2404
	(2.75)	(2.14)	(1.59)	(1.59)
Adj. R-squared	-0.0076	0.1443	0.1605	0.1524
Observations	135	135	135	135

Table A3. Herding and news-based EPU: Presidential popularity

Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), on the news-based U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and the vector of financial, economic, and political controls from Eq. (5). In Panels A and B, we only include subperiods in which Gallup's presidential net disapproval ratings (ND) are positive and negative, respectively. In Panel C, we include the full sample and add an interaction term between the EPU index and net disapproval ratings, as well as standalone net disapproval ratings as a control. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. ND > 0

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0307**	0.0927***	0.1169***	0.1209***
	(2.26)	(3.97)	(4.12)	(4.27)
Adj. R-squared	-0.0048	0.1370	0.1403	0.0959
Observations	45	45	45	45

Panel B. ND < 0

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	-0.0025	0.0183*	0.0248***	0.0216**
	(-0.37)	(1.92)	(2.70)	(2.22)
Adj. R-squared	0.0655	0.2604	0.2383	0.2232
Observations	90	90	90	90

Panel C. Full sample

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0181***	0.0586***	0.0738***	0.0762***
	(3.22)	(3.66)	(3.75)	(3.41)
EPU $\times$ ND	0.0594***	0.0851***	0.0993***	0.1153***
	(4.11)	(2.99)	(2.83)	(2.84)
ND	-0.1350**	-0.2304***	-0.3416***	-0.3950***
	(-2.30)	(-2.80)	(-3.11)	(-2.85)
Adj. R-squared	0.0763	0.1680	0.1827	0.1784
Observations	135	135	135	135

Table A4. Herding and EPU: Presidential popularity breakdown, excluding elections

Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), an interaction term between the EPU index and net disapproval ratings (ND), as well as standalone net disapproval ratings as a control, and the vector of financial, economic, and political controls from Eq. (5). In Panel A, we exclude presidential election years. In Panel B, we exclude Congress election years. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Excluding presidential election years

	(1)	(2)	(3)	(4)
	H1	H5	H10	H20
EPU	0.0231***	0.0597***	0.0731***	0.0694**
	(2.93)	(3.03)	(2.64)	(2.14)
EPU × ND	0.1006***	0.2072***	0.2434***	0.2654***
	(5.37)	(3.54)	(3.10)	(2.87)
ND	-0.2768***	-0.6251***	-0.8259***	-0.9265***
	(-4.44)	(-2.97)	(-2.92)	(-2.72)
Adj. R-squared	0.0682	0.1778	0.1467	0.1075
Observations	103	103	103	103

Panel B. Excluding Congress election years

	(1)	(2)	(3)	(4)
	H1	H5	H10	H20
EPU	0.0124	0.0481***	0.0590**	0.0507*
	(1.38)	(2.58)	(2.51)	(1.80)
EPU × ND	0.1262***	0.2334***	0.2549***	0.2549**
	(3.74)	(3.28)	(2.82)	(2.49)
ND	-0.3903***	-0.8075***	-0.9554***	-0.9701**
	(-3.46)	(-2.89)	(-2.58)	(-2.25)
Adj. R-squared	0.0333	0.1499	0.1061	0.0630
Observations	67	67	67	67

Table A5. Herding and EPU: Alternative moderating variables

Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), interaction terms between the EPU index and the Baker and Wurgler (2006) index of investor sentiment (IS), excess returns on the stock market portfolio (RmRf), and a dummy variable that takes on value one if the president is a Democrat and zero otherwise, and the vector of financial, economic, and political controls from Eq. (5). The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Investor sentiment

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0154***	0.0339***	0.0400**	0.0372*
	(3.48)	(2.96)	(2.53)	(1.95)
EPU × IS	-0.0156*	0.0038	0.0184	0.0165
	(-1.79)	(0.17)	(0.84)	(0.58)
IS	0.0251	-0.0683	-0.1147	-0.1040
	(0.65)	(-0.69)	(-1.27)	(-0.89)
Adj. R-squared	0.0766	0.1449	0.1276	0.1074
Observations	135	135	135	135

Panel B. Excess stock market returns

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0140**	0.0388***	0.0478**	0.0443**
	(2.28)	(2.68)	(2.50)	(2.04)
EPU × RmRf	0.0126	-0.0394	-0.0499	-0.0537
	(0.30)	(-0.62)	(-0.69)	(-0.76)
RmRf	-0.0572	0.0551	0.0024	-0.0205
	(-0.39)	(0.21)	(0.01)	(-0.06)
Adj. R-squared	-0.0020	0.1012	0.1022	0.0925
Observations	135	135	135	135

Panel C. Presidential affiliation

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0039	0.0368	0.0642	0.0758*
	(0.28)	(1.19)	(1.63)	(1.71)
EPU × Democrat	0.0158	0.0031	-0.0255	-0.0492
	(1.06)	(0.10)	(-0.65)	(-1.05)
Democrat	-0.0521	-0.0135	0.0949	0.2059
	(-1.20)	(-0.13)	(0.70)	(1.26)
Adj. R-squared	0.0095	0.0996	0.1055	0.1069
Observations	135	135	135	135

Table A6. Herding and economic policy uncertainty: Addressing endogeneity concerns
Time-series regressions of herding measures (H) over stocks held by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data and following the methodology from Sias (2004), on the U.S. economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and the vector of financial, economic, and political controls from Eq. (5). In Panel A, we exclude periods of NBER recessions, the subprime crisis, and the tech bubble. In Panel B, we orthogonalize the EPU index to the economic controls introduced above, using an auxiliary time-series regression with heteroskedasticity- and autocorrelation-consistent standard errors. In Panel C, we instrument net disapproval using U.S. mass shootings from the Stanford Mass Shootings of America (MSA) data project. The sample period is from the first quarter of 1985 through the fourth quarter of 2019 in Panel A, and through the fourth quarter of 2015 in Panels B and C. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Excluding crises

