A comparison of forecasting performance and systematic risk across different political environments

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Abstract: In this study, we investigate whether: 1) there is a substantial difference in out-of-sample predictability US stock market returns under different political environments (and why the difference may occur); 2) whether an ICAPM risk factor is more prevalent under these environments. Traditional predictors, typically found to perform poorly compared to the historical average of market returns, work quite well under certain political environments. We find evidence that returns are more forecastable and exhibit more autocorrelation when the president is a republican or in his second-term, with the best forecasting performance occurring when the president is a second-term republican. We then examine the results from an ICAPM perspective: if returns are more predictable and exhibit more autocorrelation, then a shock to current market returns will have a larger impact on future investment opportunities, resulting in additional risk. We show that systematic risk is indeed higher under these environments.

Keywords: forecasting; presidential puzzle; return predictability; systematic risk; politics.

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1 Introduction

Politics affect market outcomes. Researchers have well documented that US stock market returns are greater on average when the president is a democrat (Santa-Clara and Valkanov, 2003). Recent studies have extended the democratic premium literature to differentiate the effects based on firm size (Sy and Zaman, 2011, 2013), timing during a presidential term (Allvine and O'Neill, 1980; Kraussl et al., 2014), and the degree of party harmony across the executive and legislative branches of government (Beyer et al., 2006; Sy and Zaman, 2011). On the economic side, Blinder and Watson (2016) find that economic performance is better under democrats. Relatedly, Henkel et al. (2011) find that out-of-sample forecasting is superior during recessions.

However, there is mixed evidence in the literature. Bohl et al. (2008, p.323) conclude that "political variables do not contribute systematically to improving the performance of simple trading rules." Santa-Clara and Valkanov (2003) present evidence that the democratic premium is not related to expected returns driven by business cycles. Instead, they assert that this premium occurs because democratic presidents generate positive systematic surprises in the marketplace, leading to higher stock returns during their terms that are not previously anticipated by market participants. Sy and Zaman (2011) further investigate the source of the democratic premium and find that returns are higher under democratic presidents because of higher systematic risk (demonstrated by higher time-varying betas using conditional asset pricing models) and hence a higher market risk premium.

We investigate whether indeed there is a sizeable difference in forecasting power under democrats versus republicans. Essentially, we attempt to confirm whether the results of Henkel et al. (2011) and Blinder and Watson (2016) converge: is forecasting performance superior under republicans? We also examine whether congressional control and first- versus second-term matter. To preview the results, we find that returns are more forecastable under republicans and second-term presidents, with the best forecasting performance occurring under second-term republicans. We then investigate possible causes: stronger autocorrelation of market returns under republicans and the possibility of a Merton (1973) ICAPM factor in these environments. We find that a simple AR(1) model results in the same pattern of forecasting performance, and autocorrelation of market returns is higher under republicans and second-term presidents. Some of our predictors' out-of-sample R^2 increase dramatically when we forecast returns during periods where republicans control both the White House and congress. For example, in our strongest case, the earnings-to-price (e/p) ratio predictor reports an increase in predictive power of more than 2.24 percentage points over the historical average forecast. We also observe much greater out-of-sample R^2 for second-term republican presidents. We observe practically no improved forecasting ability under any democratic regime.

Since market returns are both more predictable and more autocorrelated under republicans and second-term presidents, we posit a more prevalent Merton risk factor. We find that systematic risk is higher under republicans. However, the risk premia of the three Fama-French factors are typically insignificant in the times where forecasting performance is improved. Thus, a latent Merton factor with a negative risk premium could be prevalent under republicans and second-term presidents. The three-factor model is chosen as others have argued that it can be viewed as an ICAPM model (Liew and Vassalou, 2000; Zhang, 2005; Petkova and Zhang, 2005; Stivers, 2018). In related work, Ahmed and Lockwood (1998) find that risk premia and betas fluctuate over time based on stock market and business cycle conditions. Thus, political environments could affect risk premia and betas as well.

The rest of this paper proceeds as follows. Section 2 provides a literature review, dealing with different aspects of political parties and elections on stock returns. Section 3 provides the details on the data and the methodology. Section 4 discusses the results, and Section 5 concludes the study.

2 Literature review

2.1 Presidential political party and stock returns

Santa-Clara and Valkanov (2003) find that stock returns are higher under democratic presidents than they are under republican presidents, which they refer as the *presidential puzzle*. This difference is greater for stocks of small firms, reaching 22% for the smallest market capitalisation stocks. They conclude that "it is the combination of higher real market returns and lower real interest rates during democratic presidential terms that accounts for the difference in excess returns" (p.1859). The authors carefully account for the effect of business cycles on the returns by controlling for dividend yield, term spread, default spread, and relative risk-free rate. They find that the differential returns between democrats and republicans are not driven by the business cycle. They further separate the realised returns into expected (compensation for risk) and unexpected (positive surprises) components. They present evidence that the higher returns during democratic presidential terms are not a compensation for risk. The authors conclude that the return differential across the two dominant parties in the US is due to unexpected returns driven by the systematic positive surprises that democratic presidents' policies generate.

