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Presidential economic approval rating and the cross-section of stock returns $\!\!\!\!^{\star}$

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ABSTRACT

We construct a monthly presidential economic approval rating (PEAR) index from 1981 to 2019, by averaging ratings on the 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 1.00% 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 and even in other G7 countries. PEAR beta dynamically reveals a firm's perceived alignment to the incumbent president's economic policies and investors seem to misprice such an alignment.

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1. Introduction

Presidential politics have a first-order effect on asset prices. A long strand of literature has documented and examined a time-series presidential puzzle, or the striking empirical fact that stock market returns are much higher under Democratic presidencies than Republican ones (see,





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Presidential economic approval rating vs. Presidential job approval rating

Fig. 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.

e.g., Huang, 1985; Hensel and Ziemba, 1995; Santa-Clara and Valkanov, 2003; Pastor and Veronesi, 2020). Would exposures to presidential politics affect stock returns in the cross-section? We study this important question in this paper.

We start by constructing a monthly presidential economic approval rating (PEAR) index from 1981 to 2019, by averaging approval ratings on the president's handling of the economy across various national polls.¹ The monthly index is plotted in Fig. 1, together with the Gallup presidential 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 attacks, and President Trump's initial tenure. Empirically, we find that the PEAR index generates stronger cross-sectional asset pricing results, consistent with the phrase "the economy, stupid", popularized during Bill Clinton's successful 1992 presidential campaign. PEAR appears to be procyclical, and is therefore inversely related to measures of aggregate risk aversion.

Surprisingly, in the cross-section, we document a low PEAR beta premium: stocks with high betas to changes in PEAR significantly underperform those with low betas by 1.00% 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 perform worse precisely when aggregate risk aversion increases (or when PEAR decreases), they are riskier and should earn higher returns on average. Because the PEAR index might be correlated with economic conditions, we calculate PEAR beta by controlling for a set of macroeconomic variables, including the effective federal funds rate, coincident economic indicator, total monetary base, and stock market return (Williams, 1990; De Boef and Kellstedt, 2004). Further controlling for a more comprehensive list of macroeconomic variables does not qualitatively change our results.²

The low PEAR beta premium is extremely robust.³ It survives various factor-based and characteristic-based risk adjustments. It is not driven by any particular sub-samples. 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

² When the rolling window for the beta estimation includes a presidential party transition, the resulting PEAR beta will mix up the economic policies from opposing political parties. To avoid such a mix-up, we make an adjustment in our baseline PEAR beta estimation by using data during the term of a previous president from the same party. Nevertheless, we confirm that the standard rolling-window PEAR beta gives similar results, with the corresponding low PEAR beta premium of 1.00% per month on a risk-adjusted basis.

¹ The PEAR index can be downloaded from the authors' webpages.

³ Premium is used for ease of exposition, and it does not necessarily mean compensation for risk taking.

after removing the presidential transition periods (twelve 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 PEAR beta and different methods for computing innovations in PEAR. Finally, it 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 have differential exposures to presidential policies and government spending (see, e.g., Belo et al., 2013; Addoum and Kumar, 2016, among others), which result in predictable variations in industry portfolio returns across political cycles. The low PEAR beta premium is not driven by such 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 regressions, we control for a comprehensive set of return predictors which we group into three categories. The first category includes alternative measures of beta, such as market beta, the beta on the macroeconomic uncertainty of Jurado et al. (2015), and the beta on the (Baker and Wurgler, 2006) sentiment index (Chen et al., 2021). The second category includes variables related to government and politics. They are the political alignment index (Kim et al., 2012), political sensitivity (Addoum and Kumar, 2016), political connectedness (Cooper et al., 2010), and government spending exposure (Belo et al., 2013). The third category includes other firm characteristics such as size, book-to-market, momentum, short-term reversal, idiosyncratic volatility, illiquidity, and distress. None of these return predictors is highly correlated with the PEAR beta. Not surprisingly, the coefficient on PEAR beta remains negative and significant, even after simultaneously including all the control variables and industry fixed effects. Its magnitude is half of its counterpart in a univariate regression, suggesting that all the other variables, even when combined, explain at most half of the low PEAR beta premium.

Intuitively, PEAR beta measures a firm's perceived alignment to the economic policies of the incumbent president. The business of a positive PEAR beta firm must align well with the incumbent president's economic policies, so its stock price moves in tandem with the economic policies' approval rating. Some investors could have biased cash flow expectations for firms with extreme PEAR betas. In Appendix B, 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 the current president's economic policies, especially when the PEAR index is high as the index in the model proxies for the fraction of sentiment investors in the economy. At the same time, they underestimate the future earnings of negative PEAR beta firms. If risk-averse rational investors in the economy cannot fully correct such biases, the market-clearing price becomes too high (low) for positive (negative) PEAR beta firms. In the model, PEAR beta therefore becomes a self-revealed and dynamic measure of a firm's perceived alignment with the current presidential economic policies. 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 periods which we confirm in the data.

We document several pieces of supporting evidence for the mispricing-based explanation. First, if we compute PEAR beta using only months in the five-year rolling window when a former president was in power, the low PEAR beta premium ceases to be significant, highlighting the importance of alignment to the incumbent president's economic policies.

Second, consistent with the bias in cash flow expectation, we find PEAR beta to positively predict analyst forecast errors, and negatively predict future revisions in their long-term growth (LTG) forecasts as well as future revisions in the price target growth (PTG) forecasts.⁴ In addition, PEAR beta negatively predicts future earnings announcement returns. This evidence suggests that both analysts and investors are initially too optimistic (pessimistic) in forecasting high (low) PEAR beta stocks' cash flows. Portfolio analysis confirms that the majority of the low PEAR beta premium accrues on earnings announcement days, consistent with the notion that the realization of earnings corrects mispricing. Also, we find a significant positive correlation (0.19, t-statistic = 2.01) between the absolute change in PEAR index and retail turnover across all stocks. The correlation is even stronger (0.24, *t*-statistic = 2.50) for high PEAR-beta stocks, which are preferred by the sentiment investors, consistent with the mispricing explanation.

Finally, we investigate several alternative explanations for the low PEAR beta premium and find none to be satisfactory. For example, while the low PEAR beta premium cannot be explained by exposure to time-varying risk aversion, it could reflect exposure to other macroeconomic risk factors. We examine a large set of macro variables,⁵ and find that they are weakly correlated with the change in PEAR. Even the highest correlation (in absolute value) is only 0.16 (with the consumption growth). As a result, PEAR beta is not highly correlated with the betas on these macro variables. 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 regressions hardly changes the coefficient of PEAR beta, consistent with the findings in Shen et al. (2017) that the ex-

⁴ This relationship also holds at the aggregate level: the contemporaneous correlations between the level of PEAR and aggregate analyst expectations are positive and significant, but decay to zero over time.

⁵ The macro variables we examine include consumption to wealth ratio, consumption growth, capital share (Lettau et al., 2019), default premium, change in expected inflation, real GDP, industrial production index, labor income growth, term premium, total factor productivity growth, ultimate consumption growth (Parker and Julliard, 2005), unexpected inflation, unemployment rate, VIX, aggregate market volatility, variance risk premium, total monetary base, the Chicago Fed National Activity Index, CPI, CPI excluding food and energy, CPI for energy, CPI for food, the effective federal funds rate, 10-year Treasury rate, 3-month Treasury bill rate, market return, crude oil price, natural gas price, total nonfarm payroll, and the Coincident Economic Activity Index.



Fig. 2. Low PEAR beta premium: Cumulative performance. This figure plots the log cumulative return and FF5 alpha of the PEAR beta spread portfolio. The sample period is 1983:06–2019:12.

posure to macroeconomic risks generally does not explain the cross-sectional variation in average stock returns very well. One remaining question is if the PEAR index reflects expectations on the macro economy considering its strong relation with the cross-sectional stock return in the financial market but low correlations with macro factors. We employ a comprehensive set of macro expectations from various sources and examine their correlations with the PEAR index, and find that the level of PEAR index is highly correlated with several macro variables' expectations (correlations are typically around 0.5 in absolute term). However, the correlations between the change in PEAR and the changes of these macro expectations are generally lower than 0.2 (in absolute term). Controlling for these macro expectations does not affect the return predictability of PEAR beta either. Hence, the PEAR index contains unique information about asset prices that are independent of realized or expected macro factors.

Is it possible that presidential alignment leads to a government bailout during bad times? If so, a high PEAR beta stock can 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 et al., 2006). Yet, our sample excludes financial companies and the high PEAR beta stocks are generally not mega-cap stocks. Additional evidence does not support such a "hedging" story either. During bad times, as indicated by NBER-dated recessions, high PEAR beta firms earn even lower returns than low PEAR beta firms, inconsistent with the notion of receiving a bailout. In addition, PEAR beta has a low correlation with the measure of financial distress (Campbell et al., 2008). Controlling for the distress risk does not alter the low PEAR beta premium.

To the extent that PEAR captures consumer confidence (De Boef and Kellstedt, 2004; Lemmon and Portniaguina, 2006), high PEAR beta stocks could suffer from sentimentinduced overpricing, explaining their subsequent low returns when their overpricing gets corrected. Empirically, Stambaugh et al. (2015) find the long-short anomaly returns 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 (2006) sentiment index. (2) Michigan consumer sentiment index, (3) AAII bull-bear index, and (4) the PEAR index itself. 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, inconsistent with the notion that short-sale constraints with investor sentiment explain the low PEAR beta premium.

This paper contributes to several strands of literature that connect asset pricing to politics. First, there is a strand of literature focusing on stock returns over political cycles.⁶ 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 et al. (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 participate in the stock market. We focus on presidential rather than party economic approval ratings and their implications on the crosssection of individual stock returns. Our results are obtained at the firm level, not driven by any particular president or presidential party, and 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 et al. (2010) show that donating firms earn significantly higher average and risk-adjusted stock returns. Kim et al. (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 comes 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 et al., 2016; Kelly et al., 2016; Brogaard et al., 2020), industry level (Boutchkova et al., 2012), and firm level (Hassan et al., 2019; Gorbatikov et al., 2019). The main variable of interest in this paper, PEAR, has low correlations with the proxies for political risk and political uncertainty. Different from Kelly et al. (2016) and Brogaard et al. (2020) that focus on the presidential 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., 2022). Our evidence confirms that survey data contain useful insight relevant to cross-sectional asset pricing.

