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Alternative Estimates of the Presidential Premium

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Abstract: Since the early 1980's much research, including the most recent contribution of Santa-Clara and Valkanov (2003), has concluded that there is a stable, robust and significant relationship between Democratic presidential administrations and robust stock returns. Moreover, the difference in returns does not appear to be accompanied by any significant differences in risk across the presidential cycle. These conclusions are largely based on OLS estimates of the difference in returns across the presidential cycle. We re-examine this issue using more efficient estimators of the presidential premium. Specifically, we exploit the considerable and persistent heteroskedasticity in stock returns to construct more efficient weighted least squares (WLS) and generalized autoregressive conditional heteroskedasticity (GARCH) estimators of the difference in expected excess stock returns across the presidential cycle. Our findings provide considerable contrast to the findings of previous research. Across the different WLS and GARCH estimates we find that the point estimates are considerably smaller than the OLS estimates and fluctuate considerably across different sub samples. We show that the large difference between the WLS, GARCH and OLS estimates is driven by differing stock market performance during very volatile market environments. During periods of elevated market volatility, excess stock returns have been markedly higher under Democratic than Republican administrations. Accordingly, the WLS and GARCH estimators are less sensitive to these episodes than the OLS estimator. Ultimately, these results are consistent with the conclusion that neither risk nor return varies significantly across the presidential cycle.

Keywords: presidential puzzle, realized volatility, range based volatility

JEL Codes: G1, G12, G14

1. Introduction

There is a growing consensus that Democratic presidential administrations bode well for the stock market. For over twenty years, beginning with Allvine and O'Neill (1980) and continuing through the recent work of Santa-Clara and Valkanov (2003), a variety of researchers have found that Democratic presidential administrations predict robust stock market returns. Moreover, the findings of this research suggest that the political cycle in stock returns is extremely large and stable over much of the past century. Santa-Clara and Valkanov (2003), for example, estimate that the expected difference in excess returns across Democratic and Republican presidencies is over nine percent per year in the case of large stocks and over sixteen percent per year in the case of small stocks. Moreover, while previous research has concluded that the difference in returns across the presidential cycle is large there is little evidence of any difference in stock market risk across Democratic and Republican administrations, Hensel and Ziemba (1995), Santa-Clara and Valkanov (2003), resulting in what Santa-Clara and Valkanov (2003) term a "presidential puzzle".

In this paper we contribute to the debate on the existence of a political cycle in stock returns. We present more efficient estimates of the Democratic return premium that provide considerable contrast to the findings of previous research. Previous research has relied on OLS estimates of the Democratic return premium. At the same time, it is well known that stock returns exhibit considerable and persistent variation in volatility. We exploit this heteroskedasticity in stock returns in estimating the expected difference in stock returns across the presidential cycle. Specifically, we employ a variety of weighted least squares (WLS) and generalized autoregressive conditional heteroskedasticity (GARCH) estimators in investigating the evidence in favor of a large and robust Democratic return premium between 1927 - 1998.

Across all the different estimators investigated, we find that incorporating the information contained in the heteroskedasticity of stock returns into the estimator of the Democratic return premium results in a significant increase in efficiency relative to the previous OLS results and a significant decrease in the size and stability of the premium. In the case of large stocks we find that the estimated Democratic return premium falls from 8.93% per year in the case of OLS to between 2.95% and 5.41% per year depending on the specific estimator employed. In the case of small stocks the estimated premium falls from 15.67% in the case of OLS to between 4.85% and 12.10% per year. Also, unlike the OLS estimates, we find considerable instability in the WLS and GARCH point estimates across different sub samples. These findings call into question the robustness, statistical significance and magnitude of the presidential cycle in stock returns.

We investigate the underlying cause behind the discrepancy between the WLS, GARCH and OLS estimates of the Democratic return premium. We find that a large portion of the difference between these estimates can be explained by the differential stock market performance of the two parties during very volatile market environments. During periods in which annual market volatility has been in excess of 25%, approximately 11% of the time between 1927-1998, Democratic administrations have experienced vastly better stock market performance than Republican ones. Since, however, these periods of extremely high returns have coincided with high volatility these periods impart less influence on the WLS and GARCH estimates relative to the OLS estimates. When viewed through the lens of these more efficient estimators, the data are less supportive of the notion that Democratic administrations predict robust stock market returns.

This paper makes two primary contributions to the literature on the link between stock returns and presidential party affiliation. First, we are the first to provide WLS or GARCH estimates of the Democratic return premium. In light of the importance of the size of this premium for a variety of interesting economic and social questions and given the potential efficiency gain available from employing WLS and GARCH estimators of the premium, these estimates are of interest in their own right. Second, against a backdrop of nearly uniform support in favor of a large and robust premium we are the first to provide point estimates that call this conclusion into question. While others including Santa-Clara and Valkanov (2003) have noted that the results of previous studies may be questioned on the basis of data snooping and other statistical considerations, we are the first to provide point estimates of the Democratic return premium which suggest its magnitude is small. While there is some evidence of a Democratic return premium in the case of small stocks during the latter half of the sample, the overwhelming majority of the results suggest that the evidence in favor of a significant and robust premium is considerably weaker than previously reported. In this way, the results reported here help to resolve the puzzling disconnect between the findings of previous research and standard economic theory. Ultimately, our results are consistent with the notion that neither risk nor return varies substantially across the presidential cycle.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the presidential puzzle and the evidence that is most often offered in favor of a large and significant political cycle in stock returns. Section 3 discusses the alternative WLS and GARCH estimators of the Democratic return premium employed in this study. Section 4 discusses the data used in this study and how it relates to previous research. Section 5 discusses the empirical results. Section 6 investigates the cause of the large differences between the WLS, GARCH and OLS estimates. Section 7 summarizes our findings and provides concluding remarks.

2. The Presidential Puzzle

Since the early 1980's, a steady stream of research has argued that a large and stable difference in stock returns exists across Democratic and Republican presidential administrations, Allvine and O'Neill (1980), Herbst and Slinkman (1984), Huang (1985), Hensel and Ziemba (1995), Siegel (1998), Johnson, Chittenden and Jensen (1999), Santa-Clara and Valkanov (2003). The primary evidence offered in favor of a political cycle in stock returns has been sample average stock returns across Democratic and Republican presidencies over varying sample periods. Specifically, each of these studies reports OLS results from the regression,

$$\begin{aligned} y_{t+1} &= DD+(RD-DD)\pi_t+\varepsilon_{t+1} \\ (rd-dd)_{OLS} &= \frac{\sum \pi_t(y_t-\bar{y})}{T\bar{\pi}(1-\bar{\pi})} \quad , \\ \bar{x} &= \frac{1}{T}\sum x_t \end{aligned} \tag{1}$$

where y_{t+1} is a financial asset return, π_t is a dichotomous variable that signals one of the two political parties and T is the sample size. For the purposes of this study, we choose to normalize

π_t in such a way that π_t=1 refers to a Republican administration. Several measures of financial asset returns, y_{t+1}, have been used as dependent variables in the regression above. Huang (1985) focuses on a broad measure of common stock returns, Hensel and Ziemba (1995) and Johnson, Chittenden and Jensen (1999) examine the returns of both small and large capitalization stocks, Siegel (1998) focuses on the return of firms in the Standard and Poor's index. More recently, Santa-Clara and Valkanov (2003) examine both real returns and excess returns on a variety of small and large capitalization stock portfolios using CRSP data.

Each of these authors find evidence in favor of higher stock returns, of one sort or another, during Democratic presidential administrations. The congruence of these findings is not too surprising, however, since each study uses similar stock return data over similar sample periods. What is perhaps most surprising about these findings is the sheer size of the estimated Democratic premium. Santa-Clara and Valkanov (2003) report that the sample average of excess returns on the CRSP value weighted portfolio is over nine percentage points higher during Democratic administrations between 1928 and 1998. In the case of small capitalization stocks, the average return difference is even greater. Over the same sample period, Santa-Clara and Valkanov (2003) report that the average excess return on the CRSP equal weighted portfolio was over sixteen percentage points higher under Democratic administrations.