Sy and Zaman (2011) also empirically investigate the presidential puzzle. The innovation in their paper is that they allow the systematic risk to change across different presidential terms by using a conditional capital asset pricing model (CAPM). They find that betas are higher under democratic presidential terms, explaining the higher returns (thus the presidential puzzle) when the president is a democrat. After accounting for time-varying betas, the presidential premium turns statistically insignificant for all size deciles. However, the authors still find an economically (not statistically) significant presidential premium of 7.15% per annum for the smallest decile stocks. The authors further use conditional three-factor asset pricing model by incorporating the size and the value factors in addition to the market factor. This further adjustment results in both an economically and statistically insignificant presidential premium for all size deciles.

Novy-Marx (2014) uses the political party of the US President among other variables to explain return anomalies. Similar to Santa-Clara and Valkanov (2003), he also finds evidence in favour of the presidential puzzle: stock returns are higher when the president is a democrat. However, Novy-Marx (2014) uses a different explanation than those of Santa-Clara and Valkanov (2003) and Sy and Zaman (2011). Instead of positive systematic shocks or time-varying systematic risk, he asserts that the puzzle is driven by a flight to quality. Novy-Marx argues that big-business-friendly republican presidents advance policies that are detrimental to the broader economy. Anticipating a downward economic trajectory, investors chase high quality assets when the president is a republican. Novy-Marx (2014) implicitly defines high quality stocks as

1 stocks with low volatility

2 stocks of highly profitable corporations (measured by earnings-to-price yield)

3 stocks of corporations with low probability of bankruptcy.

He supports his ‘flight to quality’ argument by showing that these high-quality stocks have significantly higher returns during the terms of republican presidents.

Pastor and Veronesi (2017) also tackle the presidential puzzle by constructing a theoretical model. In their model, risk aversion drives the political cycles such that the periods of high risk aversion are associated with voter preferences to choose the party that will enable more government spending. Since higher risk aversion is also associated with higher returns, the time-varying risk aversion predicts both the election of a democratic president and higher future returns.

In addition to higher market returns under democrats, Blinder and Watson (2016) present evidence that the economic performance (using several measures but mainly real GDP growth) is superior under democrats. The authors suggest that the economic differences are not due to policy differences but rather oil shocks and consumer expectations, among other factors. Henkel et al. (2011) find that out-of-sample forecasting performance is superior during recessions. Therefore, republican presidencies may offer superior forecasting. We directly test this, while also examining the forecasting performance and systematic risk under other political environments.

2.2 Politics and the stock market

Li and Born (2006) find that US presidential elections induce return variability when the outcome of a given election is considered an uncertain event (i.e., when neither candidate is a dominant one). Li and Born (2006) also show that once the prospect of a democratic candidate winning the presidential election becomes certain, both returns and returns variability decline. The authors assert that “[t]he failure to observe high returns before the virtually certain election of a democrat suggests that the high subsequent returns reported during democratic-led administrations [by Santa-Clara and Valkanov (2003)] were unexpected” (p.13). Goodell and Vähämaa (2013) also examine the potential volatility induced by US presidential elections and find that the presidential elections in the US affect implied stock market volatility and that this effect is present in the data regardless of the party of the winning candidate [see Pantzalis et al. (2000) and Białkowski et al. (2008) for some of the international evidence of election effects on financial markets]. The effect of politics also extends to firm value. Gropper et al. (2013) find a positive relationship between performance of banks located in a state and the power of congressional representation from that state. They present evidence that members of congress who chair banking committees are good for the value of local banks (i.e., banks located in the states that they represent in congress), which the authors refer to as the chair effect. Based on the extant evidence of higher stock returns and higher government spending during democratic presidencies, Gropper et al. (2013) also investigate the role of democratic presidents on the chair effect and find that the chair effect is stronger when the president is a democrat. Marshall et al. (2018) find that markets are more liquid during democratic presidencies than republican presidencies. The reason given is that markets under democrats have lower information asymmetry, volatility, and economic policy uncertainty.

In a historical study over 1928–2013, Charles and Darné (2014) attribute some of the drastic changes affecting the volatility of the Dow Jones industrial average (DJIA) index to political events. For example, they observe that the DJIA twice dropped more than 3% in the first week of November in 1948, and they attribute these large daily drops to the surprise re-election of democratic incumbent Harry Truman and the fear that democrats would re-establish income taxes following their election victory. In another historical study focusing on World War II, Choudhry (2010) finds that many historical events affected the DJIA, including the death of President Roosevelt.

It is clear that politics (and presidential parties) affect both the economy and the stock market. We investigate whether the effects are systematic, i.e., predictable. We extend the literature in this area to examine more than just presidential party, and we also investigate possible reasons for the forecasting power differences.

3 Data and methodology

3.1 Data

The stock return sample starts in January 1927 and ends in December 2015. Forecasting starts in January 1947, giving an initial estimation window of 20 years or 240 months. Forecasting ends in December 2015 and is done at a monthly frequency. As a measure of the market return, we use the CRSP value-weighted average return, and the equity premium is the market return less the one-month treasury bill rate. We obtain these data from Ken French's website.[1]

Following Welch and Goyal (2008), we use 12-month moving sums of dividends paid on the S&P 500 as a measure of dividends, 12-month moving sums of earnings on the S&P 500 as earnings, the S&P 500 index value as a market price measure, the ratio of book value to market value on the DJIA as the book-to-market measure, and net equity issues (12-month moving sums) over end-of-year market capitalisation for NYSE stocks as a measure of net equity expansion. While the original data come from various sources, we obtain the preceding data from Amit Goyal's website.