2. Data and key variables

This section describes the data on PEAR and other key variables used in the 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 affairs, health policy, etc, we focus on the responses to an economy-specific question: "Do you approve or disapprove of the way (name of a 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.⁷ We conjecture that PEAR 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 2019.⁸ We do not consider a few polls irregularly conducted between 1971 and 1981. We exclude organizations conducting less than five 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 in Online Appendix 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 the president is handling the economy. We construct the PEAR index by simply averaging ap-

⁶ In the foreign exchange market, Liu and Shaliastovich (2022) show that high presidential job approval ratings forecast a decline in the dollar risk premium, a persistent increase in economic growth, and a reduction in future economic volatility. These findings are more pronounced in an intermediate horizon, 6 to 60 months. In contrast, we focus on the cross-section of stock returns and a firm's perceived alignment with the presidential economic policy. The fact that low PEAR beta stocks earn higher returns and such a premium is significant for a shorter horizon, up to 12 months, is more consistent with an interpretation based on mispricing.

⁷ The wording of this question is basically the same across polling organizations, while the predefined responses to the question can be slightly 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 (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.

⁸ 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 these polls as conducted by ABC News, The Washington Post, or both.

proval 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 four. We fill these missing entries with the previous month's 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 News/Wall Street Journal (NBCWSJ). In Online Appendix Table A2, 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 are higher than those from ARG and CBS. ARG's results are lower than those from NBCWSJ. The differences are smaller than 4% in all three cases. Persistent bias in polls will have little impact on our results as we focus on the change in rating in our analysis.

According to the Online Appendix Table A2, polling results are highly correlated among the top six agents during overlapping months. Not surprising, each of the six polling results is also highly correlated with our PEAR index. With the exception of ARG, the correlations are all higher than 0.94. In a robustness check, we also construct an alternative PEAR index (PEAR₆) using polling results from these six agents only and find similar results.⁹ Each of the six polling results is highly correlated with PEAR₆. The minimum correlation is 0.94. Overall, these diagnostics suggest that different polls are highly correlated and our findings are unlikely driven by a specific single polling agent. Fig. A1 in Online Appendix plots PEAR, 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.

Fig. 1 plots the time-series dynamics of PEAR, together with PJAR 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 attacks, and President Trump's initial tenure. The contrast between PEAR and PJAR supports the phrase "the economy, stupid," popularized during Bill Clinton's successful 1992 presidential campaign. In Section 3, we confirm that PEAR generates stronger results in asset pricing tests than PJAR does.

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 et al., 2016). All the time series are at the monthly frequency and over the April 1981 to December 2019 period, except for the quarterly aggregate political risk and sentiment being over the first quarter of 2002 to the last quarter of 2019, and political uncertainty being over January 1985 to December 2019.

Panel A of Table 1 presents the mean, median, min, max, volatility, and the first- and 12th-order autocorrelations (AR(1) and AR(12)). The PEAR index ranges from 17.5 to 77, with a mean of 46.98, 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, PJAR 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 of around 90, but a lugubrious economic approval rating of 50.

To examine the relationships between PEAR and 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 PJAR, with level correlations of 0.62 and 0.65, and change correlations of 0.07 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 in PEAR. Motivated by the political science literature that finds the PEAR index to be correlated with economic conditions (e.g., Williams, 1990; De Boef and Kellstedt, 2004), we calculate PEAR beta by controlling for a set of macroeconomic variables to isolate the information contained in PEAR that is orthogonal to the overall economic conditions.¹⁰ 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,

 $R_{i,t} = \alpha + \beta_{i,0} \Delta \text{PEAR}_t + \beta_{i,1} \Delta \text{PEAR}_{t-1} + \beta_{i,\text{Macro}} \text{Macro}_t + \varepsilon_{i,t}, \quad (1)$

where $R_{i,t}$ is the excess return of stock *i* in month *t*, and Δ PEAR_t is the change of PEAR from month t - 1 to month *t*. Macro_t consists of the change of the effective federal funds rate, log change of the Coincident Economic Activity Index, log change of total monetary base, and stock market return.¹¹ The regression includes the lagged change of

⁹ We fill in the missing values for this alternative index using the dyad ratios algorithm of <u>Stimson (1999</u>), which uses smoothing and interpolation to deal with irregular, non-balanced, and sparse panel data.

¹⁰ Williams (1990) finds that the monetary base is significantly associated with the PEAR index as politicians try to maximize their ratings and votes by manipulating the monetary policies. De Boef and Kellst-edt (2004) further show that economic conditions including the federal funds rate, coincident economic indicator index, and unemployment rate are significantly affecting the presidential economic evaluations and votes in the short and long terms. Since the unemployment rate is highly correlated with the coincident economic indicator (correlation = -0.94), we do not include the unemployment rate in the calculation of PEAR beta to avoid the potential multicollinearity issue.

¹¹ Including Macro_{t-1} in (1) generates similar results.

Summary statistics of PEAR and other related indexes. This table reports the summary statistics and the 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, 2022), aggregate political risk and sentiment (Hassan et al., 2019), and political uncertainty [measured by economic policy uncertainty in Baker et al. (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 1981:04–2019:12 period, except for investor sentiment being 1981:04–2018:12, quarterly aggregate political risk and sentiment being 2002Q1–2019Q4, and political uncertainty being 1985:01–2019:12.

Panel A: Summary stati	stics						
	Mean	Median	Min	Max	Volatility	AR(1)	AR(12)
PEAR	46.98	46.00	17.50	77.00	11.62	0.93	0.60
Consumer sentiment	87.75	90.90	55.30	112.00	11.92	0.95	0.66
Investor sentiment	0.25	0.03	-0.94	2.94	0.70	0.98	0.47
Presidential approval	51.65	50.00	27.00	89.80	11.72	0.93	0.48
Political risk	7.78	7.81	6.05	10.26	1.00	0.75	0.05
Political sentiment	4.65	4.63	1.77	6.68	1.00	0.91	0.47
Political uncertainty	108.49	83.07	44.36	370.16	75.00	0.97	0.73
Panel B: Correlations							
	PEAR	Investor	Consumer	Presidential	Political	Political	Political
		sentiment	sentiment	approval	risk	sentiment	uncertainty
Correlation between le	vels						
PEAR	1.00						
Investor sentiment	0.23***	1.00					
Consumer sentiment	0.62***	0.20***	1.00				
Presidential approval	0.65***	0.13***	0.25***	1.00			
Political risk	0.09	-0.53***	-0.46***	0.07	1.00		
Political sentiment	0.22*	0.18	0.65***	-0.36***	-0.17	1.00	
Political uncertainty	-0.23***	-0.35***	-0.59***	-0.18***	0.53***	-0.25**	1.00
Correlation between ch	anges						
PEAR	1.00						
Investor sentiment	-0.06	1.00					
Consumer sentiment	0.07	-0.04	1.00				
Presidential approval	0.23***	-0.04	0.07	1.00			
Political risk	-0.18	-0.08	-0.37***	-0.12	1.00		
Political sentiment	0.10	0.23*	0.13	-0.07	-0.29**	1.00	
Political uncertainty	0.02	0.04	-0.19***	0.15***	0.24**	-0.16	1.00

PEAR to accommodate the non-synchronicity between the timing of the survey and return measurement. Following Dimson (1979), PEAR beta, β_{PEAR} , is defined as

$$\beta_i = \beta_{i,0} + \beta_{i,1},\tag{2}$$

where we abbreviate the time subscript for brevity.

One potential issue with Eq. (1) is that when the rolling window for PEAR-beta estimation includes a presidential party transition, the resulting PEAR beta will mix up the economic policies from opposing political parties. To avoid such a mix-up, especially during a new president's early tenure, we make use of a back-filling procedure. Specifically, from the first to the forty-seventh month after each new president's inauguration, we use the information from the last president in the same party to fill in the time series till we have 48-month data to calculate the PEAR beta. For example, when Donald Trump becomes new president in February 2017, we use the last 47-month information from George W. Bush's second term, together with information in February 2017, to calculate the PEAR beta at the end of February 2017. The implicit assumption is that economic policies are relatively more stable within the same presidential party due to slow-moving ideologies than across presidential parties. The downside of this back-filling procedure is that it slightly shortens our sample period. Since we require at least 24-month non-missing information to calculate beta, the first 23 months of Bill Clinton's presidency are missing, as the PEAR index from the previous Democratic president (Jimmy Carter) are not available. In the end, we estimate the PEAR beta from June 1983 to December 2019 with 416 non-missing months in total.¹²

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 less than \$1 and stocks with missing returns. We adjust stock returns for delisting to avoid survivorship bias following Shumway (1997).

¹² We also compute the PEAR beta using the standard 60-month backward rolling window (with a minimum of 24 months), regardless of the identities of the presidents during that window. We find the standard PEAR beta generates qualitatively similar results as shown in Online Appendix Table A3.

To ensure that return predictive power of our PEAR beta is not driven by other similar return predictors, we consider a set of control variables. We estimate market beta (β_{CAPM}), sentiment beta (β_{BW}), and uncertainty-beta (β_{UNC}) as Bali et al. (2017b). We calculate firm size (SIZE) as the logarithm of the product of price and the number of shares outstanding. 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 (Fama and French, 1992).¹³ Firms with negative book values are excluded from the analysis. We 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 an 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 et al. (2006), idiosyncratic volatility (IVOL) is the standard deviation of the stock's daily idiosyncratic returns relative to the Fama-French three-factor model. We measure the illiquidity (ILLIQ) of a stock as the ratio of the daily absolute stock return to the daily dollar trading volume averaged in each month, which is further scaled by 10⁶ (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 et al. (2008).¹⁴

We consider four politics-related variables. Following Kim et al. (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 corporate PAC makes a contribution to a candidate (regardless of party affiliation) in the last 5 years following Cooper et al. (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 et al. (2013), we calculate the industry-level government spending exposure (GSE) as the proportion of the industry's total output (3digit SIC) being purchased by the government sector for final use to capture the impact of political cycles on asset prices. Appendix A details the constructions of the main 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 0.80 and 0.27, suggesting that PEAR beta is persistent. This persistence is not surprising given that it is estimated using a five-year backward rolling window. As such, PEAR beta is very different from other stock characteristics such as past returns and volatility, which are more volatile in time series.

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 return, the correlation between PEAR beta and CAPM beta is close to zero (0.05). 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, if there is any, is unlikely 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 on future stock returns. We perform a number of tests to show that our results are robust.

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 sorting results. The first row presents the average PEAR betas of the decile portfolios, which increase from -1.78 for decile 1 to 2.10 for decile 10. In the second row, the monthly average excess returns of the PEAR beta portfolios decrease from 1.19% for decile 1 to 0.08% for decile 10, with the difference equals to 1.11% (*t*-value = 4.47).

We calculate the risk-adjusted returns of the PEAR beta portfolios with four factor models and the Daniel et al. (1997) characteristics model (DGTW). The four factor models are the Fama and French (2015) five-factor model (FF5), the Hou et al. (2015) *q*-factor model (HXZ), the Stambaugh and Yuan (2017) mispricing-factor model (SY), and the Daniel et al. (2020) behavioral-factor model (DHS).¹⁵

The rest rows of Panel A present the factor- and characteristic-adjusted returns and make two observations. First, although the four models we use represent the most recent advancements in asset pricing, they cannot explain the PEAR beta portfolios well. The abnormal return of the PEAR beta spread portfolio ranges from 0.59% with DGTW

¹³ 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.

