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Another Presidential Puzzle? Presidential Economic Approval Rating and the Cross-Section of Stock Returns*

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Abstract

We construct a monthly Presidential Economic Approval Rating (PEAR) index from 1981 to 2019, by averaging ratings on president's handling of the economy across various national polls. In the cross-section, stocks with high betas to changes in the PEAR index significantly under-perform those with low betas by 0.96% per month in the future, on a risk adjusted basis. The low-PEAR-beta premium persists up to one year, and is present in various sub-samples (based on industries, presidential cycles, transitions, and tenures) and even in other G7 countries. It is also robust to different risk adjustment models and controls for other related return predictors. Since the PEAR index is negatively correlated with measures of aggregate risk aversion, a simple risk model would predict the low PEAR-beta stocks to earn lower (not higher) expected returns. Instead, the PEAR beta captures a firm's perceived alignment to the current president's economic policy and market misprices such alignments.

Keywords: Presidential puzzle, political cycle, presidential economic approval rating, presidential job approval rating, sentiment

JEL Classification: G41, G14

1 Introduction

The well-known presidential puzzle refers to the striking empirical fact that stock market returns are much higher under Democratic presidencies than Republican ones. Since first noted by Huang (1985) and Hensel and Ziemba (1995) and carefully documented by Santa-Clara and Valkanov (2003), the pattern remains robust. It is only recently that Pastor and Veronesi (2020) provide an ingenious solution to this puzzle. Their model of political cycles predicts that when risk aversion and therefore equity risk premium are high, agents elect Democrats, explaining the subsequent higher stock market returns during Democratic presidencies.

In this paper, we document a different presidential puzzle in the cross-section of individual stocks. We start by constructing a monthly Presidential Economic Approval Rating (PEAR) index from 1981 to 2019, by averaging approval ratings on president's handling of the economy across various national polls. The monthly index is plotted in Figure 1, together with the Gallup presidential overall job approval rating. The two ratings are clearly positively correlated (with a correlation of 65%), yet they also diverge from time to time. Notable examples include the Gulf war, the September 11 terrorist attack, and President Trump's initial tenure. Empirically, we find the PEAR index to generate stronger asset pricing results among individual stocks. Consistent with the phrase "the economy, stupid," popularized during Bill Clinton's successful 1992 presidential campaign, PEAR seems to better correlate with the political cycles in that a low (high) PEAR predicts a Democratic (Republican) president in the future, suggesting that PEAR is inversely related to the aggregate risk aversion modeled in Pastor and Veronesi (2020). We confirm such an inverse relation using four different measures of aggregate risk aversion.

Surprisingly, in the cross-section, stocks with high betas to changes in PEAR significantly under-perform those with low betas by 0.96% per month in the future, on a risk adjusted basis. A simple extension of a risk-based model of the aggregate stock market, say Pastor and Veronesi (2020), to the cross-section, would predict the opposite. Since high PEAR-beta stocks do worse precisely when aggregate risk aversion increases (or when PEAR decreases), they are therefore

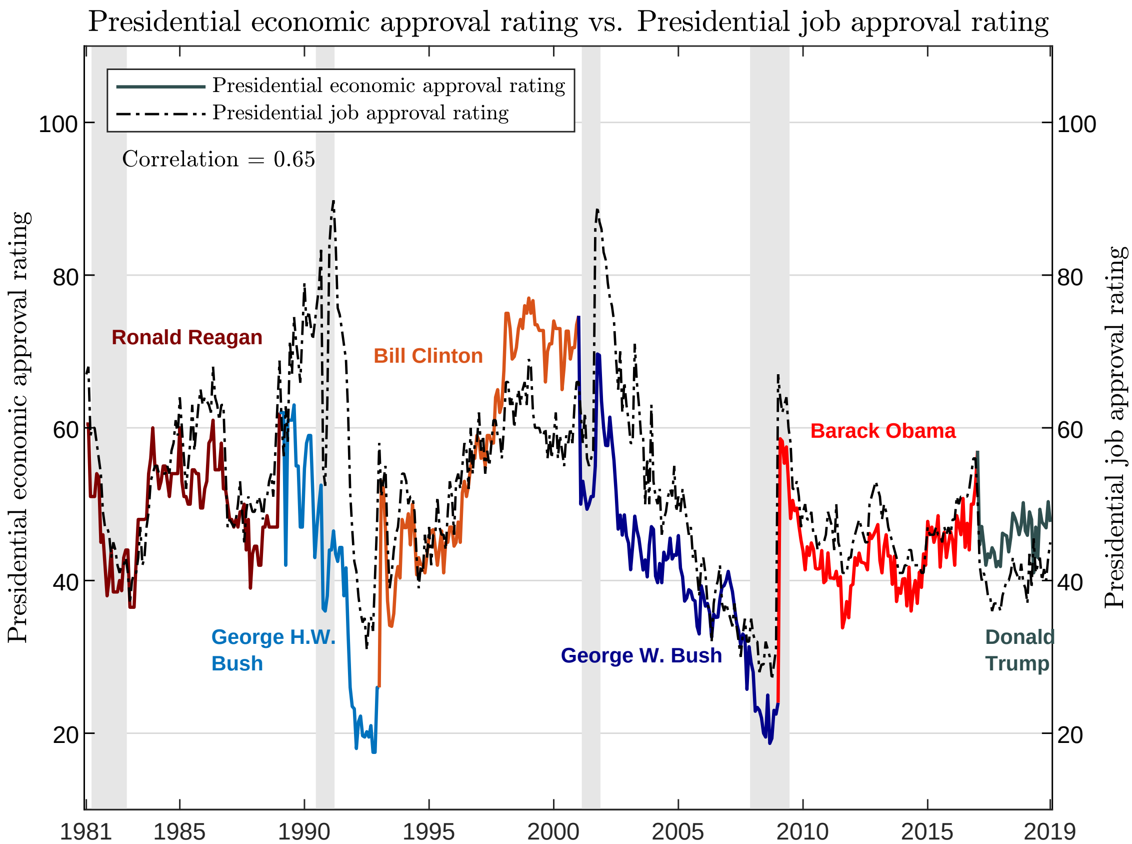

Figure 1: Presidential economic approval rating (PEAR)

This figure depicts the presidential economic approval rating (PEAR) from April 1981 to December 2019, which is based on 1,713 polls conducted by 21 polling organizations and collected by the Roper iPoll at the Roper Center for Public Opinion. It takes the average value if there are multiple polls conducted by different polling organizations in one month. The Gallup presidential job approval rating is also plotted for comparison.

more risky and should earn higher returns on average.

The low-PEAR-beta premium is extremely robust. It survives various factor-based and characteristic-based risk adjustment models. It is not driven by any particular sub-sample periods. For example, it is present during the tenure of each of the six presidents in our sample. It is present in each of the four years of the president's term. It is positive and significant during both Democratic and Republican presidents, or after removing the presidential transition periods (six months surrounding the change of a president). The premium is even larger among large and liquid stocks and it persists up to one year after portfolio formation. It is robust to different backward rolling windows used to estimate the beta and different methods for computing innovations in PEAR. Finally, it even shows up in other G7 countries and is significant in Canada, Germany, Japan and the UK, four countries with particularly strong trade links to the US.

Existing literature provides evidence that different industries may have differential exposures to presidential policies and government spending [see, e.g., Belo, Gala, and Li (2013) and Addoum and Kumar (2016), among others], which may result in predictable variations in industry portfolio returns across political cycles. The low-PEAR-beta premium is not driven by such an industry-level return predictability, as it is equally strong when we examine industry-demeaned betas. In contrast, sorting industry portfolios based on their PEAR betas does not generate a low-PEAR-beta premium.

In Fama-MacBeth cross-sectional regressions, we control for a comprehensive set of potential return predictors which we group into three categories. The first category includes alternative measures of beta, such as the market beta, the beta on the macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015), and the beta on the Baker and Wurgler (2006) sentiment index (Chen, Han, and Pan, 2020). The second category includes variables related to government and politics. They are the political alignment index (Kim, Pantzalis, and Park, 2012), political sensitivity (Addoum and Kumar, 2016), political connectedness (Cooper, Gulen, and Ovtchinnikov, 2010), and government spending exposure (Belo, Gala, and Li, 2013). The third category includes other firm characteristics such as size, book-to-market, momentum, short-term reversal, idiosyncratic volatility, illiquidity, and distress. Neither of these return predictors is highly correlated with the PEAR beta. Not surprisingly, we find that the coefficient on the PEAR beta remains negative and significant, even after simultaneously including all the control variables and industry fixed effects. Its magnitude is still more than half of its counterpart in an univariate regression, suggesting that all the other variables, even when combined, explain less than half of the low-PEAR-beta premium.

While the low-PEAR-beta premium cannot be explained by exposure to time-varying risk aversion, can it reflect exposure to other macroeconomic risk factors? We examine a large set of macro variables, including industrial production growth, unexpected inflation, change in expected inflation, term premium, default premium, total factor productivity growth, labor income growth, capital share growth (Lettau, Ludvigson, and Ma, 2019), consumption growth, ultimate consumption growth (Parker and Julliard, 2005), change in consumption-wealth ratio, change in aggregate market volatility, change in VIX, variance risk premium, GDP growth, and change in unemployment rate. The correlations between the change in PEAR and the macro variables are low in general. Even the highest correlation (in absolute term) is only 0.18 (with the ultimate consumption growth). As a result, the PEAR beta is not highly correlated with the betas on these macro variables either. In other words, the low-PEAR-beta premium does not seem to capture exposures to these additional risk factors. Including these macro betas in the Fama-MacBeth cross-sectional regressions hardly changes the coefficient on the PEAR beta, consistent with the findings in Shen, Yu, and Zhao (2017) that the exposure to macroeconomic risks generally does not explain the cross-sectional variation in average stock returns very well.

Stocks with positive PEAR betas experience higher returns when the presidential economic approval rating improves. To the extent that PEAR may indicate consumer confidence (De Boef and Kellstedt, 2004), high PEAR-beta stocks could suffer from sentiment-induced overpricing, explaining their subsequent low returns when their overpricing gets corrected. Indeed, Stambaugh, Yu, and Yuan (2015) find the long-short anomaly return spread to be much stronger following high levels of sentiment. They also find this pattern to be especially true for the short legs of various anomaly strategies, consistent with short-sale impediments. Unfortunately, such sentiment-induced overpricing does not seem to fully explain the low-PEAR-beta premium. We examine four measures of investor sentiment: (1) Baker and Wurgler's (2006) sentiment index, (2) Michigan consumer sentiment index, (3) AAII bull-bear index, and (4) the PEAR index itself. We find significantly higher low-minus-high beta return spreads following high levels of sentiment, only when the PEAR index is used. However, we do not find any evidence that the short-leg (high PEAR-beta stocks) alpha is higher following high levels of sentiment. In fact, in all cases, the long-leg has a higher alpha (in absolute term) than the short-leg does, inconsistent with the notion that short sale constraints may explain the low-PEAR-beta premium.

Intuitively, the PEAR beta could measure a firm's perceived alignment to the economic policies of the current president. The business of a positive PEAR-beta firm must align well with the current presidential economic policies, so its stock price moves in tandem with the policies' economic approval rating. Could such a "presidential alignment" lead to a government bailout during bad times? If so, a high PEAR-beta stock could be a hedge for downside risk and thus will earn a lower expected return. Empirically, corporate bailouts are relatively rare and tend to happen to mega firms or firms in the finance sector (Faccio, Masulis, and McConnell, 2006). Yet, our sample excludes finance companies and the high-PEAR-beta stocks are not mega-cap stocks either. Additional evidence does not support such a "hedging" story either. During bad times, as indicated by NBER recession dates, high-PEAR-beta firms earn even lower returns than low-PEAR-beta firms, inconsistent with the notion of receiving a bailout. In addition, the PEAR beta has a low correlation with the measure of financial distress (Campbell, Hilscher, and Szilagyi, 2008). Controlling for the distress risk does not alter the low-PEAR-beta premium.

Instead, some investors have biased cash flow expectations for firms with extreme PEAR betas. In the appendix, we sketch a stylized model that features sentiment investors in the economy who overestimate future earnings of positive PEAR-beta firms, or firms that align well with current president's economic policies, especially when the PEAR index is high. At the same time, they underestimate future earnings of negative PEAR-beta firms. Risk-averse rational investors in the economy cannot fully correct such biases, and as a result, the market-clearing price is too high (low) for positive (negative) PEAR beta firms. Mispricing disappears when future earnings are realized, and the price correction results in the low PEAR-beta premium. The model further predicts that such a premium should be higher following high PEAR period which we confirm in the data.

We document several pieces of additional supporting (though not conclusive) evidence for the mispricing-based explanation. First, if we compute the PEAR beta using only months in the five-year rolling window when a previous president was in power, the low-PEAR-beta premium ceases to be significant, highlighting the importance of alignment to the current presidential economic policies. Second, consistent with the bias in cash flow expectation, we find the PEAR beta to negatively predict analyst forecast errors, future revisions in their long term growth (LTG) forecasts and stock recommendations. In addition, the PEAR beta negatively predicts future earnings announcement returns. The evidence suggests that both analysts and investors are initially too optimistic (pessimistic) in forecasting high- (low-) PEAR-beta stocks' cash flow. Finally, we find the low PEAR-beta premium to be stronger among stocks receiving lower investor attention, suggesting that attention constraints contribute to expectation errors.

This paper contributes to several strands of literature that connects asset pricing to politics. First, there is a literature focusing on stock returns over political cycles. In time series, Santa-Clara and Valkanov (2003) and Blinder and Watson (2016) find that the US stock market and economy perform better when the president is a Democrat rather than a Republican—the presidential puzzle—which has been recently explained by Pastor and Veronesi (2020) with a time-varying risk aversion model. In the cross-section, Belo, Gala, and Li (2013) find that industries with greater exposure to government spending earn higher returns during Democratic presidencies, while the opposite pattern holds true during Republican presidencies. Addoum and Kumar (2016) show that industries with greater political-sensitivity earn higher returns. More recently, Ke (2021) presents a partisan gap that Democrats are less likely than Republicans to participant in the stock market. We focus on presidential rather than party economic approval ratings and their implications on the cross-section of individual stock returns. Our results are obtained at firm level and are not driven by any particular president or presidential party, and are distinct from existing findings.

Second, there is another strand of literature that documents a relationship between political connection and stock returns in the cross-section. For example, Cooper, Gulen, and Ovtchinnikov (2010) show that donating firms earn significant higher average and risk-adjusted stock returns. Kim, Pantzalis, and Park (2012) find that firms located in the US states that are more politically aligned with the presidential party earn higher average returns. Brown and Huang (2020) find that corporate executives' meetings with key policymakers are associated with positive abnormal stock returns. Our paper departs from this literature in that our PEAR beta captures a firm's perceived alignment to the current president who could come from either party. Such an alignment is dynamically and self-revealed by a stock's return correlation with changes in the PEAR index.

Third, our paper is related to the growing literature that analyzes theoretical and empirical connections between financial markets and fluctuations in political/policy uncertainty, where fluctuations are defined and measured at the aggregate level (Pastor and Veronesi, 2012, 2013; Brogaard and Detzel, 2015; Baker, Bloom, and Davis, 2016; Kelly, Pastor, and Veronesi, 2016; Brogaard et al., 2020) and firm level (Hassan et al., 2019; Gorbatikov et al., 2019). The main variable of interest in this paper, the PEAR index, has low correlations with the proxies for political risk and political uncertainty. Different from Kelly, Pastor, and Veronesi (2016) and Brogaard et al. (2020) that focus on the president election periods, we find that our results continue to hold after excluding these presidential transition and election periods.

Finally, our paper is related to the literature that tests finance theories with survey data, which has become a new norm in asset pricing (Brunnermeier et al., 2021; Liu et al., 2021). Our evidence confirms that survey data contains useful insight relevant for cross-sectional asset pricing.

