Politics, Stock Markets, and Model Uncertainty

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Abstract

Numerous studies have attempted to analyze the impact of political variables on stock market performance. The majority of these studies document a statistically insignificant response of stock markets to changes in the political environment. Possible explanations include the market's ability to price future events accurately and the existence of model uncertainty in empirical studies. We explicitly address model uncertainty by applying Bayesian Model Averaging (BMA) to a novel data set for 17 countries spanning the period between 1944 and 1995. Except for the case of multi-party minority governments, changes in the political environment have no significant effect on excess returns. Stock market volatility, however, is shown to be significantly affected by a number of political variables. These results show that most political variables affect the higher moments of stock returns. Finally, we test the robustness of our results by controlling for unobserved heterogeneity at the country level.

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1 Introduction and Prior Work

One of the most active areas of research in economics and finance is the influence of the political environment on economic outcomes. Voters' preferences, as well as the voting process itself, may have significant effects on a country's economic and financial performance, both in the short- and long-run. There is plenty of anectodal evidence which suggests that stock market react to some political events. For instance, the Turkish stock market (IMKB) reached its historical peak the day after the results of 2007 elections were announced to the public. While several highly intuitive conclusions may be arrived at, the majority of empirical research has so far failed to document statistically significant effects of political variables on financial markets. As one of the few exceptions, Santa-Clara and Valkonov (2003) document that the excess cumulative return in the US stock market is higher under Democratic than under Republican presidencies[1]. Döpke and Pierdzioch (2006), on the other hand, provide VAR-based evidence for Germany that stock returns are not significantly different under right-wing and left-wing governments. Similarly, by using a data set for twenty-four OECD countries, Bialkowski et al. (2006a) show that there are no statistically significant differences in returns between left-wing and right-wing governments. Around election dates, Pantzalis et al. (2000) document positive abnormal returns prior to the election week. They also show that the positive reaction is a function of a country's degree of political freedom.While confirming the aforementioned partisan cycle and the presidential cycle[2] in the general U.S. stock market, Jacobsen and Stangl (2007) reject the hypothesis of these cycles being driven by particular industries.

The scant and mixed evidence provided by the previous literature may be attributed to two reasons: (i) Anticipatory pricing in financial markets implies that the political risk associated with, for instance, election outcomes is incorporated into share prices long before the uncertainty is completely resolved on election day; and (ii) the empirical models estimated by the previous literature suffer from omitted variable bias as there is a good degree of model uncertainty regarding the selection of political

[1] We need to emphasize that we differ in our approach by investigating the contemporaneous response of the stock market to a variety of political shocks, rather than comparing the cumulative stock returns under right-wing or left-wing governments.

[2] The presidential cycle refers to the observation that US stock returns tend to be higher during the second half of a four year presidential term. The presidential cycle is confirmed by Booth and Booth (2003), who controlled for business cycle effects, the President's party and the incumbency status of the president.

variables. Illustrative of the latter point is that even though previous studies showed the importance of single party versus coalition governments for economic outcomes[3], no previous study attempted to test whether the type of government is important for stock market returns. Moreover, in light of the fact that previous studies presented evidence that the political orientation of the government matters for economic performance[4], the data set used in this study also allows for testing test whether the political orientation of alternative types of governments is important.

We contribute to the literature by using a data set; assembled by Woldendorp, Keman and Budge (1998), which is novel to this literature, as well as by addressing the model uncertainty that has plagued earlier research with applying the method of Bayesian Model Averaging (BMA). The data set consists of a number of political variables on party governments for twenty democratic countries for a time period which goes back to World War II and stcovers up to 1995. To our knowledge, this is the first study which uses this well known data set in the fields of economics and finance. The panel nature of the data set allows us to control for unobserved heterogeneity at the country level and therefore eliminate some types of omitted variable bias.

The choice of explanatory variables to be included in a regression should, as far as it is possible, be guided by theory. There is, however, no solid theoretical background that justifies the use of particular empirical models in numerous studies. One popular approach in model selection is to estimate a model with a very large number of explanatory variables, remove variables which show no statistical significance, and re-estimate a reduced model. The problem with such an approach is that it treats the selected model as the only one ever considered, assigning a zero probability to other models and ignores model uncertainty.

The results documented in the existing literature suggest that there is a high de-

[3]See Alesina and Perotti (1995) which documents for a sample of OECD countries that "coalition governments [as opposed to single party, or minority governments] are generally unable to carry out successful fiscal adjustments".