This difference in average returns is strikingly large. It is interesting to note that the difference in excess returns across the presidential cycle (9.0%) is larger than the average excess return itself (6.5%). To put the magnitude of this estimate in perspective it is useful to compare its size with that of other well known and thoroughly researched stock market anomalies. Consider, for example, the difference in stock returns between the month of January and all other months, i.e. the "January Effect". Using the Standard & Poor's total return index, Siegel (1998) reports the January Effect to be 4.8% per year between 1925 and 1997 which is roughly half the size of the estimated Democratic return premium on the value weighted portfolio. The anomalous increase in stock value observed just after a stock is included in the S&P 500 or "indexation effect" is reported by Shleifer (1986) to be 2.8%. The anomalous persistent increase in stock returns following positive earnings surprises or "post-announcement drift" documented by Foster, Olsen and Shevlin (1984) is on the order of 4.0%. Relative to these well documented and thoroughly researched anomalies, the sheer magnitude of the "presidential puzzle" is staggering. Accordingly, it is not surprising that Huang (1985) warns "investors who ignore the remarkably consistent pattern [in stock returns] do so at their own peril".

In light of the large and puzzling difference in average returns across Democratic and Republican presidential administrations that are unaccompanied by any difference in risk, we further examine the evidence in favor of a presidential premium using a set of estimators that are more efficient than OLS. In this sense, our work is similar in spirit to Hsieh and Merton's (1990) re-examination of the link between margin requirements and stock market volatility. Hsieh and Merton (1990) employ a GLS estimator of the relationship between margin requirements and volatility and find that the GLS estimation results reverses the findings of previous estimates based on OLS.[1] Ultimately they conclude that the GLS results are both more

[1]Specifically, they estimate the parameters of the regression model, $y_t = x_t\beta + \varepsilon_t$, by regressing Δy_t onto Δx_t. This procedure can be viewed as the GLS estimator that is appropriate in the case that the regression errors follow an AR(1) process in which the autocorrelation between successive errors approaches unity (see Hamilton, 1990).

informative and consistent with standard economic theory.[2] A key difference between our work and theirs is the underlying motivation for GLS estimation. In their context, the main deviation from homoskedasticity arose from highly persistent residuals. In our context, homoskedasticity is violated due to time variation in the volatility of excess returns while serial correlation is less of an issue. As a result, we propose a set of estimators that explicitly account for the time variation in the volatility of excess returns.

3. An Alternative Estimator of the Democratic Return Premium

In this paper we take an alternative approach to measuring the difference in expected excess returns across Democratic and Republican presidential administrations. Our point of departure from the rest of the presidential cycle literature starts with how we choose to handle the considerable and persistent time series heteroskedasticity present in stock returns. Since the influential work of Schwert (1989a, 1989b, 1990), financial economists have recognized that the most pervasive feature of asset returns is the large and predictable variation in their volatility. Previous research that has estimated the difference in expected stock returns across the presidential cycle has either ignored this feature of the data, Huang (1985), Hensel and Ziemba (1995), Johnson Chittenden and Jensen (1999), or have used "robust" variance estimators, such as the Newey-West (1987) HAC variance estimator, which allows for appropriate asymptotic

[2] Hsieh and Merton (1990) take issue with the findings of previous research that suggested increasing margin requirements dampened stock market volatility. They argue that market speculators and arbitrageurs step in when prices move away from fundamental values and hence increasing their cost of entering the market by raising margin requirements should lead to higher volatility. Once the relationship between margin requirements and volatility is estimated using a GLS estimator they indeed find this to be the case.

inference in the presence of heteroskedasticity, Santa-Clara and Valkanov (2003).[3]

Rather than appeal to OLS estimation of the Democratic return premium and robust inferential procedures which are asymptotically valid in the presence of heteroskedasticity, we choose to employ more efficient estimators that directly incorporate the heteroskedasticity of stock returns into our estimator of the Democratic return premium. These more efficient estimates of the Democratic return premium serve as a further robustness check on the size and significance of the results presented in previous studies. We incorporate the information in the volatility of returns into an estimator of the Democratic return premium in two ways.

Non-parametric Volatility Measurement and Weighted Least Squares Estimators

The first estimator that we employ in estimating the Democratic return premium is the Weighted Least Squares, WLS, estimator. In particular, we consider estimation of the following model,

$$\begin{aligned} y_{t+1} &= DD + (RD - DD)\pi_t + \varepsilon_{t+1} \\ Var(\varepsilon_{t+1} | I_t) &= \sigma^2_{t+1|t} \end{aligned}, \qquad (2)$$

or in stacked form,

[3]The tendency of HAC robust tests to over reject in finite samples is well known, Andrews (1991), Andrews and Monahan (1992). Recently, Kiefer and Vogelsang (2002a,b) suggest an asymptotic framework in which both the numerator and the denominator of the robust HAC t-statistic are treated as random variables. They find that this asymptotic framework results in a much tighter relationship between the asymptotic and finite sample distribution of the test. None of the previous studies, however, make use of this recent development in interpreting the statistical significance of their findings.

$$
\begin{aligned}
Y &= X\tilde{\beta}+\tilde{\varepsilon} \\
E\left(\tilde{\varepsilon}\tilde{\varepsilon}' \middle| X\right) &= \Omega \qquad , \\
\Omega &= diag\left(\sigma^2_{1|0},\sigma^2_{2|1},..,\sigma^2_{T|T-1}\right)
\end{aligned}
\tag{3}
$$

via GLS. Importantly, the specification of the conditional mean that we estimate is identical to that of the previous presidential cycle literature. Our main innovation is to directly incorporate the information contained in the volatility of returns, $\sigma^2_{t+1|t}$, into the estimator. The diagonal nature of Ω results in the WLS estimator. In the context of the specific model considered here the WLS estimator of the Democratic return premium may be expressed as,

$$
\begin{aligned}
(rd-dd)_{WLS} &= \sum_{\pi_t=1} y_{t+1}w_{1,t}-\sum_{\pi_t=0} y_{t+1}w_{0,t} \\
w_{j,t} &= \frac{\sigma^{-2}_{t+1|t}}{\sum_{\pi_t=j}\sigma^{-2}_{t+1|t}} \qquad ,
\end{aligned}
\tag{4}
$$

so that the OLS estimator typically employed in previous research is a special case of the WLS estimator in which volatility is taken to be constant. To the extent that volatility fluctuates over time, the WLS estimator will enjoy an efficiency gain over the OLS estimator.

In order to construct the WLS estimator it is necessary to have a consistent estimate of Ω. We exploit recent developments in the volatility measurement literature, Andersen, Bollerslev and Diebold (2004), Alizadeh, Brandt and Diebold (2002), to construct non-parametric estimates of Ω. Specifically, we use both a realized volatility estimator and a range based estimator of the notional variance of monthly excess returns, σ_t, which is then incorporated into the WLS estimator above.

In the case of the realized volatility estimator we use the monthly average of daily squared returns,

$$\hat{\sigma}_{t,realized} = \sqrt{\sum_{j=1}^{J(M)} r_{j,t}^2 + 2\sum_{j=1}^{j=J(M)-1} r_{j,t} r_{j+1,t}}, \tag{5}$$

where $J(M)$ refers to the number of trading days in month M to approximate the notional volatility during month t[4]. The realized variance estimator has a long tradition in finance. Schwert (1989a,1989b), for example, employs this estimator of notional variance in exploring the links between stock market volatility and the macroeconomy. Additionally, the realized volatility estimator has taken a central role in recent developments in the theory of non-parametric volatility measurement. In particular, recent work by Andersen, Bollerslev and Diebold (2004) and Barndorff-Nielsen and Shepard (2002) shows that as the partition of time within the month grows finer and finer, i.e. bi-weekly, weekly, daily, hourly, etc., the realized volatility estimator provides an error free estimate of the monthly notional volatility, σ_t.

We also employ an additional estimator of the monthly notional volatility of excess returns based on the daily range. Specifically, for each month of the sample we construct the log range of the log price index,

$$\log(R_t) = \log\left(p_t^{High} - p_t^{Low}\right), \tag{6}$$

[4]Following, French, Schwert and Stambaugh (1987) we include the cross product of adjacent returns to control for autocorrrelation that may arises as a result of asynchronous trading.

where p_t represents the log of the price index series. We then use the log range to construct an estimate of the notional volatility as follows,

$$\log(\hat{\sigma}_{t,range}) = \log(R_t) , \tag{7}$$

which Alizadeh, Brandt and Diebold (2002) demonstrate to be an effective estimator of the log notional volatility, $\log(\sigma_t)$.[5] We employ both the range and the realized volatility estimator of notional volatility for two reasons. First, both methods serve as a check on each other ensuring that our results are not due to the idiosyncracies of a single volatility measurement framework. Second, while the realized volatility estimator has desirable statistical properties, these estimators are known to suffer from biases and other problems in the presence of market microstructure effects. The range estimator, however, has been shown to be robust to the kinds of market microstructure effects that are present in stock markets. In particular, the realized volatility estimator can be sensitive to the intricacies of the market's open and close while the range estimator is not. As a result, we choose to calculate WLS estimators of the Democratic return premium using both volatility measures.