¹⁴ We obtain firm characteristics including β_{CAPM} , BM, MOM, IVOL, ILLIQ, and Distress risk from Chen and Zimmermann (2022), which is available at https://www.openassetpricing.com.

¹⁵ When the FF5 is augmented by the betting-against-beta factor (BAB) (Frazzini and Pedersen, 2014), the MAX factor (FMAX) (Bali et al., 2017a), and the Left-Tail Momentum factor (LTM) (Atilgan et al., 2020), the alpha of the PEAR beta spared portfolio equals 1.04% (t-value = 4.17), 0.98% (t-value = 3.96), and 1.04% (t-value = 4.14), respectively.

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 et al., 2017b), sentiment beta (β_{BW} , Chen et al., 2021), political alignment index (PAI, Kim et al., 2012), political sensitivity (PS, Addoum and Kumar, 2016), political connectedness (PC, Cooper et al., 2010), government spending exposure (GSE, Belo et al., 2013), log firm size (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), idiosyncratic volatility (IVOL), illiquidity (ILLIQ, Amihud, 2002), and failure probability (Distress, Campbell et al., 2008). 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.

	$\beta_{ ext{PEAR}}$	β_{CAPM}	β_{UNC}	$eta_{ m BW}$	PAI	PS	PC	GSE	SIZE	BM	MOM	STR	IVOL	ILLIQ	Distress
Panel A: Au	itocorrelatio	n													
AR(1)	0.80	0.82	0.78	0.80	0.92	0.82	0.96	0.82	0.82	0.87	0.74	-0.05	0.33	0.91	0.31
AR(12)	0.27	0.37	0.23	0.29	0.33	0.29	0.70	0.45	0.34	0.24	-0.16	0.00	0.10	0.22	0.11
Panel B: Pa	irwise correl	lation: standa	rd (rank) co	rrelation abov	ve (below) th	e diagonal									
β_{PEAR}		0.05	0.07	0.06	-0.01	-0.02	-0.03	0.02	-0.05	0.00	-0.02	-0.00	0.05	0.02	0.04
β_{CAPM}	0.04		0.10	0.20	-0.01	-0.08	-0.16	0.05	-0.12	-0.07	-0.00	0.00	0.24	-0.03	0.19
β_{UNC}	0.06	0.06		0.02	-0.00	-0.02	-0.01	-0.01	0.01	-0.06	-0.00	0.02	0.02	-0.01	0.02
β_{BW}	0.04	0.19	0.04		-0.02	-0.08	-0.07	-0.00	-0.10	-0.05	0.03	0.01	0.12	0.02	0.10
PAI	-0.01	0.01	-0.00	-0.02		0.06	-0.01	-0.00	-0.01	-0.01	0.01	0.00	0.01	-0.00	0.01
PS	-0.02	-0.07	-0.01	-0.08	0.06		-0.01	-0.07	0.04	0.01	0.05	0.01	-0.04	-0.01	-0.04
PC	-0.04	-0.17	-0.02	-0.10	-0.02	0.00		0.10	0.42	-0.07	0.00	-0.00	-0.16	-0.05	-0.15
GSE	0.03	0.07	-0.00	0.02	0.01	-0.07	0.01		0.01	-0.02	0.00	0.00	0.02	0.00	0.01
SIZE	-0.05	-0.11	0.03	-0.13	-0.02	0.04	0.37	-0.00		-0.29	0.13	0.03	-0.43	-0.28	-0.32
BM	0.02	-0.04	-0.06	-0.03	-0.01	0.00	-0.07	-0.04	-0.32		0.00	0.02	0.03	0.12	0.01
MOM	-0.03	-0.08	-0.02	-0.01	0.00	0.07	0.04	-0.00	0.23	-0.01		-0.01	-0.09	-0.01	-0.09
STR	-0.01	-0.03	0.00	-0.01	0.00	0.02	0.02	-0.00	0.09	0.01	0.01		0.20	0.04	0.09
IVOL	0.05	0.33	0.00	0.15	0.02	-0.04	-0.24	0.03	-0.53	0.07	-0.20	-0.01		0.27	0.67
ILLIQ	0.05	0.06	-0.04	0.12	0.01	-0.03	-0.37	-0.00	-0.93	0.34	-0.12	-0.03	0.50		0.18
Distress	0.05	0.33	-0.00	0.14	0.02	-0.05	-0.25	0.03	-0.53	0.08	-0.26	-0.07	0.91	0.50	

Low PEAR beta premium. This table reports monthly average excess returns and alphas (in %) of PEAR beta (β_{PEAR}) decile portfolios, 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 et al. (2015) *q*-factor model (HXZ), Stambaugh and Yuan (2017) mispricing-factor model (SY), Daniel et al. (2020) behavioral-factor model (DFGW). 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.

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(4.34) (1.39) (0.62) (-0.85) (0.29) (-0.30) (-3.16) (-0.62) (0.11) (-1.69) (4.16) (-0.62) (0.11) (-1.69) (4.16) (-0.62) (0.11) (-1.69) (-0.62) (0.11) (-0.62) (0.12) (0.	.04) 93
	93
α_{HXZ} 0.71 0.19 0.14 -0.05 0.05 0.02 -0.15 0.02 0.06 -0.22 0.9	
(4.11) (1.64) (1.47) (-0.59) (0.70) (0.25) (-1.65) (0.17) (0.41) (-1.14) (3.5)	.64)
α_{SY} 0.55 0.19 0.12 -0.12 0.03 0.02 -0.28 -0.03 -0.04 -0.37 0.9	92
(3.01) (1.60) (1.23) (-1.56) (0.35) (0.21) (-3.01) (-0.27) (-0.24) (-1.78) (3.60) (-1.78)	.46)
α_{DHS} 0.71 0.19 0.20 -0.05 -0.01 0.01 -0.18 0.11 0.07 -0.11 0.8	82
(3.80) (1.53) (2.00) (-0.67) (-0.16) (0.10) (-1.82) (0.93) (0.45) (-0.55) (3.80) (0.45) (-0.55) (3.80) (0.45) (-0.55) (3.80) (0.45) (0.4	.07)
DGTW 0.31 0.03 0.04 0.04 0.06 -0.04 -0.13 -0.01 0.02 -0.28 0.5	59
(1.95) (0.36) (0.56) (0.68) (1.00) (-0.71) (-1.83) (-0.16) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (0.17) (-1.58) (2.56) (.92)
Panel B: Sort on industry demeaned $eta_{ extsf{PEAR}}$	
β_{PEAR} -1.84 -0.84 -0.52 -0.30 -0.11 0.06 0.25 0.49 0.84 1.97 3.8	81
Excess 1.21 0.74 0.76 0.82 0.76 0.80 0.61 0.57 0.55 0.15 1.0	06
(3.39) (2.84) (3.36) (3.85) (3.61) (3.63) (2.52) (2.24) (1.90) (0.39) (4.52)	.69)
α_{FF5} 0.77 0.06 0.03 0.06 0.01 -0.01 -0.12 -0.15 -0.11 -0.20 0.9	96
(4.60) (0.55) (0.29) (0.83) (0.09) (-0.19) (-1.24) (-1.41) (-0.92) (-1.35) (4.60)	.23)
α_{HXZ} 0.79 0.11 0.11 0.11 0.03 0.05 -0.05 -0.05 -0.07 -0.17 0.9	96
(4.58) (0.96) (1.11) (1.51) (0.47) (0.70) (-0.55) (-0.49) (-0.58) (-0.97) (4.56) (-0.58) (-0.97) (4.56) (-0.58) (-0.97) (4.56) (-0.58) (-0	.09)
α_{SY} 0.62 0.09 0.03 0.07 -0.01 0.03 -0.11 -0.19 -0.15 -0.26 0.8	87
(3.36) (0.75) (0.32) (0.94) (-0.14) (0.34) (-1.12) (-1.74) (-1.20) (-1.35) (3.6) (-1.26) (.58)
α_{DHS} 0.78 0.14 0.08 0.05 0.07 0.05 -0.08 -0.04 0.01 -0.05 0.8	83
(4.26) (1.12) (0.79) (0.63) (0.93) (0.61) (-0.80) (-0.39) (0.10) (-0.27) $(3.$.37)
DGTW 0.36 -0.02 -0.06 0.08 0.05 0.05 -0.01 -0.08 -0.02 -0.26 0.6	61
(2.25) (-0.21) (-0.83) (1.32) (0.75) (0.93) (-0.14) (-0.96) (-0.15) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (3.5) (-1.59) (-1.59) (3.5) (-1.59	

to 1.00% with FF5, suggesting that at least 50 percent of the average return of the PEAR beta spread portfolio is not explained by existing asset pricing models. Second, unlike the well-known anomalies in Stambaugh et al. (2015), the performance of the PEAR beta spread portfolio is mainly from the long leg. The low PEAR beta portfolio is undervalued, whereas the high PEAR beta portfolio is generally overvalued with a smaller magnitude. For this reason, we label the significant alpha in the last column (L-H) as 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 et al. (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 -1.84 for decile 1 to 1.97 for decile 10, with the difference quantitatively close to the case without industry demeaning (3.88 vs. 3.81). The average returns of the PEAR beta portfolios decrease from 1.21% for decile 1 to 0.15% for decile 10, with the difference equals to 1.06% (*t*-value = 4.69). This value sug-

gests that industry dynamics do not affect the predictive power of 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 the top five PEAR beta industry portfolios.

When turning to the risk-adjusted return, the low PEAR beta premium also remains unaffected. It ranges from 0.61% with DGTW to 0.96% with FF5. All the values are statistically significant and economically sizeable. For simplicity, we use FF5 as the benchmark for calculating the risk-adjusted returns in the subsequent analyses.

In Table A3 of Online Appendix, we consider the standard rolling window estimation for PEAR beta, which ignores the mixup of the economic policies from the opposing political party. The result shows that this alternative PEAR beta still generates highly significant return premium, even though the premium is slightly smaller than that of the benchmark PEAR beta.

To explore how much an investor can make if she trades for the low PEAR beta premium, Fig. 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 makes a risk-adjusted profit of \$39.65, which does not suffer from large drawdowns. Hence, trading the PEAR beta spread portfo-





Fig. 3. Low PEAR beta premium after portfolio 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

lio can greatly expand the investor's investment opportunities. Indeed, the low PEAR beta premium implies an annual Sharpe ratio of 0.76, and it is higher than the market Sharpe ratio of 0.55.