2 Data and Key Variables

This section describes the data on PEAR and other key variables used in this paper.

2.1 The PEAR index

To measure public opinion on the president's handling of the economy, we construct a presidential economic approval rating (PEAR) index by using various national polls. Unlike the Gallup presidential job approval rating (PJAR) index that captures the extent to which people approve or disapprove of the way the current president is handling the economy, foreign affair, health policy, etc, we focus on the responses to an economy-specific question: "Do you approve or disapprove of the way (name of president) is handling the economy?", which is closely related to the conceptualization of "confidence in the president's economic stewardship". The data are from Roper iPoll at the Roper Center for Public Opinion.[1] We conjecture that the presidential economic approval rating is more relevant for stock market outcomes. Our subsequent results confirm this conjecture.

Specifically, we collect 2,100 polls in total from 46 organizations over the period from April 1981 to December 2019.[2] We do not consider a few polls irregularly conducted between 1971 and 1981. We exclude organizations conducting less than 5 polls in our sample. We also exclude polls that are conducted in one month but released in subsequent months, so that the public opinion is captured in a timely fashion. In doing so, we are left with 1,713 polls from 21 polling organizations. Hence, each month we have about 3.7 polls on average. Table A1 presents the summary statistics of each polling organization used in the construction of the PEAR index.

From each poll, we obtain an approval rating, a percentage number indicating the proportion of respondents who approve of the way of the president handling the economy. We construct the PEAR index by simply averaging approval ratings available in each month. In our sample period, there are 50 months with missing data and the maximum number of consecutive months with missing data is just four. We fill these missing entries with the previous month values to ensure that the PEAR index is a real-time series.

Six polling agents appear most frequently in our data: ABC News / Washington Post (ABCWP), American Research Group (ARG), CBS News (CBS), CBS News / New York Times (CBSNYT), Gallup and NBC Bews / Wall Street Journal (NBCWSJ). In Table A3 of the Appendix, we conduct pairwise comparisons to see whether one poll reports significantly higher results than the other during overlapping months. We find only three significant differences. ABCWP's results

[1]The wording of this question is basically the same across polling organizations, while the predefined responses to the question can be sightly different. Specifically, most polling questions simply ask if a respondent approves or disapproves of the president, while very few questions break out approval or disapproval into subcategories to indicate whether the respondent "strongly" or "somewhat" approves or disapproves of the president. We follow the standard treatment in polling and sum up the percentages of both "strongly" and "somewhat" approve choices as the ratio of approval rating overall.

[2]Some polls may be conducted by one organization but sponsored by another organization. For example, since 1981, ABC News and The Washington Post, both separately and together, have commissioned polls on this issue. These surveys are conducted by themselves and other organizations, including Chilton Research Services, Taylor Nelson Sofres Intersearch, Langer Research Associates, etc. To ensure data consistency, we classify theses polls as conducted by ABC News, The Washington Post, or both.

are higher than those from ARG and CBS. ARG's results are also lower than those from NBCWSJ. The differences are smaller than 4% in all three cases. Persistent bias in a poll will have little impact on our results as we focus on changes in the rating in our analysis.

According to Table A3, polling results are highly correlated among the top six agents during overlapping months. Not surprising, each of the six polling result is also highly correlated with our PEAR index. With the exception of ARG, the correlation is all higher than 0.94. In a robustness check, we also construct an alternative PEAR index (PEAR_6) using polling results from these six agents only and find similar results.[3] Each of the six polling result is highly correlated with PEAR_6. The minimum correlation is 0.94. Overall, these diagnostics suggest that different polls produce highly correlated results and our result is not driven by any single poll. Figure A1 plots the PEAR index, together with upper and lower bounds that are based on the highest and lowest polling results in that month. The figure shows that the dispersion across different polls in the same month is relatively small.

Figure 1 plots the time series dynamics of the PEAR index, together with the Gallup presidential job approval rating (PJAR) index for comparison. The two ratings are clearly positively correlated (with a correlation of 65%), yet they also diverge from time to time. Notable examples include the Gulf war, the September 11 terrorist attack, and President Trump's initial tenure.

According to Figure 1, the PEAR index correlates well with the political cycles in that a low (high) PEAR predicts a Democratic (Republican) president in the future. More formally, we find that the PEAR index positively predicts the fraction of a Republican being the president in the following eight years, and negatively predicts the following eight-year market returns (t-values are based on the Newey-West standard errors that handle the autocorrelations with a lag of 95):

$$\text{Fraction of Republicans}_{t+1,t+96} = a + 1.43 \times \text{PEAR}_t + u_{t+1,t+96}, \quad t\text{-value} = 9.47, \tag{1}$$

$$R_{t+1,t+96} = \alpha - 3.06 \times \text{PEAR}_t + \varepsilon_{t+1,t+96}, \quad t\text{-value} = -2.31. \tag{2}$$

[3] We fill in the missing values for this alternative index using the dyad ratios algorithm of Stimson (1999), which uses smoothing and interpolation to deal with irregular, non-balanced, and sparse panel data.

In contrast, the PJAR predicts the political cycle with weaker significance and does not predict future stock market returns at all:

$$\text{Fraction of Republicans}_{t+1,t+96} = a + 0.92 \times \text{PJAR}_t + u_{t+1,t+96}, \quad t\text{-value} = 2.06, \tag{3}$$

$$R_{t+1,t+96} = \alpha - 0.34 \times \text{PJAR}_t + \varepsilon_{t+1,t+96}, \quad t\text{-value} = -0.21. \tag{4}$$

The contrast between the PEAR index and the PJAR index supports the phrase "the economy, stupid," popularized during Bill Clinton's successful 1992 presidential campaign. In Section 3, we confirm that the PEAR index generates much stronger results in asset pricing tests than the PJAR index.

Table 1 reports the summary statistics of PEAR and six other sentiment and politics-related indexes, including Baker and Wurgler (2006) (orthogonalized) investor sentiment, Michigan consumer sentiment, presidential job approval rating, (equally-weighted) aggregate political risk and sentiment (Hassan et al., 2019), and political uncertainty [measured by the economic policy uncertainty of Baker, Bloom, and Davis (2016)]. All the time series are at the monthly frequency and over the 1981:04–2019:12 period, except for the quarterly aggregate political risk and sentiment being over 2002Q1–2019Q4, and political uncertainty being over 1985:01–2019:12.

Panel A of Table 1 presents the mean, median, min, max, volatility, AR(1), and AR(12), where AR(1) and AR(12) refer to the first- and 12th-order autocorrelations. The PEAR index ranges from 17.5 to 77, with a mean of 47, suggesting that on average less than half of respondents consent to the way how the president is handling of the economy. Two extreme examples are George H.W. Bush and George W. Bush, whose ratings drop to below 20 at the end of their tenures. In contrast, the presidential job approval rating is generally higher than PEAR, with a mean of 51.65. This pattern is especially pronounced during the presidency of George H.W. Bush and George W. Bush. For example, after the Gulf war, President George H.W. Bush has a job approval rating around 90, but a lugubrious economic approval rating, which is below 50.

To examine the relationships between PEAR and the six other sentiment and politics-related variables, Panel B of Table 1 reports their level and change correlations. PEAR is highly positively correlated with Michigan consumer sentiment and presidential job approval rating, with level correlations of 0.63 and 0.65, and change correlations of 0.14 and 0.23, thereby suggesting that these three indexes capture some common low frequent movements, say the presidential cycles, but they capture different salient events at the monthly frequency. Another interesting observation is that PEAR is not highly correlated with political sentiment and political uncertainty, especially with their changes.

2.2 PEAR beta

We use PEAR beta to measure how the stock price of a firm responds to the change of PEAR. For each stock and each month from June 1981, we run the following time series regression with a 60-month rolling window, requiring at least 24 observations,

$$R_{i,t} = \alpha + \beta_{i,0}\Delta\text{PEAR}_t + \beta_{i,1}\Delta\text{PEAR}_{t-1} + \beta_{i,\text{MKTRF}}\text{MKTRF}_t + \varepsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ is the excess return of stock i in month t, and ΔPEAR_t is the change of PEAR from month $t-1$ to month t, MKTRF_t is the market excess return in month t.[4] We control for MKTRF to isolate the component in PEAR that is orthogonal to the overall market performance. The regression includes the lagged change of PEAR to accommodate the non-synchronicity between the timing of the survey and that of return measurement. Following Dimson (1979), PEAR beta, β_{PEAR}, is defined as

$$\beta_i = \beta_{i,0} + \beta_{i,1}, \tag{6}$$

where we abbreviate the time subscript for brevity.

Since we require at least 24 months of non-missing observations for each stock to run the regression, we use an expanding window over the 1981:06–1983:05 period and a fixed 60-month

[4] Including lagged market return in (5) generates similar results.

rolling window after June 1983. Thus, our empirical analysis spans the 1983:06–2019:12 period, 439 months in total.

2.3 Other variables

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) and quarterly and annual accounting data from Compustat. Our data sample includes all common stocks listed on the NYSE, Amex, and Nasdaq exchanges. Financial and Utility firms are excluded from our analysis. In addition, we exclude stocks with a price per share less than \$1 and stocks with missing returns. We adjust stock returns for delisting to avoid survivorship bias following Shumway (1997).

We estimate market beta (β_{CAPM}), sentiment beta (β_{BW}), and uncertainty-beta (β_{UNC}) as Bali, Brown, and Tang (2017). We calculate firm size (SIZE) as the logarithm of the product of price per share and the number of shares outstanding (in millions of dollars). The logarithm of book to market ratio (BM) is calculated as the book value of shareholder equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stocks at the end of the last fiscal year, $t-1$, scaled by the market value at the end of December of year $t-1$.[5] Firms with negative book values are excluded from the analysis. We follow Fama and French (1992) and match the annual BM information in year $t-1$ to monthly returns from July of year t to June of year $t+1$.

We define momentum (MOM) as the cumulative return of a stock over a 11-month window ending one month before the portfolio formation. Short-term reversal (STR) is defined as the stock return over the prior month. Following Ang, Hodrick, Xing, and Zhang (2006), the monthly idiosyncratic volatility (IVOL) is the standard deviation of the stock's daily idiosyncratic returns relative to the Fama and French (1993) three-factor model over the prior month. We measure the illiquidity (ILLIQ) of a stock as the ratio of the daily absolute stock return to the daily dollar trading

[5] Depending on availability, the stockholders' equity, common equity plus the carrying value of preferred stock, or total assets minus total liabilities in that order is used as shareholders' equity. Similarly, we use redemption, liquidation, or par value in that order depending on availability to estimate the book value of preferred stocks.

volume averaged in the prior month, which is further is scaled by 10^6 (Amihud, 2002). A stock is required to have at least 15 valid daily returns to calculate the IVOL and ILLIQ. Distress risk is constructed following Campbell, Hilscher, and Szilagyi (2008). The mispricing score (MISP) is from Stambaugh, Yu, and Yuan (2015), which is a rank variable constructed by 11 anomalies. The higher the score, the more likely the stock is overvalued. MISP ends in 2016 and we extend it to 2019 by ourselves.

We consider four politics-related variables. Following Kim, Pantzalis, and Park (2012), we use the state-level political alignment index (PAI) of each state's leading politicians with the ruling (presidential) party to proxy for local firms' proximity to political power. We use political sensitivity (PS) to capture the return sensitivity of industry segments over the presidential cycles (Addoum and Kumar, 2016). We define political connectedness (PC) as a dummy variable as to whether a firm made a contribution to the PAC (regardless of party affiliation) in the last 5 years following Cooper, Gulen, and Ovtchinnikov (2010) and Addoum and Kumar (2016). We do not separate the contribution to each party as most of the firms in our sample contribute almost equally to both parties. As in Belo, Gala, and Li (2013), we calculate the industry-level government spending exposure (GSE) as the proportion of the industry's total output (3-digit SIC) being purchased by the government sector for final use to capture the impact of political cycles on asset prices. Table A2 details the construction of these variables.

Table 2 reports the autocorrelations and pairwise correlations of the key variables used in this paper. In Panel A, the monthly and yearly autocorrelations of PEAR beta are 0.81 and 0.32, suggesting that the PEAR beta is persistent. The persistence is not surprising given that the beta is estimated using a five-year backward rolling window. In this way, the PEAR beta is very different from other stock characteristics such as past returns and volatility, which are more time-varying.

Panel B of Table 2 shows that PEAR beta has low correlations with all other variables. The absolute values are all smaller than 0.10. For example, since we control for the market excess return, the correlation between the PEAR beta and the CAPM beta is close to zero (0.02). In addition, PEAR beta has negligible correlations with the four politics-related variables (PAI, PS, PC and GSE), suggesting that the PEAR-beta effect on stock returns is unlikely to be explained by these variables and the economic mechanisms underlying them.

3 Empirical Results

In this section, we conduct portfolio analyses and Fama-MacBeth regressions to assess the predictive power of PEAR beta over future stock returns. We perform a number of tests to show that our results are robust qualitatively and quantitatively.

3.1 Average and risk adjusted returns of PEAR-beta decile portfolios

At the beginning of each month from June 1983 to November 2019, we form decile portfolios by sorting firms into ten groups based on their PEAR betas in the prior month, where decile 1 (10) contains stocks with the most negative (positive) PEAR betas. We value-weight stocks in these portfolios and rebalance them monthly. The PEAR-beta spread portfolio (L-H) refers to the strategy that buys stocks in decile 1 and sells stocks in decile 10.

Panel A of Table 3 reports the portfolio sorting results. The first row presents the average PEAR betas of the decile portfolios, which increase from -1.56 for decile 1 to 1.97 for decile 10. In the second row, the monthly average excess returns of the PEAR-beta portfolios decrease from 1.04% for decile 1 to 0.08% for decile 10, with the difference between the low and high PEAR-beta portfolios equal to 0.96% (t-value $= 4.18$).

We calculate the risk adjusted returns of the PEAR-beta portfolios with five factor models and the Daniel et al. (1997) characteristics model (DGTW). The five factor models include the Fama and French (2015) five-factor model (FF5), the Hou, Xue, and Zhang (2015) q-factor model (HXZ), the Stambaugh and Yuan (2017) mispricing-factor model (SY), and the Daniel, Hirshleifer, and Sun (2020) behavioral-factor model (DHS).[6]

Rows 3 to 7 of Panel A present the factor-adjusted results and make two observations. First, although the six models we use represent the most recent advancements in asset pricing, they cannot explain the returns on PEAR-beta sorted portfolios well. The abnormal return of the PEAR-beta spread portfolio ranges from 0.60% with the DGTW model to 0.96% with the FF5 model, suggesting that at least 60 percent of the average return of the PEAR-beta spread portfolio is not explained by existing asset pricing factors or firm characteristics. Second, unlike the well-known anomalies in Stambaugh, Yu, and Yuan (2015), the performance of the PEAR-beta spread portfolio is mainly from the long-leg. The low PEAR-beta portfolio is generally undervalued, whereas the high PEAR-beta portfolio is fairly priced. The only exception is the DGTW model, where the high PEAR-beta portfolios is mispriced. For this reason, we label the significant alpha in the last column (L-H) the low-PEAR-beta premium.

Panel B of Table 3 reports the results of portfolios sorted by industry demeaned PEAR betas, where 48 industries are classified following Fama and French (1997). If the low-PEAR-beta premium is an industry-level phenomenon, such as Belo, Gala, and Li (2013) and Addoum and Kumar (2016), the average PEAR betas of the decile portfolios after industry demeaning should have a small spread, and the low-PEAR-beta premium should become negligible.

The results in Panel B show that the industry effect contributes a small fraction of the low-PEAR-beta premium. The average PEAR betas increase from -1.68 for decile 1 to 1.79 for decile 10, with the difference quantitatively close to the case without industry demeaning (-3.47 vs. -3.53). The average returns of the PEAR-beta portfolios decrease from 1.02% for decile 1 to 0.05% for decile 10, with the difference equal to 0.97% (t-value $= 4.67$). This value suggests that the industry dynamics do not affect the predictive power of the PEAR beta. Indeed, when we sort the 48 industry portfolios based on their PEAR betas, the average return of the bottom five PEAR-beta industry portfolios does not differ significantly from that of the top five portfolios.