From these data (which also include long-term government bond yields and returns, corporate bond yields and returns) and based on the above definitions, we obtain the following variables [constructed as in Welch and Goyal (2008)]: book-to-market (**b**/**m**), long-term yield (**lty**): the yield on long-term US Government bonds, net equity issuance (**ntis**), risk-free rate (**Rfree**): one-month T-bill rates, default return spread (**dfr**): the difference between AAA and BAA bond returns, dividends-to-price ratio (**d**/**p**), and earnings-to-price ratio (**e**/**p**).[2] These variables are picked as they are the set of predictors used in both Welch and Goyal (2008) and Campbell and Thompson (2008).[3]

We match these financial data with political data from the Office of the Clerk of the House of Representatives. We separately analyse the ability to forecast returns based on the party composition of congress and the presidency. Specifically, we contrast periods in which

1 the president and the majority of both congressional chambers were the same party (harmony)
2 the president and the majority of both congressional chambers were not the same party (gridlock)
3 the president and the majority of both congressional chambers were republican
4 the president and the majority of both congressional chambers were democrats
5 the president was republican, but the majority of at least one of the congressional chambers was democrat
6 the president was democrat, but the majority of at least one of the congressional chambers was republican.

We also examine the results of periods when the president is in the first-term versus second-term, and split that by political party (i.e., first-term democrats, first-term republicans, second-term democrats, and second-term republicans).

Table 1 Predictor variables

Name	*Abbreviation*	*Definition*
Book to market value	B/M	The ratio of book value to market value on the Dow Jones industrial average
Long-term yield	LTY	The yield on long-term US Government bonds
Net equity issuance	NTIS	The ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalisation of NYSE stocks
Risk-free rate	Rfree	One-month T-bill rates from 1920 to 2005
Default return spread	DFR	The difference between long-term corporate bond and long-term government bond returns
Dividends-to-price	D/P	The difference between the log of dividends and the log of prices (S&P 500)
Earnings-to-price ratio	E/P	The difference between the log of earnings and the log of prices (S&P 500)

Source: All variables obtained from Amit Goyal's website (https://drive.google.com/file/d/1ACbhdnIy0VbCWgsnXkjcddiV8HF4feWv/view)

3.2 Forecasting methodology

We perform the following recursive forecasting regression, with an expanding estimation window:

$$r_t^m = \alpha_i + \beta_t X_{t-1} + \varepsilon_t, \tag{1}$$

where r_t^m is the excess market return (equity premium) and X is the corresponding predictor. We use the following predictors: **b/m**, **lty**, **ntis**, **Rfree**, **dfr**, **d/p**, **e/p**, and r^m. In addition, we run a kitchen-sink regression with all predictors except r^m. After running equation (1) up to time t, we then obtain the next month's ($t + 1$) forecast:

$$\hat{r}_{t+1}^m = \hat{\alpha}_t + \hat{\beta}_t X_t, \tag{2}$$

based on the estimated coefficients from equation (1).

As in Campbell and Thompson (2008), we calculate an out-of-sample R-squared value (OOS-R^2 hereafter) based on comparison to the historical average of the equity premium as the forecast. OOS-R^2 is calculated as:

$$OOS\text{-}R^2 = 1 - \frac{\sum_{t=1}^{T} (\hat{r}_t - r_t)^2}{\sum_{t=1}^{T} (\overline{r}_t - r_t)^2}, \tag{3}$$

where T is the last month of the forecast sample, r is the market return, $\hat{r}$ is the forecast of the market, and r is the current historical average (at time t). Note that the OOS-R^2 statistic has a range of $(-\infty, 1]$ and provides a measure of how much better the forecast is compared to the historical mean.

To examine the difference in forecasting power between the historical average and the competing model, the MSE-F statistic of McCracken (2004) is applied, as in Welch and Goyal (2008).[4] This statistic is calculated as follows:

$$MSE_F = T * \left(\frac{MSE_{mean} - MSE}{MSE_i} \right), \tag{4}$$

where T is the number of periods (months) in the forecast sample, MSE is mean squared error, mean refers to using the historical average as the forecast, and i refers to the appropriate model i. The critical values for this statistic are obtained via a bootstrapping procedure for each parameter for the full sample.[5]

After forecasting the equity premium from January 1947 to December 2015 and obtaining the forecasted equity premium and realised return, we then split the sample based on several political variables. The baseline scenario involves splitting the sub-samples based on republican or democratic US President for that particular month.[6] This allows for calculation of the OOS-R^2 for each political state, as well as the average return, standard deviation, and Sharpe ratio. We report the full-sample statistics as well for comparison. We additionally perform the following analysis: splitting the sample based on presidential party and control of both congressional chambers (creating four possibilities: republican president and congress, republican president with democrat controlled house or senate, democratic president with republican controlled house or senate, and democratic president and congress), splitting based on first-term or second-term president, and finally splitting based on first-term democratic/republican presidents and second-term democratic/republican presidents.