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. Fig. 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 it does not reflect the price pressure from liquidity-induced trading. This result is comparable with the uncertainty beta premium documented in Bali et al. (2017b), which is persistent and significant up to 11 months. Examining the FF5 alphas in Panel B shows a slightly more persistent pattern, thereby ruling out short-term market frictions such as liquidity shocks in driving the result.

In sum, this subsection shows that high PEAR beta stocks underperform 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 crosssectional 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 as 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 169 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 1.26% (t-value = 3.32) under Democratic presidencies and 1.01% (t-value) = 3.07) under Republican presidencies, with the difference (0.25%) insignificant from zero (t-value = 0.50). The riskadjusted returns are 1.31% (t-value = 3.09) and 0.79% (tvalue = 2.62) under Democratic and Republican presidencies, respectively. In this case, the difference is 0.52% and insignificant (t-value = 1.06). Thus, the PEAR beta premium is related to, but differs from, the time-series presidential puzzle.

Panel A of Fig. 4 goes one step further by plotting the average and risk-adjusted returns of the PEAR beta spread portfolio within each president's 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 Republican presidencies, echoing the pattern in Fig. 2. Indeed, in the four-year term of President George H.W. Bush, the PEAR beta spread portfolio has an average return of 1.41% and an FF5 alpha of 1.21% per month, which is lower than President Bill Clinton's term (2.11% and 2.13%). Although the worst performance is also from the Republican presidency, Ronald Reagan, the average and risk-adjusted returns are still positive, 0.55% and 0.21%.

In addition, we examine how the PEAR beta spread portfolio performs across the four years of a president's tenure. In the literature, Belo et al. (2013) show that government spending exposure has stronger power in predicting future stock returns in years 2 and 3 of a president's 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 Fig. 4 shows that the low PEAR beta premium is different from Belo et al. (2013) and Addoum and Kumar (2016). Its performance, especially after risk adjustment, is stronger in the first three years of a president's term. Importantly, the low PEAR beta premium is present in each of the four years.

3.2.2. Performance over the presidential transition and non-transition periods

Addoum and Kumar (2016) and Meeuwis et al. (2021) find that investors rebalance their portfolios dramatically around presidential elections, because of political climate change or political disagreement. To explore if such presidential transitions drive the low PEAR beta premium, we split the sample into transition and non-transition periods. A transition period consists of 12 months before and after a new president's inauguration. With six presidents, we have five transitions, covering 113 months in total.

Panel B of Table 4 shows that the average and riskadjusted returns in transition periods are slightly higher than that in non-transition periods, but they are not statistically different between these two sub-periods, with the differences equal to -1.21% (*t*-value = -1.83) and -0.89% (*t*-value = -1.50). The result is similar if we use November of the election year as the event month as in Brogaard et al. (2020). Thus, the low PEAR beta premium is different from and beyond the political climate change in Addoum and Kumar (2016).

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 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 2.06% and 1.53% in recessions, whereas the counterparts in NBER expansions are 1.03% and 0.95%. 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 et al., 2015). In this subsection, we examine how the low PEAR beta premium performs among firms with low and high limits-to-arbitrage.

Low PEAR beta premium: Robustness. This table reports the monthly average excess returns and FF5 alphas of PEAR beta (β_{PEAR}) spread portfolios in different subsamples. Panels A, B, and C split the sample in time series into Democratic and Republican presidency periods, president transition and non-transition periods (transition periods are defined as twelve months surrounding the January of new president inauguration), and NBER-dated recessions and expansions, respectively. Panels D, E, and F split the sample in cross section based on idiosyncratic volatility (IVOL) (Ang et al., 2006), illiquidity (Amihud, 2002), and firm size according to the median breakpoints, respectively. 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, including using the innovation of the AR(1) process of Δ PEAR, the president job approval rating, and the index based on the polls from the 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: Democra	atic vs. Republica	n presidents		Panel B: Transition vs. non-tr	ansition periods				
Democratic	1.26	1.31	169	Transition	1.99	1.65	113		
	(3.32)	(3.09)			(3.25)	(2.92)			
Republican	1.01	0.79	247	Non-transition	0.78	0.77	303		
	(3.07)	(2.62)			(3.12)	(2.84)			
Difference	0.25	0.52		Difference	-1.21	-0.89			
	(0.50)	(1.06)			(-1.83)	(-1.50)			
Panel C: Recessions vs. expansions				Panel D: Low vs. high IVOL firms					
Recession	2.06	1.53	34	Low IVOL	1.10	1.04			
	(1.61)	(1.26)			(4.17)	(3.77)			
Expansion	1.03	0.95	382	High IVOL	0.77	0.74			
	(4.18)	(3.57)			(2.97)	(2.74)			
Difference	-1.03	-0.58		Difference	-0.33	-0.30			
	(-0.79)	(-0.47)			(-1.13)	(-0.97)			
Panel E: Liquid v	s. illiquid firms			Panel F: Small vs. big firms					
Liquid	1.09	1.01		Small	0.53	0.38			
	(4.12)	(3.80)			(3.58)	(2.54)			
Illiquid	0.44	0.25		Big	1.09	0.99			
	(2.47)	(1.40)			(4.09)	(3.73)			
Difference	-0.65	-0.76		Difference	0.55	0.61			
	(-2.47)	(-2.73)			(2.09)	(2.20)			
Panel G: Alternat	ive $\beta_{ ext{PEAR}}$ estimat	tion		Panel H: Alternative PEAR					
Excluding MKT	1.06	0.85		Innovation of $\triangle PEAR AR(1)$	1.19	1.13			
	(3.86)	(3.39)			(4.64)	(4.32)			
4-year rolling	1.03	0.80		Presidential approval rating	0.47	0.44			
	(4.17)	(3.30)			(1.95)	(1.75)			
8-year rolling	0.93	0.78		Top 6 agents	0.98	1.07			
	(3.94)	(3.26)			(3.59)	(3.88)			

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 the measure and into deciles based on PEAR beta, and then we construct a PEAR beta spread portfolio within each subgroup. Panel D of Table 4 reports the results with IVOL. Surprisingly, the low PEAR beta premium is stronger among low IVOL stocks. Its FF5 alpha is 1.04% (t-value = 3.77) among low IVOL stocks, and 0.74% (t-value = 2.74) among high IVOL stocks. This empirical pattern continues to hold when we measure limits-to-arbitrage with Amihud (2002) illiquidity or firm size (Panels E and F). The FF5 alphas of the low PEAR beta premiums are 1.01% and 0.25% among liquid and illiquid stocks, and 0.99% (t-value = 3.73) and 0.38% (t-value = 2.54) among big and small firms, respectively. These findings imply that the low PEAR beta premium is economically meaningful as it goes bevond transaction costs.

The low PEAR beta premium is distinct from most of the anomalies that are typically concentrated among high IVOL, small, and illiquid firms, or stocks facing limits to arbitrage (Stambaugh et al., 2015). In Online Appendix Table A4, we confirm that investor attention, measured by analyst coverage, is much higher among low IVOL, liquid, or large firms. In subsequent analyses, we show that the low-PEAR-beta premium arises because investors (including analysts) misprice a firm's perceived alignment to the incumbent president's economic policies. The subsample results, therefore, suggest that attention-grabbing stocks are more likely to be subject to such mispricing.

3.2.5. Alternative PEAR beta estimates

This paper estimates PEAR beta with Eq. (2). Because the market return is included when estimating PEAR beta, one natural question is what happens if we exclude the market return. To answer this question, we exclude the market return in regression (1), redo single portfolio sorting in 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 1.06% (*t*-value = 3.86) and 0.85% (*t*-value = 3.39), which are close to the case controlling for the market return (1.10% and 1.00%).

We also examine the robustness of different rolling windows used to estimate the PEAR beta, four and eight years (coinciding with one or two presidential terms). The



Panel A: Across different presidencies



Fig. 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's term (Panel B). The sample period is 1983:06-2019:12.

results are qualitatively 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 in the construction of the PEAR index.

First, in the main analyses, we use the change of PEAR to calculate PEAR beta, and implicitly assume that the change 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 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 1.19% (*t*-value = 4.64) and 1.13% (*t*-value = 4.32), which are quantitatively similar to the baseline results. A caveat here is that the AR(1) estimation uses the full sample and thus introduces a forwardlooking bias. We thus prefer estimating PEAR beta using simple changes.

Second, as shown in Table 1, the presidential job approval rating index, PJAR, is highly correlated with PEAR. So one interesting question is whether this alternative in-

dex can generate similar results in the cross-section. Panel H of Table 4 shows that the average return and FF5 alpha are 0.47% (*t*-value = 1.95) and 0.44% (*t*-value = 1.75), respectively. These values are much smaller than those using PEAR, suggesting that PEAR is more relevant for the financial market.

Lastly, we consider the PEAR index constructed by polls from the top 6 polling organizations (PEAR₆), which conduct the most surveys in our sample period. By using this new index, the PEAR beta spread portfolio has an average return of 0.98% and an FF5 alpha of 1.07%. This weaker result is due to the smoothing and interpolation when constructing the index, thereby calling for using more polls to better capture the underlying public perspective regarding the president's handling of the economy, especially during the early years, which is exactly what we do in the main analyses.

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

This subsection performs 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.

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 et al. (2010); Ince and Porter (2006); Hou et al. (2011).¹⁶ We collect the major stock market indexes for these countries from Fact-Set, 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 the 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 are available from July 1991 to January 2018. Finally, following Frankel and Rose (1998), we construct a trade intensity measure between each of the G7 countries and the US to capture the economical closeness, where trade intensity is estimated 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 most of the G7 countries. The PEAR beta spread portfolios have positive risk-adjusted returns in all the countries and they are significant in Canada, Germany, Japan, and the UK. The last column of Table 5 shows that Canada, Germany, Japan, and the UK 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 more affected by the PEAR index.

3.4. Fama-MacBeth regressions

So far we have tested the significance of PEAR beta as a determinant of the cross-section of future returns at the portfolio level. This portfolio level analysis has nonparametric merit in the sense that we do not impose a functional form on the relation between PEAR beta and future returns. However, it also has two disadvantages. First, it gives up a large amount of information in the crosssection via aggregation. Second, it is hard to control for multiple effects or factors simultaneously. To address these concerns, in this subsection we run Fama–MacBeth 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 PEAR beta.

In Fama–MacBeth 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 et al. (2015) macroeconomic uncertainty index (Bali et al., 2017b), and the beta on the Baker and Wurgler (2006) sentiment index (Chen et al., 2021). The second category includes variables related to government and politics. They are the political alignment index (Kim et al., 2012), political sensitivity (Addoum and Kumar, 2016), political connectedness (Cooper et al., 2013). The third category includes other firm characteristics such as size, bookto-market, momentum, short-term reversal, idiosyncratic volatility, illiquidity, and distress.