[6] We also argument the Fama and French (2015) five-factor model with the betting-against-beta factor (BAB) (Frazzini and Pedersen, 2014), or with the MAX factor (FMAX) (Bali et al., 2017), or with the Left-Tail Momentum factor (LTM) (Atilgan et al., 2020). Our results are robust to these three alternative factor models with their corresponding alphas 1.03% (t-value = 4.48), 0.97% (t-value = 4.24), and 0.99% (t-value = 4.27).

When turning to the risk adjusted return, the low-PEAR-beta premium also remains unaffected. It ranges from 0.67% for the DGTW model to 0.94% for the FF5 model. All the values are statistically significant and economically sizeable. For simplicity, we use the FF5 model as the benchmark for calculating the risk adjusted returns for the subsequent analyses.

To explore how much an investor can make if she trades on the low-PEAR-beta premium, Figure 2 plots the log cumulative returns and log cumulative FF5 alphas of the PEAR-beta spread portfolio. In our sample period from June 1983 to December 2019, the investor can make a risk adjusted profit of $42.87, which does not suffer from large drawdowns. Thus, trading the PEAR-beta spread portfolio can greatly expand an investor's investment opportunities in our sample period. Indeed, the low-PEAR-beta premium implies an annual Sharpe ratio of 0.69.

In this paper, we rebalance the PEAR-beta portfolios at the monthly frequency. A natural question is how long the low-PEAR-beta premium persists. Figure 3 presents the average returns and FF5 alphas of the PEAR-beta spread portfolio up to 36 months after formation. With 1.96 as the critical value for significance, the figure in Panel A shows that the low-PEAR-beta premium is persistent and generally significant up to 12 months after formation. Moreover, the premium does not display a reversal pattern, suggesting that the premium does not reflect the price pressure from trading. This result is comparable with the uncertainty-beta premium documented in Bali, Brown, and Tang (2017), which is persistent and significant up to 11 months. Examining the FF5 alphas in Panel B shows an even more persistent pattern. The persistent premium rules out short-term market frictions such as liquidity shocks in driving the result.

In sum, this subsection shows that high PEAR-beta stocks under-perform low PEAR-beta stocks in the future in terms of average, industry- and risk-adjusted returns, which we label as the low-PEAR-beta premium. A strategy trading for this premium generates statistically and economically significant profits.

3.2 Robustness

This subsection performs a battery of robustness checks to show that the low-PEAR-beta premium is not specific to a sub-sample or a sub-period, and is robust to different estimation methods.

3.2.1 Performance over political cycles

The well-known presidential puzzle refers to the striking time series fact that stock market returns are much higher under Democratic presidencies than Republican ones. While our low-PEAR-beta premium is a cross-sectional phenomenon, one may be still curious if it is also stronger under Democratic presidencies.

We split the sample into two sub-periods, Democratic and Republican. A month is defined to be Democratic if the president is a Democrat in that month. Since the inauguration of a new president is always around the 20th of January, we assume February is the commencement of the four-year term as a new president. In doing so, we have identified 192 months as Democratic and 247 months as Republican. Panel A of Table 4 reports the average and risk adjusted returns of the PEAR-beta spread portfolio in these two sub-periods. The average return is 1.31% (t-value = 3.84) under Democratic presidencies and 0.69% (t-value = 2.32) under Republican presidencies, with the difference (0.62%) insignificant from zero (t-value = 1.34). The risk adjusted returns are 1.49% (t-value = 3.13) and 0.56% (t-value = 2.07) under Democratic and Republican presidencies, respectively. In this case, the difference is 0.94% and marginally significant (t-value = 1.93). While the premium is higher during Democratic presidency, especially after risk adjustments, importantly, it is also positive and significant during the Republican presidency.

Panel A of Figure 4 goes one step further by plotting the average and risk adjusted returns of the PEAR-beta spread portfolio within each president tenure. Our sample covers six presidents, two Democrats and four Republicans. The figure shows that while the low-PEAR-beta premium is stronger during Democratic presidencies, it is also strong during a Republican presidency, echoing the pattern in Figure 2. Indeed, in the four-year term of President George H.W. Bush, the PEAR-beta spread portfolio has an average return of 1.49% and an FF5 alpha of 1.34% per month, which is slightly lower than, with the President Bill Clinton term (1.86% and 2.02%). Of course, the worst performance is also from the Republican presidency, Ronald Reagan, which has mediocre average and risk adjusted returns (0.39% and 0.26%).

In addition, we examine how the PEAR-beta spread portfolio performs across the four years of a president tenure. In the literature, Belo, Gala, and Li (2013) show that the government spending exposure has stronger power in predicting future stock returns in years 2 and 3 of a president tenure. In contrast, Addoum and Kumar (2016) find that stock prices are more sensitive to the political climate change in the first and fourth years. Panel B of Figure 4 shows that the low-PEAR-beta premium is different from Belo, Gala, and Li (2013) and Addoum and Kumar (2016). Its performance, especially after risk adjustment, is stronger in the first three years during a president term. Importantly, the low-PEAR-beta premium is present in each of the four years.

3.2.2 Performance over presidential transition and non-transition periods

Addoum and Kumar (2016) and Meeuwis et al. (2020) find that investors rebalance their portfolios dramatically around president elections, because of political climate change or political disagreement. To explore if such presidential transitions drive our low PEAR-beta premium, we split the sample into transition and non-transition periods. A transition period consists of six months before and after a new president's inauguration. With six presidents, we have five transitions, covering 65 months in total.

Panel B of Table 4 shows that the average return in the transition period is higher than that in the non-transition period (1.35% vs. 0.89%), but the risk adjusted returns are statistically indifferent in these two sub-periods, with the difference equal to -0.28 (t-value $= -0.45$). The result is similar if we use November of the election year as the event month as in Brogaard et al. (2020).

3.2.3 Performance over NBER recessions and expansions

As shown in Pastor and Veronesi (2020), financial crises or economic recessions are more likely to happen during a Republican president's term, which raises an interesting question that whether the low-PEAR-beta premium is weaker during economic recessions, given the time series presidential puzzle.

When splitting the sample period into NBER-dated economic recessions and expansions, we find that the low-PEAR-beta premium is stronger in NBER recessions. Specifically, the average return and FF5 alpha are 2.59% and 2.06% in recessions, whereas the counterparts in NBER expansions are 0.81% and 0.85%. This result is reported in Panel C of Table 4, and has two immediate implications. First, although the low-PEAR-beta premium is stronger under the Democratic presidencies, it can be even stronger over economic downturns during a Republican presidency. Second, high PEAR-beta firms do not perform better than those with low PEAR betas, suggesting in turn that they do not benefit from the Republican president or party policies.

3.2.4 Performance among different firms

Limits-to-arbitrage or transaction costs are an important determinant of mispricing, and plague the existing asset pricing models (Fama and French, 2015; Hou, Xue, and Zhang, 2015). In this subsection, we examine how the low-PEAR-beta premium performs among firms with low and high limits-to-arbitrage.

We consider three measures of limits-to-arbitrage, IVOL (Ang et al., 2006), illiquidity (Amihud, 2002), and firm size. For each measure, at the beginning of each month, we independently sort firms into two subgroups based on each measure and into deciles based on the PEAR-beta in the prior month, then we construct a PEAR-beta spread portfolio for each subgroup. Panel D of Table 4 reports the results with IVOL. Surprisingly, the low-PEAR-beta premium is even stronger among low IVOL stocks. Its FF5 alpha is 0.91% (t-value = 2.88) among low IVOL stocks, and 0.75% (t-value = 3.23) among high IVOL stocks. This empirical pattern continues to hold when we measure limits-to-arbitrage with Amihud's (2002) illiquidity or firm size (Panels E and F). The FF5 alphas of the low-PEAR-beta premiums are 1.00% and 0.05% among liquid and illiquid stocks, and 1.06% (t-value = 3.41) and 0.39% (t-value = 2.33) among big and small firms, respectively. These findings imply that the low-PEAR-beta premium is economically significant as it goes beyond transaction costs. Thus, it is different from most of anomalies that are concentrated among small and illiquid firms (Hou, Xue, and Zhang, 2015).

3.2.5 Alternative PEAR-beta estimates

In this paper, we estimate the PEAR beta with (6). Because the market return is included in our estimation, one natural question is what happens if we exclude the market return when estimating the PEAR beta. To answer the above question, we exclude the market return in regression (5) to estimate the PEAR beta, redo the single portfolio sorting as Table 3, and report the results in Panel G of Table 4. In this case, the average and risk adjusted returns of the PEAR-beta spread portfolio are 1.11% (t-value = 4.13) and 0.90% (t-value = 3.77), which are close to the case controlling for the market return (0.96% and 0.96%).

We also examine the robustness to different rolling windows used to estimate the PEAR beta, four and eight years (coinciding with one or two presidential terms). The results are quantitatively similar to the baseline results with a five-year rolling window. Thus, the low-PEAR-beta premium is robust to alternative estimation methods.

3.2.6 Alternative PEAR indexes

In this subsection, we show that the low-PEAR-beta premium is robust to three variations to the construction of the PEAR index.

First, in the main analyses, we use the change of PEAR to calculate the PEAR beta, and implicitly assume that it is independent over time, which may not be true empirically. To address this concern, we assume that the change of PEAR follows an AR(1) process and use the residual to estimate the PEAR beta. Panel H of Table 4 shows that, with this variation, the average and risk adjusted returns of the PEAR-beta spread portfolio are 0.92% (t-value = 3.97) and 0.76% (t-value = 3.41), which are slightly weaker than the baseline results. A caveat here is that the AR(1) estimation uses the full sample and thus introduces a forward-looking bias. We thus prefer estimating the PEAR beta using the simple changes.

Second, as shown in Table 1, the presidential job approval rating (PJAR) index is highly correlated with PEAR. So one interesting question is whether this alternative index can generate similar results in the cross-section. Panel H of Table 4 reports the average return and FF5 alpha are 0.72% (t-value = 2.84) and 0.50% (t-value = 2.18), respectively. These values are much smaller than those using PEAR, suggesting that PEAR is more relevant for the financial market.

Lastly, we consider polls from top 6 polling organizations, which conduct the most surveys in our sample period. In this case, since there are many missing values, especially in the early years, we fill in the missing values using the dyad ratios algorithm of Stimson (1999). This algorithm is popular in political science, and it uses smoothing and interpolation to deal with irregular, non-balanced, and sparse panel data. By using this new index, the PEAR-beta spread portfolio has an average return of 0.76% and an abnormal return of 0.72%. This slightly worse performance suggests that we need more polling results from other polling agents to better capture the underlying public perspective regarding the president's handling of the economy, especially during the early years.

To conclude, this subsection shows that the low-PEAR-beta premium is largely robust to alternative methods for constructing the PEAR index.

3.3 International evidence

In this subsection, we conduct an out-of-sample test by showing that the low-PEAR-beta premium continues to hold in other G7 countries. That is, the US PEAR index also affects the stock returns of other G7 countries.

Specifically, we collect firm-level stock returns and marketcaps of Canada, France, Germany, Italy, Japan, and the UK from DataStream, and use similar filters as Griffin, Kelly, and Nardari

(2010) and Hou, Karolyi, and Kho (2011).[7] We collect the major stock market indexes for these countries from FactSet, including the FTSE 100 index for the UK, the Nikkei 225 index for Japan, the DAX index for Germany, the CAC 40 index for France, the S&P/TSX Composite index for Canada, and the FTSE MIB index for Italy. Because the results using US dollar and local currencies are similar, we report the results with local currencies in Table 5. Same as the baseline, all portfolios are valued-weighted and rebalanced at the monthly frequency. The sample period starts from the available date of the market index for each country to December 2019. The FF5 factor data are from Schmidt et al. (2019) and only available after 1991:07, except from Japan that starts from 1990:07. Finally, following Frankel and Rose (1998), we also construct a trade intensity measure between each of G7 countries and the US, which captures the economical closeness between these countries and the US Specifically, trade intensity is calculated as the sum of bilateral trade (imports and exports) between each country and the US divided by the sum of their GDPs.

Overall, Table 5 shows that the low-PEAR-beta premium exists in the most of G7 countries. The average and risk adjusted returns of the PEAR-beta spread portfolios are positive in all the countries, except for Italy. In particular, the PEAR-beta spread portfolios have significant average and risk adjusted returns in Canada, Germany, Japan, and the UK. The last column of Table 5 shows that Canada, Germany, Japan, and the UK also have tighter trade linkages (higher average trade intensity value) with the US, suggesting that firms in countries that are more economically linked to the US will be affected by the US PEAR index.

3.4 Fama-MacBeth regressions

So far we have tested the significance of the PEAR beta as a determinant of the cross-section of future returns at the portfolio level. This portfolio-level analysis has non-parametric merit in the

[7] In particular, we require that firms selected for each country are domestically incorporated based on their home country information (GEOGC); We eliminate non-common stocks such as preferred stocks, warrants, REITs, and ADRs. If a stock has multiple share classes, only the primary class is included. To filter out suspicious stock returns, we set returns to missing for stocks with returns higher than 300%. Specifically, if R_t or R_{t-1} is greater than 300%, and $(1+R_t)\times(1+R_{t-1})-1<50\%$, then both R_t and R_{t-1} are set to missing. We also treat the monthly returns as missing that fall outside the 0.1% to 99.9% range in each country.

sense that we do not impose a functional form on the relation between the PEAR beta and future returns. However, it also has two disadvantages. First, it gives up a large amount of information in the cross-section via aggregation. Second, it is hard to control for multiple effects or factors simultaneously using portfolio-level analysis. To address these concerns, in this subsection we run Fama-MacBeth cross-sectional regressions of firms' one-month-ahead excess returns on their PEAR betas and various firm- and industry-specific characteristics to gauge the incremental return predictive power of the PEAR beta.

In Fama-MacBeth cross-sectional regressions, we control for a comprehensive set of potential return predictors which we group into three categories. The first category includes alternative measures of beta, such as the CAPM beta, the beta on the Jurado, Ludvigson, and Ng (2015) macroeconomic uncertainty index (Bali, Brown, and Tang, 2017), and the beta on the Baker and Wurgler (2006) sentiment index (Chen, Han, and Pan, 2020). The second category includes variables related to government and politics. They are the political alignment index (Kim, Pantzalis, and Park, 2012), political sensitivity (Addoum and Kumar, 2016), political connectedness (Cooper, Gulen, and Ovtchinnikov, 2010), and government spending exposure (Belo, Gala, and Li, 2013). The third category includes other firm characteristics such as size, book-to-market, momentum, short-term reversal, idiosyncratic volatility, illiquidity, and distress.

Table 6 reports the results. In column 1, the univariate regression shows that the PEAR beta has a significantly negative coefficient of -0.13 with a t-value of -3.38. Economically, the absolute t-value is proportional to the Sharpe ratio of the PEAR-beta spread portfolio, which equals to the annualized Sharpe ratio times $\sqrt{T}$, the number of years in the sample. So the -3.38 t-value suggests that an investor can earn an annualized Sharpe ratio of 0.56 (i.e., $3.38/\sqrt{37}$) if he trades for the low-PEAR-beta premium. This value is higher than the market Sharpe ratio of 0.51. In column 2, when we control for firm characteristics in the regression, the coefficient of PEAR beta drops to -0.11 but the t-value slightly increases to -3.60 in magnitude, suggesting that the predictive power of PEAR beta is robust to these well-known firm characteristics.