4 Results

4.1 OOS-R^2 results based on political party

Table 2 shows the out-of-sample forecasting results with sub-samples based on presidential party, after we run equations (1) and (2) above. The table reports the OOS-R^2 for each predictor and the kitchen-sink approach. We also report the average of all seven predictors.[7] Column 1 shows the full-sample results, column 2 shows the sub-sample results when a democratic president is in office, and column 3 shows the sub-sample results when a republican president is in office.[8]

The results show that in most cases, the full-sample predictability is poor when compared to simply using the trailing historical average of the equity premium as the forecast. Also, the kitchen-sink approach works poorly in all instances, which is consistent with Campbell and Thompson (2008) and others who have found these traditional predictors to work poorly.[9]

Table 2 Forecasting results based on presidential party

	(1) OOS-R^2	*(2) Dem. OOS-R^2*	*(3) Rep. OOS-R^2*
b/m	–1.86%	–4.23%	–0.14%
lty	–0.53%	–1.24%	–0.02%
ntis	–0.92%	0.22%*	–1.74%
Rfree	0.13%**	–1.33%	1.19%***
dfr	0.16%**	–0.43%	0.59%**
d/p	0.23%**	–1.44%	1.43%***
e/p	–0.40%	–2.26%	0.94%***
Average	–0.46%	–1.53%	0.32%
Kitchen-sink	–6.00%	–7.30%	–5.05%

Notes: This table shows the full-sample OOS-R^2 when forecasting the excess market return for each predictor as well as a kitchen-sink approach with all predictors and an average of the seven individual predictors. Also shown is the OOS-R^2 for months when the president is a democrat and when the president is a republican. OOS-R^2 is calculated based on the historical average, as in Campbell and Thompson (2008). The initial estimation window starts in January 1927, and forecasting starts in January 1947 and ends in December 2015. The estimation window is expanding, with monthly recursive forecasting performed. See Table 1 for variable definitions. Significance levels are based on McCracken's (2004) MSE-F statistic of superior forecast power, where critical values are obtained via bootstrapping. *** represents significance at 1%, ** represents significance at 5%, and * represents significance at 10%.

A significant difference is noticeable between the two sub-samples, however. For 8 of the 9 specifications, the OOS-R^2 is higher under republican presidencies. Further, only one of the predictors (**ntis**) offers a positive OOS-R^2 under democratic presidential regimes (significant at 10%), while four predictors offer a positive OOS-R^2 under republican presidential regimes (with three being significant at 1% and the other at 5%). This stark difference is noticeable in the average OOS-R^2 for all seven predictors as well. These results show that the traditional predictors offer forecasting value, but only during republican presidencies.

Tables 3 and 4 provide a further breakdown based on which party controls the house and senate, while also repeating the same full-sample results (OOS-R^2) of Table 2 for comparison. Table 3 shows two different breakdowns: in column 2, sub-sample results where either a republican president presides over a democrat-controlled (majority) house or senate or a democratic president presides over a republican-controlled (majority) house or senate (representing possible gridlock); in column 3, sub-samples that are the opposite of column 2, meaning either democrats control both the presidency and congress or republicans control both (representing possible harmony). Column 2 shows that when there is potential gridlock (opposite party controls at least one chamber of congress), there is poor predictability for most predictors (although three predictors do offer positive OOS-R^2 with two being significant at 1% and another at 10%). There is not much improvement in column 3 (representing potential political harmony), with only two predictors offering positive OOS-R^2.

Table 3 Presidential party and congressional party

	(1) OOS-R^2	*(2) Gridlock*	*(3) Harmony*
b/m	–1.86%	–2.15%	–1.34%
lty	–0.53%	–0.23%	–1.06%
ntis	–0.92%	–1.52%	0.13%*
Rfree	0.13%**	1.09%***	–1.55%
dfr	0.16%**	1.34%***	–1.92%
d/p	0.23%**	0.12%*	0.41%**
e/p	–0.40%	–0.57%	–0.11%
Average	–0.46%	–0.27%	–0.78%
Kitchen-sink	–6.00%	–7.69%	–3.03%

Notes: This table shows two additional sub-samples (columns 2–3) of OOS-R^2 results when forecasting the excess market return for each predictor as well as a kitchen-sink approach with all predictors and an average of the seven individual predictors: in column 2, sub-sample results where either a republican president presides over a democrat controlled (majority) house or senate or a democratic president presides over a republican-controlled (majority) house or senate (representing possible gridlock); in column 3, sub-samples that are the opposite of column 2, meaning either democrats control both the presidency and congress or republicans control both (representing harmony). Column 1 again shows the full-sample results. OOS-R^2 is calculated based on the historical average, as in Campbell and Thompson (2008). The initial estimation window starts in January 1927, and forecasting starts in January 1947 and ends in December 2015. The estimation window is expanding, with monthly recursive forecasting performed. See Table 1 for variable definitions. Significance levels are based on McCracken's (2004) MSE-F statistic of superior forecast power, where critical values are obtained via bootstrapping. *** represents significance at 1%, ** represents significance at 5%, and * represents significance at 10%.