[4]See Alesina and Roubini (1992), which - studying output growth, the unemployment rate, and the inflation rate in a sample of OECD countries - documents evidence consistent with both opportunistic and partisan political business cycles. For US data, Alesina, Roubini and Cohen (1997) find that the quarterly growth rate in the first six quarters after the beginning of a Democratic administration is significantly higher, about 3.5 percentage points higher than after the beginning of a Republican administration. For a sample of OECD countries the fiugure is lower; about 2.2 percentage points.

gree of uncertainty about the impact of political variables on financial markets. More specifically, it is unclear which independent variables to include in the regression. An elegant way to handle model uncertainty is to use a Bayesian approach and treat the model itself as a random variable. Bayesian Model Averaging is based on this fundamental idea. Instead of estimating a single model, BMA analyzes an entire model space, i.e., all the possible models which can be constructed from a given number of regressors[5]. We describe the methodology in greater detail in Section 2.

Needless to say, we are the not the first ones to rely on Bayesian methods to solve the model uncertainty present in the empirical analyses of return predictability. Avramov (2002) performs out-of-sample tests of return predictability to show the superiority of Bayesian methods.Cremers (2002) also through the use of BMA methodology, compares all previously suggested models simultaneously, without the inclusion of any political variables.

BMA has its drawbacks. Aside from computational concerns in analyzing large model spaces, the main issue in applying Bayesian techniques is the specification of priors. In this paper, we employ the approach proposed by Fernandez et al. (2001) in which an improper non-informative prior[6] is employed. We perform extensive robustness checks with respect to the prior distribution[7]. Their techniques allow, in particular, for the computation of posterior inclusion probabilities ; probabilities that a certain variable is significant in a regression ; for many potential regressors.

In the second part of this study, we build on the results of the BMA analysis and test whether variables identified as significant in the BMA analysis remain significant when taking full advantage of our panel data set in accounting for country specific effects.

[5]In the context of the linear regression model with k possible regressors, the model space consists of 2^k models. In principle, every single model should be estimated which is computationally difficult as k increases. Therefore, the model space is analyzed through the use of numerical methods.

[6]An improper non-informative prior is the limit of an informative prior as it becomes non-informative. With an unbounded parameter space of the parameters to be estimated, the use of a uniform distribution as a diffuse prior is not available.

[7]Robustness checks are discussed in detail in section 2. Overall, the methodology is robust to the choice of prior distributions.

2 Data and Methodology

2.1 Data

This paper uses the data collected by Woldendorp, Keman, and Budge (1998) who assembled a comprehensive dataset on party governments in twenty democratic countries. A summary of variables and data coverage can be found in Table 1. The variables can be separated into two groups. The first group describes the process of the observed government changes. The dates of government changes are identified to within a day and the reason for termination is recorded. The second group of variables describes each government in greater detail. It includes the number of seats that each governing party disposes of in parliament and the political complexion of the various governments (a variable measured on a scale of 1 to 5, 1 being right-wing dominated, 5 being left wing dominated). Finally, six types of governments are identified: Single party; minimal winning coalition; surplus coalition; single party minority; multi party minority and caretaker governments[8]. These variables allow us to go beyond the analysis of 'left vs. right' governments, and explore the impact of government structures on financial markets in greater detail.

We use several dependent variables in the analysis - raw returns, excess returns, and realized volatilities. For each country we use monthly returns on the composite stock index that has the longest history of daily return observations. Excess returns are computed by subtracting 3-month treasury bill rates from monthly returns, and realized monthly volatilities are computed using daily raw return observations. Short histories of available daily treasury bill yields prevented the computing of realized excess return volatilities. Table 2 presents the data ranges for the available data series. Finland, Iceland and Luxembourg were dropped from the original panel due to data limitations. Even though Woldendorp et al. (1998) pinpoint the government changes to within a day, our analysis is performed on a monthly level due to the high persistence in the independent variables. In the end, after deleting missing observations, there are 19 independent variables spanning 9310 observations for raw returns, 6649 observations for excess returns and 4524 observations on realized volatilities.

[8]See Woldendorp et al. (1998) for detailed variable definitions.

2.2 Methodology

2.2.1 BMA: An Overview

As noted above, there is no consensus among researchers regarding the choice of independent variables in the analysis of political influence on financial market outcomes. The results are not robust to the choice of potential regressors. The problem arises from the fact that economic theory offers little guidance on the specific choice of independent variables. Using BMA analysis Sala-i-Martin, Doppelhofer and Miller (1997, SDM) address the same issue in the economic growth literature:

> ... The problem is hardly unique to the growth literature: "Artistic" economic theory is often capable of suggesting an enormous number of potential explanatory variables in any economic field.

Another difficulty which researchers face in the model selection process is outlined in Raftery (1994). It is often the case that alternative model specifications fit the data almost equally well, but lead to different conclusions. In this instance, the researcher essentially faces three alternatives: (1) Report the results of just one model; which is an undesirable strategy, because the researcher exposes him/herself to a wave of potential criticism. (2) report the results of all models; although this is somewhat better a strategy than the first choice, it may imply reporting mutually exclusive results, which is of little use when it comes to predictions and policy making. (3) explicitly accounting for model uncertainty; which is where Bayesian Model Averaging (BMA) comes in.