In column 3, when we further include other beta predictors (i.e., β_{CAPM}, β_{UNC}, and β_{BW}), the regression coefficient on PEAR beta slightly changes to -0.09 with a t-value of -3.09. Interestingly, the sentiment beta, β_{BW}, has a significantly negative regression coefficient in this case, consistent with the argument in Baker and Wurgler (2006). The CAPM beta loses power and the uncertainty beta is marginally significant. In column 4, we instead control for political variables (i.e, political alignment index, political sensitivity, political connectedness, and government spending exposure), and find the coefficient of PEAR beta to be -0.10 (t-value $= -3.13$). This result suggests that the interpretations underlying these politics-related variables are unlikely to completely explain the low-PEAR-beta premium.

In column 5, when we pool all the three categories of controls in the regression, the coefficient on PEAR beta remains -0.08 with a t-value of -2.88. This magnitude is about three quarters of its counterpart in column 1, suggesting that all the controlling variables, even when combined, explain at most one quarter of the low-PEAR-beta premium. This result is not surprising because, as we have shown in Table 2, PEAR beta has low correlations with these variables.

In column 6—the last column of Table 6—we run the Fama-MacBeth regression by controlling for the Fama-French 48 industry fixed effects. We drop the industry-level predictor political sensitivity as it is calculated based on Fama-French 48 industries. The regression coefficient of PEAR beta becomes -0.07 with a t-value of -2.59. Again, the low-PEAR-beta premium is different from Belo, Gala, and Li (2013) and Addoum and Kumar (2016), and it is not an industry-level phenomenon.

Regarding other control variables in our regressions, their coefficients are generally consistent with the literature except for the idiosyncratic volatility (IVOL), which exhibits positive and significant coefficients. This is due to its high correlation with the distress variable (0.92), as evident in the Table 2. We confirm that the coefficient on IVOL will be negative and significant if we exclude the distress variable in the regression.

In sum, a significant part of the low-PEAR-beta premium cannot be explained by existing well-known return predictors.

4 Interpreting the Results

In this section, we provide four potential channels to understand our main findings, and show that they are at most partially explaining the low-PEAR-beta premium.

4.1 Risk aversion

To explain the presidential puzzle, Pastor and Veronesi (2020) develop a model of political cycles driven by time-varying risk aversion. They argue that when risk aversion is high, agents are more likely to elect Democrats that promise more redistribution. In contrast, when risk aversion is low, agents are more likely to elect Republicans to take more business risk. With risk aversion as an exogenous driver, the risk premium of the stock market is expected to be high during Democratic presidencies and low during Republican presidencies. Our PEAR index seems negatively related to the risk aversion and therefore correlates well with the political cycle, as low PEAR strongly predicts Democratic presidents and higher stock market returns in the next 8 years.

More formally, we consider four different measures of aggregate risk aversion, including the unemployment rate, aggregate risk aversion from Miranda-Agrippino and Rey (2020), negative of the surplus consumption ratio from the habit model of Campbell and Cochrane (1999), and option-based risk aversion from Faccini et al. (2019). Figure 5 shows that PEAR is indeed negatively correlated with these four risk aversion measures, and the coefficients of regressing these measures on PEAR are always negative and significant, thereby PEAR appearing to be capturing aggregate risk aversion.

In the cross-section, however, a standard risk model would predict the opposite of the low-PEAR-beta premium. If PEAR measures the negative of risk aversion, high PEAR-beta stocks do worse precisely when aggregate risk aversion increases (or when PEAR decreases), and they are therefore more risky and should earn higher returns. Such a risk-based story is therefore inconsistent with our empirical findings that high PEAR-beta stocks under-perform the low PEAR-beta stocks in the future.

4.2 Macroeconomic risk

Although risk aversion does not provide a full explanation to our findings, it is possible that the low-PEAR-beta premium actually reflects exposure to other macroeconomic risk factors. We examine this possibility by studying a large set of macro variables, including industrial production growth, unexpected inflation, change in expected inflation, term premium, default premium, total factor productivity growth, labor income growth, capital share growth (Lettau, Ludvigson, and Ma, 2019), consumption growth, ultimate consumption growth (Parker and Julliard, 2005), consumption-wealth ratio, change in aggregate market volatility, change in VIX, variance risk premium, GDP growth, and change in unemployment rate.

Panel A of Table 7 presents the correlation between the change of PEAR and the macro variables. Generally, the correlations are very low, and the highest one is 0.18 between the change of PEAR and the ultimate consumption growth. However, according to Parker and Julliard (2005), ultimate consumption growth is unlikely to be an explanation to the low-PEAR-beta premium, because it demands a positive risk premium.

Panel B of Table 7 reports the correlations between PEAR beta and the marco betas. To mitigate the potential outlier effects, we also consider the rank correlations that are calculated based on the cross-sectional ranks of these betas. In this panel, the PEAR beta has the highest correlation (in absolute term) with the VRP beta (-0.15). However, the VRP beta is unable to explain the low-PEAR-beta premium either, because it does not have any power in predicting future stock returns in our sample period.

Therefore, although there is always the possibility that PEAR captures a state variable related to macroeconomic risk, and that PEAR beta and its pricing dynamically vary with this state variable, it seems safe to conclude that existing rational channels are unable to fully explain the low-PEAR-beta premium.

4.3 Sentiment-induced overpricing and short sale constraints

Because the PEAR index is based on the responses to "Do you approve or disapprove of the way (name of president) is handling the economy?", one may interpret it as a measure of investor sentiment like the Michigan consumer sentiment index. In this way, stocks with positive PEAR betas experience higher returns when the presidential economic approval rating improves. To the extent that PEAR may indicate investor confidence (De Boef and Kellstedt, 2004), high PEAR-beta stocks could suffer from sentiment-induced overpricing, explaining their subsequent low returns when their overpricing gets corrected. Indeed, Stambaugh, Yu, and Yuan (2012) find the long-short anomaly return spread to be much stronger following high levels of sentiment. They also find this pattern to be especially true for the short legs of the anomaly strategies, consistent with short-sale impediments.

Unfortunately, such sentiment-induced overpricing does not seem to fully explain the low-PEAR-beta premium. We examine four measure of investor sentiment: (1) Baker and Wurgler (2006) sentiment index, (2) Michigan consumer sentiment index, (3) AAII bull-bear index, and (4) the PEAR index itself. We split the sample into two subsamples based on the median values of the four sentiment measures, and examine the difference of the low-PEAR-beta premium in these two periods. In Table 8 we find significantly higher PEAR-beta spread portfolio returns following high levels of sentiment, only when the PEAR index is used. However, we do not find any evidence that the short-leg (high PEAR-beta stocks) alpha is higher following high levels of sentiment. In fact, in all cases, the long-leg has a higher alpha (in absolute term) than the short-leg does, inconsistent with the notion that short sale constraints may fully explain the low-PEAR-beta premium.

4.4 Hedge for downside risk?

Intuitively, the PEAR beta could measure a firm's perceived alignment to the economic policies of the current president. The business of a positive PEAR-beta firm must align well with the current presidential economic policies, so its stock price moves in tandem with the policies' approval rating. It is possible that such a "presidential alignment" leads to a government bailout during bad times. If that happens, a high PEAR-beta stock could actually be a good hedge for downside risk. Could their lower future returns reflect the hedging benefits? We believe the answer is No.

Empirically, corporate bailouts are relatively rare. For stance, Faccio, Masulis, and McConnell (2006) finds that over a sample period from 1997 to 2002, of the 450 political connected firms from 35 countries, only 51 firms received bailouts. In the US, financial firms, especially banks, are more likely to be bailed out since these firms are deeply intertwined with the economy through debts and obligations, as evident by a list of historical bailouts in the US collected by the non-profit investigative journalism group, ProPublica. However, financial firms are excluded in our analysis. For non-financial firms, only those mega firms have higher chances of receiving bailouts. We confirm that these mega firms tend not to have extreme PEAR betas and therefore rarely enter deciles 1 and 10. The low PEAR-beta premium hardly changes when we remove the largest 25 firms from our sample each month.

Additional evidence does not support such a "hedging" story either. During bad times, as indicated by NBER recession dates, high-PEAR-beta firms earn even lower returns than low-PEAR-beta firms (see Panel C of Table 4), inconsistent with the notion of a bailout. In addition, the PEAR beta has a low correlation, 0.07 as shown in Panel B of Table 2, with the measure of financial distress (Campbell, Hilscher, and Szilagyi, 2008). Table 6 further shows that controlling for the distress risk does not alter the low-PEAR-beta premium.

In sum, this section presents four possible interpretations and finds none of them seems promising to explain the low-PEAR-beta premium, thereby suggesting us searching for a new economic mechanism, which is the focus of the next section.

5 PEAR Beta and Mispricing Presidential Alignment

Instead, it is possible that sentiment investors misprice stocks perceived to be well-aligned or misaligned with the current president's economic policies. As a concrete example, consider two energy companies: Renewable Energy Group Inc (NASDAQ: REGI) and Panhandle Oil & Gas Inc (NYSE: PHX). As their names imply, the first company aligns well with Obama era's clean energy policy while the second company, being a traditional gas and drilling firm, better aligns with the energy policy from the Trump's administration.

Their current presidential alignments are nicely captured by their PEAR betas, as evident in Panel A of Figure 6. During the Obama's presidency (2014-2016), Renewable Energy has a large and positive PEAR beta and Panhandle has a negative PEAR beta. After Trump's election in 2017, their PEAR betas start to converge. After a year, they flip. Renewable Energy has a negative PEAR beta while Panhandle has a positive PEAR beta. In this example, PEAR beta becomes a self-revealed and dynamic measure of a firm's perceived alignment with the current presidential economic policies. Panel B confirms that this is a general pattern for high and low PEAR-beta firms. After a change of president, their betas quickly converge during the first few months.

In Appendix B, we sketch a stylized model in which sentiment investors have biased cash flow expectations of firms with extreme PEAR betas. Using the above example, during Obama's term, sentiment investors overestimate future earnings of Renewable Energy and underestimate future earnings of Panhandle, especially when Obama's PEAR index is high. In the model, the PEAR index does not contain any additional fundamental information, so the PEAR beta captures sentiment investors' biased cash flow expectation. Risk-averse rational investors cannot fully correct such biases, and a result, the market-clearing price is too high for Renewable Energy and too low for Panhandle. Mispricing disappears when future earnings are realized. As result, Renewable Energy earns lower returns and Panhandle earns higher returns in the future, resulting in the low PEAR-beta premium. The model further predicts that such a premium should be higher following high PEAR period, a pattern we confirm in Panel D of Table 8.

We provide three pieces of additional supporting (though not conclusive) evidence for such a mispricing-based explanation. First, in each month, we split the past 60 months into two sub-samples (if applicable), one coming from months when the current president is in power and the other from months when the previous president is in power, with a requirement of at least 12 observations in each subsample. We then estimate two betas for that firm using each subsample: a current president beta and a previous president beta. Finally, we explore the low-PEAR-beta premium with respect to these two betas. Panel A of Table 9 shows that the low-PEAR-beta premium exists and is only significant when the current president beta is used for sorting. For example, the FF5 alpha of the PEAR-beta spread portfolio is 0.69% (t-value $= 3.42$) with the current president beta, whereas it is -0.04% (t-value $= -0.16$) with the previous president beta. The evidence highlights the importance of perceived alignment to the *current* presidential economic policies.

Second, consistent with biases in cash flow expectations, we find the PEAR beta to negatively predict analyst forecast errors, future revisions in their long term growth (LTG) forecasts and stock recommendations. In addition, the PEAR beta negatively predicts future earnings announcement window returns. The results can be found in Panel B of Table 9, which suggest that both analysts and investors are initially too optimistic (pessimistic) in forecasting the cash flows of high (low) PEAR-beta stocks and subsequent earnings announcements facilitate the correction of mispricing.

Finally, we provide evidence that limited investor attention may contribute to sentiment investors' biased expectations and mispricing. We consider two proxies for investor attention, abnormal google search volume and abnormal trading volume. Same as Da, Engelberg, and Gao (2011), the abnormal google search volume is calculated as the change of google search volume in the current month relative to the average search volume in the past two months. Following Gervais, Kaniel, and Mingelgrin (2001), the abnormal trading volume is defined as the change of trading volume (turnover) in the last week of each month relative to the trading volume in the previous nine weeks. Each month, we sort firms into two subgroups based on one of the attention measures, and within each subgroup we further sort firms into deciles based on the PEAR beta. Panel C of Table 9 reports the FF5 alphas of these portfolios. As expected, the low-PEAR-beta premium is much stronger among firms that receive less investor attention. For example, the FF5 alphas of the PEAR-beta spread portfolios are 0.98% (t-value $= 2.97$) and 0.47% (t-value $= 1.38$) in the low and high abnormal google search volume stocks, respectively. The result by using the abnormal trading volume is also similar (1.28% vs. 0.81%).

6 Conclusion

In this paper, we construct a novel monthly presidential economic approval rating (PEAR) index from 1981 to 2019, and show that, in the cross-section, stocks with high PEAR beta significantly under-perform those with low PEAR beta by 0.96% per month in the future, on a risk adjusted basis. The low-PEAR-beta premium persists up to one year and remains significant in a number of robustness tests. Contrary to the sentiment-induced overpricing, this premium does not come primarily from the short leg during high sentiment period. Since the PEAR index is negatively correlated with measures of aggregate risk aversion, a standard risk model would predict the low PEAR-beta stocks to earn lower (not higher) expected returns. In addition, PEAR-betas do not correlate with measures of macroeconomic risk exposure and high PEAR-beta stocks do not enjoy bailouts to justify their low expected returns. Instead, the PEAR beta captures a firm's perceived alignment to the current president's economic policy and market seems to overprice firms with positive PEAR betas and underprice firms with negative ones.

A number of topics are of interest for future research. First, extending our stylized sentiment model to allow for time-varying risk aversion and studying their interactions is desirable. Second, extending our results to other markets or asset classes could be worthwhile. Finally, given the data availability, we examine the low-PEAR-beta premium over the past four decades. We look forward to finding a way to extend the PEAR index to a longer period.

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Table 1 Summary statistics of PEAR and other related indexes

This table reports level and change correlations between the presidential economic approval rating (PEAR) and other sentiment and politics related indexes, consisting of (orthogonalized) investor sentiment (Baker and Wurgler, 2006), University of Michigan consumer sentiment, presidential job approval rating (Liu and Shaliastovich, 2021), aggregate political risk and sentiment (Hassan et al., 2019), and political uncertainty [measured by economic policy uncertainty in Baker, Bloom, and Davis (2016)]. AR(1) and AR(12) refer to the first- and 12th-order autocorrelations. All the time series are at the monthly frequency and over the 1981:04–2020:12 period, except for investor sentiment being 1981:04-2018:12, quarterly aggregate political risk and sentiment being 2002Q1–2020Q4, and political uncertainty being 1985:01–2019:12.