Table 4 provides a further breakdown of gridlock and harmony based on party. Column 5 shows that when the harmonious party is the Democratic Party, the forecasting power is typically poor with only two predictors offering positive OOS-R^2. When gridlock is headed by a democratic president (column 4), there is again poor predictability with only one predictor (**dfr**) offering positive OOS-R^2. Columns 2 and 3 clearly provide the best results in terms of forecasting power, when republicans control the presidency. When republicans control both the presidency and congress (column 2), three of the seven predictors have a significantly positive OOS-R^2, and several of them offer much-improved OOS-R^2 (e.g., ranging up to 2.24% for **e**/**p**) compared to the other columns. When a republican president presides over gridlock (column 3), four of the seven predictors offer positive OOS-R^2 (three of those significant at 1%), with the highest being almost 2% (**d**/**p**).

Table 4 Presidential party and control of congress

	(1) OOS-R^2	*(2) Republicans control*	*(3) Rep. president, non-cong. control*	*(4) Dem. president, non-cong. control*	*(5) Democrats control*
b/m	–1.86%	0.03%*	–0.18%	–7.33%	–2.00%
lty	–0.53%	0.50%**	–0.15%	–0.44%	–1.81%
ntis	–0.92%	–0.48%	–2.07%	–0.07%	0.43%*
Rfree	0.13%**	–0.09%	1.51%***	–0.03%	–2.27%
dfr	0.16%**	–3.39%	1.61%***	0.63%*	–1.20%
d/p	0.23%**	–0.52%	1.94%***	–4.66%	0.86%**
e/p	–0.40%	2.24%**	0.61%**	–3.66%	–1.25%
Average	–0.46%	–0.24%	0.47%	–2.22%	–1.03%
Kitchen-sink	–6.00%	–3.67%	–5.41%	–13.69%	–2.71%

Notes: This table shows sub-samples split based on congressional and presidential control: (2) – republicans control both chambers of congress (majority) and the presidency; (3) – republican president and democratic congress; (4) – democratic president and republican congress; (5) – democrats control congress and the presidency column 1 again shows the full-sample results. OOS-R^2 is calculated based on the historical average, as in Campbell and Thompson (2008). The initial estimation window starts in January 1927, and forecasting starts in January 1947 and ends in December 2015. The estimation window is expanding, with monthly recursive forecasting performed. See Table 1 for variable definitions. Significance levels are based on McCracken's (2004) MSE-F statistic of superior forecast power, where critical values are obtained via bootstrapping. *** represents significance at 1%, ** represents significance at 5%, and * represents significance at 10%.

Table 5 splits the sub-samples based on whether the president is in his first or second-term. These results are shown in columns 2 and 3, respectively, after the full-sample results are repeated in column 1. Comparing columns 2 and 3 shows that all but two predictors offer better performance when the president is in his second-term. Columns 4–7 show the sub-sample results by both party and term. Again, republican regimes provide better predictability. First-term republicans (column 4) sub-samples result in higher OOS-R^2 for all but one predictor compared to first-term democratic sub-samples. Column 6 (second-term republican sub-sample) provides the best results for most predictors, ranging as high as 2.53% OOS-R^2 (**d/p**, which is the best OOS-R^2 for any predictor and sub-sample).

Finally, we also investigate the forecasting performance of an AR(1) model (lagged market return as the predictor) in these various sub-samples. Table 6 shows the OOS-R^2 of the AR(1) model. Similar to the other predictors, OOS-R^2 is significantly positive under republicans and 2nd-term presidents but is negative under democrats and 1st-term presidents. Also, the best forecasting performance (3.11% OOS-R^2) occurs under 2nd-term republicans. Thus, it may not be anything special about the standard predictors we have used thus far, but that market returns are in general more predictable out of sample.

Table 5 Presidential term and party

	(1) OOS-R^2	*(2) 1st term*	*(3) 2nd term*	*(4) 1st term rep.*	*(5) 1st term rep.*	*(6) 2nd term rep.*	*(7) 1st term dem.*
b/m	–1.86%	–3.11%	0.12%*	–1.54%	–5.54%	2.36%***	–2.48%
lty	–0.53%	–1.25%	0.60%**	–0.46%	–2.47%	0.77%**	0.39%**
ntis	–0.92%	0.24%**	–2.74%	–0.23%	0.97%*	–4.44%	–0.77%
Rfree	0.13%**	–0.05%	0.40%**	1.47%***	–2.40%	0.68%**	0.08%*
dfr	0.16%**	0.52%**	–0.42%	1.46%***	–0.93%	–0.97%	0.23%*
d/p	0.23%**	–0.14%	0.79%**	0.82%**	–1.62%	2.53%***	–1.21%
e/p	–0.40%	–1.39%	1.16%***	0.16%*	–3.80%	2.35%***	–0.21%
Average	–0.46%	–0.74%	–0.01%	0.24%	–2.26%	0.47%	–0.57%
Kitchen-sink	–6.00%	–6.63%	–5.00%	–4.27%	–10.29%	–6.45%	–3.33%