Table 6 reports the results. In column 1, the univariate regression shows that PEAR beta has a significantly negative coefficient of -0.14 with a *t*-value of -4.12. Economically, the absolute *t*-value is proportional to the Sharpe ratio of the PEAR beta spread portfolio, which equals the annualized Sharpe ratio times \sqrt{T} , the number of years in the sample. So the -4.12 *t*-value suggests that an investor can earn an annualized Sharpe ratio of 0.68 (i.e., $4.12/\sqrt{37}$) if she trades for the low PEAR beta premium. This value is slightly lower than that with portfolio analysis in Section 3.1 (0.76), and reaffirms Table 4 that the low PEAR beta premium is slightly stronger among big firms. In column 2, when we control for firm characteristics in the regression, the coefficient of PEAR beta drops to -0.11 and the *t*-value slightly decreases to -4.09 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 betas (i.e., β_{CAPM} , β_{UNC} , and β_{BW}), the regression coefficient on PEAR beta slightly changes to -0.10 with a *t*value of -3.43. Interestingly, sentiment beta, β_{BW} , has an insignificantly negative regression coefficient in this

¹⁶ In particular, we require that firms selected for each country are domestically incorporated based on their home country information (GE-OGC); 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.

Low PEAR beta premium: International evidence. This table reports monthly average excess returns and FF5 alphas (in %) of PEAR beta (β_{PEAR}) portfolios in other G7 countries. Stock return and market capitalization information are from Datastream. All returns and market capitalizations are based on local currencies, the 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 between each country and the US, which is defined as the sum of bilateral (imports and exports) between each country and the US divided by the sum of their GDPs (Frankel and Rose, 1998). All portfolios are value-weighted and rebalanced at a monthly frequency. Reported in parentheses are *t*-values. The sample periods for results of excess returns are 1987:01–2019:12 for Canada, 1989:12–2019:12 for France and Germany, 1999:12–2019:12 for Italy, 1983:06–2019:12 for Japan, and 1987:12–2019:12 for the UK. The sample period for FE5 factors is 1991:07–2018:01.

		Excess return			FF5 alpha		Trade
	P1	P10	L-H	P1	P10	L-H	intensity
Canada	0.31 (0.61)	-0.55 (-1.15)	0.86 (1.87)	0.23 (0.38)	-0.99 (-2.15)	1.22 (2.24)	2.86
France	0.49 (1.35)	0.39 (0.87)	0.10 (0.25)	-0.01 (-0.04)	-0.55 (-1.73)	0.54 (1.23)	0.35
Germany	0.60 (1.62)	-0.19 (-0.91)	0.79 (2.01)	0.21 (0.77)	-0.84 (-2.77)	1.05 (2.31)	0.65
Italy	0.44 (1.00)	0.24 (0.43)	0.20 (0.38)	-0.03 (-0.12)	-0.22 (-0.53)	0.18 (0.32)	0.29
Japan	0.72 (2.25)	0.08 (0.25)	0.65 (2.22)	0.50 (2.98)	-0.23 (-1.16)	0.73 (2.53)	1.20
UK	0.72 (2.05)	-0.36 (-0.92)	1.08 (2.97)	0.39 (1.31)	-0.59 (-2.10)	0.98 (2.20)	0.57

case, consistent with the argument in Baker and Wurgler (2006). Both the CAPM and uncertainty betas are insignificant either. 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 -0.09 (*t*-value = -3.30). 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 three categories of controls in one regression, the coefficient of PEAR beta remains -0.09 with a *t*-value of -2.75. The magnitude suggests that all the controlling variables, even when combined, explain about one-third 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 political sensitivity variable as it is calculated based on the Fama-French 48 industries. The regression coefficient of PEAR beta becomes -0.07 with a *t*-value of -2.32. Thus, the low PEAR beta premium is different from Belo et al. (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 IVOL, which exhibits positive and significant coefficients. This is due to its high correlation with the distress variable (0.67), as evident in Table 2 (IVOL is a component in constructing the distress measure). We confirm that the coefficient on IVOL would turn 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. Perceived alignment with the incumbent president

Intuitively, PEAR beta could measure a firm's perceived alignment with the economic policies of the incumbent president. The business of a positive PEAR beta firm must align well with the incumbent president's economic policies, so its stock price moves in tandem with the policies' approval rating. As a concrete example, consider two energy companies: Renewable Energy Group Inc (NASDAQ: REGI), which is a company focuses on bio-based diesel, and New Concept Energy Inc (NYSE: GBR), which is a traditional oil company. As their business imply, the first company aligns well with President Obama era's clean energy policy while the second company, being a traditional oil and gas firm, better aligns with the energy policy of President Trump's administration.

Their alignments with the incumbent president are nicely captured by their PEAR betas, as evident in Panel A of Fig. 5.¹⁷ During President Obama's presidency (2014–2016), the Renewable Energy has a large and positive PEAR beta and the New Concept Energy has a negative PEAR beta. After Trump's election in 2017, their PEAR betas start to converge. After one year, they even flip. The Renewable Energy has a negative PEAR beta while the New Concept Energy 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. While a flip in the sign of PEAR beta

¹⁷ The Renewable Energy Group was listed in 2012, which means that its PEAR betas are missing in the first 23 months during Donald Trump's term. We re-estimate the PEAR betas with a requirement of at least 12 months to obtain a longer sample period for comparison.

Fama–Macbeth regressions. This table reports the results of Fama–MacBeth regressions of onemonth-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 et al., 2008), β_{CAPM} , β_{UNC} (Bali et al., 2017b), β_{BW} (Chen et al., 2021), political alignment index (PAI, Kim et al., 2012), political sensitivity (PS, Addoum and Kumar, 2016), government spending exposure (GSE, Belo et al., 2013), and political connectedness (PC, Cooper et al., 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 have 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)
$\beta_{ ext{PEAR}}$	-0.14^{***}	-0.11^{***}	-0.10^{***}	-0.09^{***}	-0.09^{***}	-0.07^{**}
β_{CAPM}	((1100)	0.06	(5.50)	0.05	0.06
$\beta_{ m UNC}$			(0.03) -0.04 (1.28)		-0.04	-0.05
eta_{BW}			(-1.20) -0.05 (-1.22)		(-0.02)	(-0.02)
PAI			(-1.22)	0.03	(-0.30) 0.04 (1.57)	0.02
PS				(1.0 <i>9</i>) 0.18*** (2.15)	0.17***	(1.07)
РС				(3.13) 0.10* (1.70)	(3.00) 0.12**	0.09*
GSE				(1.79) -0.00	(2.32) 0.01	0.02
SIZE		-0.13*	-0.15**	(-0.02) -0.13^{*}	(0.13) -0.14^{**}	(0.67) -0.12*
ВМ		(-1.96) 0.12	(-2.37) 0.12*	(-1.83) 0.11	(-2.21) 0.12*	(-1.85) 0.19***
МОМ		(1.61) 0.19**	(1.77) 0.19**	(1.59) 0.16*	(1.80) 0.16**	(3.67) 0.13*
STR		(2.16) -0.42^{***}	(2.40) -0.48^{***}	(1.85) -0.48^{***}	(2.24) -0.53^{***}	(1.80) -0.60^{***}
IVOL		(-0.42) 0.07	(-0.94) 0.08	(-0.00) 0.10	(-0.92) 0.11	(-7.41) 0.07
ILLIQ		(0.73) 0.13***	(0.79) 0.15***	(0.91) 0.12** (2.20)	(1.00) 0.14*** (2.04)	(0.66) 0.15***
Distress		(2.08) -0.45^{***}	(3.54) -0.46^{***}	(2.30) -0.38***	(2.94) -0.40^{***}	(3.20) -0.36***
Industry FEs	No	(-3.40) No	(-3.58) No	(-2.80) No	(-2.97) No	(-2.84) Yes
#(obs.) Adj. <i>R</i> ²	1,222,759 0.002	1,048,446 0.039	1,025,342 0.049	797,594 0.049	779,088 0.059	779,088 0.077

is rare, Panel B confirms that after a change of president, PEAR betas of high- and low-beta firms quickly converge during the first few months.

In Appendix B, we sketch a stylized model in which sentiment investors have biased cash flow expectations on extreme PEAR beta firms. Using the above example, during Obama's term, sentiment investors overestimate future earnings of Renewable Energy and underestimate future earnings of New Concept Energy. In the model, the PEAR index does not contain any additional fundamental information but measures the fraction of sentiment investors, so the PEAR beta captures sentiment investors' biased cash flow expectation. Risk-averse rational investors cannot fully correct such biases, and as a result, the market-clearing price is too high for Renewable Energy and too low for New Concept Energy. Mispricing disappears when future earnings are realized. Thus, Renewable Energy earns lower returns and New Concept Energy earns higher returns in the future, resulting in the low PEAR beta premium. The model predicts that such a premium should be higher following high PEAR periods, or periods with higher fractions of sentiment investors, a pattern we confirm in Panel D of Table 9.

In the model, when sentiment investors enter or exit the market, trading volume increases, leading to a positive relationship between the absolute change in the PEAR index and the trading volume of sentiment investors. The prediction is confirmed when we proxy sentiment investors' trading volume using retail investors' turnover, which is calculated by applying the method in Boehmer et al. (2021) to the TAQ data starting from 2010. We find a significant positive correlation (0.19, *t*-statistic



Fig. 5. Trend of PEAR beta. Panel A plots the PEAR betas of two anecdotal examples (New Concept Energy Inc. vs. Renewable Energy Group) during Obama's and Trump's terms. Panel B plots the average values of PEAR beta in decile 1 and decile 10 around the presidential transition periods. The sample period is 1983:05–2019:12.

= 2.01) between the absolute change in the PEAR index and retail turnover across all stocks. The correlation is even stronger (0.24, *t*-statistic = 2.50) for high PEAR-beta stocks which are preferred by the sentiment investors.