Panel A: Summary statistics

	Mean	Median	Min	Max	Volatility	AR(1)	AR(12)
PEAR	47.00	46.17	17.50	77.00	11.48	0.93	0.59
Investor sentiment	0.29	0.16	−0.89	3.20	0.62	0.97	0.33
Consumer sentiment	87.54	90.80	55.30	112.00	11.91	0.95	0.64
Presidential approval	51.65	50.00	27.00	89.80	11.72	0.93	0.48
Political risk	5.65	5.48	4.39	7.72	0.77	0.73	−0.02
Political sentiment	3.82	3.72	1.54	5.61	0.88	0.92	0.59
Political uncertainty	111.47	104.24	52.05	264.40	36.10	0.72	0.37

Panel B: Correlations

	PEAR	Investor sentiment	Consumer sentiment	Presidential approval	Political risk	Political sentiment	Political uncertainty
Correlation between levels							
PEAR	1.00						
Investor sentiment	0.22***	1.00					
Consumer sentiment	0.63***	0.26***	1.00				
Presidential approval	0.65***	0.12***	0.26***	1.00			
Political risk	0.07	−0.56***	−0.54***	0.09	1.00		
Political sentiment	0.19	0.24*	0.59***	−0.35***	−0.23***	1.00	
Political uncertainty	−0.15***	−0.17***	−0.45***	−0.02	0.61***	0.05	1.00
Correlation between changes							
PEAR	1.00						
Investor sentiment	−0.09*	1.00					
Consumer sentiment	0.14***	−0.04	1.00				
Presidential approval	0.23***	−0.05	0.14***	1.00			
Political risk	0.18	−0.09	0.16	0.22*	1.00		
Political sentiment	−0.12	−0.04	−0.14	−0.17	−0.40***	1.00	
Political uncertainty	0.03	0.06	−0.19***	0.11**	−0.02	−0.03	1.00

Table 2 Autocorrelations and pairwise correlations

This table reports autocorrelations and pairwise correlations of firm-specific characteristics, including PEAR-beta (β_{PEAR}), market-beta (β_{CAPM}), economic uncertainty-beta (β_{UNC}, Bali, Brown, and Tang, 2017), sentiment beta (β_{BW}, Chen, Han, and Pan, 2020), political alignment index (PAI, Kim, Pantzalis, and Park, 2012), political sensitivity (PS, Addoum and Kumar, 2016), political connectedness (PC, Cooper, Gulen, and Ovtchinnikov, 2010), government spending exposure (GSE, Belo, Gala, and Li, 2013), log firm size (SIZE), log book-to-market ratio (BM), momentum, short-reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ, Amihud, 2002), failure probability (Distress, Campbell, Hilscher, and Szilagyi, 2008), and mispricing score (MISP, Stambaugh, Yu, and Yuan, 2015). AR(1) and AR(12) refer to the first- and 12th-order autocorrelations. The sample period is 1983:05–2019:12, except for β_{BW} being 1983:05 -2018:12.

	β_{PEAR}	β_{CAPM}	β_{UNC}	β_{BW}	PAI	PS	PC	GSE	SIZE	BM	MOM	STR	IVOL	ILLIQ	Distress	MISP
Panel A: Autocorrelation																
AR(1)	0.81	0.84	0.78	0.80	0.90	0.85	0.94	0.67	0.84	0.88	0.76	−0.03	0.27	0.46	0.32	0.70
AR(12)	0.32	0.34	0.24	0.31	0.17	0.18	0.53	0.26	0.16	0.08	−0.17	−0.01	0.06	0.04	0.10	−0.02
Panel B: Pairwise correlation: standard (rank) correlation above (below) the diagonal																
β_{PEAR}		0.02	0.09	0.05	−0.01	−0.01	−0.03	0.01	−0.06	0.02	−0.01	0.00	0.06	0.02	0.05	0.02
β_{CAPM}	0.02		0.07	0.11	−0.02	−0.08	−0.08	0.06	0.06	−0.13	−0.01	−0.01	0.13	−0.06	0.10	0.20
β_{UNC}	0.08	0.06		0.03	0.00	−0.02	−0.01	−0.00	0.00	−0.04	−0.01	0.01	0.02	−0.00	0.02	0.02
β_{BW}	0.02	0.12	0.04		−0.02	−0.07	−0.07	−0.02	−0.10	−0.05	0.03	0.01	0.11	0.01	0.09	0.08
PAI	−0.01	−0.00	0.00	−0.02		0.05	−0.01	−0.00	−0.01	−0.01	0.00	0.00	0.01	−0.00	0.00	0.01
PS	−0.01	−0.08	−0.01	−0.08	0.06		−0.02	−0.03	0.03	0.02	0.05	0.02	−0.03	−0.01	−0.03	−0.06
PC	−0.05	−0.07	−0.02	−0.10	−0.02	−0.01		0.08	0.42	−0.06	0.00	−0.00	−0.16	−0.04	−0.15	−0.19
GSE	0.03	0.08	−0.01	0.00	0.00	−0.06	0.01		0.02	−0.02	0.01	−0.00	0.01	−0.01	0.00	0.03
SIZE	−0.07	0.09	0.02	−0.13	−0.01	0.03	0.36	0.02		−0.25	0.14	0.04	−0.40	−0.23	−0.33	−0.22
BM	0.04	−0.13	−0.05	−0.03	−0.02	0.02	−0.06	−0.04	−0.28		0.01	0.02	−0.01	0.10	0.01	−0.09
MOM	−0.02	−0.05	−0.03	−0.01	−0.00	0.06	0.04	−0.00	0.24	0.01		−0.01	−0.10	−0.07	−0.11	−0.20
STR	−0.01	−0.02	−0.00	−0.01	−0.00	0.02	0.02	−0.00	0.10	0.02	0.02		0.21	0.00	0.10	−0.00
IVOL	0.06	0.19	0.01	0.15	0.02	−0.03	−0.24	0.03	−0.48	0.01	−0.21	0.00		0.25	0.68	0.31
ILLIQ	0.06	−0.10	−0.03	0.11	0.01	−0.03	−0.35	−0.03	−0.91	0.30	−0.25	−0.07	0.50		0.20	0.03
Distress	0.07	0.19	0.01	0.15	0.02	−0.04	−0.24	0.02	−0.54	0.07	−0.27	−0.07	0.92	0.53		0.30
MISP	0.02	0.21	0.01	0.08	0.02	−0.04	−0.19	0.03	−0.18	−0.07	−0.31	−0.03	0.38	0.16	0.49	

Table 3 Average returns and alphas of PEAR-beta portfolios

This table reports monthly average excess returns and alphas (in %) of decile portfolios sorted by PEAR beta (β_{PEAR}), where P1 (P10) refers to the portfolio with low (high) β_{PEAR}, and L-H refers to the strategy that buys P1 and sells P10. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (2015) five-factor model (FF5), Hou, Xue, and Zhang (2015) q-factor model (HXZ), Stambaugh and Yuan (2017) mispricing-factor model (SY), Daniel, Hirshleifer, and Sun (2020) behavioral-factor model (DHS), and Daniel et al. (1997) characteristics-based model (DGTW). Reported in parentheses are t-values. Industry demeaned β_{PEAR} is based on the Fama-French 48 industries. The sample period is 1983:06–2019:12.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	L-H
Panel A: Sort on β_{PEAR}											
β_{PEAR}	−1.56	−0.67	−0.37	−0.17	−0.00	0.16	0.34	0.57	0.91	1.97	−3.53
Excess	1.04	0.96	0.82	0.76	0.66	0.65	0.52	0.56	0.50	0.08	0.96
	(3.05)	(3.85)	(3.81)	(3.66)	(3.12)	(3.08)	(2.26)	(2.19)	(1.63)	(0.21)	(4.18)
α_{FF5}	0.60	0.29	0.07	0.03	−0.05	−0.10	−0.16	−0.13	−0.05	−0.36	0.96
	(3.84)	(2.48)	(0.91)	(0.39)	(−0.68)	(−1.25)	(−1.88)	(−1.12)	(−0.40)	(−2.35)	(4.20)
α_{HXZ}	0.66	0.38	0.12	0.04	−0.06	−0.05	−0.07	−0.05	0.01	−0.21	0.87
	(4.10)	(3.19)	(1.51)	(0.58)	(−0.77)	(−0.68)	(−0.79)	(−0.41)	(0.09)	(−1.25)	(3.71)
α_{SY}	0.57	0.46	0.09	−0.04	−0.04	−0.07	−0.09	−0.07	−0.06	−0.37	0.94
	(3.33)	(3.70)	(1.11)	(−0.52)	(−0.55)	(−0.89)	(−1.02)	(−0.62)	(−0.42)	(−1.92)	(3.77)
α_{DHS}	0.64	0.34	0.12	−0.02	−0.07	−0.07	−0.03	0.07	−0.01	−0.02	0.66
	(3.58)	(2.66)	(1.43)	(−0.22)	(−0.81)	(−0.83)	(−0.35)	(0.62)	(−0.05)	(−0.09)	(2.65)
DGTW	0.24	0.12	0.08	0.05	−0.03	−0.02	−0.08	−0.08	−0.10	−0.35	0.60
	(1.60)	(1.40)	(1.34)	(0.95)	(−0.55)	(−0.41)	(−1.23)	(−0.98)	(−0.82)	(−2.12)	(3.06)
Panel B: Sort on industry demeaned β_{PEAR}											
β_{PEAR}	−1.68	−0.78	−0.49	−0.29	−0.12	0.04	0.21	0.43	0.76	1.79	−3.47
Excess	1.02	0.85	0.66	0.77	0.77	0.66	0.72	0.52	0.54	0.05	0.97
	(2.95)	(3.46)	(3.14)	(3.63)	(3.80)	(3.05)	(3.12)	(2.16)	(1.85)	(0.13)	(4.67)
α_{FF5}	0.59	0.24	−0.05	0.10	0.01	−0.10	0.00	−0.23	−0.06	−0.35	0.94
	(3.77)	(2.34)	(−0.68)	(1.52)	(0.23)	(−1.35)	(0.02)	(−2.25)	(−0.48)	(−2.49)	(4.62)
α_{HXZ}	0.66	0.28	0.02	0.10	0.03	−0.04	0.05	−0.13	0.00	−0.24	0.90
	(4.14)	(2.63)	(0.19)	(1.39)	(0.44)	(−0.45)	(0.58)	(−1.25)	(0.02)	(−1.48)	(4.27)
α_{SY}	0.52	0.28	−0.07	0.04	0.05	0.00	0.02	−0.18	−0.01	−0.32	0.84
	(2.99)	(2.64)	(−0.80)	(0.57)	(0.67)	(0.02)	(0.20)	(−1.71)	(−0.06)	(−1.75)	(3.78)
α_{DHS}	0.68	0.28	−0.05	0.01	0.07	0.01	0.08	−0.10	0.07	−0.05	0.72
	(3.86)	(2.49)	(−0.55)	(0.13)	(0.99)	(0.09)	(0.88)	(−0.93)	(0.51)	(−0.25)	(3.19)
DGTW	0.25	0.11	−0.03	0.02	0.07	−0.01	0.09	−0.17	−0.11	−0.42	0.67
	(1.66)	(1.32)	(−0.47)	(0.31)	(1.34)	(−0.19)	(1.29)	(−2.23)	(−1.07)	(−2.65)	(3.54)

Table 4 Subperiod/subsample analyses of PEAR-beta portfolios

This table reports the monthly average excess returns and FF5 alphas of PEAR-beta (β_{PEAR}) portfolio in different subsamples. Panel A splits the sample into Democratic and Republican presidency periods. Panel B considers president transition and non-transition periods, where transition periods are defined as six months surrounding the January of new president inauguration. Panel C splits the sample into NBER-dated recessions and expansions. Panel D splits the sample based on the idiosyncratic volatility (IVOL) (Ang et al., 2006). Panel E splits the sample into two subsamples based on illiquidity (Amihud, 2002). Panel F splits stocks into two size groups based on the median NYSE breakpoints. Panel G considers alternative β_{PEAR} estimations: estimating β_{PEAR} by excluding the MKT factor or using a 4-year or 8-year rolling window. Panel H considers alternative PEAR indexes, such as using the innovation of the AR(1) process of PEAR, the president job approval rating, and the index based on the polls from top 6 polling agents [the missing values are filled by using the dyad ratios algorithm of Stimson (1999)]. All portfolios are value-weighted and rebalanced at a monthly frequency. Reported in parentheses are t-values. The sample period is 1983:06–2019:12.

	Excess return	FF5 alpha	#(obs.)		Excess return	FF5 alpha	#(obs.)
Panel A: Democratic vs. Republican presidents				Panel B: Transition vs. non-transition periods			
Democratic	1.31	1.49	192	Transition	1.35	1.20	65
	(3.84)	(3.13)			(2.26)	(2.07)	
Republican	0.69	0.56	247	Non-transition	0.89	0.92	374
	(2.32)	(2.07)			(3.59)	(3.11)	
Difference	−0.62	−0.94		Difference	−0.46	−0.28	
	(−1.34)	(−1.93)			(−0.71)	(−0.45)	
Panel C: Recessions vs. expansions				Panel D: Low vs. high IVOL firms			
Recession	2.59	2.06	34	Low IVOL	1.02	0.91	
	(2.64)	(2.07)			(3.29)	(2.88)	
Expansion	0.81	0.85	405	High IVOL	0.76	0.75	
	(3.47)	(3.42)			(3.32)	(3.23)	
Difference	−1.78	−1.21		Difference	−0.27	−0.16	
	(−1.77)	(−1.19)			(−0.84)	(−0.48)	
Panel E: Liquid vs. illiquid firms				Panel F: Small vs. big firms			
Liquid	0.98	1.00		Small	0.55	0.39	
	(4.04)	(3.64)			(3.25)	(2.33)	
Illiquid	0.30	0.05		Big	1.03	1.06	
	(1.76)	(0.32)			(3.34)	(3.41)	
Difference	−0.68	−0.95		Difference	0.48	0.68	
	(−2.69)	(−3.64)			(1.76)	(2.38)	
Panel G: Alternative β_{PEAR} estimation				Panel H: Alternative PEAR			
Excluding MKT	1.11	0.90		Innovation of PEAR AR(1)	0.92	0.76	
	(4.13)	(3.77)			(3.97)	(3.41)	
4-year rolling	0.74	0.62		Presidential approval rating	0.72	0.50	
	(3.18)	(2.74)			(2.84)	(2.18)	
8-year rolling	0.79	0.77		Top 6 agents	0.76	0.72	
	(3.55)	(3.54)			(2.98)	(3.01)	

Table 5 International evidence

This table reports monthly average excess returns and FF5 alphas (in %) of decile portfolios based on PEAR beta in other G7 countries. Stock return and market capitalization information are from Datastream. All returns and market capitalizations are based on local currencies, risk-free rate for each country is the 90-day interbank rate, and the international Fama-French five-factor data are from Schmidt et al. (2019). P1 (P10) refers to the portfolio with low (high) PEAR beta, and L-H refers to the strategy that buys P1 and sells P10. The last column reports the average trade intensity (Frankel and Rose, 1998) between each country and the US, which is defined as the sum of bilateral trade (imports and exports) between each country and the US divided by the sum of their GDPs. All portfolios are value-weighted and rebalanced at a monthly frequency. Reported in parentheses are t-values. The sample period for results of excess returns are 1987:01-2019:12 for Canada, 1989:12-2019:12 for France, 1996:01-2019:12 for Germany, 1999:12-2019:12 for Italy, 1983:06-2019:12 for Japan, and 1987:12-2019:12 for the UK given the availability of the country's prevalent stock market index. The sample period for FF5 factors is 1991:07–2019:12 (1990:07–2019:12 for Japan).

	Excess return			FF5 alpha			Trade intensity
	P1	P10	L-H	P1	P10	L-H	
Canada	0.35	−0.97	1.32	−0.04	−1.19	1.15	2.86
	(0.68)	(−1.79)	(2.37)	(−0.08)	(−2.45)	(2.01)	
France	0.46	0.22	0.24	−0.02	−0.33	0.31	0.35
	(1.57)	(0.52)	(0.67)	(−0.10)	(−1.04)	(0.81)	
Germany	0.41	−0.39	0.80	0.02	−1.12	1.15	0.65
	(0.87)	(−0.97)	(1.67)	(0.06)	(−3.04)	(2.04)	
Italy	0.08	−0.00	0.08	−0.12	0.04	−0.16	0.29
	(0.19)	(−0.01)	(0.21)	(−0.50)	(0.13)	(−0.38)	
Japan	0.37	−0.08	0.44	0.24	−0.25	0.49	1.20
	(1.43)	(−0.23)	(1.71)	(1.89)	(−1.54)	(2.17)	
UK	1.03	0.10	0.93	0.65	−0.30	0.94	0.57
	(3.79)	(0.29)	(3.04)	(3.20)	(−1.15)	(2.69)	

Table 6 Fama-Macbeth regressions

This table reports the results of Fama-MacBeth regressions of one-month-ahead stock excess returns on PEAR beta (β_{PEAR}), controlling for other firm-specific characteristics, which include log firm size (SIZE), log book-to-market ratio (BM), price momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ, Amihud, 2002), failure probability (Distress, Campbell, Hilscher, and Szilagyi, 2008), β_{CAPM}, β_{UNC} (Bali, Brown, and Tang, 2017), β_{BW} (Chen, Han, and Pan, 2020), political alignment index (PAI, Kim, Pantzalis, and Park, 2012), political sensitivity (PS, Addoum and Kumar, 2016), government spending exposure (GSE, Belo, Gala, and Li, 2013), and political connectedness (PC, Cooper, Gulen, and Ovtchinnikov, 2010). In Column 6, we include 48 industry dummies classified following Fama and French (1997). All independent variables except for industry dummies are winsorized at the 1st and 99th percentiles, and then normalized to zero mean and standard deviation of one. Intercepts are included in all the regressions but unreported for brevity. Newey-West t-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1983:06–2019:12.