After estimating the monthly notional volatility, σ_t, we estimate the ex-ante volatility of excess returns, $Var(y_{t+1}|I_t) = \sigma^2_{t+1|t}$, by fitting a third order autoregressive model to the both the estimated realized volatility and range series and then use the predicted ex-ante volatility, $\hat{\sigma}_{t+1|t}$, in the construction of the WLS estimator. In closing, we note that while we interpret the above

[5]Instead of constructing the range over each month, one could construct the range at the daily frequency and then aggregate the daily ranges to construct a measure of monthly notional volatility. Doing so produces results that are nearly identical to the method that uses the monthly range. The simple correlation between these two volatility series is 0.93 over the sample period.

WLS procedure in terms of recent developments in the volatility measurement literature, this empirical approach to the WLS estimation of regression models is not new to the finance literature. French, Schwert and Stambaugh (1987), for example, employ precisely this approach in exploring the link between expected returns and volatility.

Parametric Volatility Measurement - GARCH Models

Another approach for dealing with heteroskedasticity in financial asset returns is to model the time series process for ex-ante volatility, $\sigma_{t+1|t}$, directly. In doing so, we draw on the extensive literature documenting the time series behavior of stock market volatility. One of the most well recognized features of asset returns is that unsigned returns exhibit significant autocorrelation. This "volatility clustering" is the hallmark feature of a wide class of volatility models that are known as generalized autoregressive conditional heteroskedasticity or GARCH models, first introduced by Engle (1982) and Bollerslev (1986). The use of GARCH models in characterizing financial asset returns is, by now, standard. Bollerslev, Chou and Kroner (1992), provide an extensive review of the evidence in favor of GARCH dynamics and their use in modeling the volatility of financial asset returns. The baseline GARCH model that we employ in our empirical analysis is the GARCH(1,1),

$$\begin{aligned} y_{t+1} &= DD + (RD - DD)\pi_t + \varepsilon_{t+1} \\ \varepsilon_{t+1} &\sim N(0, \sigma_{t+1|t}) \\ \sigma^2_{t+1|t} &= \omega + \alpha\varepsilon^2_t + \beta\sigma^2_{t|t-1} \end{aligned} \quad , \qquad (8)$$

in which current ex-ante volatility, $\sigma_{t+1|t}$, is related to past ex-ante volatility, $\sigma_{t|t-1}$, and the squared return shocks ε_t^2. Importantly, the persistence of shocks to volatility is measured by $\alpha+\beta$. As $\alpha+\beta$ approach unity, current shocks to volatility have a larger and larger influence on future volatility.

While GARCH models of the sort outlined above go a long way towards picking up the dynamics of stock return volatility these models are unable to account for one important feature of stock return volatility, namely the presence of leverage effects. Since Black (1976), financial economists have observed that stock market volatility tends to increase more after a large negative stock return than after a large positive return. This phenomenon has been widely observed in both stock return data and in option market data in which an aggregate stock index serves as the underlying, French, Schwert and Stambaugh (1987), Pagan and Schwert (1990), Campbell and Hentschel (1992), Bakshi, Cao and Chen (1997). Pure GARCH models of the form specified above are incapable of producing this feature of the data. Only the absolute value of ε_t and not its sign is important for determining future volatility. In an effort to incorporate this important feature of stock return volatility into our analysis we also specify and estimate Nelson's (1991) EGARCH(1,1) model. The specification of the EGARCH(1,1) model is identical to that of the GARCH(1,1) model except that the volatility function now takes the form,

$$\log\sigma_{t+1|t}^2=\omega+\beta\log\sigma_{t|t-1}^2+\alpha\left|\frac{\varepsilon_t}{\sigma_{t|t-1}}-\sqrt{\frac{2}{\pi}}\right|+\gamma\frac{\varepsilon_t}{\sigma_{t|t-1}}, \tag{9}$$

so that the model is specified in terms of log volatility and note that the parameter γ controls the extent to which stock returns have an asymmetric effect on volatility. If γ is negative then negative shocks to stock returns increase volatility and vice versa. It is the ability of EGARCH models to produce this asymmetric effect of stock returns on volatility that separates them from pure GARCH models.

Lastly, we explore a variety of different specifications of the baseline GARCH and EGARCH volatility models. While the GARCH(1,1) and EGARCH(1,1) are both tried and true volatility models, it may well be the case that these models are too restrictive in their specification to adequately model the dynamics of stock return volatility. Accordingly, we investigate the class of GARCH(p,q) and EGARCH(p,q) models specified by,

$$\begin{aligned} \sigma^2_{t+1|t} &= \omega + \sum_{i=1}^{p} \beta_i \sigma^2_{t+1-i|t+1-i-1} + \sum_{j=1}^{q} \alpha_j \varepsilon^2_{t+1-j} \\ \log\sigma^2_{t+1|t} &= \omega + \sum_{i=1}^{p} \beta_i \log\sigma^2_{t+1-i|t+1-i-1} + \sum_{j=1}^{p} \left(\alpha_j \left| \frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t+1-j-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma_j \frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t+1-j-1}} \right), \end{aligned} \tag{10}$$

in which both p and q are allowed to range between zero and two.[6] In our empirical analysis we report the results for the model that minimizes the Schwarz Information Criteria (SIC), the EGARCH(1,2) model, in addition to the GARCH(1,1) and EGARCH(1,1) specifications.[7]

4. Data

[6]A value of $p=0$ and $q=0$ refers to a homoskedastic model while a model in which $p=0$ and $q\neq 0$ refers to a pure ARCH specification. The combination $p\neq 0$ and $q=0$ is not admissible.

[7]Interestingly, the EGARCH(1,2) model is also the model that provides the best in and out of sample fit to the realized volatility estimates of notional volatility in the 1834-1925 sample investigated by Pagan and Schwert (1990).

We examine the monthly excess return on the CRSP value and equal weighted portfolios between 1927 and 1998. We focus on excess returns because of their high correlation with other return measures such as real returns and because excess returns are the major focus of the return forecasting literature. We choose our data and sample to coincide with that of Santa-Clara and Valkanov (2003) to facilitate comparison with the most recent contribution to the presidential cycle literature. In keeping with the analysis of Santa-Clara and Valkanov (2003), we also examine the behavior of excess returns across the presidential cycle during two different sub samples 1927-1962 and 1963-1998.

Unfortunately, neither daily return data nor daily range data are available for either of the CRSP indices as far back as 1927. As a result, we use two additional data sources to construct the realized volatility and range based notional volatility estimators that are employed in the construction of the WLS estimators. We use Schwert's (1990a, 1990b) data on the daily return of the S&P 500 composite portfolio between 1928-1998 in constructing the realized volatility estimates. The range estimator is based on the daily high and low index prices of the Dow Jones Industrial Average (DJIA). These data are only available since 1929.

5. Empirical Results: WLS Estimators

The empirical results of the WLS estimators are contained in Table 1 in the case of the value weighted portfolio and Table 2 in the case of the equal weighted portfolio. Before discussing the empirical results it is useful to examine the estimated ex-ante volatility series, $\sigma_{t+1|t}$, that are produced from the realized volatility and range based estimators. Time series plots of these estimated series are contained in Figure 1. Looking at both plots the two series appear to be highly correlated, both track considerable and persistent movements in the volatility of excess returns.[8] In general, volatility rises considerably during the period of the Great Depression and World War II. Volatility also rises, though to a lesser extent, during the late 1960's and into the middle 1970's and also in the middle of the 1980's. The effect of the increased volatility during these periods will ultimately have important effects on the estimated magnitude of the Democratic return premium.