According to the BMA methodology, prior probabilities are assigned to the various possible models. The model itself, therefore, becomes a random variable. Both parameter and model uncertainty are thus accounted for. Using the sample evidence, posterior probabilities are estimated for each model. These probabilities give the probability that a particular model is the best possible model given the data. The inference is averaged over all models, with posterior probabilities used as weights. Marginal posterior probabilities are also computed for each potential regressor. These are simply the sum of the posterior probabilities of all those models which include the respective regressor.

In the following paragraphs an outline is privided for the BMA methodology in the linear regression context[9]. We employ the methodology of Fernández, Ley and Steel (2001, FLS), which is also followed by Masanjala and Papageorgiou (2005) in an empirical growth context. We consider linear regression models with raw index returns, excess index returns, and volatility as $n \times 1$ vectors of the dependent variables y. The respective independent variable is regressed on a $n \times 1$ vector of ones ι_n and a $n \times k$ matrix X of k potential independent variables, n denoting the number of observations. The the full $k \times 1$ vector of regression coefficients is denoted by β. We restrict ourselves to regression models M_j that include a constant term. Otherwise, any subset of regressors can be included. We can, therefore, estimate 2^k possible linear regressions. If $k = 19$, the number of possible models is 524,288.

The model that uses the subset of regressors collected in matrix X_j is denoted by M_j:

$$y = \alpha\iota_n + X_j\beta_j + \sigma\epsilon \tag{1}$$

where $\beta_j \in \mathcal{R}^{k_j}$, $(0 \leq k_j \leq k)$ is a $k_j \times 1$ vector collecting regression coefficients and $\sigma \in \mathcal{R}_+$ is a scale parameter. It is assumed that ϵ follows a multivariate normal distribution with zero mean and identity covariance matrix. If a regressor is excluded, the corresponding element of β is set equal to zero.

One of the main factors limiting the popularity of Bayesian techniques is that researchers wishing to employ these techniques need to specify prior distributions for parameters and, in the context of model uncertainty, for alternative models. Typically, therefore, model and parameter posterior distributions depend on prior distributions which may be arbitrarily chosen.[10] Such results are difficult to interpret. Moreover, while a researcher in a different context may wish to inlcude prior information in his set up, with the implication of the prior not being washed away too easily by the sample information, we are interested in a set up that minimizes the impact of the prior distribution on posterior inference. Intuitively speaking, in a situation of ignorance one would prefer the posterior probabilities to depend as much as possible on the sample information and be unaffected by the prior. Based on theoretical results, as well as extensive simulations, FLS propose a *benchmark* prior structure satisfying the requirements. We adopt their approach, and use improper non-informative priors for

[9]Hall et al. (2002) apply Bayesian variable selection methodology in the context of Seemingly Unrelated Regressions.

[10]The sensitivity of posterior model probabilities with respect to the choice of prior distributions is addressed in Kass and Raftery (1995) and George (1999).

the parameters that are common to all of the models, α and σ, and a g-prior structure for β_j, which is represented as the product of the expressions in (2) and (3):

$$p(\alpha, \sigma) \propto \sigma^{-1} \tag{2}$$

and

$$p(\beta_j|\alpha, \sigma, M_j) = f_N^{k_j}\left(\beta_j|0, \sigma^2(gX_j'X_j)^{-1}\right) \tag{3}$$

where $f_N^q(w|m, V)$ denotes the density function of a q-dimensional Gaussian distribution on w with mean m and covariance matrix V. FLS consider many possible choices for g in equation (3), and conclude that setting $g = 1/\max\{n, k^2\}$ produces robust results.

We also perform extensive robustness checks concerning both the choice of prior distributions[11] and the inclusion of various potential independent variables. Even though the marginal posterior probabilities were somewhat sensitive to the choice of g-structure, the ranking of independent variables according to marginal posterior probabilities remained essentially unchanged. This leads us to believe that although prior distribution selection is important, the BMA algorithm is able to determine which variables are the most important ones. Having delivered essentially the same results for a wide range of prior distributions renders the algorithm very robust.

The key aspect behind BMA is model uncertainty, which, in this study, refers to uncertainty with regard to the appropiate choice of regressors. It is, therefore, necessary to specify a prior distribution over the space $\mathcal{M}$ of all 2^k possible models:

$$P(M_j) = p_j, \quad j = 1, \ldots, 2^k, \quad \text{with } p_j > 0, \text{ and } \sum_{j=1}^{2^k} p_j = 1. \tag{4}$$

Prior information absent, it is intuitive to assume a uniform distribution[12] over the model space $p_j = 2^{-k}$ implying that the prior probability of a regressor being included is equal to $1/2$, and that the expected model size $k/2$ increases in the number of explanatory variables available. The choice of a prior probability for including regressors is disputed. An alternative logical choice would be down-weighting[13] models

[11] Robustness checks were performed along two dimensions. First, various g-structures described in Fernandez et al (2001) were used as prior distributions. Second, we have modified the number of candidate independent variables.