	DepVar.: One-month-ahead excess returns (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
β_{PEAR}	-0.13^{***}	-0.11^{***}	-0.09^{***}	-0.10^{***}	-0.08^{***}	-0.07^{***}
	(-3.38)	(-3.60)	(-3.09)	(-3.13)	(-2.88)	(-2.59)
β_{CAPM}			0.07		0.08	0.08
			(0.88)		(0.94)	(1.05)
β_{UNC}			-0.05^{*}		-0.05	-0.07^{**}
			(-1.68)		(-1.44)	(-2.23)
β_{BW}			-0.08^{*}		-0.05	-0.05
			(-1.73)		(-1.18)	(-1.13)
PAI				0.07^{**}	0.06^{**}	0.04^{*}
				(2.13)	(2.01)	(1.84)
PS				0.18^{***}	0.17^{***}	
				(3.14)	(3.33)	
PC				0.14^{**}	0.15^{***}	0.15^{***}
				(2.28)	(2.68)	(2.73)
GSE				0.02	0.03	0.04
				(0.55)	(0.79)	(1.51)
SIZE		-0.17^{***}	-0.20^{***}	-0.17^{**}	-0.19^{***}	-0.18^{**}
		(-2.60)	(-2.90)	(-2.44)	(-2.63)	(-2.48)
BM		0.22^{***}	0.21^{***}	0.22^{***}	0.22^{***}	0.27^{***}
		(2.94)	(3.06)	(3.12)	(3.31)	(4.96)
MOM		0.21^{**}	0.22^{***}	0.18^{**}	0.19^{***}	0.17^{***}
		(2.55)	(3.11)	(2.32)	(2.88)	(2.83)
STR		-0.44^{***}	-0.50^{***}	-0.52^{***}	-0.58^{***}	-0.63^{***}
		(-6.89)	(-7.37)	(-7.35)	(-7.65)	(-8.49)
IVOL		0.36^{***}	0.39^{***}	0.25^{**}	0.28^{**}	0.25^{**}
		(3.30)	(3.69)	(2.17)	(2.51)	(2.42)
ILLIQ		0.06	0.07^{*}	0.05	0.07	0.07^{*}
		(1.26)	(1.83)	(1.00)	(1.63)	(1.77)
Distress		-0.76^{***}	-0.81^{***}	-0.55^{***}	-0.58^{***}	-0.55^{***}
		(-5.30)	(-5.76)	(-3.51)	(-3.76)	(-3.87)
Industry FEs	No	No	No	No	No	Yes
#(obs.)	1,374,724	1,220,378	1,196,935	743,936	731,174	749,207
Adj. R^2	0.002	0.038	0.045	0.047	0.055	0.070

Table 7 The relationship between PEAR and macro variables

Panel A reports the correlations between the change in PEAR and other macro variables, and Panel B reports the correlations of their betas, where raw corr refers to the correlation without transforming the variables, and rank corr refers to the rank correlation after transforming each variable into a rank one. Macro variables include industrial production growth (IPG), unexpected inflation (UI), change in expected inflation (DEI), term premium (TERM), default premium (DEF), total factor productivity growth (TFP), labor income growth (LIG), capital share growth (CSG, Lettau, Ludvigson, and Ma, 2019), consumption growth (CG), ultimate consumption growth (UCG, Parker and Julliard, 2005), change in consumption to wealth ratio (CAY), change in aggregate market volatility (VOL), change in VIX, variance risk premium (VRP), growth in gross domestic product (GDP), and change in unemployment rate (UNPR). The correlations of PEAR with TFP, CS, CG, UCG, CAY, and GDP are at the quarterly frequency. β_{CS}, β_{CG}, β_{UCG}, β_{CAY}, β_{TFP}, and β_{GDP} are estimated from regressions of quarterly excess returns on the current and lagged values of the variables as well as excess market returns in the past 10 years. β_{VIX} is estimated from regressions of excess stock returns on the excess market returns and the current and lagged changes in VIX using daily data in a month. Other monthly betas are estimated using the same specification of estimating β_{PEAR}. We flip the signs of β_{UI}, β_{DEI}, β_{TERM}, β_{DEF}, β_{VOL}, β_{VIX}, β_{VRP}, and β_{UNPR} so that they are capturing the correct direction of risk (i.e., high beta implies high risk). The sample period is 1983:05–2019:12, except for UCG being 1983:05–2017:03, and VIX and VRP being 1990:01–2019:12.

Panel A: Correlations between the change in PEAR and other macro variables

	IPG	UI	DEI	TERM	DEF	TFP	LIG	CSG
Raw corr	0.03	−0.06	−0.05	0.01	0.03	0.12	−0.06	0.16
	CG	UCG	CAY	VOL	VIX	VRP	GDP	UNPR
Raw corr	0.10	0.18	0.05	0.05	0.02	0.10	0.16	0.02

Panel B: Correlations between β_{PEAR} and macro betas

	β_{IPG}	β_{UI}	β_{DEI}	β_{TERM}	β_{DEF}	β_{TFP}	β_{LIG}	β_{CSG}
Raw corr	−0.06	0.08	0.06	0.04	0.00	−0.03	−0.07	0.08
Rank corr	−0.06	0.08	0.05	0.03	−0.00	−0.02	−0.05	0.10
	β_{CG}	β_{UCG}	β_{CAY}	β_{VOL}	β_{VIX}	β_{VRP}	β_{GDP}	β_{UNPR}
Raw corr	0.03	0.05	−0.03	−0.04	0.00	−0.15	0.00	−0.04
Rank corr	0.03	0.05	−0.02	−0.04	0.00	−0.10	0.01	−0.04

Table 8 Low-PEAR-beta premiums in high and low sentiment periods

This table reports the monthly average excess returns and FF5 alphas (in %) of PEAR-beta (β_{PEAR}) decile portfolios in high and low sentiment periods. We consider four indexes as the proxy for investor sentiment, including Baker and Wurgler (2006) sentiment index, Michigan consumer sentiment index, AAII bull-bear index, and PEAR itself. A month is defined as a high sentiment month if the sentiment index in the previous month is above its median. P1 and P10 refer to the low and high β_{PEAR} portfolios, and L-H refers to their difference. All portfolios are value-weighted and rebalanced at a month frequency. Reported in parentheses are t-values. The sample period is 1983:06–2019:12.

	Low sentiment	High sentiment	Difference
Panel A: Baker and Wurgler (2006) sentiment index			
P1	0.91	0.45	−0.46
	(3.39)	(2.12)	(−1.45)
P10	−0.40	−0.31	0.09
	(−1.66)	(−1.60)	(0.30)
LS	1.32	0.76	−0.55
	(3.61)	(2.50)	(−1.24)
Panel B: Michigan consumer sentiment index			
P1	0.46	0.71	0.25
	(2.11)	(2.94)	(0.83)
P10	−0.12	−0.53	−0.41
	(−0.48)	(−2.86)	(−1.38)
LS	0.58	1.23	0.66
	(1.66)	(3.92)	(1.47)
Panel C: AAII bull-bear index			
P1	0.56	0.64	0.09
	(2.26)	(2.60)	(0.27)
P10	−0.52	−0.32	0.20
	(−2.29)	(−1.42)	(0.66)
LS	1.08	0.96	−0.12
	(3.10)	(2.73)	(−0.25)
Panel D: PEAR			
P1	0.16	1.08	0.92
	(0.84)	(3.92)	(2.98)
P10	−0.19	−0.53	−0.34
	(−0.98)	(−2.30)	(−1.14)
LS	0.35	1.61	1.26
	(1.26)	(4.20)	(2.75)

Table 9 PEAR beta and presidential alignment

This table reports the results of PEAR beta reflecting a new type of sentiment. In Panel A, at the end of each month, we split the past 60 months into two sub-samples, one coming from months when the current president is in power and the other from months when the previous president is in power (with a requirement of at least 12 observations), and then estimate a current president beta and a previous president beta for each firm accordingly. In Panel B, we run Fama-MacBeth regressions of measures of analyst reaction and three-day cumulative abnormal return (CAR, in %) around earnings announcement days (Edays) on the past PEAR beta (β_{PEAR}) as well as firm-specific characteristics (same as model 2 in Table 6). The measures of analyst reaction include analyst forecast errors (AFE_{t+12}, in%), revisions in long-term growth rate forecasts ($\Delta\text{LTG}_{t+12} = \text{LTG}_{t+12} - \text{LTG}_t$, in %), and revisions in analyst recommendations ($\Delta\text{Rec}_{t+12} = \text{Rec}_{t+12} - \text{Rec}_t$, in %). The CARs' results, adjusted by Daniel et al. (1997) characteristics-matched benchmark returns, are at the quarterly frequency and based on the quarter-end month PEAR betas. In Panel C, we sort stocks into two subgroups based on their abnormal Google search volume or abnormal trading volume, and explore the low-PEAR-beta premium within each subgroup. The constructions of the abnormal Google search volume and abnormal trading volume follow Da, Engelberg, and Gao (2011) and Gervais, Kaniel, and Mingelgrin (2001), respectively. Reported in Panels A and C are the FF5 alphas. The sample period is 1983:06–2019:12, expect for analyst recommendations being 1994:12–2019:12 and abnormal Google search volume being 2004:04–2019:12.

Panel A: Low-PEAR-beta premiums constructed by current and previous president betas

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	L-H
Current	0.47	0.26	0.03	0.03	−0.04	−0.12	−0.16	0.03	−0.01	−0.21	0.69
	(3.15)	(2.19)	(0.28)	(0.43)	(−0.47)	(−1.37)	(−1.93)	(0.26)	(−0.11)	(−1.50)	(3.42)
Previous	−0.13	0.11	0.01	−0.14	0.08	−0.01	−0.03	0.11	0.15	−0.08	−0.04
	(−0.78)	(0.80)	(0.13)	(−1.51)	(0.92)	(−0.06)	(−0.29)	(0.77)	(0.97)	(−0.40)	(−0.16)

Panel B: Analyst reactions and CARs around Edays

	AFE_{t+12}	ΔLTG_{t+12}	ΔRec_{t+12}	CAR_{q+1}	CAR_{q+2}	CAR_{q+3}
β_{PEAR}	-0.76^{***}	-0.07^{**}	-0.11^{*}	-0.07^{***}	-0.06^{***}	-0.04^{*}
	(−3.71)	(−2.37)	(−1.84)	(−3.25)	(−2.97)	(−1.79)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.048	0.061	0.065	0.010	0.008	0.009

Panel C: Low-PEAR-beta premiums among low and high attention stocks

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	L-H
					Abnormal Google search volume						
Low	0.43	0.36	0.09	−0.15	0.13	−0.17	−0.06	−0.32	−0.05	−0.55	0.98
	(1.63)	(1.75)	(0.61)	(−1.23)	(1.04)	(−1.52)	(−0.49)	(−1.89)	(−0.26)	(−2.33)	(2.97)
High	−0.06	0.40	0.01	0.31	−0.15	−0.02	−0.20	−0.07	0.06	−0.53	0.47
	(−0.23)	(2.14)	(0.09)	(2.61)	(−1.31)	(−0.17)	(−1.53)	(−0.45)	(0.36)	(−2.18)	(1.38)
					Abnormal trading volume						
Low	0.48	−0.03	−0.07	−0.13	−0.40	−0.38	−0.41	−0.37	−0.23	−0.80	1.28
	(2.32)	(−0.22)	(−0.53)	(−1.25)	(−3.37)	(−3.22)	(−3.28)	(−2.53)	(−1.28)	(−4.45)	(4.50)
High	0.62	0.36	0.12	0.09	0.09	−0.03	0.06	0.12	0.08	−0.19	0.81
	(3.31)	(2.76)	(1.23)	(0.91)	(1.03)	(−0.57)	(0.55)	(0.67)	(0.63)	(−1.04)	(2.87)

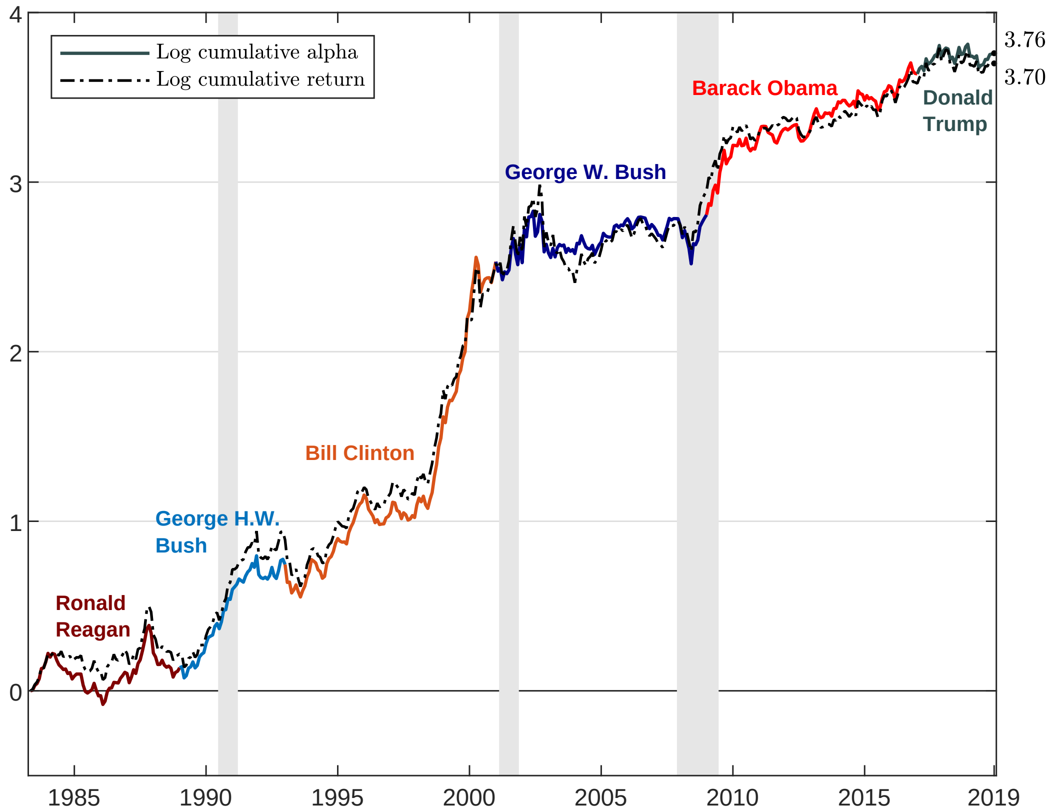

Figure 2: Log cumulative return and alpha of the PEAR-beta spread portfolio

This figure plots the log cumulative return and FF5 alpha of the PEAR-beta spread portfolio. The sample period is 1983:06-2019:12.