We further provide three pieces of supporting evidence for the mispricing-based explanation to the low PEAR beta premium. First, each month, we split the past 60 months into two sub-samples (if applicable), one coming from months when the incumbent president is in power and the other from months when the former president is in power, with a requirement of at least 12 observations. For each sub-sample, we estimate a PEAR beta for each firm (incumbent president beta or former president beta), and explore the low PEAR beta premium in the next month. Table 7 shows that the low PEAR beta premium exists and is only significant when the incumbent president beta is used for sorting. The FF5 alpha of the PEAR beta spread portfolio is 0.86% (*t*-value = 4.10) with the incumbent president beta, whereas it is 0.44% (*t*-value = 1.60) with the former president beta. This evidence highlights the importance of perceived alignment with the incumbent presidential economic policies.18

Second, consistent with biases in cash flow expectations, in Panel A of Table 8 we find PEAR beta to positively predict analyst forecast errors, and negatively predict future revisions in their long-term growth (LTG) forecasts as well as future revisions in price target growth (PTG) forecasts. It also negatively predicts the next two guarters' earnings announcement returns. This finding also holds at the aggregate level in time series. Specifically, we aggregate the firm-level analyst expectation measures at each point in time into three time series and examine their contemporaneous relationship with the PEAR index. In Online Appendix Table A5, we confirm that the PEAR index is positively and significantly correlated with these three analyst expectation measures, suggesting that the expectation errors are systematic. We then examine how PEAR is related to analyst expectations in the future, and regress each of the three aggregate measures in month t + i on PEAR in month *t* for j = 0, 1, ..., 48. If the mispricing-based explanation is true, we should see that the regression betas decay over time because analysts would correct their perceptions about firms' future cash flows when new fundamental information comes out. This is exactly what we have in Fig. 6. These results suggest that both analysts and in-

¹⁸ We could have reported results using the incumbent president beta only. The downside is that the incumbent president beta will be missing or imprecisely estimated during the early years of a new president's term

due to a lack of data, which will result in fewer observations from the sample compared to the benchmark specification.

Low PEAR beta premium: Incumbent vs. former president betas. This table reports the monthly average excess returns and FF5 alphas of PEAR beta (β_{PEAR}) decile portfolios, where PEAR beta is calculated conditioning on the months whether the incumbent (former) president is in power. Specifically, at the end of each month, we split the past 60 months into two sub-samples, one coming from months when the incumbent president is in power and the other from months when the former president is in power (with a requirement of at least 12 observations), and then estimate an incumbent president beta and a former president beta for each firm accordingly. The sample period is 1983:06–2019:12.

	P1	P2	Р3	P4	P5	P6	P7	P8	P9	P10	L-H
Panel A: Incumbent president beta											
Excess return	0.83	0.83	0.76	0.59	0.60	0.62	0.48	0.48	0.43	-0.03	0.86
	(2.13)	(2.94)	(3.13)	(2.59)	(2.66)	(2.62)	(1.97)	(1.80)	(1.30)	(-0.07)	(4.21)
$\alpha_{\rm FF5}$	0.62	0.24	0.14	-0.08	-0.07	0.04	-0.20	-0.12	0.10	-0.24	0.86
	(3.95)	(1.92)	(1.36)	(-1.03)	(-0.95)	(0.42)	(-2.45)	(-1.15)	(0.80)	(-1.69)	(4.10)
Panel B: Forme	r presiden	it beta									
Excess return	1.12	1.16	1.14	0.85	0.97	0.97	0.88	0.86	0.97	0.62	0.50
	(2.83)	(3.68)	(3.88)	(2.99)	(3.65)	(3.46)	(2.92)	(2.90)	(2.77)	(1.35)	(1.87)
$\alpha_{\rm FF5}$	0.21	0.11	0.07	-0.16	-0.02	0.10	-0.01	-0.06	0.21	-0.23	0.44
	(1.27)	(0.69)	(0.67)	(-1.72)	(-0.20)	(0.90)	(-0.06)	(-0.43)	(1.29)	(-1.07)	(1.60)

Table 8

Analyst expectation and low PEAR beta premium: Edays vs. non-Edays. Panel A reports the results from Fama–MacBeth regressions of analyst expectation measures and three-day cumulative abnormal returns (CAR, in %) around earnings announcement days (Edays) on PEAR beta (β_{PEAR}), controlling for firm-specific characteristics (same as column 2 of Table 6). Analyst expectation measures include analyst forecast error (AFE_t = (Consensu_t – Actual)/PRC_{t-1}, in%), revision in long-term growth rate forecasts ($\Delta LTG_{t+12} = LTG_{t+12} - LTG_t$, in %), and revision in analyst price target growth forecasts ($\Delta PTG_{t+12} = (PT_{t+12} - PT_t)/PRC_{t-1}$, in %). The CAR results, adjusted by Daniel et al. (1997) benchmark returns, are at the quarterly frequency and based on the quarter-end month PEAR betas. Panel B reports the daily average returns of PEAR beta decile portfolios on Edays and non-Edays, respectively. Also reported are daily returns adjusted by Daniel et al. (1997) characteristics-based returns and market returns. The sample period is 1983:06–2019:12, except for analyst price target forecasts being 1999:03–2019:12.

Panel A: A	Analyst reaction	s and CARs around E	days			
	AFE _t	ΔLTG_{t+12}	ΔPTG_{t+12}	CAR_{q+1}	CAR_{q+2}	CAR_{q+3}
β_{PEAR}	0.38***	-0.08**	-15.67***	-0.07***	-0.06**	-0.02
	(2.62)	(-2.18)	(-3.50)	(-2.65)	(-2.43)	(-0.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R ²	0.133	0.039	0.045	0.014	0.013	0.013

Panel B: lo	ow PEAR b	oeta premi	ums amor	ng Edays a	nd non-Eo	lays					
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	L-H
Earnings announcement days											
Excess	14.06	11.78	6.85	9.27	4.38	3.37	5.57	15.43	1.00	-4.81	18.88
	(2.19)	(2.59)	(2.01)	(2.75)	(1.37)	(0.93)	(1.17)	(3.42)	(0.17)	(-0.76)	(2.59)
DGTW	12.33	7.32	2.36	4.14	0.31	0.96	3.13	6.65	-1.86	-5.11	17.44
	(2.41)	(1.98)	(2.09)	(1.86)	(0.86)	(1.13)	(1.30)	(2.94)	(-0.53)	(-1.13)	(2.61)
MKT	13.92	9.94	3.64	6.78	1.92	3.06	3.55	11.54	0.81	-5.90	19.82
	(2.50)	(2.75)	(1.36)	(2.41)	(0.72)	(1.02)	(1.09)	(3.05)	(0.16)	(-1.08)	(2.76)
				Non-	earnings	announce	ment days				
Excess	5.53	4.50	4.05	4.05	3.85	3.70	2.55	2.55	2.63	1.52	4.02
	(3.22)	(3.72)	(3.62)	(3.91)	(3.76)	(3.42)	(2.35)	(1.96)	(1.72)	(0.77)	(3.41)
DGTW	2.16	1.29	0.15	0.63	0.39	0.10	-0.96	-0.61	-0.69	-1.14	3.31
	(2.44)	(2.89)	(0.51)	(2.00)	(1.44)	(0.35)	(-2.48)	(-1.38)	(-1.06)	(-1.21)	(3.23)
MKT	3.48	2.48	2.13	2.12	1.87	1.64	0.55	0.67	0.55	-0.52	4.01
	(3.45)	(4.73)	(5.50)	(5.59)	(5.55)	(4.29)	(1.35)	(1.08)	(0.70)	(-0.47)	(3.46)

vestors 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.

Third, we conduct portfolio analyses to examine the performance of the PEAR beta spread portfolio on future earnings announcement days and non-earnings announcement days. At the end of each quarter (March, June, September, and December), we form decile portfolios based on the average PEAR beta within the quarter, and examine their daily average (value-weighted) returns on the earnings announcement days (the day before, the day, and the day after the announcement) and non-earnings announcement days in the next one quarter. Panel B of Table 8 shows that the average return on earnings announcement days is four times as high as that on non-earnings announcement days (18.88 bps vs. 4.02 bps), consistent with the notion that the realization of earnings corrects mispricing arising from prior errors in earnings expectation (Engelberg et al., 2020).

In sum, all the empirical results suggest that PEAR beta dynamically reveals a firm's perceived alignment to the in-



Fig. 6. PEAR vs. analyst expectation. This figure plots the coefficients of regressions of the aggregate analyst expectation measures in month t + j on the PEAR index in month t for j = 0, 1, ..., 48. The analyst expectation measures include analyst forecast error (AFE), long-term growth forecast (LTG), and price target implied growth (PTG). AFE is defined as the difference between the consensus earnings forecast and the actual reported earnings, scaled by the closing stock price in the previous month. LTG is defined as the consensus long-term growth rate forecast. PTG is defined as the consensus price target forecast scaled by the stock price in the previous month. The sample period is 1981:04–2019:12, except for analyst price target forecasts being 1999:03–2019:12.

cumbent president's economic policies and investors seem to misprice such an alignment.

5. Alternative explanations

In this section, we investigate four alternative explanations to our main findings, and show that they are at most partially explaining the low PEAR beta premium.

5.1. 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 risks. 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 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 surplus consumption ratio from the habit model of Campbell and Cochrane (1999), and optionbased risk aversion from Faccini et al. (2019). Fig. 7 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 riskier and should earn higher returns. Such a risk-based story is therefore inconsistent with our empirical findings that high PEAR beta stocks underperform the low PEAR beta stocks in the future.

5.2. 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 consumption to wealth ratio (CAY), consumption growth (CG), capital share (CS, Lettau et al., 2019), default premium (DEF), change in expected inflation (DEI), real GDP (GDP), industrial production index (INDPRO), labor income growth (LIG), term premium (TERM), total factor productivity growth (TFP), ultimate consumption growth (UCG, Parker and Julliard, 2005), unexpected inflation (UI), unemployment rate (UNPR), VIX, aggregate market volatility (VOL), variance risk premium (VRP), total monetary base (BOGMBASE), the Chicago Fed National Activity Index (CFNAI), CPI, CPI excluding food and energy (CPI_core), CPI for energy (CPI_energy), CPI for food (CPI_food), the effective federal funds rate (FED-FUNDS), 10-year Treasury rate (GS10), 3-month Treasury bill rate (TB3MS), market return (MKT), crude oil price (OILPRICE), natural gas price (GASPRC), total nonfarm payroll (PAYEMS), and the Coincident Economic Activity Index (USPHCI).

Fig. 8 presents the correlations between the change of PEAR at time t with each macro variable at time t - 1, t, and t + 1, respectively. Several variables are highlighted



Fig. 7. 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.

if they are most positively or negatively correlated with the change in PEAR. Generally, the correlations are very low, and the highest one is 0.16 between the change of PEAR and consumption growth (CG). However, according to Parker and Julliard (2005), consumption growth is unlikely to be an explanation to the low PEAR beta premium, because it explains a small portion of the crosssectional variation in average returns. Past natural gas price change (GASPRC) has the lowest correlation with the change of PEAR (-0.14). For the remaining macro variables, the correlations generally fluctuate between -0.10and 0.10. Therefore, the PEAR index is not highly correlated with past, current, or future growths/changes of macro variables.¹⁹

For robustness, we consider additional 132 macro variables (Jurado et al., 2015; McCracken and Ng, 2016), and calculate their correlations with the change in PEAR as presented in Online Appendix Fig. A2. For brevity, we plot only 10 variables that are most positively and negatively correlated with the change in PEAR at time t - 1, t, and t + 1, respectively. Apparently, real personal consumption expenditure (RPCE) has the overall highest contemporaneous correlation (0.16) with the change in PEAR, followed by consumer sentiment (UMCSENTx) in the current quarter (0.13). In contrast, reserves of depository institutions (NONBORRES) has the lowest contemporaneous correlation with the change in PEAR (-0.17). Untabulated results confirm that controlling for these macro variables with the highest absolute correlations with the change in PEAR does not quantitatively change the main results either.