Value Weighted Portfolio

Turning to the empirical results, Table 1 presents both OLS and WLS results for the value weighted portfolio. The OLS results are contained in the top row and the WLS results are contained in the middle rows of the table. Over the full sample, the OLS estimate of $(RD-DD)$, -8.93%, is consistent with the findings of other researchers including the recent contribution of Santa-Clara and Valkanov (2003). The WLS results offer considerable contrast to the OLS estimates. In the case of the realized volatility WLS estimates, the magnitude of the estimate falls to -2.95%, a decline of nearly 67%. The WLS estimate that employs the range based estimates is -5.41%, a smaller but still sizeable decline in the magnitude of the estimated Democratic premium. Across both WLS estimators, the use of the information in the heteroskedasticity of excess returns results in a considerable efficiency gain. The standard error

[8] At this point, we note that while excess returns are the main object of interest, the realized volatility and range based estimators use raw stock returns rather than excess returns. This is necessitated by the fact that daily data on short term t-bill returns as far back as 1927 are impossible to obtain. In principle this would present a problem if a considerable portion of the volatility in excess returns was due to the volatility of T-bill returns. On the contrary, however, the volatility of excess returns is dominated by the volatility of stock returns. Since 1927 the volatility of stock returns is roughly 18 times that of T-bill returns. As a result, we are not concerned that the variance estimators used in this study suffer from any considerable biases.

of the WLS results are between 74% and 86% of the OLS standard errors with the realized volatility WLS estimator exhibiting the largest efficiency gain. Despite the considerable increase in efficiency, the sizeable drop in the point estimate of the Democratic premium results in an erosion of its statistical significance. In the case of the most efficient WLS estimator, the t-statistic falls from 1.90 in the case of the OLS estimate to 0.85. In light of these results, the evidence in favor of a large and significant Democratic return premium over the full sample period is considerably weaker than that suggested by the OLS estimate.

Santa-Clara and Valkanov (2003) examine two sub samples 1927-1962 and 1963-1998 in their examination of the "presidential puzzle". They find that the OLS estimates of the Democratic return premium are similar in magnitude across each sub sample and take this finding as a measure of the stability and robustness of the estimated presidential cycle in stock returns. We also estimate the Democratic return premium over these sub samples using the more efficient WLS estimators. While the OLS estimates are relatively stable over these sub samples the WLS estimates are not. In the case of the early sub sample, the magnitude of the estimated effect falls from -9.96% per year in the case of the OLS estimates to between -2.70% to 2.16% in the case of the WLS estimates. Over the second sub sample there is more agreement between the WLS and OLS point estimates. While the most efficient WLS estimator still suggests that the OLS estimates overstate the size of the Democratic return premium, -7.60% (OLS) vs. -6.49% (realized vol.-WLS), the estimates are similar in magnitude though statistically insignificant due the halving of the sample. The most predominant feature of the sub sample results is the large variation in the WLS estimates across the two periods. If stability of point estimates across sub samples is considered to be a substantive robustness check, then the variability of the WLS estimates across these two sub samples would appear to call the robustness of the Democratic return premium into question.

Equal Weighted Portfolio

Table 2 contains the OLS and WLS results in the case of the equal weighted portfolio. Before discussing the results it is important to note that we do not have any separate realized volatility or range based estimates of the volatility of the excess returns of small stocks. If there are significant differences over time in the volatility of small and large stock returns then the weighting procedure employed here will not be appropriate. Given, however, the lack of data necessary to compute realized volatility and range based volatility estimates for small stocks we press on with the volatility estimates for large stocks. The GARCH estimates, to be presented in the next section, will serve as a robustness check on the WLS estimates reported here.

In the case of the full sample results, 1927-1998, the qualitative pattern in the results is identical to the case of the value weighted portfolio. The magnitude of the Democratic return premium falls relative to the OLS estimates and the standard errors of the WLS estimators decrease relative to those of the OLS estimator. Quantitatively, there are some differences between the value and equal weighted portfolio results. Most importantly, while the WLS point estimates are reduced relative to the OLS estimates the degreee of attenuation is smaller. The WLS estimates lie between -12.10% and -11.64% as compared to the OLS point estimate of -15.67%. While this still represents a sizeable reduction in the magnitude of the OLS point estimate it is not quite as large as in the case of the value weighted portfolio. The smaller reduction in the magnitude of the estimated effect coupled with the increased efficiency of the

WLS estimators results in little change in the statistical significance of the estimated Democratic premium. In the case of the most efficient WLS estimator, realized vol. - WLS, the t-statistic associated with the Democratic return premium is 2.62 which is actually marginally higher than the t-statistic of 2.45 in the case of the OLS estimator.

The pattern of results across the two sub samples in the case of the equal weighted portfolio is more in line with those of the value weighted portfolio, both qualitatively and quantitatively. In the first sub sample the estimated Democratic return premium is nearly eliminated in the case of the WLS estimators. The most efficient WLS estimator results in a point estimate of -2.52% per year which stands in stark contrast to the OLS estimate of -16.53%. The range based WLS estimator suggest a slightly larger magnitude of -7.81% but is still less than half the size of the OLS estimate. As in the case of the value weighted portfolio, the WLS estimates are more in line with the OLS results in the second sub sample. Both the realized volatility and range based WLS estimators actually result in point estimates which are slightly larger in magnitude than the OLS estimates. As a result, the magnitude of the estimated difference in excess stock returns changes considerably between the two sub samples.

Empirical Results: GARCH Estimators

The bottom rows of Tables 1 and 2 present the GARCH model estimation results of the Democratic return premium. Before discussing the results, we briefly examine the estimated volatility functions and discuss how these results relate to the point estimates contained in Table 1 and 2. The volatility function estimates are contained in Table 3 along with a few other model statistics for the GARCH(1,1) model, EGARCH(1,1) model and the EGARCH(1,2) model. Each of these models was estimated via maximum likelihood assuming conditional normality of excess stock returns.[9] We present the results of a homoskedastic (OLS) model alongside the GARCH results for comparison.

The predominant feature of the results contained in Table 3 is the extent to which allowing for heteroskedasticity in excess stock returns improves the model's fit both in terms of the likelihood and in term of the AIC and SIC selection criteria. Allowing for simple GARCH dynamics, as in the case of the GARCH(1,1), increases the log likelihood by over 100 log points and reduces the Akaike and Schwarz Information Criteria considerably.

Consistent with the findings of previous research, both the equal and value weighted excess stock returns exhibit considerable and persistent conditional heteroskedasticity. The half life of a shock is estimated to be roughly 69 months in the case of both the value and equal weighted portfolios when the GARCH(1,1) model is employed. The results of the EGARCH(1,1) model also suggests that asymmetry is an important feature of these data. Both the value and equal weighted portfolios exhibit a negative point estimate of γ which though not statistically significant does reduce both the AIC and SIC criteria relative to the baseline GARCH(1,1) specification.

We plot the estimated conditional standard deviation from the various GARCH models, along witht the corresponding excess return series, in Figure 2. As expected, the equal weighted portfolio exhibits somewhat higher volatility though the general pattern in volatility is similar

[9]The MLE procedure can be viewed as a quasi-maximum likelihood procedure as well. Bollerslev and Woolridge (1992) show that the MLE estimator is consistent and asymptotically normal as long as the mean and volatility specifications are correct. This is one consideration that motivates our examination of a variety of functional form specifications of the conditional variance specification. In presenting the estimates we compute Bollerslev-Wooldridge QMLE consistent standard errors.

across both portfolios and the different volatility models. As was the case with the plots contained in Figure 1, the volatility series exhibit pronounced increases in volatility during the period surrounding the Great Depression, World War II and the late 1960's through early 1970's as well as the middle of the 1980's though to a lesser extent. The resemblance between the plots contained in Figures 1 and 2 make clear that the main effect of the explicit modeling of the volatility of excess stock returns is to provide a means of weighting different time periods when estimating the Democratic return premium. To the extent that the realized volatility, range based volatility and GARCH volatilites coincide we also expect the WLS and GARCH results to coincide as well.

Value Weighted Portfolio

The bottom rows of Table 1 present the maximum likelihood estimates of the three different GARCH models for the value weighted portfolio. Over the full sample, the magnitude of the GARCH point estimates are uniformly smaller than those of the OLS estimates across all three models falling in a narrow range between -3.25% and -3.84%. Interestingly, these GARCH results all lie within the bounds of the corresponding WLS results, suggesting that both estimators control for the variations in volatility similarly. The direct modeling of the conditional heteroskedasticity results in an even larger efficiency gain relative to the OLS estimates shrinking the standard errors of the GARCH estimates by roughly 65%.[10] Just as in the case of the WLS results, however, the large decline in the magnitude of the point estimates

[10] Comparing the efficiency of the WLS and GARCH estimators is somewhat difficult. Under the assumptions of the WLS model, Ω is fixed so that the WLS is the MLE and is hence the most efficient estimator. The GARCH models violate the assumption that Ω is fixed. Accordingly, the non-nested nature of the two volatility structures makes direct comparison of the two estimators difficult.

dominates the increase in efficiency resulting in a net decline in statistical significance. The t-statistic of the EGARCH(1,2) model, which minimizes the SIC criteria, is only 1.16 as compared to the t-statistic of 1.90 in the case of the OLS estimator.