[12] With 19 potential explanatory variables, the prior probability of each model is tiny and equal to only 1.90735e-06.

[13] SDM, for instance, are doing so.

which use a large number of independent variables. Assigning a probability of 1/2 across the board also means that the regressor inclusion probabilities are independent of each other. Some researchers (e.g. Brock et al., 2003) argue that such an approach may be inappropriate when some regressors are similar in nature and others are quite different.

The posterior distribution $P_{\Delta|y}$ of any quantity (say Δ) is an average of the posterior distributions under each model $P_{\Delta|y,M_j}$ where the posterior model probabilities $P(M_j|y)$ are used as weights. Therefore:

$$P_{\Delta|y} = \sum_{j=1}^{2^k} P_{\Delta|y,M_j} P(M_j|y). \tag{5}$$

Choosing Δ appropriately this formula delivers, for instance, the posterior distribution of the regression coefficients. As suggested by (5), the marginal posterior probability for the inclusion of a particular regressor is calculated as the weighted sum of the posterior probabilities of all models (model averaging) which include that particular regressor. Turning now in more detail to the constituent parts of (5), observe that the posterior distribution $P_{\Delta|y,M_j}$ of Δ under model M_j is a standard object.[14] The other constituent part, the posterior model probabilities $P(M_j|y)$, are calculated as follows:

$$P(M_j|y) = \frac{l_y(M_j)p_j}{\sum_{h=1}^{2^k} l_y(M_h)p_h} \tag{6}$$

where $l_y(M_j)$ is the marginal likelihood of model M_j, given by

$$l_y(M_j) = \int p(y|\alpha, \beta_j, \sigma, M_j)p(\alpha, \sigma)p(\beta_j|\alpha, \sigma, M_j)d\alpha d\beta_j d\sigma \tag{7}$$

where $p(y|\alpha, \beta_j, \sigma, M_j)$ represents the sampling model described in (1), and $p(\alpha, \sigma)$ and $p(\beta_j|\alpha, \sigma, M_j)$ are the priors described in (2) and (3) respectively.

2.2.2 Panel Estimations

In the second part of our analysis, we re-estimate the models chosen by the BMA methodology using panel data estimation techniques. The panel nature of our data set allows us to control for unobserved heterogeneity at the country level. Time-series and cross-section studies not controlling for this heterogeneity run the risk of obtaining biased results. A panel data model may be expressed as follows:

$$y_{it} = \alpha_{it} + \sum_{k=1}^{K} x_{kit}\beta_{kit} + u_{it}$$

[14] See, for instance, Leamer (1978, chapter 3.3).

where $i = 1, \ldots, N$ refers to a cross sectional unit (also referred to as an individual) and $t = 1, \ldots T$ refers to a given time period. Therefore, y_{it} records the value of dependent variable i at time t and x_{kit} records the value of the k^{th} explanatory variable for individual i at time t. In general, the parameters β_{kit} may vary across individuals and time. In our application we restrict the slope coefficients to be constant across time and individuals. The intercept, however, is assumed to vary across individuals. Given the aforementioned assumptions, our panel data model is

$$y_{it} = \alpha + \sum_{k=1}^{K} x_{kit}\beta_k + u_{it} \tag{8}$$

where

$$u_{it} = \mu_i + v_{it}.$$

where μ_i denotes the unobservable individual effect completed by the stochastic disturbance term v. We allow for both fixed and random individual effects[15].

3 Results

3.1 BMA Analysis

3.1.1 Raw Returns

The results in this section are based on the Bayesian model outlined in equations (1) − (4). As mentioned previously, the g-structure of the prior described in (3) is set at $g = 1/\max\{n, k^2\}$. As $n > k^2$ in our case, we set $g = 1/n$. We run 500,000 MC^3 draws[16] after an initial 100,000 discarded draws. The MC^3 sampler visited 205 models.[17] The results are presented in Table 3. The cumulative posterior probability of the 20 best models (those with posterior probabilities greater than 0.25%) accounts for 98.18% of the total posterior mass. The posterior probability of the best model (i.e. the one that includes a constant as the only independent variable) is 79.52%. This is a very high number, as some previous studies report posterior probabilities of best models of a magnitude of 1 to 3%. In FLS (2001b) which investigate cross-country growth regressions, for instance, the posterior probability of the best model is 1.24%. Masanjala and Papageorgiou (2006) report a posterior probability of the best model of 1.99%. Here, the posterior mass is essentially concentrated on a single

[15] Also respectively known as dummy-variable and error components models.

[16] MC^3 refers to the Markov Chain Monte Carlo Model Composition sampler proposed by Madigan and York (1995).

[17] The program was kindly provided by Eduardo Ley.

model. In our opinion, this supports the view expressed by SDM that when the ratio of observations to potential regressors is relatively high (as it is in our case), regression coefficients of irrelevant regressors converge to zero. In our case, all potential regressors proved to be irrelevant. Nevertheless BMA is applicable because there is substantial uncertainty regarding the impact of political variables on stock returns.