Another possibility is that these macro variables may not have large correlations with the change of PEAR but could still correlate with returns associated with PEAR. Or the firm-level exposures to these macro factors are likely to correlate with the PEAR beta. We examine this possibility by calculating the correlations of PEAR beta with macro betas or the correlations of the low PEAR beta premium with the changes of macro variables. Fig. A3 in Online Appendix presents the results and further confirms our con-

¹⁹ While the core and non-core inflation betas have different asset pricing implications (Fang et al., 2021), they have low correlations with PEAR beta, and controlling for them has a negligible effect on the low PEAR beta premium.



Fig. 8. PEAR vs. macro variables. This figure plots the correlations of the change in PEAR at time *t* with the changes/growths of macro variables at time t - 1 (past), *t* (current), and t + 1 (future), respectively. Variables that are most positively or negatively correlated with the change in PEAR are highlighted in the figure. Macro variables include consumption to wealth ratio (CAY), consumption growth (CG), capital share (CS, Lettau et al., 2019), default premium (DEF), change in expected inflation (DEI), real GDP (GDP), industrial production index (INDPRO), labor income growth (LIG), term premium (TERM), total factor productivity growth (TFP), ultimate consumption growth (UCG, Parker and Julliard, 2005), unexpected inflation (UI), unemployment rate (UNPR), the Chicago Board Options Exchange's volatility index (VIX), aggregate market volatility (VOL), variance risk premium (VRP), total monetary base (BOGMBASE), the Chicago Fed National Activity Index (CFNAI), CPI excluding food and energy (CPL_core), CPI for energy (CPL_energy), CPI for food (CPL_food), the effective federal funds rate (FEDFUNDS), 10-year Treasury rate (GS10), 3-month Treasury bill rate (TB3MS), market return (MKT), WTI crude oil price (OILPRICE), Henry Hub natural gas price (GASPRC), total nonfarm payroll (PAYEMS), and the Conomic Activity Index (USPHCI). We use log changes for BOGMBASE, CPI, CPI_core, CPI_food, GDP, INDPRO, OILPRC, GASPRC, PAYEMS, UNPR, USPHCI, VIX as well as VOL, and simple changes for CAY, CS, FEDFUNDS, GS10, and TB3MS. The rest of the macro variables are already constructed as changes. The sample period is 1981:05–2019:12, except for UCG being 1981:05–2017:03, VIX and VRP being 1990:01–2019:12, and GASPRC being 1997:01–2019:12.

clusion that the low PEAR beta premium is unlikely driven by macro risks.

Finally, as the PEAR index has a strong relation with the cross-sectional stock return in the financial market, one may conjecture that much of the variation in PEAR index may reflect expectations of the economic policies of the incumbent president to have a impact on asset prices. Hence, we examine the correlations between the PEAR index and investors' expectations on macro variables. Following Greenwood and Shleifer (2014), we collect AAII sentiment index. expectation of stock market return from Graham and Harvey CFO survey, and Shiller's individual investors' confidence index. We also employ survey data about consumers' opinions on macro economy from University of Michigan Consumer Survey and expected growths on macro variables from Survey of Professional Forecasters (SPF) by the Federal Reserve Bank of Philadelphia.

Panel A of Fig. A4 in Online Appendix shows that PEAR is positively correlated with investors' expectation on macro economy. The correlation is as high as 0.55 for consumers' opinion on expected change in financial situation in a year (ECFS) and the others are generally positive. This suggests that our PEAR index is likely connected to investors' expectation on macro economy, and thus, affects asset prices. However, when examining the correlations between the change of PEAR index and the changes of these macro expectations, Panel B shows that the correlations are generally smaller than 0.2 (in absolute term). Untabulated results confirm that controlling these macro expectations in the estimation of PEAR beta does not change the main results either. Hence, the asset pricing implication of our PEAR index is unique and orthogonal to these macro expectation measures.

Overall, it seems safe to conclude that macroeconomic factors cannot fully explain the low PEAR beta premium.

5.3. Hedge for downside risk?

Given that high PEAR beta firms are perceived to better align with the incumbent president, it is possible that such a "presidential alignment" could lead to government bailouts during bad times. If that happens, a high PEAR beta stock actually can be a good hedge for downside risk. Do their lower future returns reflect the hedging benefits? We believe the answer is no.

Empirically, corporate bailouts are relatively rare. For stance, Faccio et al. (2006) find that over the sample period 1997 to 2002, of the 450 politically 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 nonprofit investigative journalism group, ProPublica. However, financial firms are excluded from our analysis. For nonfinancial 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.

Low PEAR beta premium: High vs. low sentiment periods. This table reports the monthly 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 monthly frequency. Reported in parentheses are *t*-values. The sample period is 1983:06–2019:12.

Panel A: Baker and Wurgler (2006) sentimut index P1 0.75 0.79 0.04 P1 (3.02) (3.02) (0.12) P10 -0.40 -0.13 0.27 (-1.94) (-0.48) (0.82) LS 1.14 0.91 -0.23 (3.34) (2.46) (-0.48) Panel B: Michigan consumer sentiment index P1 P1 0.40 1.06 0.66 (1.80) (3.87) (2.06) P10 -0.08 -0.46 -0.38 (-0.37) (-2.01) (-1.25) LS 0.48 1.52 1.04 (1.45) (4.14) (2.22) Panel C: AAII bull-bear index P10 0.70 0.75 0.05 (2.66) (2.80) (0.15) P10 0.22 (-1.50) (-0.24) LS 0.99 1.12 0.13 (2.52) (2.99) (0.25) Panel C: PEAR P1 0.22		Low sentiment	High sentiment	Difference
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Panel	A: Baker and Wu	rgler (2006) sentim	ent index
$ \begin{array}{ccccccccccccccccccccccccccccccccccc$	P1	0.75	0.79	0.04
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(3.02)	(3.02)	(0.12)
$\begin{array}{c c c c c c c c } & (-0.48) & (0.82) \\ & (-0.48) & -0.23 \\ & (3.34) & (2.46) & (-0.48) \\ \hline \\ Panel & & & & & & & & & & & & & & \\ P1 & 0.40 & 1.06 & 0.66 \\ & (1.80) & (3.87) & (2.06) \\ P10 & -0.08 & -0.46 & -0.38 \\ & (-0.37) & (-2.01) & (-1.25) \\ LS & 0.48 & 1.52 & 1.04 \\ & (1.45) & (4.14) & (2.22) \\ \hline \\ Panel & & & & & & & & & \\ P10 & -0.29 & -0.37 & -0.08 \\ & (-1.22) & (-1.50) & (-0.24) \\ & (2.66) & (2.80) & (0.15) \\ P10 & -0.29 & -0.37 & -0.08 \\ & (-1.22) & (-1.50) & (-0.24) \\ LS & 0.99 & 1.12 & 0.13 \\ & (2.52) & (2.99) & (0.25) \\ \hline \\ Panel & & & & & & & \\ P11 & 0.22 & 1.27 & 1.05 \\ & (1.04) & (4.46) & (3.24) \\ P10 & 0.03 & -0.59 & -0.61 \\ & (0.15) & (-2.27) & (-1.99) \\ LS & 0.19 & 1.85 & 1.66 \\ & (0.63) & (4.70) & (3.54) \\ \hline \end{array}$	P10	-0.40	-0.13	0.27
LS 1.14 0.91 -0.23 (3.34) (2.46) (-0.48) Panel B: Michigan consumer sentiment induce (-0.48) P1 0.40 1.06 0.66 (1.80) (3.87) (2.06) P10 -0.08 -0.46 -0.38 (-0.37) (-2.01) (-1.25) LS 0.48 1.52 1.04 (1.45) (4.14) (2.22) Panel C: AAII bull-bear index (-0.37) -0.08 P10 -0.29 -0.37 -0.08 (-1.22) (-1.50) (-0.24) P10 -0.29 -0.37 -0.08 (-1.22) (-1.50) (-0.24) LS 0.99 1.12 0.13 (2.52) (2.99) (0.25) Panel D: PEAR [-0.22 1.27 1.05 (1.04) (4.46) (3.24) P10 0.03 -0.59 -0.61 (0.15)		(-1.94)	(-0.48)	(0.82)
	LS	1.14	0.91	-0.23
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		(3.34)	(2.46)	(-0.48)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Panel	B: Michigan cons	umer sentiment ind	lex
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	P1	0.40	1.06	0.66
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(1.80)	(3.87)	(2.06)
$\begin{array}{cccccccc} (-0.37) & (-2.01) & (-1.25) \\ (0.48 & 1.52 & 1.04 \\ (1.45) & (4.14) & (2.22) \end{array} \\ \hline Panel C: AAII bull-bear index \\ P1 & 0.70 & 0.75 & 0.05 \\ (2.66) & (2.80) & (0.15) \\ (2.66) & (2.80) & (0.15) \\ (-1.22) & (-1.50) & (-0.24) \\ LS & 0.99 & 1.12 & 0.13 \\ (2.52) & (2.99) & (0.25) \\ \hline Panel D: PEAR \\ P1 & 0.22 & 1.27 & 1.05 \\ (1.04) & (4.46) & (3.24) \\ P10 & 0.03 & -0.59 & -0.61 \\ (0.15) & (-2.27) & (-1.99) \\ LS & 0.19 & 1.85 & 1.66 \\ (0.63) & (4.70) & (3.54) \\ \hline \end{array}$	P10	-0.08	-0.46	-0.38
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(-0.37)	(-2.01)	(-1.25)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	LS	0.48	1.52	1.04
Panel C: AAII bull-bear index P1 0.70 0.75 0.05 (2.66) (2.80) (0.15) P10 -0.29 -0.37 -0.08 (-1.22) (-1.50) (-0.24) LS 0.99 1.12 0.13 (2.52) (2.99) (0.25) Panel D: PEAR -0.59 -0.61 (1.04) (4.46) (3.24) P10 0.03 -0.59 -0.61 (0.15) (-2.27) (-1.99) LS 0.19 1.85 1.66 (0.63) (4.70) (3.54) -0.54 -0.54 -0.54		(1.45)	(4.14)	(2.22)
$\begin{array}{ccccccc} P1 & 0.70 & 0.75 & 0.05 \\ & (2.66) & (2.80) & (0.15) \\ P10 & -0.29 & -0.37 & -0.08 \\ & (-1.22) & (-1.50) & (-0.24) \\ LS & 0.99 & 1.12 & 0.13 \\ & (2.52) & (2.99) & (0.25) \\ \hline \\ Panel \end {lem bmatrix} & & \\ P1 & 0.22 & 1.27 & 1.05 \\ & (1.04) & (4.46) & (3.24) \\ P10 & 0.03 & -0.59 & -0.61 \\ & (0.15) & (-2.27) & (-1.99) \\ LS & 0.19 & 1.85 & 1.66 \\ & (0.63) & (4.70) & (3.54) \\ \end{array}$	Panel	C: AAII bull-bear	index	
$\begin{array}{ccccc} (2.66) & (2.80) & (0.15) \\ P10 & -0.29 & -0.37 & -0.08 \\ (-1.22) & (-1.50) & (-0.24) \\ LS & 0.99 & 1.12 & 0.13 \\ (2.52) & (2.99) & (0.25) \\ \hline \\ Panel D: PEAR & & \\ P1 & 0.22 & 1.27 & 1.05 \\ (1.04) & (4.46) & (3.24) \\ P10 & 0.03 & -0.59 & -0.61 \\ (0.15) & (-2.27) & (-1.99) \\ LS & 0.19 & 1.85 & 1.66 \\ (0.63) & (4.70) & (3.54) \\ \hline \end{array}$	P1	0.70	0.75	0.05
$\begin{array}{cccccccc} P10 & -0.29 & -0.37 & -0.08 \\ & (-1.22) & (-1.50) & (-0.24) \\ LS & 0.99 & 1.12 & 0.13 \\ & (2.52) & (2.99) & (0.25) \\ \hline \\ Panel D: PEAR \\ P1 & 0.22 & 1.27 & 1.05 \\ & (1.04) & (4.46) & (3.24) \\ P10 & 0.03 & -0.59 & -0.61 \\ & (0.15) & (-2.27) & (-1.99) \\ LS & 0.19 & 1.85 & 1.66 \\ & (0.63) & (4.70) & (3.54) \\ \hline \end{array}$		(2.66)	(2.80)	(0.15)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	P10	-0.29	-0.37	-0.08
LS 0.99 1.12 0.13 (2.52) (2.99) (0.25) Panel D: PEAR P1 0.22 1.27 1.05 (1.04) (4.46) (3.24) P10 0.03 -0.59 -0.61 (0.15) (-2.27) (-1.99) LS 0.19 1.85 1.66 (0.63) (4.70) (3.54)		(-1.22)	(-1.50)	(-0.24)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	LS	0.99	1.12	0.13
Panel D: PEAR P1 0.22 1.27 1.05 (1.04) (4.46) (3.24) P10 0.03 -0.59 -0.61 (0.15) (-2.27) (-1.99) LS 0.19 1.85 1.66 (0.63) (4.70) (3.54)		(2.52)	(2.99)	(0.25)
$\begin{array}{cccccccc} P1 & 0.22 & 1.27 & 1.05 \\ (1.04) & (4.46) & (3.24) \\ P10 & 0.03 & -0.59 & -0.61 \\ (0.15) & (-2.27) & (-1.99) \\ LS & 0.19 & 1.85 & 1.66 \\ (0.63) & (4.70) & (3.54) \\ \end{array}$	Panel	D: PEAR		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	P1	0.22	1.27	1.05
$\begin{array}{ccccccc} P10 & 0.03 & -0.59 & -0.61 \\ (0.15) & (-2.27) & (-1.99) \\ LS & 0.19 & 1.85 & 1.66 \\ (0.63) & (4.70) & (3.54) \end{array}$		(1.04)	(4.46)	(3.24)
(0.15) (-2.27) (-1.99) LS 0.19 1.85 1.66 (0.63) (4.70) (3.54)	P10	0.03	-0.59	-0.61
LS 0.19 1.85 1.66 (0.63) (4.70) (3.54)		(0.15)	(-2.27)	(-1.99)
(0.63) (4.70) (3.54)	LS	0.19	1.85	1.66
		(0.63)	(4.70)	(3.54)