The pattern in results across the two sub samples is quite similar to that of the WLS results. In the early sub sample the Democratic return premium is nearly eliminated, the EGARCH(1,1) model actually produces a positive point estimate. As before, there is considerably more agreement between the OLS and GARCH estimates in the second half of the sample. The GARCH estimates, however, still imply that the magnitude of the OLS estimate is too large in the second sub sample. The GARCH estimates range between -7.02% to -4.24% in comparison to the OLS estimate of -7.60%. These GARCH estimates then suggest that the OLS estimator overstates the size of the Democratic return premium in both sub samples and that the point estimates fluctuate considerably across the two sub samples ranging from roughly zero in the first sub sample to roughly -5% in the latter sub sample. Taken together these results support the findings of the WLS results. The evidence in favor of a large and stable Democratic return premium is weakened when viewed through the lens of these more efficient estimators.

Equal Weighted Portfolio

Turning to Table 2, the most noticeable feature of the full sample GARCH estimates is that, unlike the value weighted results, the GARCH estimates are uniformly smaller than the WLS estimates indicating even less evidence in favor of a significant presidential cycle in stock returns. Moreover, the discrepancy is significant. Over the full sample, the GARCH estimates range between -6.79% to -4.85% as opposed to the WLS results which range between -12.10%

and -11.64%. One potential source of the discrepancy between the WLS and GARCH results is the difference between the realized volatility and range based volatility estimates and the GARCH volatility estimates, especially in the beginning of the sample. Looking at Figure 1 and 2 there is a sizeable discrepancy between the realized volatility and equal weighted GARCH model volatilities in the beginning of the sample. Before 1930, the realized volatility estimates are rather high, in excess of 30% most of the time, while the GARCH volatilities contained in Figure 2 are typically in the range of 10%, suggesting that the WLS estimators might underweight these observations relative to the GARCH estimators. In general, the discrepancy between the GARCH and WLS results in the case of smaller stocks suggest that using the volatility of large stocks to construct a WLS estimator of the Democratic return premium in small stocks may not be completely innocuous.

Interestingly, the discrepancy between the WLS and GARCH estimates lessens when the results are computed across the two different sub samples. In the early sub sample the GARCH estimates are between -3.38% and -1.27% which is more in line with the WLS estimates of -2.52% and -7.81%. The magnitude of the estimated Democratic premium is also below that of the WLS estimates in the second sub sample though the discrepancy between the GARCH, WLS and OLS estimates during this sub sample are relatively small. The GARCH estimates range between -8.58% and -11.89% as opposed to the OLS estimate of -14.37% which, though smaller in magnitude than the OLS estimates, does provide some evidence in favor of a difference in excess returns across presidential administrations for small stocks during the latter sub sample. As was the case with the WLS estimates, however, the GARCH estimates vary considerably across the two sub samples suggesting a general instability in the relationship between presidential administration and excess stock returns.

6. A Decomposition of the Difference Between GARCH, WLS and OLS Results

The large discrepancy between the WLS, GARCH and OLS estimates of the Democratic return premium is somewhat puzzling. The OLS, WLS and GARCH estimators are each consistent estimators of the underlying population difference in excess returns across the presidential cycle.[11] Employing a more efficient estimator would be expected to increase the precision of the estimates without imparting a considerable influence on the point estimate. Our results show that while both the WLS and GARCH estimators are more efficient than the OLS estimator, the point estimates disagree considerably. Examining the relationship between the OLS and WLS estimators yields some insight into the nature of the discrepancy between the point estimates. Considering the formula for the WLS estimator,

$$(rd-dd)_{WLS}=\sum_{\pi_t=1} y_{t+1}w_{1,t}-\sum_{\pi_t=0} y_{t+1}w_{0,t}, \qquad (11)$$

along with the fact that the OLS estimator is a special case of the WLS estimator with $w_{1,t}=\frac{1}{T_1},\ w_{0,t}=\frac{1}{T_0}$ where $T_1,\ T_0$ represent the relative sample sizes under Democratic and

Republican administrations implies, in a mechanical sense, that the divergence between the OLS and WLS estimator must owe to the relationship between w_t and y_{t+1}. Moreover, since the weights in the WLS estimator are simply functions of $\sigma_{t+1|t}$ the divergence between the OLS and

[11] In the case of the GARCH models, consistency requires that both the conditional mean and conditional variance functions are correctly specified. Consistency of these estimators, however, does not depend on the conditional normality of excess returns, Bollerslev and Wooldridge (1992).

WLS estimators can be described in terms of the relationship between $\sigma_{t+1|t}$ and y_{t+1}.

We investigate the relationship between $\sigma_{t+1|t}$ and y_{t+1} by calculating a variety of "local average" or non-parametric regression functions. Specifically, we calculate,

$$
\begin{aligned}
g_{Rep}(\sigma) &= \sum\nolimits_{\pi_t=1} w_1\left(\frac{\sigma_{t+1|t}-\sigma}{h}\right) y_{t+1} \\
g_{Dem}(\sigma) &= \sum\nolimits_{\pi_t=0} w_0\left(\frac{\sigma_{t+1|t}-\sigma}{h}\right) y_{t+1}, \\
w_j(x) &= \frac{\exp\left(-\frac{x^2}{2}\right)}{\sum\nolimits_{\pi_t=j}\exp\left(-\frac{x^2}{2}\right)}
\end{aligned}
\tag{12}
$$

for both the equal and value weighted portfolios. Since the estimated functions can be very sensitive to the choice of bandwidth, we show results for three different choices of the bandwidth. We then plot $g_{Rep}(\sigma)$ and $g_{Dem}(\sigma)$ against σ in Figure 3 for each bandwidth choice. The non-parametric regression functions are calculated using the realized volatility estimates of $\sigma_{t+1|t}$ that are plotted in the left hand panel of Figure 1.

Before discussing the results of this analysis we stress that this exercise is not intended to investigate the evidence in favor of a non-linear relation between excess returns and volatility as is often the goal of non-parametric regression analyses. Rather, it is intended solely to shed light on the source of the discrepancy between the WLS, GARCH and OLS estimates contained in Tables 1 and 2. The top row of Figure 3 shows the estimated regression functions in the case of a very large bandwidth. Note that in the case that the bandwidth is chosen to be arbitrarily large then $w_1(x)=\frac{1}{T_1}$ and $w_0(x)=\frac{1}{T_0}$. Accordingly, this implies that $g_{Dem}(\sigma)=\frac{1}{T_0}\sum_{\pi_t=0} y_{t+1}$ and

$g_{Rep}(\sigma)=\frac{1}{T_1}\sum_{\pi_t=1} y_{t+1}$ so that $g_{Rep}(\sigma)-g_{Dem}(\sigma)$ is identical to the OLS estimates contained in

Tables 1 and 2. In this sense, the non-parametric regression plots contained in Figure 2 can be thought of as a descriptive tool for decomposing the OLS estimation results. The bandwidth in the top row of Figure 3 has been chosen to be large enough so that it mimics the OLS estimates.

The plots below the top row use successively smaller bandwidths, providing a finer and finer decomposition of the OLS results. In our opinion, the bandwidth employed in the middle plots of Figure 3 provides the most sensible description of the data. Looking at these plots, reveals that the difference between excess returns across Democratic and Republican candidates is most apparent at very high levels of market volatility. This feature of the plots is consistent across both the value and equal weighted portfolio and across both of the bandwidths employed in the bottom two rows of the figure. In the case of the value weighted portfolio, the difference in excess returns across Democratic and Republican administrations is relatively small until the level of volatility reaches roughly 20%. In the case of the equal weighted portfolio, the difference between Democratic and Republican administrations is relatively small until volatility reaches roughly 30%. As volatility rises beyond these levels the plots reveal that Democratic administrations have experienced extremely large returns during these volatile periods while the performance of the stock market during Republican administrations is less sensitive to the volatility of returns. The considerable volatility surrounding those periods which are most responsible for the magnitude of the OLS estimates results in a very low weighting in the WLS estimator. It is also of considerable interest to note that the discrepancy between the OLS and WLS estimates is driven by a relatively small number of observations. Specifically, only 11% of the observations occur during periods in which market volatility exceeded 25%. In contrast to the OLS estimates, the returns associated with these episodes of extreme volatility do not exhibit a considerable influence on the WLS estimates.