We now turn to the discussion of marginal posterior probabilities for the inclusion of particular regressors. As mentioned earlier, these probabilities are respectively given by the weighted sum of the posterior probabilities of all models that include the respective regressor. Table 4 presents the results. As there is virtually no posterior weight assigned to models that include any potential regressors - recall that the posterior mass is largely concentrated on the model containing only a constant - marginal probabilities are extremely low[18], ranging from 3.12% to 0.96%. Consistent with many of the prior findings (Doepke and Pierdzioch ,2006; Jacobsen and Stangl, 2007; Lin and Wang, 2007; among others), we find no evidence on the influence of political variables on raw stock returns.

3.1.2 Excess Returns

The analysis of excess returns produces results similar to those obtained for raw returns: the model including a constant only has the largest posterior probability, 52.95%. The posterior probability of the five best models is presented in Table 5. With 12.36% posterior probability the data also lends some support to a model including a constant and the multi-party minority government variable. Models 3 to 5 receive considerably less support with posterior probabilities ranging from 2.6% to 2.99%. The cumulative posterior probability of all models with a posterior probability greater than .25% is 92.31%. Similar to the case of raw returns, the posterior mass is highly concentrated with approximately 53% of the mass falling on the constant only model.

Table 6 presents the marginal posterior probabilities of individual regressor inclusion. Corresponding to the results for posterior model probabilities, BMA inclusion probabilities for regressors are quite low with one regressor standing out: The posterior inclusion probability of the multi-party minority government variable is 18.77%. Intuitively appealing, the impact of this variable on excess returns is negative. Note

[18] In contrast, FLS (2001b) find one regressor (GDP level in 1960) with a posterior inclusion probability of 100% and three regressors with inclusion probabilities beyond 94%.

that; even though the inclusion probability of this variable was, with only 1.24%, considerably lower when studying raw returns, the variables impact was negative too and it featured the fourth highest inclusion probability. To shed more light on the importance of this variable, its significance is tested within the panel data estimations outlined below.

3.1.3 Volatility

It has been suggested[19] that political variables affect higher moments of stock returns, rather than their averages. We test this proposition by using monthly realized volatilities, estimated as standard deviations of daily returns within each month. The MC^3 sampler visited 758 models, the best of which featured a posterior probability of 29.05%. Table 7 presents the posterior probabilities of the five best models. The cumulative posterior probability of the 42 models with a posterior probability greater than .25% is 87.30%. In comparison to the analysis of raw and excess returns, posterior model probabilities of realized volatilities have a substantially greater spread spread. The second most favoured model in terms of the data features a posterior model probability of 13.54%. The other three top five models receive support levels ranging from 3.58% to 6.97%. None of the top five models features only a constant.

Turning to the marginal posterior probabilities of regressor inclusion, Table 8 documents that the top five regressors have inclusion probabilities beyond 81.7%. Dissension within government and lagged dissension have marginal posterior probabilities of 100%, implying that all models with a non-zero probability of being the *true* model include these regressors. Other independent variables with high posterior probabilities are government party alignment at 99.17%, minimal winning coalition at 89.71%, and single party minority government at 81.71%. With posterior probabilities close to 35% the regressors lagged lack of parliamentary support and multi-party minority government also receive considerable levels of support. As intuition suggests, the top three regressors impact return volatility positively while the other two top five regressors' impact on volatility is negativ. Note that the top five regressors according to inclusion probabilities correspond neatly to the top five models according to posterior model probabilities. Each of the top five models contains all of the top

[19] For instance, Bialkowski et al. (2006b), studying return volatility in a sample of twenty-seven OECD countries, find that elections are accompanied by elevated volatility. A strong abnormal rise starts on election day and continues for a number of days thereafter. Siokis and Kapopoulos (2007), studying the Greek stock market index (ASX), find that different political regimes impact the conditional variances of the stock market index.

five regressors. The best model includes only the top five regressors and a constant. The second best model includes in addition to the regressors contained in the best model the regressor lagged parliamentary support.

Several variables are found to be important in determining stock return volatilities. It is important to note that while the identification of individual regressors' posterior probabilities provides useful insights with respect to the relative importance of regressors, when we want to select the best model in a linear regression setting, it is important to know how well regressors perform in combination with other regressors. In determining this, i.e., assigning low posterior probability to models with collinear regressors and overfitting, BMA analysis, as documented by the respective regressors included in the best five models according to posterior probabilities, addresses this concern.

3.2 Panel Data Estimation

One disadvantage of the BMA methodology is that it pools all observations. Therefore it does not allow for controlling for the unobserved heterogeneity at the country level. Both stock markets and countries' political systems are heterogeneous. Given a panel data set, it is possible to test whether this heterogeneity is of concern for the realtionship between (1) returns and political variables, and (2) volatility and political variables. Time-series and cross-section studies which do not control for this heterogeneity run the risk of obtaining biased results. Therefore, we present additional estimations of best models, as chosen by the BMA analysis, that use panel data estimation techniques in this section.