Additional evidence does not support such a "hedging" story either. During bad times, as indicated by NBER-dated recessions, 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, PEAR beta has a low correlation, 0.04 as shown in Panel B of Table 2, with the measure of financial distress (Campbell et al., 2008). Table 6 further shows that controlling for the distress risk does not alter the low PEAR beta premium.

5.4. 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 a 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 captures investor confidence (De Boef and Kellstedt, 2004; Lemmon and Portniaguina, 2006), high PEAR beta stocks could suffer from sentiment-induced overpricing, explaining their subsequent low returns when their overpricing gets corrected. Indeed, Stambaugh et al. (2012) find the long-short anomaly returns 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 is not empirically supported. We consider four measures 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 between the high and low sentiment periods. In Table 9 we find significantly higher PEAR beta spread portfolio returns following high levels of sentiment, when the PEAR index is used, consistent with the prediction of our stylized model. The low PEAR beta premium is also higher following high Michigan consumer sentiment periods, but the magnitude is much smaller than that of following high PEAR periods. This is not surprising given the correlation between these two indexes is around 0.62. More importantly, we do not find any evidence that the short-leg (high PEAR beta stocks) alpha is higher following high levels of sentiment for other two sentiment measures. In fact, in all cases, the long-leg has a higher alpha (in absolute term) than the short-leg, inconsistent with the notion that short-sale constraints together with investor sentiment fully explain the low PEAR beta premium.

In sum, this section examines four alternative explanations and finds none to explain the low PEAR beta premium.

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 underperform those with low PEAR beta by 1.00% 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 the 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, the low PEAR beta premium is unlikely driven by macro factors, 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 incumbent president's economic policy and investors seem overpricing firms with positive PEAR betas and underpricing 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 are 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.

Appendix A. Variable definitions

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

Variable	Description
Other betas	
Sentiment beta	$eta_{ extsf{BW}}$ is calculated using 60-month rolling
$(\beta_{\sf BW})$	regressions of excess stock returns on changes
	and lagged changes of the Baker and
	Wurgler (2006) sentiment index, with the
	requirement of at least 24-month non-missing
	data (Chen et al., 2021).
UNC beta (β_{UNC})	eta_{UNC} is computed 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-month non-missing data (Bali et al.,
	2017b).
Political variable	<u>es</u>
Political	PAI is calculated as the degree of a state's
alignment index	governor, control of its legislature, and the bulk
(PAI)	of its members in Congress aligned with the
	presidential party (Kim et al., 2012).
Political	PS is estimated using the 15-year monthly rolling
sensitivity (PS)	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	PC is defined as a dummy that equals one if a
connectedness	corporate PAC makes a contribution to a
(PC)	candidate (regardless of party affiliation) in the
	last 5 years and zero otherwise (Cooper et al.,
	2010; Addoum and Kumar, 2016).
Government	GSE is calculated as the proportion of an
spending	industry's total output (3-digit SIC) being
exposure (GSE)	purchased by the government sector for final use
	(Belo et al., 2013).

Analyst variables

Analyst earnings	The difference between the consensus earnings
forecast error	forecast and the actual reported earnings, scaled
(AFE)	by the closing stock price in the previous month
	t - 1.
Revision in	The difference between the consensus long-term
long-term	growth rate forecast in the future month and its
growth rate	value in the current month <i>t</i> .
forecasts (Δ LTG)	
Revision in	The difference between the consensus price target
analyst price	forecast in the future month and its value in the
target growth	current month <i>t</i> , scaled by the stock price in the
forecasts (Δ PTG)	previous month $t - 1$ (Brav and Lehavy, 2003).
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).

Appendix B. A stylized model of investor sentiment towards presidential alignment

In this section, we presents a stylized model to show that the PEAR beta captures a firm's perceived alignment to the incumbent president's economic policy and investors overprice firms with positive PEAR betas and underprice firms with negative betas, thereby generating the low PEAR beta premium.

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 $d = (d_1, \dots, d_N)'$, which follow a one factor structure such that, for each *i*,

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

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 $\theta = (\theta_1, \dots, \theta_N)'$ 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 (labeled as r) and sentiment investors (labeled as s). 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 investors observe a fundamental signal g = f + e with $e \sim N(0, \sigma_e^2)$. Rational investors correctly update their beliefs as

$$\mathbf{E}_{r}[d|g] = \theta \lambda g, \tag{B.2}$$

where $\lambda = \sigma_f^2 / (\sigma_f^2 + \sigma_e^2)$. In contrast, sentiment investors believe that those firms that are aligned (unaligned) with the incumbent president's economic policy will benefit from (be hurt by) the policy and have higher future cash flows. They update their beliefs as

$$\mathbf{E}_{s}[d|g] = \theta \lambda g + b, \tag{B.3}$$

where $b = (b_1, \dots, b_N)'$ are firms' presidential alignments with $b_1 < \dots < b_N$. Hence, sentiment investors are optimistic about those firms that are aligned well with the current president's economic policies ($b_i > 0$) but pessimistic about those firms that are not aligned well with the current president's economic policy ($b_i < 0$).

Sentiment investors account for a fraction z of the economy at time 1, while rational investors account for the remaining 1 - z, with $z \in [0, 1]$. Different from the literature, we assume z is time varying in a similar spirit of Elkamhi and Jo (2021) and Pan et al. (2022), and independent of g and e.²⁰

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

$$w_r = \frac{1}{\gamma} \Sigma^{-1} (\theta \lambda g - p_1). \tag{B.4}$$

²⁰ Alternatively, we could assume $z = g + \eta$ with η being 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*.

The sentiment investors' demand is

$$w_s = \frac{1}{\gamma} \Sigma^{-1} (\theta \lambda g + b - p_1). \tag{B.5}$$

With the market clearing condition,

$$(1-z)w_r + zw_s = 0,$$
 (B.6)

we have

$$p_1 = \theta \lambda g + zb. \tag{B.7}$$

Thus, when there is no sentiment investor (z = 0), there is no mispricing. Otherwise, asset *i*, $i \in \{1, \dots, N\}$, 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

$$R_{1,i} = p_{1,i} - p_{0,i} = \theta_i \lambda g + z b_i.$$
(B.8)

PEAR beta is

$$\beta_{\text{PEAR},i} = \frac{\text{Cov}(R_i, z)}{\text{Var}(z)} = b_i. \tag{B.9}$$

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

$$R_{2,i} = d_i - p_{1,i} = d_i - \theta_i \lambda g - z b_i = \theta_i f + \varepsilon_i - \theta_i \lambda g - z \beta_{\text{PEAR},i}.$$
(B.10)

Suppose a 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

$$E(R_{PEAR,2}) = z(b_N - b_1) = z(\beta_{PEAR,N} - \beta_{PEAR,1}).$$
(B.11)

Thus, Eqs. (B.10) and (B.11) 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 9 confirms implication 2.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco. 2022.10.004.

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