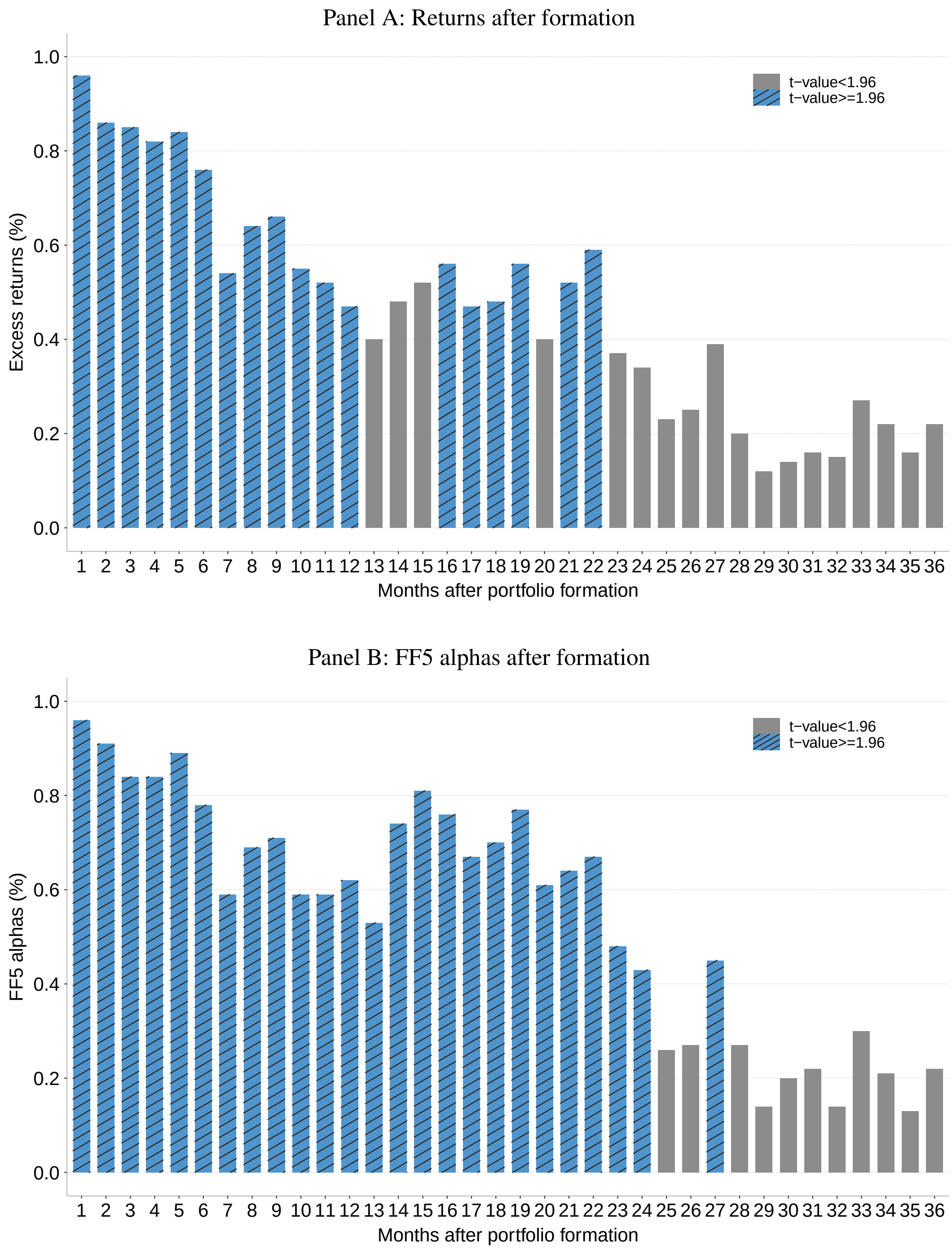

Figure 3: PEAR-beta spread portfolio performance after formation

This figure plots the average excess returns (Panel A) and FF5 alphas (Panel B) of the PEAR-beta spread portfolio after formation. Grey (blue) indicates that the t-value is smaller (larger) than 1.96. The sample period is 1983:06–2019:12.

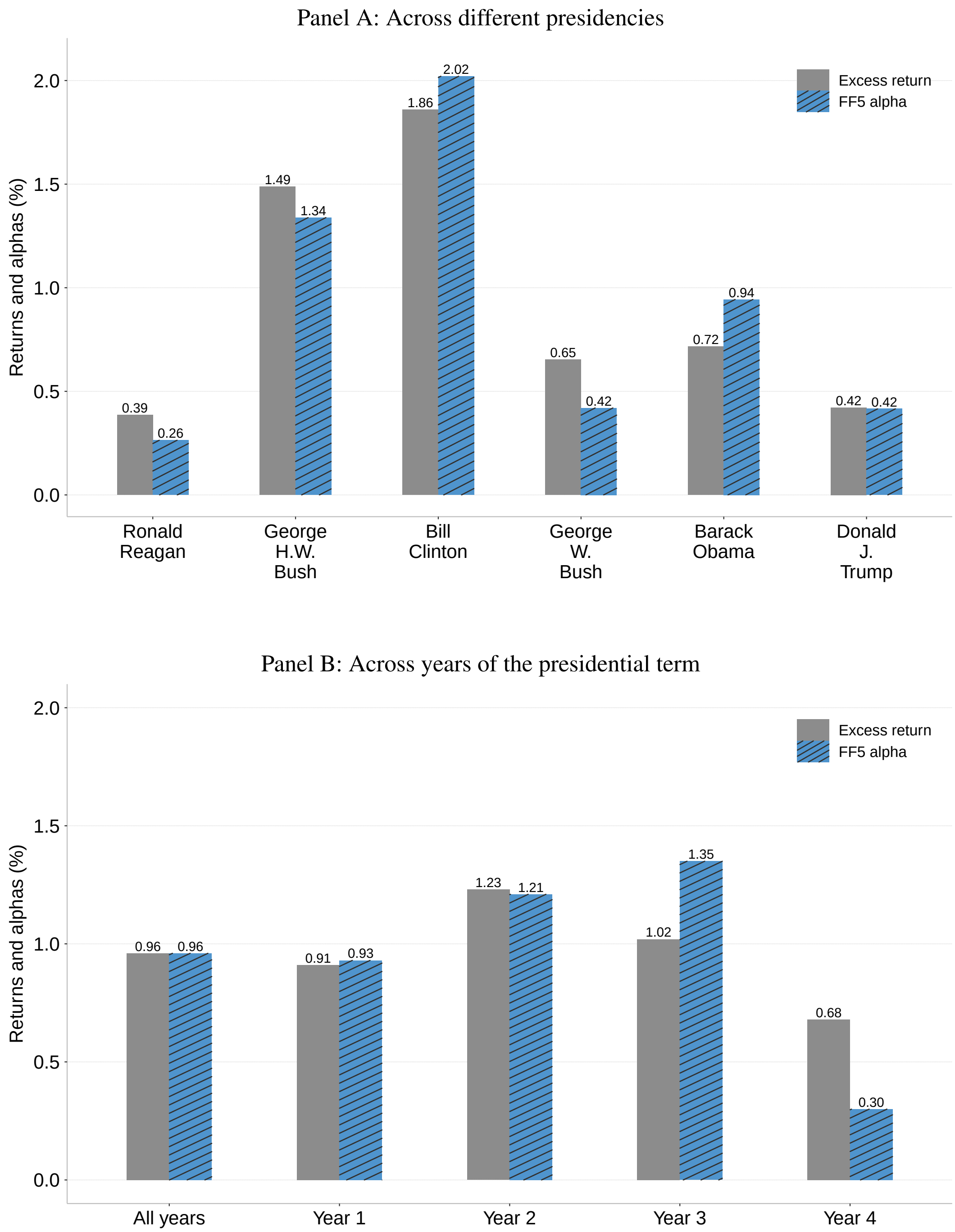

Figure 4: Low-PEAR-beta premiums over president cycles

This figure plots the monthly average excess returns and FF5 alphas of the PEAR-beta spread portfolio across different presidents (Panel A) and across years of the president term (Panel B). The sample period is 1983:06-2019:12.

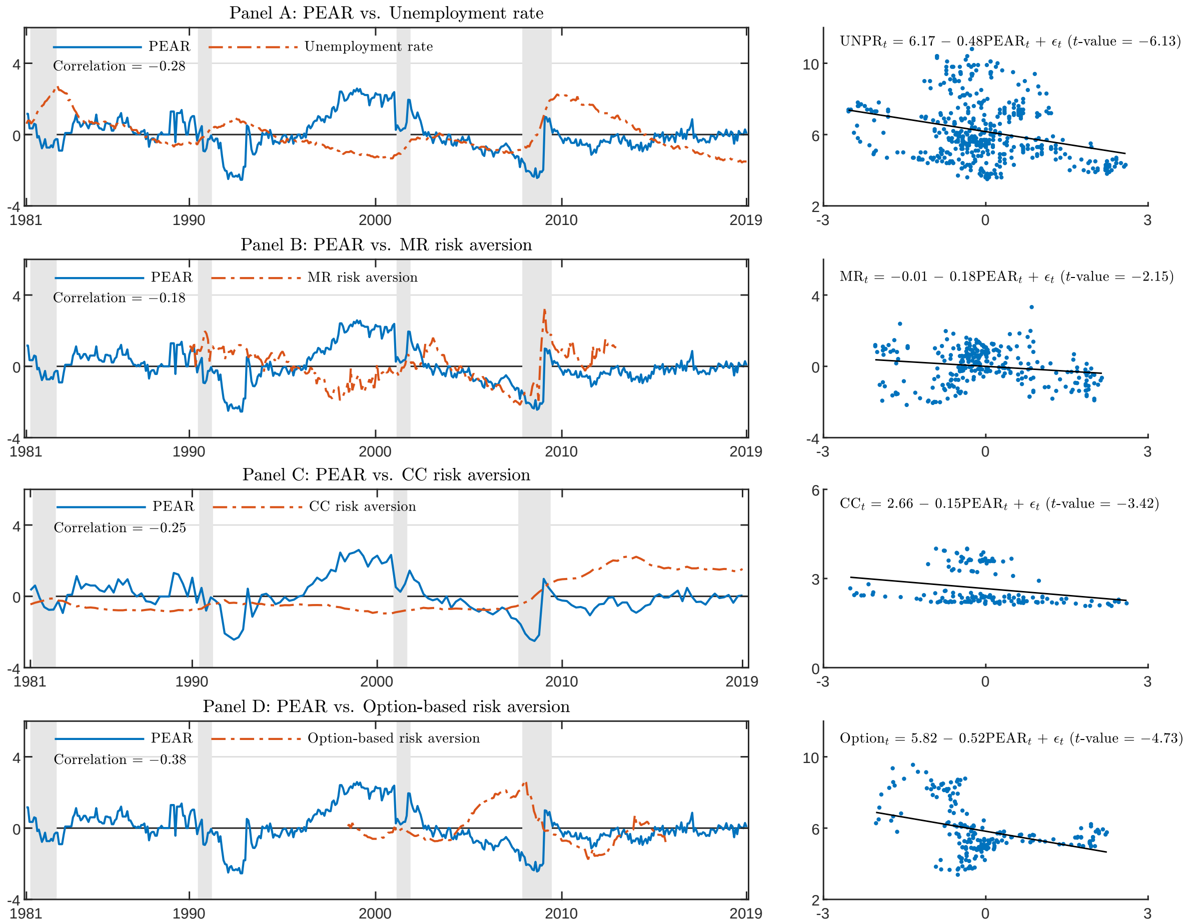

Figure 5: PEAR vs. risk aversion

This figure plots the time series dynamics and scatter diagrams of PEAR and risk aversion. We consider four risk aversion measures, including unemployment rate (UNPR) (Pastor and Veronesi, 2020), aggregate risk aversion (MR, Miranda-Agrippino and Rey, 2020), negative of surplus consumption ratio (CC, Campbell and Cochrane, 1999), and option-based risk aversion (Option) (Faccini et al., 2019). The sample period is 1981:04–2019:12 for UNPR and CC, 1990:01–2012:12 for MR, and 1998:07–2015:08 for the option-based risk aversion.

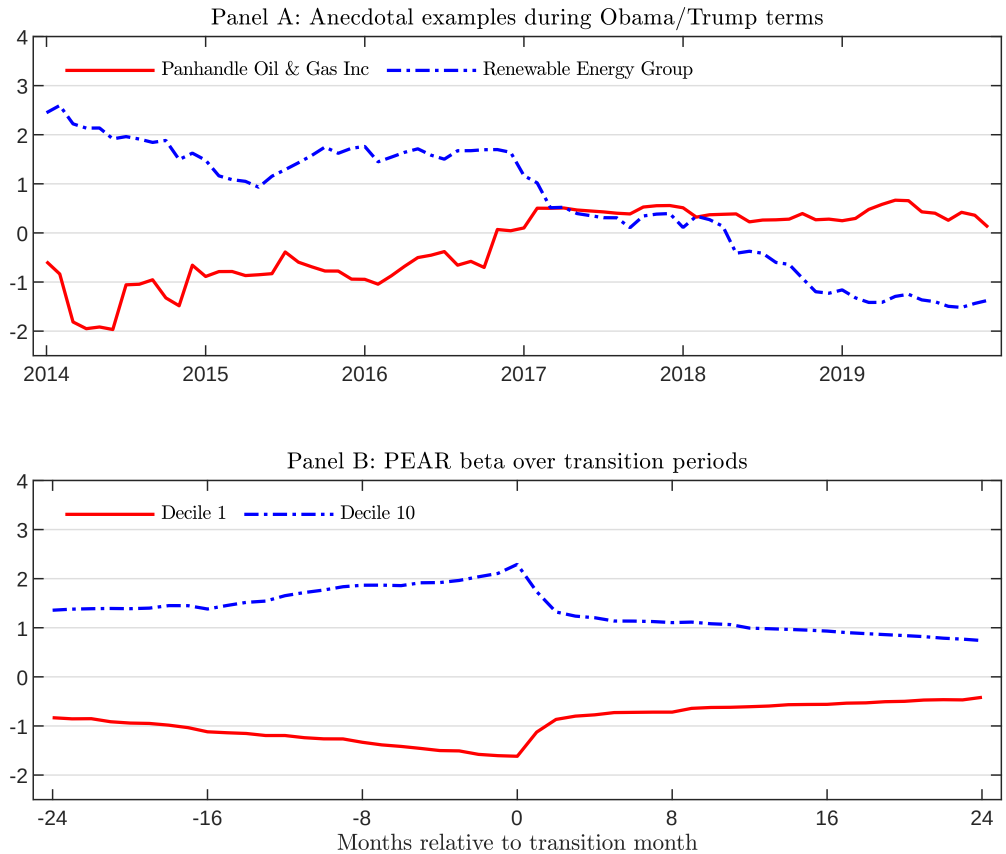

Figure 6: Trend of PEAR beta

Panel A plots the PEAR betas of two anecdotal examples (Panhandle Oil & Gas Inc. vs. Renewable Energy Group) during Obama's and Trump's terms. Panel B plots the average values of PEAR beta in portfolio decile 1 and decile 10 around the presidential transition months. The sample period is 1983:05-2019:12.

Appendix A: Additional Tables and Figures

Table A1 Data sources of PEAR

This table reports the summary statistics of the survey data used to construct our PEAR index. Reported are polling organization name, sample period, the total number of polling results, and the typical question wording of each polling organization. In total, there are 21 polling organizations with 1,713 polling results included in the sample.