Given the very high volatility of the stock market during the period surrounding the Great Depression and World War II, it is tempting to conclude that the extreme returns during Democratic presidencies are only a feature of pre-1960 data. This is not the case. In Table 4, we show the average excess return during periods in which volatility exceeded 20% per year. Average excess returns are calculated for each sub sample investigated by Santa-Clara and Valkanov (2003) separately. As before, volatility is defined as the ex-ante volatility measure estimated from the realized volatility estimates shown in Figure 1. We chose a volatility level of 20% per year as a cutoff because this level is approximately one standard deviation above the median volatility level. Accordingly, these are periods of above average volatility but they are not so infrequent as to make an analysis of these periods meaningless.

In the case of both the equal and value weighted portfolio, the difference between excess returns during Republican and Democratic administrations exceeds the OLS estimate when volatility exceeds 20%. In the case of the value weighted portfolio during the later sub sample, for example, excess returns were 52.03% percentage points higher, at an annualized rate, during Democratic administrations when market volatility exceeded 20%. The data contained in Table 4 demonstrates that the extreme difference between Republican and Democratic administrations during very volatile periods is a consistent feature of the data that is present in both sub samples. Moreover, it is precisely the differing stock market performance during volatile markets that accounts for much of the magnitude of the presidential premium that has been reported at regular intervals since the early 1980's.

The relationship between $\sigma_{t+1|t}$ and y_{t+1} documented in Figure 3 and Table 4 has an economic as well as a statistical implication. Much of the presidential cycle literature questions how such a large difference in stock returns could possibly escape the attention of rational investors. Huang (1985) and Hensel and Ziemba (1995), for example, point to the apparent profitability of a variety of different presidential trading strategies. Santa-Clara and Valkanov (2003) also openly question why rational investors haven't "learned about the difference in party policies and adjusted stock prices when the result of the election becomes known"? These results suggest that this does not occur for two reasons. First, the large difference in returns between Democratic and Republican administrations is largely due to a few episodes of extremely good returns during Democratic administrations. Importantly, the WLS and GARCH estimates contained in Tables 1 and 2 suggest that the Democratic return premium is non-existent across both large and small stocks before 1962. Accordingly, it is unclear that investors would have had any substantive basis for expecting better stock market performance under Democratic administrations prior to 1962. Secondly, these extreme returns occurred during periods of high volatility when the effects of any particular policy on the stock market, political or otherwise, would have been difficult to predict. Even if investors were aware that Democratic administrations would coincide with better stock returns during very volatile market conditions, it is unclear that this would result in an increase in portfolio allocations to stocks since the increased performance coincides with heightened stock market risk.

7 Conclusion

The existence of a large and systematic difference in excess returns between Democratic and Republican presidential administrations raises a variety of puzzling questions. How could there be such a systematic divergence in returns when there appears to be no similar divergence in risk across the presidential cycle? If there really is a systematic difference across the presidential cycle what exactly are the systematic differences in fiscal, taxation or social policies that lead to divergent stock market performance? Against a backdrop of near uniform support in favor of a large "presidential puzzle" we provides the first estimates of the presidential premium that suggest it is not as large as previously reported.

A variety of WLS and GARCH estimates of the Democratic return premium provide considerable contrast to the results of previous research that employs OLS estimates of the Democratic return premium. In the case of large stocks, over the whole sample, we estimate that the premium is insignificant and the point estimate is significantly lower than previously reported. The average across all five estimators is 3.82% per year which is less than half the size of the OLS point estimate of 8.93%. In the case of small stocks, the full sample WLS and GARCH estimates are also uniformly smaller than the OLS estimate of 15.67% per year. In terms of statistical significance, the results are somewhat less clear. The WLS results average 11.87% per year and would be considered statistically significant at most conventional significance levels. The GARCH results average 6.06% per year and would not be considered statistically significant at conventional significance levels.

These results also question the stability of the point estimates over time. Unlike the OLS estimates, the WLS and GARCH estimates can swing quite dramatically, in some cases from positive to negative over time indicating a lack of robustness to the sample period examined. In general, however, the point estimates do suggest relatively more evidence in favor of better stock market performance, especially in the case of small stocks, during Democratic presidencies in the latter half of the sample. In light of the small WLS and GARCH estimates of the Democratic premium in the first half of the sample, however, it is not clear that investors would have had an obvious incentive to bid stock prices up during Democratic administrations after 1962.

We find that the rift between these results and the results of previous studies employing the OLS estimator results from the performance of the stock market across Democratic and Republican presidencies during volatile market conditions. During periods of high market volatility Democratic administrations have experienced significantly higher stock market returns than Republican administrations. Since this large difference in stock market performance has occurred during more volatile periods this evidence is down weighted in the WLS and GARCH estimators relative to the OLS estimator. Once the effect of stock market performance during rather volatile market environments is controlled for the apparent discrepancy between the stock market performance of Democrats and Republicans is largely reduced. Accordingly, the apparent disconnect between risk and return is partially resolved: these results are consistent with the notion that neither risk nor return is significantly different across the presidential cycle.

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Table 1
Alternative Estimates of The Presidential Puzzle
Value Weighted Returns: 1927 - 1998

	1927:01 - 1998:12			1927:01 - 1962:12			1963:01 - 1998:12		
	RD	DD	RD-DD	RD	DD	RD-DD	RD	DD	RD-DD
OLS									
OLS	1.34 (3.76)	10.27 (2.84)	-8.93 (4.71)	1.22 (7.13)	11.17 (4.51)	-9.96 (8.43)	1.43 (3.98)	9.02 (2.65)	-7.60 (4.81)
WLS									
Realized Vol.	4.38 (2.63)	7.33 (2.29)	-2.95 (3.49)	9.59 (4.12)	7.43 (3.52)	2.16 (5.42)	0.77 (3.43)	7.26 (3.02)	-6.49 (4.57)
Range	3.42 (3.38)	8.83 (2.27)	-5.41 (4.07)	6.20 (4.96)	8.90 (2.69)	-2.70 (5.64)	1.01 (4.62)	8.65 (4.29)	-7.65 (6.30)
GARCH									
GARCH(1,1)	5.73 (2.81)	9.57 (2.14)	-3.84 (3.58)	11.37 (3.52)	12.54 (3.24)	-1.17 (4.76)	1.76 (4.48)	7.21 (3.00)	-5.44 (5.40)
EGARCH(1,1)	5.70 (2.51)	8.95 (2.04)	-3.25 (3.08)	12.16 (3.50)	10.60 (3.11)	1.57 (4.57)	0.60 (3.56)	7.62 (2.51)	-7.02 (4.35)
EGARCH(1,2)	4.21 (2.44)	7.87 (2.18)	-3.66 (3.16)	11.32 (3.20)	11.64 (3.72)	-0.32 (4.85)	-0.36 (3.67)	3.88 (2.70)	-4.24 (4.51)

The table above reports estimates of the mean parameters using monthly, value weighted excess returns from the model, $y_{t+1}=DD+(RD-DD)\pi_t+\varepsilon_{t+1}$, where π_t indicates whether or not a republican president is in office. The first panel reports OLS estimates with Newey-West (1987) standard errors in parentheses. The second panel reports weighted least squares (WLS) results with standard errors in parentheses which use either realized volatility or range based estimates of $\sigma_{t+1|t}$ in constructing the weights. The third panel reports GARCH estimates from a three different GARCH models. In the case of the GARCH(1,1) model, $\sigma^2_{t+1|t}=\omega+\alpha\varepsilon^2_t+\beta\sigma^2_{t|t-1}$ and in the case of the EGARCH specifications, $\log\sigma^2_{t+1|t}=\omega+\beta\log\sigma^2_{t|t-1}+\sum_{j=1}^{q}\left(\alpha_j\left|\frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t-j}}-\sqrt{\frac{2}{\pi}}\right|+\gamma_j\frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t-j}}\right)$ for q=1,2. The GARCH models were estimated via QMLE assuming normality of ε_t. Bollerslev-Wooldridge (1992) standard errors are reported in parentheses under the parameter estimates. In the case of two sub-samples,1927-1962 and 1963-1998, we report parameter estimates of the mean parameters and associated standard errors from the model, $y_{t+1}=I_1[DD_1+(RD_1-DD_1)\pi_t]+I_2[DD_2+(RD_2-DD_2)\pi_t]+\varepsilon_{t+1}$ where I_1 and I_2 are dummy variables that indicate each of the two sub-samples.