Rewriting (8) where the $1 \times k$ vector X_{it} collects the regressors of the best model in the case of volatility (i.e., constant, government party alignment, dissension, lagged dissension, single party government, and minimal coalition) and of the second best model in the case of excess returns (i.e. constant and multi-party minority government) produces

$$y_{it} = \alpha + X_{it}\beta + u_{it},$$

with

$$u_{it} = \mu_i + v_{it}$$

where μ_i captures the unobservable individual effect. We allow for both fixed and random individual effects. A fixed effects model is used when individuals are a well defined group (for instance N OECD countries). This allows the constant to differ across cross-sectional units and estimates a different constant α_i for each cross-section. The random effects estimator assumes that the term α_i is equal to the sum of a common constant α and a time invariant, cross-section specific random variable. Tables 9 and 10 present panel data regression estimates for excess returns and volatility.

The panel estimations for the excess returns are presented in Table 9. The empirical results mostly support our previous findings. Multi-party minority governments have a negative and significant effect on excess returns in three out of four specifications (regressions 1, 3, and 4). Nevertheless, once country dummies are included the coefficient of our main interest variable, multi-party minority government, becomes marginally insignificant . On the other hand, once we take full advantage of the panel nature of our data set, we document a significantly negative effect of multi-party minority governments on excess returns.

The panel estimations for volatility are presented in Table10. The political orientation of the government is found to have a positive significant effect on stock market volatility in all specifications (regressions 1-4). Volatility appears to be higher during more left-oriented governments. In contrast to our findings, Santa Clara and Valkanov (2003), studying the U.S. stock market, find that volatility is somewhat higher in Republican presidencies. It is also important to note that a dummy variable for elections is not included. This is in contrast to some studies that document a significant impact of elections on volatility (Bialkowski et al. (2006b), Li and Bern (2006) to name a few). The coefficient for minimal winning coalition is negative and significant in all specifications (regressions 1 to 4). Initially, we do not find statistically significant coefficients for the variables dissension and lagged dissension (regressions 1 to 2). However, both variables become statistically significant when we control for unobserved heterogeneity using panel estimation methods (regressions 3 to 4). The most interesting results are documented for single party governments. Without any further controls the OLS estimation provides a negative and significant effect of single party governments on stock market volatility (regression 1). On the other hand, once we control for country specific effects (regression 2) or employ panel estimation methods we find a positive and significant effect of single party governments on stock market volatility. This result points to the importance of the bias of estimates when not accouting for unobserved heterogeneity[20]. The postitive effect of single party governments on volatility may be due to an increased likelihood of status-quo changes.

[20]However, we should also note that when we revisit our BMA analysis with the country dummies, we get consistent results with the fixed effects estimations

Single party governments are less constrained in their decision making than are coalition governments. An increase in the likelihood of policy changes which is likely to imply increased uncertainty with respect to the future economic environment should be reflected in increased volatility.

4 Discussion

The impact of the political environment on financial markets is one of the most intriguing topics in financial economics. While many variables which measure political activity are intuitively expected to affect market performance, most of the current empirical research fails to document clear-cut relationships. One of the major difficulties when investigating the relationship between political events and financial markets is model uncertainty.

This paper contributes to the existing literature in the following ways. First, it utilizes a unique dataset that measures, among other things, the complexity of government structures, which allows us to go beyond the 'left vs. right' analysis. Second, we explicitly account for model uncertainty by using Bayesian Model Averaging. Our results confirm the presence of model uncertainty, with posterior probabilities spread over a large number of models in the case of stock market volatility. Consistent with some prior work, we document that no variables influence the level of raw returns, and very few influence the level of excess stock returns. In fact, only the multi-party minority government dummy variable is included in the second best model (posterior probability of 12.36%). This demonstrates that even after explicitly addressing model uncertainty, few political variables seem to have an impact on the level of stock returns. This points out that most political events could indeed be anticipated by market participants. Nonetheless, more variables are found to influence excess return volatility supporting the view that most political variables affect higher moments of stock returns.

Our results shed light on model construction strategies in analyzing the interactions of political and financial variables. Some opportunities for future research may include investigating whether the effects we document in this paper are more pronounced under different political systems. Future research might also differentiate between expected versus unanticipated political events, which is beyond the scope of this paper.

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(Chapter head:)**Data**

Variable	**Definition**
Date of termination of government	Date on which the power is transferred to the new government.
Reason for termination	These include: elections, voluntary resignation, prime minister resignation due to health reasons, dissension within government, lack of parliamentary support, intervention of the head of state.
Government type	These include: single party government, minimal winning coalition, surplus coalition, single party minority government, multi party minority government, caretaker government.
Gov't party, seats in parliament	Gives the number of seats in parliament for each party represented in the government. Government fractionalization is computed using this information as a sum of squared shares of seats.
Political complexion of parliament and government	An indicator that attempts to account for relative strength of parties in government. It is measured on a scale of 1 through 5, 1 being right-wing dominated, 5 being left-wing dominated.