Survey organization	Period	*N*	Typical question wording
ABC News	1981:09-2003:09	22	Do you approve or disapprove of the way Ronald Reagan/(George) Bush/(Bill) Clinton/(George W.) Bush is handling the nation's economy?
ABC News/Washington Post	1981:10-2019:09	203	Do you approve or disapprove of the way Reagan/(President George) Bush/(Bill) Clinton/(George W.) Bush/(Barack) Obama/(Donald) Trump is handling the economy?
American Research Group	2001:07-2019:12	210	Do you approve or disapprove of the way George W. Bush/Barack Obama/Donald Trump is handling the economy?
The Associated Press-NORC Center for Public Affairs Research	2002:11-2019:10	12	Overall, do you approve, disapprove, or neither approve nor disapprove of the way George W. Bush/Barack Obama/Donald Trump is handling the economy?
CBS News	1991:01-2019:05	150	How about the economy? Do you approve or disapprove of the way George Bush/Bill Clinton/George W. Bush/Barack Obama/Donald Trump is handling the economy?
CBS News/New York Times	1981:04-2016:07	196	Do you approve or disapprove of the way Ronald Reagan/Bill Clinton/George W. Bush/Barack Obama is handling the economy?
Consumer News and Business Channel (CNBC)	2009:12-2019:12	11	Do you generally approve or disapprove of the way Barack Obama/Donald Trump is handling the economy?
Cable News Network (CNN)	2006:05-2019:11	58	Do you approve or disapprove of the way George W. Bush/Barack Obama/Donald Trump is handling the economy?
FOX news (FOX)	2017:03-2019:09	21	Do you approve or disapprove of the way Donald Trump is handling... the economy?

Table A1 (continued)

Survey organization	Period	*N*	Typical question wording
Gallup Organization	1992:01-2019:11	169	Do you approve or disapprove of the way President Reagan/Bush/Bill Clinton/George W. Bush/Barack Obama/ Donald Trump is handling the economy?
Gesellschaft fr Konsumforschung (CfK)	2009:02-2018:10	43	Overall, do you approve, disapprove, or neither approve nor disapprove of the way Barack Obama/Donald Trump is handling... the economy?
Greenberg	2005:07-2011:05	11	Do you approve or disapprove of the way George (W.) Bush/Barack Obama is handling the economy?
Ipsos	2002:01-2008:07	139	And when it comes to handling the economy, do you approve or disapprove or have mixed feelings about the way George W. Bush is handling that issue?
Los Angeles Times	1981:04-2008:05	56	Do you approve or disapprove of the way Ronald Reagan/(Bill) Clinton/George W. Bush is handling the economy?
Marist College Institute for Public Opinion	2003:04-2019:09	32	Do you approve of disapprove of how President George (W.) Bush/Barack Obama/Donald Trump is handling the economy?
NBC News/Wall Street Journal	1988:07-2019:08	183	Do you generally approve or disapprove of the job Ronald Reagan/George Bush/Bill Clinton/Barack Obama/Donald Trump is doing in handling the economy?
Princeton Survey Research Associates	1994:10-2017:02	92	Do you approve or disapprove of the way Bill Clinton/George W. Bush/Barack Obama/Donald Trump is handling the economy?
Quinnipiac University Polling Institute	2002:02-2019:12	64	Do you approve or disapprove of the way George W. Bush/Barack Obama/Donald Trump is handling the economy?
The Tarrance Group	1994:01-2003:09	8	Do you approve or disapprove of the way President George W. Bush/Bill Clinton is handling the economy?
Time magazine	2004:04-2013:06	25	Do you approve or disapprove of the job President (George W.) Bush/(Barack) Obama is doing in each of these areas... handling the economy
Washington Post	1990:03-2010:03	8	Do you approve of the way (Bill) Clinton/(George W.) Bush/(Barack) Obama is handling... the economy?

Table A2 Variable definitions

This table describes the constructions of main variables used in this paper.

Variable	Description
Other betas	
CAPM beta (β_{CAPM})	We estimate the market beta using a 60-month rolling window, with the requirement of at least 24 months of data are available (Fama and French, 1992).
Sentiment beta (β_{BW})	We estimate the sentiment beta using changes and lagged changes of the Baker and Wurgler (2006) sentiment index in a 60-month rolling window, with the requirement of at least 24 months of data are available (Chen, Han, and Pan, 2020).
UNC beta (β_{UNC})	We estimate the UNC beta using 60-month rolling regressions of excess stock returns on UNC index together with market, size, book-to-market, momentum, liquidity, investment, and profitability factors, with the requirement of at least 24 months of data are available (Bali, Brown, and Tang, 2017).
Political variables	
Political alignment index (PAI)	PAI is calculated as the degree of a state's governor, control of its legislature, and the bulk of its members in Congress aligned with the presidential party (Kim, Pantzalis, and Park, 2012).
Political sensitivity (PS)	PS is estimated using the 15-year monthly rolling regressions of Fama and French (1997) 48 industry value-weighted excess returns on market excess return and a Republican dummy (Addoum and Kumar, 2016).
Political connectedness (PC)	PC is defined as a dummy variable which equals to one if a firm makes a contribution to a PAC (regardless of party affiliation) in the last 5 years and zero otherwise (Cooper, Gulen, and Ovtchinnikov, 2010; Addoum and Kumar, 2016).
Government spending exposure (GSE)	GSE is calculated as the proportion of an industry's total output (3-digit SIC) being purchased by the government sector for final use (Belo, Gala, and Li, 2013).
Analyst variables	
Analyst earnings forecast revisions (AFE)	The difference between actual reported earnings and the consensus earnings forecast, scaled by the closing stock price in the previous month.
Revision in analyst recommendations (ΔRec)	The difference between the current consensus recommendation and its value over one previous month.
Revision in long-term growth rate forecasts (ΔLTG)	The difference between the current consensus long-term growth rate forecast and its value over one previous month.

Table A2 (continued)

Variable	Description
Other anomaly variables	
Size	The logarithm of the product of price per share and the number of shares outstanding (in millions of dollars).
Book-to-market ratio (BM)	The book value of shareholder equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stocks at the end of fiscal year $t-1$, scaled by the market value at the end of December of year $t-1$ (Fama and French, 1992).
Momentum (MOM)	The cumulative return of a stock over a 11-month window ending one month before the portfolio formation (Jegadeesh and Titman, 1993).
Short-term reversal (STR)	The return of a stock over the prior month (Jegadeesh, 1990).
Idiosyncratic volatility (IVOL)	The standard deviation of a stock's daily idiosyncratic returns relative to the Fama and French (1993) three-factor model over the prior month (Ang et al., 2006).
Illiquidity ratio (ILLIQ)	The ratio of the daily absolute stock return to the daily dollar trading volume averaged in the prior month (Amihud, 2002).
Failure probability (Distress)	Distress is defined as $-9.164 - 0.058 * \text{PRICE} + 0.075 * \text{MB} - 2.13 * \text{CASHMTA} - 0.045 * \text{RSIZE} + 1.41 * \text{IdioRisk} - 7.13 * \text{EXRETAVG} + 1.42 * \text{TLMTA} - 20.26 * \text{NIMTAAVG}$, where all other variables are calculated following Campbell, Hilscher, and Szilagyi (2008).
Other variables	
Trade intensity	Sum of bilateral trade (imports and exports) between each country and the US divided by the sum of their GDPs (Frankel and Rose, 1998).

Table A3 Summary statistics of polling results from top 6 agents

This table reports the summary statistics of the polling results from the top six agents. For the first six columns, the upper triangular area reports the correlation of polling results between each pair of six agents, and the lower triangular area denotes which agent's polling results are statistically higher than the paired agent's results with the difference indicated in the bracket. The last two columns reports the correlations of polling results between each of six agents and the benchmark PEAR index as well as the PEAR index ($PEAR_6$) constructed using polls from top six agents [the missing values are filled by using the dyad ratios algorithm of Stimson (1999)].

Agents	ABCWP	ARG	CBS	CBSNYT	Gallup	NBCWSJ	PEAR	$PEAR_6$
ABCWP		0.80	0.91	0.95	0.92	0.94	0.97	0.97
ARG	ABCWP (3.7)		0.71	0.86	0.73	0.87	0.88	0.96
CBS	ABCWP (3.9)			0.93	0.93	0.96	0.97	0.95
CBSNYT					0.93	0.96	0.98	0.98
Gallup						0.96	0.97	0.94
NBCWSJ		NBCWSJ (3.0)					0.99	0.98

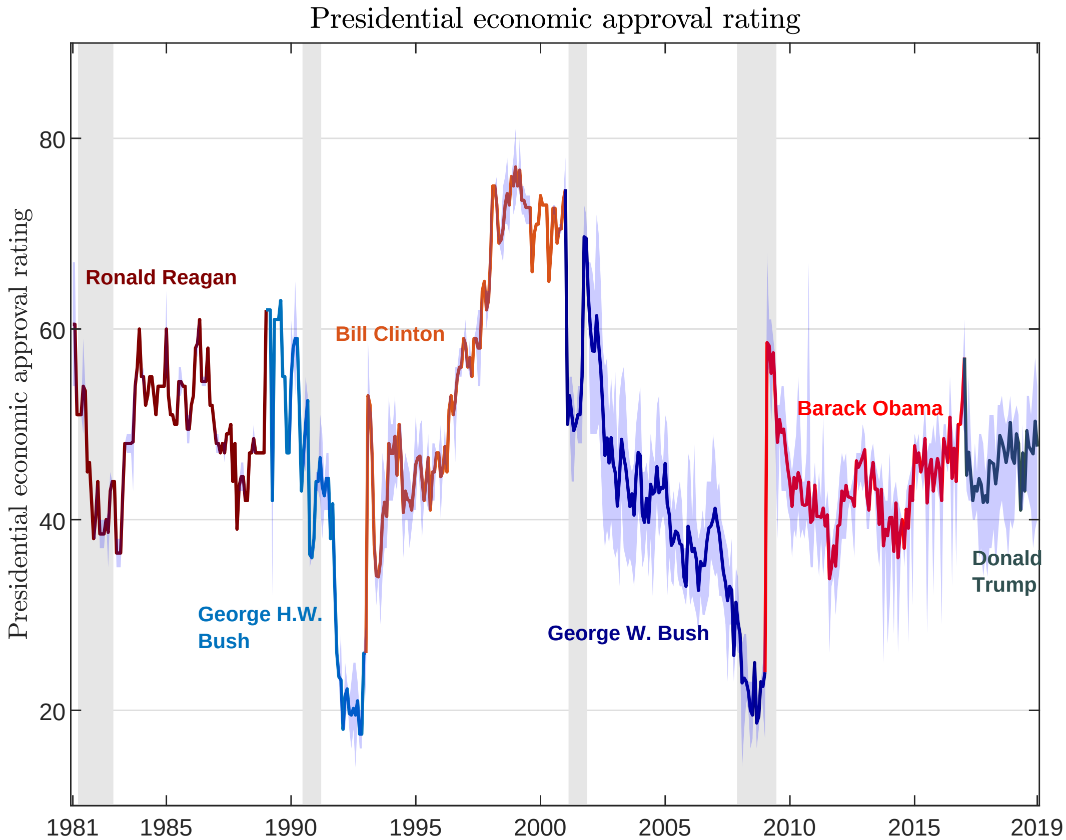

Figure A1: PEAR

This figure depicts the presidential economic approval rating (PEAR) from 1981:04 to 2019:12, with the upper and lower bounds presented in the shaded area.

Appendix B: A Stylized Model of Investor Sentiment towards Presidential Alignment

We consider an economy with three dates, $t = 0, 1, 2$. There are N risky assets with supplies zero and one risk-free asset with return zero. At date 2, the risky assets deliver dividends $d = (d_1, \cdots, d_N)'$, which follow a one factor structure such that, for each i,

$$d_i = \theta_i f + \varepsilon_i, \; i = 1, \cdots, N, \tag{A1}$$

where θ_i is the loading of d_i on f, $f \sim N(0, \sigma_f^2)$, $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$, and f, ε_1 through ε_N are mutually uncorrelated. In matrix notation, we write $d \sim N(0, \Sigma)$ with $\Sigma = \sigma_f^2 \theta\theta' + \Sigma_\varepsilon$, where $\theta = (\theta_1, \cdots, \theta_N)'$ and Σ_ε is a diagonal matrix with each diagonal entry σ_ε^2.

There are two types of agents in the market: rational investors (labelled as r) and sentiment investors (labelled as s). Sentiment investors account for a fraction m of the economy, while rational investors account for the remaining $1 - m$. Both types of investors have a CARA utility over their end-of-period consumption,

$$U_j(C_j) = \mathrm{E}_j(C_j) - \frac{\gamma}{2}\mathrm{Var}_j(C_j),$$

where $j \in \{r, s\}$ and γ is the coefficient of risk-aversion.

At date 0, all investors correctly price and trade each risky asset i at $p_{0,i} = 0$.

At date 1, all investor observe a fundamental signal $g = f + e$ with $e \sim N(0, \sigma_e^2)$, and a presidential economic approval rating (PEAR) $z \in [0, 1]$, where $z = 0$ indicates that no respondent approves the current president's handling of the economy, whereas $z = 1$ indicates that all respondents approve. Assume that z does not provide any additional information for d, i.e., $\mathrm{Cov}(z, g) = 0$ and $\mathrm{Cov}(z, \varepsilon_i) = 0$ for $i = 1, \cdots, N$.[8] Rational investors correctly ignore z and update

[8] We assume $\mathrm{Cov}(z, g) = 0$ without loss of generality. Alternatively, we could assume $z = g + \eta$ where η is uncorrelated with all other variables. The main implications of the model remain unchanged. The key is that z does not provide any additional information for d above and beyond g.

their beliefs as

$$\mathrm{E}_r[d|g] = \theta\lambda g, \tag{A2}$$

where $\lambda = \sigma_f^2/(\sigma_f^2 + \sigma_e^2)$. In contrast, sentiment investors incorporate z into their beliefs as

$$\mathrm{E}_s[d|g,z] = \theta\lambda g + bz, \tag{A3}$$

where $b_1 \leq \cdots \leq b_N$ ($b_1 < b_N$) are the sensitivities of the N risky assets to z. b can be thought of as assets' presidential alignments. Sentiment investors are too optimistic regarding the future cash flows of assets aligned well with the current president's economic policies ($b_i > 0$), especially when such policies are more popular. In contrast, they are too pessimistic on assets with negative b.

Suppose the N risky asset prices at time 1 are p_1. At the equilibrium, the rational investors' demand is

$$w_r = \frac{1}{\gamma}\Sigma^{-1}(\theta\lambda g - p_1). \tag{A4}$$

The sentiment investors' demand is

$$w_s = \frac{1}{\gamma}\Sigma^{-1}(\theta\lambda g + bz - p_1). \tag{A5}$$

With the market clearing condition,

$$(1-m)w_r + mw_s = 0, \tag{A6}$$

we have

$$p_1 = \theta\lambda g + mzb. \tag{A7}$$

Hence, when there is no sentiment investor ($m = 0$) or respondents disapprove the president's handling of the economy ($z = 0$), there is no mispiricing. Otherwise, asset i, $i \in \{1, \cdots, N\}$, can be either overpriced with $b_i > 0$ or underpriced with $b_i < 0$.

Now we define the return of asset i from date 0 to date 1 (given that the risk-free rate is 0) as

$$R_{1,i} = p_{1,i} - p_{0,i} = \theta_i \lambda g + mzb_i. \tag{A8}$$

The PEAR-beta is

$$\beta_{\text{PEAR},i} = \frac{\text{Cov}(R_i, z)}{\text{Var}(z)} = mb_i. \tag{A9}$$

The return of asset i from date 1 to date 2 is

$$R_{2,i} = d_i - p_{1,i} = d_i - \theta_i \lambda g - mzb_i = \theta_i f + \varepsilon_i - \theta_i \lambda g - z\beta_{\text{PEAR},i}. \tag{A10}$$

Suppose the low-PEAR-beta strategy is constructed by buying the lowest PEAR-beta stock and selling the highest PEAR-beta stock. The expected return of this strategy at date 1 is

$$\text{E}(R_{\text{PEAR},2}) = mz(b_N - b_1) = z(\beta_{\text{PEAR},N} - \beta_{\text{PEAR},1}). \tag{A11}$$

Thus, Equations (A10) and (A11) generate two implications.

1. The higher the PEAR-beta, the lower the stock return.
2. The higher the PEAR index, the higher the low-PEAR-beta premium.

Table 3 confirms implication 1 and Table 8 confirms implication 2.