Table 2
Alternative Estimates of The Presidential Puzzle
Equal Weighted Returns: 1927 - 1998

	1927:01 - 1998:12			1927:01 - 1962:12			1963:01 - 1998:12		
	RD	DD	RD-DD	RD	DD	RD-DD	RD	DD	RD-DD
OLS									
OLS	0.07	15.75	-15.67	0.24	16.78	-16.53	-0.04	14.33	-14.37
	(4.64)	(4.31)	(6.37)	(8.05)	(6.99)	(10.65)	(5.48)	(3.85)	(6.72)
WLS									
Realized Vol.	1.16	12.80	-11.64	8.30	10.82	-2.52	-3.77	14.27	-18.04
	(3.35)	(2.92)	(4.45)	(5.24)	(4.48)	(6.89)	(4.36)	(3.26)	(5.81)
Range	0.93	13.04	-12.10	5.07	12.88	-7.81	-2.65	13.45	-16.10
	(4.48)	(3.02)	(5.40)	(6.58)	(3.57)	(7.48)	(6.13)	(5.69)	(8.36)
GARCH									
GARCH(1,1)	5.45	12.24	-6.79	11.08	14.46	-3.38	-1.21	10.68	-11.89
	(3.42)	(3.05)	(4.67)	(3.43)	(4.01)	(5.28)	(7.33)	(4.43)	(8.66)
EGARCH(1,1)	5.16	11.70	-6.53	9.92	11.19	-1.27	-2.15	11.94	-14.10
	(2.62)	(2.68)	(3.57)	(3.44)	(4.07)	(5.16)	(4.70)	(3.40)	(5.54)
EGARCH(1,2)	7.30	12.16	-4.85	10.40	12.46	-2.06	3.17	11.75	-8.58
	(2.61)	(4.70)	(3.44)	(3.35)	(4.16)	(5.16)	(4.14)	(3.22)	(5.06)

The table above reports estimates of the mean parameters using monthly, value weighted excess returns from the model, $y_{t+1}=DD+(RD-DD)\pi_t+\varepsilon_{t+1}$, where π_t indicates whether or not a republican president is in office. The first panel reports OLS estimates with Newey-West (1987) standard errors in parentheses. The second panel reports weighted least squares (WLS) results with standard errors in parentheses which use either realized volatility or range based estimates of $\sigma_{t+1|t}$ in constructing the weights. The third panel reports GARCH estimates from a three different GARCH models. In the case of the GARCH(1,1) model, $\sigma^2_{t+1|t}=\omega+\alpha\varepsilon^2_t+\beta\sigma^2_{t|t-1}$ and in the case of the EGARCH specifications, $\log\sigma^2_{t+1|t}=\omega+\beta\log\sigma^2_{t|t-1}+\sum_{j=1}^{q}\left(\alpha_j\left|\frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t-j}}-\sqrt{\frac{2}{\pi}}\right|+\gamma_j\frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t-j}}\right)$ for q=1,2. The GARCH models were estimated via QMLE assuming normality of ε_t. Bollerslev-Wooldridge (1992) standard errors are reported in parentheses under the parameter estimates. In the case of two sub-samples,1927-1962 and 1963-1998, we report parameter estimates of the mean parameters and associated standard errors from the model, $y_{t+1}=I_1[DD_1+(RD_1-DD_1)\pi_t]+I_2[DD_2+(RD_2-DD_2)\pi_t]+\varepsilon_{t+1}$ where I_1 and I_2 are dummy variables that indicate each of the two sub-samples.

Table 3
Alternative Volatility Models
Value and Equal-Weighted Portfolios: 1927-1998

	Value-Weighted Returns: 1927-1998									
	ω	α_1	α_2	γ_1	γ_2	β	half-life	log$L$	AIC	SIC
CONSTANT (OLS)	4,337.54 (73.78)	--	--	--	--	--	--	-4843.00	11.22	11.22
GARCH(1,1)	98.58 (50.93)	0.12 (0.03)	--	--	--	0.87 (0.03)	68.96	-4711.81	10.92	10.95
EGARCH(1,1)	0.07 (0.12)	0.22 (0.06)	--	-0.05 (0.03)	--	0.97 (0.02)	22.75	-4706.09	10.91	10.94
EGARCH(1,2)	-0.02 (0.11)	-0.06 (0.09)	0.30 (0.09)	-0.32 (0.07)	0.28 (0.08)	0.98 (0.01)	34.31	-4685.82	10.87	10.90

	Equal-Weighted Returns: 1927 - 1998									
	ω	α_1	α_2	γ_1	γ_2	β	half-life	log$L$	AIC	SIC
CONSTANT (OLS)	7570.74 (128.78)	--	--	--	--	--	--	-5083.62	11.77	11.78
GARCH(1,1)	148.33 (58.47)	0.12 (0.03)	--	--	--	0.87 (0.02)	68.96	-4918.33	11.39	11.42
EGARCH(1,1)	0.05 (0.09)	0.20 (0.04)	--	-0.05 (0.03)	--	0.98 (0.01)	34.31	-4906.76	11.37	11.40
EGARCH(1,2)	-0.05 (0.08)	0.20 (0.10)	0.01 (0.10)	-0.28 (0.09)	0.24 (0.09)	0.99 (0.01)	68.96	-4896.61	11.35	11.39

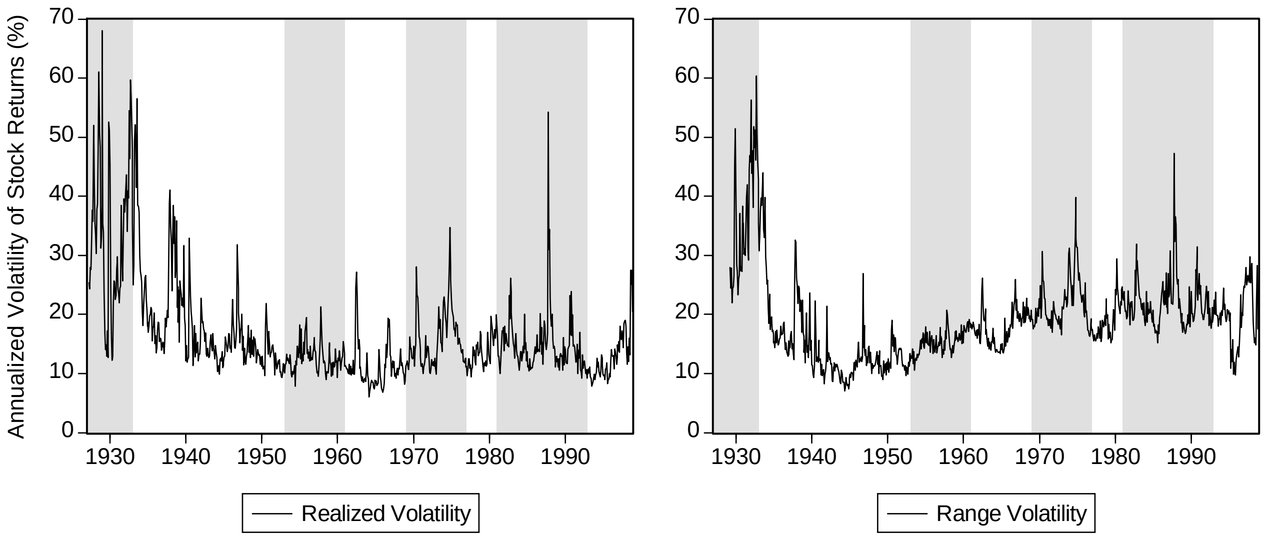
The table above displays maximum likelihood estimates of the volatility parameters from the model, $y_{t+1} = DD + (RD - DD)\pi_t + \varepsilon_{t+1}$, where π_t indicates whether or not a republican president is in office, σ_t represents the conditional standard deviation of returns and ε_t is assumed to be distributed iid and standard normal. In the case of OLS $\sigma^2_{t+1|t} = \sigma^2$, in the case of the GARCH(1,1), $\sigma^2_{t+1|t} = \omega + \alpha\varepsilon_t^2 + \beta\sigma^2_{t|t-1}$ and in the case of the EGARCH specifications, $\log\sigma^2_{t+1|t} = \omega + \beta\log\sigma^2_{t|t-1} + \sum_{j=1}^{q}\left(\alpha_j\left|\frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t-j}} - \sqrt{\frac{2}{\pi}}\right| + \gamma_j\frac{\varepsilon_{t+1-j}}{\sigma_{t+1-j|t-j}}\right)$ for q=1,2. Bollerslev-Wooldridge (1992) standard errors are reported in parentheses under the parameter estimates. The column labeled half-life contains the estimated half-life of a shock to volatility in months for each model. The column labeled *LogL* contains each model's log-likelihood and the columns labeled AIC and SIC contain each model's Akaike and Schwarz Information Criteria.