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0162***	0.0488***	0.0616***	0.0593**
	(3.56)	(3.45)	(3.13)	(2.53)
EPU × ND	0.0645***	0.2196***	0.2676***	0.3066***
	(3.25)	(4.53)	(4.13)	(4.00)
Adj. R-squared	0.1291	0.2486	0.2107	0.1910
Observations	116	116	116	116

Panel B. Orthogonalized EPU index

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0187***	0.0483***	0.0592***	0.0586***
	(3.45)	(3.21)	(3.46)	(3.34)
EPU × ND	0.0626***	0.1409***	0.1735***	0.1986***
	(3.53)	(2.59)	(2.97)	(3.31)
Adj. R-squared	0.0580	0.1458	0.1537	0.1486
Observations	135	135	135	135

Panel C. Instrumented net disapproval

	(1) H1	(2) H5	(3) H10	(4) H20
EPU	0.0436***	0.0659***	0.0887***	0.0840***
	(3.96)	(3.96)	(3.67)	(3.12)
EPU × ND (IV)	0.2246***	0.2358**	0.3334**	0.3230
	(2.61)	(2.02)	(2.14)	(1.43)
Adj. R-squared	0.0614	0.1664	0.1568	0.1537
Observations	123	123	123	123

Table A7. Two-year future stock returns: Subsamples

Fama-MacBeth regressions of quarterly future excess returns on stock i, calculated over a two-year period, on the fraction of institutional buyers for stock i ($\Delta_{i,t}$), calculated over stocks held respectively by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data, and applying the methodology from Sias (2004), further divided into a component that is explained by stock-level economic policy uncertainty (EPU) betas, calculated using the U.S. EPU index from Baker, Bloom, and Davis (2016), and an unexplained (residual) component. All regressions include the vector of controls from Eq. (6). The sample period is from the first quarter of 1985 through the fourth quarter of 2019. In Panels A and B, we respectively consider the subperiods 1985-1999 and 2000-2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. 1985-1999

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	-0.0005	-0.0036	0.0073	-0.0014
	(-0.08)	(-0.46)	(0.90)	(-0.17)
Unexplained $\Delta_{i,t}$	0.0075	-0.0074	-0.0208*	-0.0302*
	(0.36)	(-1.15)	(-1.67)	(-1.96)
Adj. R-squared	0.6871	0.6995	0.7029	0.7131
Average number of stocks	3,560	2,699	2,074	1,455
Number of time periods	56	56	56	56

Panel B. 2000-2019

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0570***	0.0627***	0.0770***	0.0862***
	(6.39)	(6.66)	(7.84)	(8.92)
Unexplained $\Delta_{i,t}$	0.0307	-0.0009	0.0331	0.0407*
	(1.04)	(-0.02)	(1.10)	(1.77)
Adj. R-squared	0.6721	0.6645	0.6583	0.6465
Average number of stocks	2,861	2,561	2,289	1,984
Number of time periods	80	80	80	80

Table A8. Future stock returns: Fixed-effects regressions

Panel regressions of future quarterly excess returns on stock i on the fraction of institutional buyers for stock i ($\Delta_{i,t}$), calculated over stocks held respectively by at least 1, 5, 10, or 20 institutional traders, constructed using U.S. 13F institutional ownership quarterly data, and applying the methodology from Sias (2004), further divided into a component that is explained by stock-level economic policy uncertainty (EPU) betas, calculated using the U.S. EPU index from Baker, Bloom, and Davis (2016), and an unexplained (residual) component. All regressions include the vector of controls from Eq. (6), along with firm and time fixed-effects. In Panel A, we consider the full sample. Returns are calculated cumulatively over a two-year period in Panel A, three to five years ahead in Panel B, and over a five-year period in Panel C. The sample period is from the first quarter of 1985 through the fourth quarter of 2019. Heteroskedasticity- and autocorrelation-consistent t-stats are in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Two-year returns

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0173***	0.0225***	0.0271***	0.0291***
	(7.52)	(8.15)	(8.29)	(7.24)
Unexplained $\Delta_{i,t}$	-0.0136***	-0.0189***	-0.0179***	-0.0081***
	(-12.60)	(-13.67)	(-10.97)	(-4.20)
Overall R-squared	0.4841	0.4857	0.4883	0.4930
Observations	428,322	356,112	299,332	240,257

Panel B. Returns over years three to five

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	-0.0058**	-0.0071**	-0.0039	-0.0020
	(-2.15)	(-2.28)	(-1.04)	(-0.48)
Unexplained $\Delta_{i,t}$	0.0032**	0.0024	0.0036*	0.0081***
	(2.31)	(1.44)	(1.87)	(3.58)
Overall R-squared	0.4955	0.4942	0.4958	0.5001
Observations	428,322	356,112	299,332	240,257

Panel C. Five-year returns

	(1) H1	(2) H5	(3) H10	(4) H20
Explained $\Delta_{i,t}$	0.0124***	0.0160***	0.0231***	0.0285***
	(4.74)	(5.54)	(6.91)	(7.18)
Unexplained $\Delta_{i,t}$	-0.0140***	-0.0186***	-0.0152***	-0.0009
	(-11.17)	(-11.48)	(-7.97)	(-0.38)
Overall R-squared	0.6575	0.6574	0.6554	0.6524
Observations	428,322	356,112	299,332	240,257