Table 1: Description of Political Data: Political variables used as potential regressors in the linear regression setting. Data from Woldendorp et al. (1998).

No	Country	Raw Return	Excess Return	Volatilities
1	Australia	07.1945 - 12.1995	07.1945 - 12.1995	01.1958 - 12.1995
2	Austria	02.1986 - 12.1995	02.1986 - 12.1995	02.1986 - 12.1995
3	Belgium	08.1945 - 12.1995	01.1948 - 12.1995	01.1985 - 12.1995
4	Canada	08.1945 - 12.1995	08.1945 - 12.1995	01.1976 - 12.1995
5	Denmark	11.1945 - 12.1995	01.1976 - 12.1995	01.1979 - 12.1995
6	France	11.1945 - 12.1995	01.1960 - 12.1995	09.1968 - 12.1995
7	Germany	09.1949 - 12.1995	01.1953 - 12.1995	01.1970 - 12.1995
8	Ireland	02.1948 - 12.1995	12.1969 - 12.1996	01.1987 - 12.1995
9	Israel	03.1949 - 12.1995	01.1992 - 12.1995	06.1981 - 12.1995
10	Italy	07.1946 - 12.1994	07.1946 - 12.1994	12.1956 - 12.1994
11	Japan	08.1946 - 12.1995	01.1960 - 12.1995	01.1955 - 12.1995
12	Netherlands	07.1946 - 12.1995	07.1946 - 12.1995	01.1980 - 12.1995
13	New Zealand	12.1946 - 12.1995	03.1978 - 12.1995	01.1970 - 12.1995
14	Norway	01.1970 - 12.1995	01.1984 - 12.1995	01.1983 - 12.1995
15	Sweden	10.1946 - 12.1995	01.1955 - 12.1995	01.1980 - 12.1995
16	Switzerland	12.1944 - 12.1995	01.1980 - 12.1995	01.1969 - 12.1995
17	UK	07.1945 - 12.1995	07.1945 - 12.1995	01.1968 - 12.1995

Table 2: Data Ranges: Raw Returns, Excess Returns, and Realized Volatilities; stock index data and 3-months-treasury bill rates from Global Financial Data (www.golbalfinancialdata.com)

No	Regressors	Post. Prob.
1	Constant	79.52%
2	Constant, Dissension within Gov't	2.59%
3	Constant, Elections	1.09%
4	Constant, lagged resignation due to health	1.06%
5	Constant, Multi Party Minority	1.03%

Table 3: Model Specifications for **Raw Returns** Estimation: This table presents the five best models according to posterior probabilities.

No	Variable	Post. Prob.	Impact
1	Dissension within Gov't	3.12%	Positive
2	Elections	1.29%	Positive
3	Lagged resignation due to health	1.27%	Positive
4	Multi party minority Gov't	1.24%	Negative
5	Intervention by Head of State	1.20%	Positive
6	Lagged dissension	1.09%	Negative
7	Lagged lack of parliam. Support	1.06%	Negative
8	Lagged resignation	1.05%	Negative
9	Lack of parliamentary support	1.05%	Negative
10	Lagged elections	1.02%	Positive
11	Resignation due to health	1.02%	Positive
12	Gov't party alignment	1.01%	Negative
13	Single party Gov't	1.01%	Positive
14	Single party minority Gov't	1.00%	Positive
15	Lagged interv. by HoS	.99%	Negative
16	Resignation	.98%	Negative
17	Minimal winning coal.	.98%	Positive
18	Fractionalization	.97%	Positive
19	Surplus coalition	.96%	Positive

Table 4: Posterior Probabilities of Individual Regressors in Determining the Level of **Raw Returns**: This table presents individual marginal BMA posterior probabilities.

No	Regressors	Post. Prob.
1	Constant	52.95%
2	Constant, multi party minority gov't	12.36%
3	Constant, lack of parliamentary support	2.99%
4	Constant, lagged lack of parliamentary support	2.70%
5	Constant, dissension	2.60%

Table 5: Model Specifications for **Excess Returns** Estimation: This table presents the five best models according to posterior probabilities.