Note: This table shows additional sub-samples (columns 2–7) of OOS-R^2 results when forecasting the excess market return for each predictor as well as a kitchen-sink approach with all predictors and an average of the seven individual predictors. Column 2 shows the results when the president is in his first-term, and column 3 shows the results when the president is in his second-term. The remaining columns show the sub-sample results splitting by both first or second-term and party (rep. for republican and dem. for democrats). Column 1 again shows the full-sample results. OOS-R^2 is calculated based on the historical average, as in Campbell and Thompson (2008). The initial estimation window starts in January 1927, and forecasting starts in January 1947 and ends in December 2015. The estimation window is expanding, with monthly recursive forecasting performed. See Table 1 for variable definitions. Significance levels are based on McCracken's (2004) MSE-F statistic of superior forecast power, where critical values are obtained via bootstrapping. *** represents significance at 1%, ** represents significance at 5%, and * represents significance at 10%.

To examine why that might be the case, Table 6 also reports the one-lag autocorrelation of market returns in these political sub-samples. Under republican presidents, the autocorrelation coefficient is 0.18, while under democrats it is 0.02. The pattern does not hold with 1st-term and 2nd-term presidents regardless of party (2nd-term presidents having a slightly negative autocorrelation). However, when we look at both term and party, the autocorrelation again matches the forecasting performance. 1st-term republicans have an autocorrelation of 0.19 compared to 0.11 for 1st-term democrats. Under 2nd-term presidents, the party difference is even more stark: 2nd-term republicans have an autocorrelation of 0.16 compared to –0.10 for 2nd-term democrats. Thus, the increased autocorrelation under republicans may be why forecasting performance is superior for those presidencies.

4.2 ICAPM risk factor

We now investigate whether a Merton-type ICAPM risk factor may be more prevalent during the times of increased forecasting power and market return autocorrelation (republicans and second-term presidents). When returns are more predictable and more autocorrelated, a shock to current market returns will have a more pronounced effect on future investment opportunities. Thus, an additional risk could be present. We thus investigate the differences in systematic risk under the various political environments.

Table 6 Forecasting performance of AR(1) and average autocorrelation

	OOS-R^2 of AR(1)	*Autocorrelation*
Overall	0.10%*	0.110
Dem. pres.	–1.96%	0.015
Rep. pres.	1.6%***	0.184
1st-term pres.	–0.15%	0.166
2nd-term pres.	0.50%**	–0.002
1st-term rep.	0.76%**	0.190
1st-term dem.	–1.55%	0.111
2nd-term rep.	3.11%***	0.159
2nd-term dem.	–2.52%	–0.097

Notes: This table shows OOS-R^2 results when forecasting the excess market return using an AR(1) model. The overall, full-sample results are shown, as well as various presidencies: democrats (dem.), republicans (rep.), 1st-term, 2nd-term, and term based on party. OOS-R^2 is calculated based on the historical average, as in Campbell and Thompson (2008). The initial estimation window starts in January 1927, and forecasting starts in January 1947 and ends in December 2015. The estimation window is expanding, with monthly recursive forecasting performed. Significance levels are based on McCracken's (2004) MSE-F statistic of superior forecast power, where critical values are obtained via bootstrapping. *** represents significance at 1%, ** represents significance at 5%, and * represents significance at 10%. Also reported is the one-lag autocorrelation of market returns during the various presidencies.

Santa-Clara and Valkanov (2003) claim that returns under democrats are unexpected and driven by positive systematic risk surprises (but returns are not higher due to higher risk). Sy and Zaman (2011) find that once an appropriate model with time-varying betas is implemented, the democratic premium disappears. However, Sy and Zaman use ten size-sorted portfolios as test assets. A more appropriate set of test assets would have a weaker factor structure. We therefore use the 30 Fama-French industry portfolios as test assets to examine the difference in systematic risk under democratic and republican presidents.

Using the Fama-French 30 industry portfolios as test assets and a monthly frequency, we use the same 1927–2015 sample period and perform a time-series regression with two distinct samples: industry portfolio returns when a democrat is in the White House and industry portfolio returns when a republican is in the White House. Table 7 shows the

1st-pass (under a Black-Jensen-Scholes two-pass approach) time-series results for the two samples. The regression is as follows:

$$r_{p,t} = \alpha_p + \beta_{pM} r_{M,t} + \beta_{pSMB} SMB_t + \beta_{pHML} HML_t + \varepsilon_{p,t}, \tag{5}$$

where $r_{p,t}$ is the excess return on industry portfolio p at time t, $r_{M,t}$ is the excess market return, *SMB* is the Fama-French size factor, *HML* is the Fama-French value factor, α_p the intercept, and $\varepsilon_{p,t}$ is the error term at time t. The coefficients shown in Table 7 are the average of the 30 time-series coefficients for each of the three factors, along with the average t-statistics in parentheses (the average intercept is not reported). We also show the average adjusted R-squared value.

The results show that betas on the market factor and size factor are higher under republican presidents. The magnitude of average beta on the value factor is higher under republicans as well, although the sign is reversed compared to democrats. The three-factor model better explains industry portfolio returns under republican presidencies, as shown by the average first-pass fit increasing by 28% compared to democrats. The results clearly show that for industry portfolios, systematic risk is higher under republicans. However, this is different than the finding offered by Sy and Zaman (2011) that betas and systematic risk are higher under democrats when using size-sorted portfolios.

Table 7 Time-series factor model results

	Democrats	*Republicans*
β_M	1.114 (5.16)***	1.217 (6.04)***
β_{SMB}	–0.034 (–0.12)	0.713 (1.76)*
β_{HML}	0.329 (1.13)	–0.466 (1.50)
R^2	0.0636	0.0813

Notes: This table shows the results of time-series regressions for the 30 Fama-French industry portfolios using the Fama-French three-factor model. The regression is as follows:

$$r_{p,t} = \alpha_p + \beta_{pM} r_{M,t} + \beta_{pSMB} SMB_t + \beta_{pHML} HML_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on industry portfolio p, $r_{M,t}$ is the excess market return, *SMB* is the Fama-French size factor, *HML* is the Fama-French value factor, α_p is the intercept, and $\varepsilon_{p,t}$ is the error term. The returns are split into democrat and republican presidency subsamples. For republicans, the sample periods where a republican is president are used in the time-series regressions (and vice versa for democrats). The reported coefficients are the average of the 30 time-series coefficients for each of the three factors, along with the average t-statistics in parentheses (the average intercept is not reported). The average adjusted R-squared value is also reported. The sample begins in January 1927 and ends in December 2015. Significance levels are based on the average t-statistic. *** represents significance at 1%, ** represents significance at 5%.

To further investigate this discrepancy, we implement the conditional models of Sy and Zaman using the 30 industry portfolios. In results available upon request, we find that CAPM betas are almost always higher under republicans and second-term presidents. Fama-French factor betas are typically higher in those times as well. Overall, these results suggest that systematic risk is higher under republicans and second-term presidents. This would be expected if indeed an additional risk is present when market returns are more predictable (forecastable) and more autocorrelated. However, this additional risk could carry a positive or negative risk premium, thereby enforcing or mitigating market risk. Since the factor is latent (and our predictors are non-tradeable), we cannot directly observe the risk premium. However, we can look at the risk premia of the Fama-French factors under the various political environments.

Table 8 Average risk premia in various presidencies

	Dem. pres.			*Rep. pres.*		
	Rm-Rf	*SMB*	*HML*	*Rm-Rf*	*SMB*	*HML*
Mean	12.29%	5.32%	4.16%	2.64%	–0.36%	5.11%
p-value	0.000	0.003	0.018	0.385	0.810	0.008
	Gridlock			*Harmony*		
	Rm-Rf	*SMB*	*HML*	*Rm-Rf*	*SMB*	*HML*
Mean	5.94%	–1.87%	3.45%	9.26%	6.49%	5.60%
p-value	0.014	0.251	0.022	0.002	0.000	0.006
	1st-term pres.			*2nd-term pres.*		
	Rm-Rf	*SMB*	*HML*	*Rm-Rf*	*SMB*	*HML*
Mean	7.34%	3.11%	5.80%	8.26%	2.00%	3.02%
p-value	0.010	0.047	0.002	0.002	0.274	0.083
	1st-term dem.			*1st-term rep.*		
	Rm-Rf	*SMB*	*HML*	*Rm-Rf*	*SMB*	*HML*
Mean	14.21%	6.00%	5.07%	1.24%	0.55%	6.44%
p-value	0.000	0.014	0.037	0.767	0.783	0.021
	2nd-term dem.			*2nd-term rep.*		
	Rm-Rf	*SMB*	*HML*	*Rm-Rf*	*SMB*	*HML*
Mean	10.28%	4.60%	3.22%	5.16%	–2.00%	2.72%
p-value	0.005	0.086	0.210	0.198	0.341	0.178

Notes: This table shows the annualised average risk premia of the three Fama-French risk factors: excess market return (Rm-Rf), size (SMB), and book-to-market (HML) for various presidencies: democrats (dem.), republicans (rep.), gridlock: where either a republican president presides over a democrat-controlled (majority) house or senate or a democratic president presides over a republican-controlled (majority) house or senate, harmony: where either democrats control both the presidency and congress or republicans control both, 1st-term, 2nd-term, and term based on party. P-values are also reported.

We report the average annualised risk premia of the three Fama-French factors in Table 8. Under democrats, all three are significantly positive, while under republicans only the value factor is significantly positive (and the size factor is negative). This is consistent with Sy and Zaman (2011), and it seems that the size premium only exists under democrats. The size premium also goes away under gridlock, and harmony in general has higher premia. While there is not much of a difference in the premia under 1st-term and 2nd-term presidents, there is a large difference between 1st-term democrats and republicans. Again, only the value factor is significant under 1st-term republicans. While the market risk premium is 5% annually under 2nd-term republicans, all three risk premia are lower under 2nd-term republicans compared to 2nd-term democrats. Additionally, none of the three premia are significantly different from zero for 2nd-term republicans.

Thus, for republicans (especially 2nd-term republicans), systematic risk is higher (betas of higher magnitude), but the factors have lower risk premia. We argue that a Merton risk factor is more prevalent due to the more predictable and more autocorrelated market returns. This latent Merton factor may carry a negative risk premium (or a low positive one), which is driving down the observed Fama-French factors' premia. If the Merton factor does carry a negative risk premium, it would mitigate market risk. Admittedly, the three Fama-French factors may not be capturing the relevant intertemporal risk and are lower for other reasons.

5 Conclusions

In this study we investigate the out-of-sample predictability and the possibility of a Merton ICAPM factor under various US political regimes. We offer several contributions based on our findings. Our first contribution is our finding that forecasting excess market returns using standard univariate predictors is more successful (in terms out-of-sample R^2 compared to the historical average) when the president is republican or in his second-term, with second-term republicans having the best performance. The standard predictors used in the market forecasting literature offer substantial value under republicans and second-term presidents. Thus, we confirm that the results of Blinder and Watson (2016), more recessions under republicans, and Henkel et al. (2011), superior forecasting performance during recessions, simultaneously hold. This contrasts a bit with the findings of Santa-Clara and Valkanov (2003) and Bohl et al. (2008), which both argue (to an extent) that political regimes and the business cycle do not affect market returns. We also add to this literature by showing that first versus second-term affects forecasting power as well.

We use seven separate predictors to forecast returns under different political environments in the USA over the span 1927 to 2015. Specifically, we explore the variation in predictor forecast performance under scenarios of

1 democrat and republican presidencies
2 executive and legislative branch party harmony and gridlock
3 during a president's first and second-term.

We find that several predictors report greater out-of-sample R^2 under republican and second-term presidents than under democrats and first-term presidents. We also find that an AR(1) model displays the same pattern as most of our other predictors: forecasting is better under republicans, better under second-term presidents, and is typically best under second-term republicans. We find that market returns are more autocorrelated under republicans compared to democrats as well, which may explain our forecasting results and the results of Henkel et al. (2011).

Our second contribution is that we demonstrate the possibility of a more pronounced Merton factor under republican presidents. Since, as we show, returns are more predictable and more autocorrelated under republicans (especially so for second-term republicans), shocks to current market returns in those environments would have a relatively larger impact on future market returns (i.e., future investment opportunities). We find evidence that systematic risk is higher under republicans and second-term presidents. This latent Merton factor may carry a positive or negative risk premium, but we show that the risk premia of the three Fama-French factors are substantially lower under republicans and second-term presidents. It is possible that these Fama-French factors are capturing some of the latent Merton factor, which in this scenario would have a low or negative risk premium. Thus, the latent Merton factor in these environments would mitigate the additional risk that the more predictable and autocorrelated market returns cause.

Our work offers a third (and more minor) contribution confirming the main finding of Sy and Zaman (2011) that the presidential premium disappears when accounting for time-varying risk via conditional asset pricing models. We offer a different explanation for why time-varying risk explains the premium, though. When looking at a given portfolio return, under democrats the risk adjustment involves lower betas times higher factor returns (lower and higher, respectively, in relation to republicans). Under republicans, the risk adjustment involves higher betas times lower returns. A Merton risk factor with a negative risk premium could also explain the presidential premium. Ultimately, time-varying systematic risk explains the large variation in market returns across presidential party.

A general takeaway from our results is that future market forecasting research should examine subsample performance of forecasting variables. A predictor that appears inferior to the historical average forecast in a full sample may still offer valuable predictions under certain economic or market conditions. We acknowledge that a more prevalent Merton risk factor could explain the forecasting results instead of the other way around. It could also be that certain policies or economic outcomes in these environments drive systematic risk higher. There are certainly other possible explanations for the difference in forecasting performance across presidencies, but our hope is that these initial findings generate more research in this area.

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Notes

1 We would like to thank Ken French, Robert Shiller, and Amit Goyal for making their data available.

2 See Table 1 for a summary of the predictor variables.

3 Consumption-to-wealth (cay) ratio is also used by both Campbell and Thompson (2008) and Welch and Goyal (2008) but is not included here, as cay is typically measured at a quarterly or annual frequency. Additionally, the term spread is used by both but dropped here, as it is simply the difference between **lty** and **Rfree**.

4 Note that a one-parameter model and the historical mean are technically nested models. The Clark and McCracken (2001) test could also be applied to check for encompassing. These results are not reported, but available upon request.

5 For the various subsamples, the size of the subsample is used as T, but the critical values are still used based on a larger T and using the entire sample. This helps avoid a potential bias in the significance levels and punishes the subsample stats for having fewer observations.

6 When January follows a general election in the preceding year, the party that takes power during January is considered to have control for that month.

7 This average does not include the kitchen-sink approach.

8 We also implement a rolling forecast window in unreported results. The expanding window performs much better for almost all predictors. These results are available upon request from the authors.

9 We also examine several other unreported predictors: cyclically adjusted earnings-to-price, p/e (adjusted and unadjusted), inflation, long-term rate of return on government bonds, returns on corporate bonds, market return variance, default yield spread, dividends-to-earnings, and dividend yield. Qualitatively the results are the same, with republican regimes performing better and price measures performing the best. These results are available upon request. Specifically, the p/e ratio is the best predictor we examine but is left out of this analysis to be consistent with Welch and Goyal (2008) and Campbell and Thompson (2008).