Table 4
Excess Returns During Volatile Market Conditions
Republicans and Democrats: 1927 - 1962 and 1963-1998

	Realized Volatility in Excess of 20%			
	Republican	Democratic	Difference	OLS Estimate
<u>Value Weighted Portfolio</u>				
1927:1-1962:12	-12.80	23.60	-36.70	-9.96
1963:1-1998:12	10.75	62.78	-52.03	-7.60
<u>Equal Weighted Portfolio</u>				
1927:1-1962:12	-12.18	41.02	-53.20	-16.53
1963:1-1998:12	20.30	36.06	-15.76	-14.37

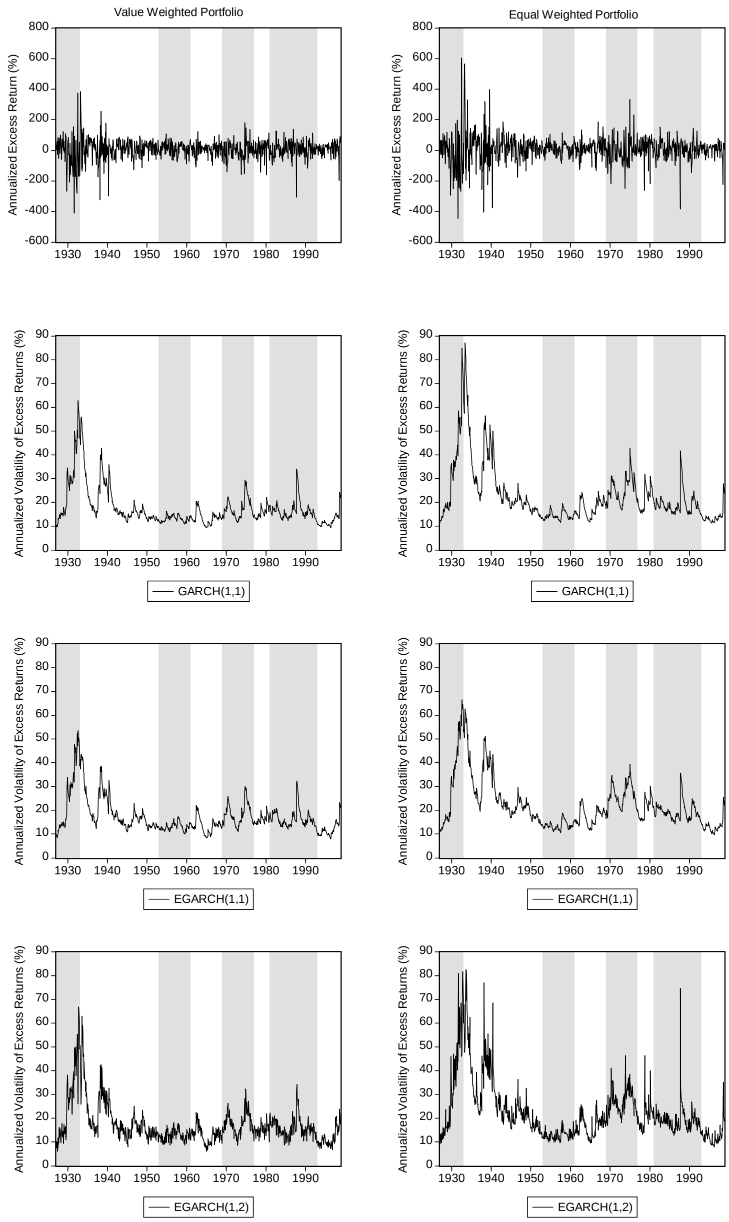
The table above reports the sample average of excess returns when the sample is limited to periods in which the estimated ex-ante volatility, $\sigma_{t+1|t}$ constructed from the realized volatility estimates exceeds 20% per year. The table reports the sample average excess return during Republican and Democratic administrations over each of the two sub samples previously examined by Santa - Clara and Valkanov (2003).

Figure 1
Estimates of Monthly Stock Return Volatility: 1927 - 1998
Realized Volatility and Range Based Estimates



Notes: The figure above plots the estimated volatility, $\sigma_{t+1|t}$, of stock returns between 1927 and 1998. The left panel plots estimates based on the average daily squared return (Realized Volatility) while the right panel plots estimates based on the average daily range (Range Volatility). The shaded areas represent Republican presidential administrations.

Figure 2
Excess Returns and Estimated Volatility Series: 1927-1998
Value and Equal Weighted Portfolios

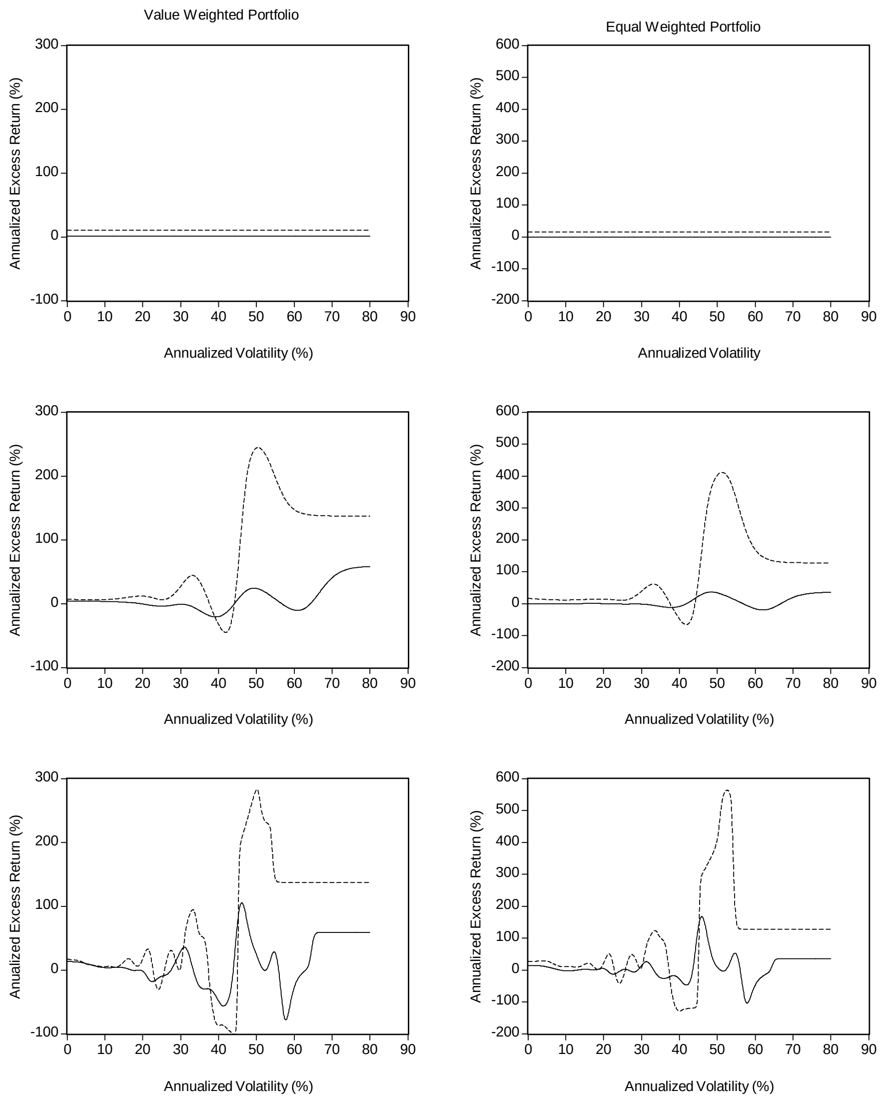


Notes: The above figure plots annualized excess returns and the estimated volatility series, $\sigma_{t+1|t}$, using each of the three GARCH volatility models over the sample period 1927-1998. The left hand column presents the results for value weighted returns and the right hand column presents the results for equal weighted returns. The shaded regions represent Republican presidential administrations.

Figure 3

Expected Excess Returns and Volatility

Republican and Democratic Administrations: 1927-1998



The figure above displays Nadarya-Watson estimates of the conditional expectation of excess returns as a function of the standard deviation of excess returns and the party of the presidential administration, $E(y_{t+1}|\pi_t,\sigma_{t+1|t})$, using three different bandwidth choices. The estimator that employs the largest bandwidth appears at the top. Expected excess returns during Democratic administrations are shown with a dashed line (--) and expected excess returns during Republican administrations are shown with a solid line (-). Results using value weighted returns appear in the left column and results using equal weighted returns appear in the right column. Returns and standard deviations are reported in annualized percentage terms. The standard deviation of returns is measured using the realized volatility estimator discussed in the text.