No	Regressors	Post. Prob.	Impact
1	Multi party minority gov't	18.77%	Negative
2	Lack of parliamentary support	5.15%	Negative
3	Lagged lack of parliam. support	4.66%	Negative
4	Dissension within government	4.60%	Positive
5	Lagged resignation	4.06%	Negative
6	Surplus coalition	3.76%	Positive
7	Government party alignment	2.86%	Negative
8	Intervention by head of state	1.78%	Positive
9	Lagged resignation due to health	1.46%	Positive
10	Minimal winning coalition	1.44%	Positive
11	Elections	1.37%	Positive
12	Fractionalization	1.31%	Negative
13	Single party government	1.26%	Positive
14	Resignation	1.18%	Positive
15	Resignation due to health	1.17%	Negative
16	Lagged dissension	1.16%	Negative
17	Lagged elections	1.16%	Negative
18	Lagged head of state interv.	1.16%	Negative
19	Single party minority	1.08%	Positive

Table 6: Posterior Probabilities of Individual Regressors in Determining the Level of **Excess Returns**: This table presents individual marginal BMA posterior probabilities.

No	**Regressors**	**Post. Prob.**
1	Constant, government party alignment, dissension, lagged dissension, single party government, minimal coalition	29.05%
2	Constant, government party alignment, dissension, lagged dissension, lagged lack of parliamentary support, single party government, minimal coalition	13.54%
3	Constant, government party alignment, dissension, lagged dissension, single party government, minimal coalition, multi party minority	6.97%
4	Constant, government party alignment, dissension, lack of parliamentary support, lagged dissension, single party government, minimal coalition	5.88%
5	Constant, government party alignment, dissension, lagged dissension, lagged lack of parliamentary support, single party government, minimal coalition, multi party minority	3.58%

Table 7: Model Specifications for **Volatility** Estimation: This table presents the five best models according to posterior probabilities.

No	Regressors	Post. Prob.	Impact
1	Dissension	100%	Positive
2	Lagged dissension	100%	Positive
3	Gov't party alignment	99.17%	Positive
4	Minimal winning coalition	89.71%	Negative
5	Single party government	81.71%	Negative
6	Lagged lack of parliam. support	34.70%	Positive
7	Multi party minority gov't	33.81%	Positive
8	Lack of parliamentary support	18.32%	Positive
9	Surplus coalition	13.67%	Negative
10	Fractionalization	8.28%	Positive
11	Single party minority	4.79%	Negative
12	Resignation due to health	2.02%	Positive
13	Lagged resignation due to health	2.01%	Positive
14	Lagged head of state intervention	1.67%	Positive
15	Resignation	1.62%	Positive
16	Elections	1.50%	Positive
17	Lagged resignation	1.52%	Negative
18	Head of state intervention	1.36%	Negative
19	Lagged elections	1.33%	Negative

Table 8: Posterior Probabilities of Individual Regressors in Determining the Level of **Return Volatilities**: This table presents individual marginal BMA posterior probabilities.

Dep. Var.: Excess Returns	**(1)**	**(2)**	**(3)**	**(4)**
Multi-Party Minority Gov't	-0.0063^{**}	-0.0060	$-.0060^{*}$	-0.0063^{**}
	(-2.13)	(-1.59)	(-1.93)	(-2.43)
Constant	0.0008	0.0006	0.0008	0.0008
	(1.25)	(0.30)	(1.19)	(1.23)
Country Dummies?	No	Yes	Yes	No
F-Statistic	4.54^{**}	0.65	3.71^{*}	-
Wald Statistic	-	-	-	5.89^{**}
R-Square	0.0009	0.0016	0.0009	0.0009
Number of Observations	6649	6649	6649	6649
Estimation Method	OLS with White (1980)	OLS with White (1980)	Fixed Effects	Random Effects

Table 9: Panel Data Regressions for **Excess Returns**: t-statistics (z-statistics for the Random Effects regression) are presented in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Dep. Var.: Volatility	**(1)**	**(2)**	**(3)**	**(4)**
CPG	0.0002***	0.0001**	0.0001**	0.0001**
	(4.39)	(1.96)	(2.08)	(2.47)
Dissension within gov't	0.0089	0.0078	0.0078***	0.0078***
	(1.39)	(1.22)	(7.49)	(7.54)
Lagged dissens within gov't	0.0007	0.0063	0.0063***	0.0063***
	(1.17)	(0.99)	(6.02)	(6.07)
Single Party Gov't	-0.0008***	0.0011***	0.0011***	0.0008**
	(-4.76)	(3.20)	(2.88)	(2.29)
Min. winning coalition	-0.0012***	-0.0007*	-0.0007**	-0.0007**
	(6.67)	(-1.69)	(2.13)	(-2.20)
Constant	0.0083***	0.0065***	0.0077***	0.0087***
	(48.25)	(13.41)	(30.79)	(15.98)
Country Dummies?	No	Yes	Yes	No
F-Statistic	15.74***	24.87***	26.01***	-
Wald Statistic	-	-	-	128.02***
R-Square	0.0401	0.1148	0.0176	0.0224
Number of Observations	4524	4524	4524	4524
Estimation Method	OLS with White (1980)	OLS with White (1980)	Fixed Effects	Random Effects

Table 10: Panel Data Regressions for **Volatility**: t-statistics (z-statistics for the Random Effects regression) are presented in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively.