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Predicting Stock Market Movements in the United States: The Role of Presidential Approval Ratings

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Abstract

In this paper we analyze whether presidential approval ratings can predict the S&P 500 returns over the monthly period of 1941:07 to 2018:04, using a dynamic conditional correlation multivariate generalized autoregressive conditional heteroscedasticity (DCC-MGARCH) model. Our results show that, standard linear Granger causality test fail to detect any evidence of predictability. However, the linear model is found to be misspecified due to structural breaks and nonlinearity, and hence, the result of no causality from presidential approval ratings to stock returns cannot be considered reliable. When we use the DCC-MGARCH model, which is robust to such misspecifications, in 69 percent of the sample period, approval ratings in fact do strongly predict the S&P 500 stock return. Moreover, using the DCC-MGARCH model we find that presidential approval rating is also a strong predictor of the realized volatility of S&P 500. Overall, our results highlight that presidential approval ratings is helpful in predicting stock return and volatility, when one accounts for nonlinearity and regime changes through a robust time-varying model.

Keywords: US Presidential Approval Ratings; DCC-MGARCH; Stock Returns; Realized Volatility; S&P 500.

JEL Codes: C32, G10.

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1 Introduction

Stock return forecasts are important for practitioners in finance for asset allocation, while academics are interested in it, since predictability has important implications for tests of market efficiency, which in turn, helps to produce more realistic asset pricing models. However, stock return prediction is highly challenging, since it inherently contains a sizeable unpredictable component. Hence, not surprisingly, the existing literature on stock market prediction in the US is huge (see for example, Rapach et al., (2010), Rapach and Zhou (2013), Aye et al., (2016, 2017) for detailed reviews), to say the least, involving variety of (univariate and multivariate versions of linear, nonlinear, and nonparametric) models and predictors (for example, macroeconomic, financial, technical, institutional, and behavioral).

Against this backdrop, the objective of this paper is to add to the above literature, by considering the role of US presidential approval ratings in predicting S&P 500 stock return. As highlighted recently by Chong et al., (2011), Berlemann and Enkelmann (2014), Choi et al., (2016), and Dickerson (2016), presidential approval ratings are (nonlinear) functions of the state of the economy, as defined by wide-array of economic variables. Given that asset prices are functions of the state of the economy as well, movements in the presidential approval rating due to movements in the underlying economy is likely to have an impact on the stock market. In light of this, the hypothesis that we aim to test here is whether presidential approval ratings can predict the S&P 500 returns over the monthly period of 1941:07 to 2018:04. To achieve this objective, we use a dynamic conditional correlation multivariate generalized autoregressive conditional heteroscedasticity (DCC-MGARCH) model of causality. The decision to use the DCC-MGARCH model is twofold: First, this approach being a time-varying method allows us to capture the possible nonlinearity and regime changes between the stock return and the presidential approval rating, which in turn, are well-established facts in the context of stock markets and its predictors (Rapach and Wohar, 2006; Guidolin et al., 2009; Gupta et al., 2017a, b), and something that we show to hold in our data set as well. Second, we prefer to use this causal model over a (time-varying) predictive regression, since evidence by Halcoussis et al., (2009) and Fauvelle-Aymar and Stegmaier (2013) show that presidential approval ratings are also driven by stock returns. To the best of our knowledge, this is the first attempt to predict stock returns based on the information content of the presidential approval ratings using a time-varying (DCC-MGARCH) approach.[1]

[1]The only other study that we could find which is somewhat related to our work is the paper by Wisniewski (2009). The author documents that political factors (political orientation of the

The remainder of the paper is organized as follows: Section 2 describes the methodology, while Section 3 outlines the data and results. Section 4 concludes the paper.

2 Methodology

We implement the DCC-MGARCH Hong test (Lu et al., 2014) to investigate time-varying Granger causality between developments in the stock market and presidential approval ratings. Let X_t and Y_t be two series of residuals from an ARMA-GARCH model for each series. Considering the process $Z_t(j) = (X_t, Y_t)'$ (where j denotes the lag length), we use the DCC-MGARCH model to estimate dynamic correlations.

The DCC-MGARCH model is defined as follows[2]

$$\begin{aligned} Z_t(j)|I_{t-1} &\sim N\left(0, D_{t,j}R_{t,j}D_{t,j}\right) \\ D_{t,j}^2 &= \text{diag}\{\omega_{i,j}\} + \text{diag}\{\kappa_{i,j}\} \circ Z_t(j)Z_t'(j) + \text{diag}\{\lambda_{i,j}\} \circ D_{t-1,j}^2 \\ u_{t,j} &= D_{t-1,j}^{-1}Z_t(j) \\ Q_{t,j} &= S \circ \left(\iota\iota' - A - B\right) + Au_{t-1,j}u_{t-1,j}' + BQ_{t-1,j} \\ R_{t,j} &= \text{diag}\{Q_{t,j}\}^{-1}Q_{t,j}\text{diag}\{Q_{t,j}\}^{-1} \end{aligned} \tag{1}$$

Let $\rho_{pq,t}(j)$ denote the dynamic correlation estimator in the DCC-MGARCH(1,1) given by

$$\begin{aligned} \rho_{pq,t}(j) &= \overline{\rho_{pq}}(j) + \alpha_j\left(u_{p,t-1}u_{q,t-1-j} - \overline{\rho_{pq}}(j)\right) + \beta_j\left(\rho_{pq,t-1}(j) - \overline{\rho_{pq}}(j)\right) \\ & \quad r_{pq}(j)\frac{\rho_{pq}(j)}{\sqrt{\rho_{11,t}\rho_{22,t}(j)}} \end{aligned} \tag{2}$$

where $p, q = 1, 2$.

The unidirectional time-varying DCC-MGARCH Hong test for Granger causality running from Y_t to X_t is computed as follows

$$H_{1,t}(k) = \frac{T\sum_{j=1}^{T-1}k^2\left(\frac{j}{M}\right)r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{3}$$

president and approval rating, election cycle and military conflicts) can be linked to the (non-fundamental) part of (annual) stock prices which cannot be explained by the standard present value models. Unlike this paper, we however, aim to predict stock returns at a higher frequency due to presidential approval ratings using a time-varying, rather than a constant parameter approach as used by Wisniewski (2009), and hence is robust to misspecification due to nonlinearity and regime changes.

[2]see Engle (2002) for details.

where M is a positive integer and $k(\cdot)$ is the Bartlett kernel function; $C_{1T}(k) = \sum_{j=1}^{T-1}\left(1-\frac{j}{T}\right)k^2\left(\frac{j}{M}\right)$; $D_{1T}(k) = \sum_{j=1}^{T-1}\left(1-\frac{j}{T}\right)\left(1-\frac{j+1}{T}\right)k^4\left(\frac{j}{M}\right)$.

Under the null hypothesis that X_t and Y_t are mutually independent, $\alpha_j \sim N\left(0, \frac{\sigma_{1,j}^2}{T}\right)$ and β_j are nuisance parameters (See Engle and Sheppard, 2001). Therefore, the asymptotic distribution of dynamic correlations $r_{12,t}(j)$ cannot be identified. However, under the null hypothesis, it is the case that $\sqrt{T}r_{12,t}(j) = \mathcal{O}_p(1)$.

If $\overline{\rho_{pq}}(j) = \rho_{pq,0}(j) = \hat{\rho}_j = \frac{\sum_{t=j}^{T} X_t Y_{t-j}}{\sqrt{\sum_{t=1}^{T} X_t^2 \sum_{t=1}^{T} Y_t^2}}$, $\rho_{11,t12,t}(j) = \hat{\rho}_j + \hat{\alpha}_j \sum_{s=1}^{t} \hat{\beta}_j^{s-1}\xi_{t-s,j}$, where $\xi_{t,j} = u_{1,t}u_{2,t-j} - \hat{\rho}_j$, then $\rho_{11,t12,t}(j)$ corresponds to $\hat{\rho}_j$, if we ignore the second term. Therefore, under the null hypothesis that X_t and Y_t are mutually exclusive, the unidirectional DCC-MGARCH Hong test is asymptotically normally distributed, that is, $H_{1,t}(k) \overset{as.}{\sim} N(0,1)$.

3 Data and Results

The S&P 500 stock price index data is derived from the Global Financial Database (GFD), and is converted to log-returns (SR) by taking the first differences of the natural logarithm times 100 to convert it into percentages. The data on presidential approval ratings is based on as measured by Gallup, which in turn is compiled by Professor Gerhard Peters and Professor John T. Woolley, as part of the American Presidency Project. The data is available for download from: http://www.presidency.ucsb.edu/data/popularity.php. The data starts from 1941:07 (President Franklin D. Roosevelt) and currently ends in 2018:04 (President Donald J. Trump). Naturally, this is also the period of our analysis, and comprises of 922 monthly observations.[3] The data is available in mixed frequency (i.e., weekly and monthly) at times, and also has missing observations. When available weekly, we take the earliest available weekly rating as the monthly rating,[4] and missing data are linearly interpolated, following Fauvelle-Aymar and Stegmaier (2013). We use the natural logarithm of the ratings in our analysis, and call the variable LPAR. In the Appendix, Table A1 provides the summary statistics of SR and LPAR, while Figures A1(a) and A1(b) plots the two variables respectively. The augmented Dickey-Fuller (ADF) test with just a constant indicates that both series are stationary, and hence can be used in the DCC-MGARCH model without any further transformations. Both variables are strongly non-normal in the statistical

[3]Since the S&P 500 index data is available since 1791:08, we do not lose the observation for the month of 1941:07, when computing log-returns.

[4]If, when available weekly, we take the average over the weeks of the month to convert presidential approval ratings into monthly data, our results continue to remain the same. Complete details of these results are available upon request from the authors.

sense, due to negative skewness and excess kurtosis. More importantly, the fact that the ARCH-LM test rejects the null hypothesis of homoscedasticity for each series indicates the appropriateness of modelling our variables of interest as ARCH-type processes.

Though our focus is on the predictability of the stock returns using the DCC-MGARCH approach, for the sake of comparability and completeness, we also analysed the same using a standard linear Granger causality test. Based on a vector autoregressive model of order 3, with the lag-length being chosen by the Akaike Information Criterion (AIC), the null that LPAR does not Granger cause SR could not be rejected even at the 10 percent level of significance, given the $\chi^2(3)$ statistic of 5.5533 with a p-value of 0.1355. Next, applying the powerful UDmax and WDmax tests of Bai and Perron (2003), to detect 1 to M structural breaks, allowing for heterogeneous error distributions across the breaks, on the SR equation of VAR model, we identified as many as five structural breaks (1946:10, 1969:01, 1974:11, 1978:09, and 2007:11).[5] In addition, the Brock et al., (1996, BDS) test applied on the residual of the same equation, overwhelmingly rejected the null of i.i.d. residuals (i.e., indicating the presence of uncaptured nonlinearity) across various dimensions at the highest level of significance.[6] The evidence of structural breaks and nonlinearity suggests that the constant parameter VAR model is misspecified and the result of no predictability from LPAR to SR cannot be deemed reliable. This paves the way for the usage of the time-varying DCC-MGARCH model which is robust to such misspecifications. As shown in Figure 1, barring 284 months (i.e., 31 percent of 922 months), there is strong evidence of predictability from LPAR to SR.[7] Clearly then, using a constant parameter model, we would have failed to detect evidence that the S&P 500 returns is in fact predictable, in general, based on the information contained in the presidential approval ratings in the US.

Additional Analysis: Volatility and Presidential Approval Ratings

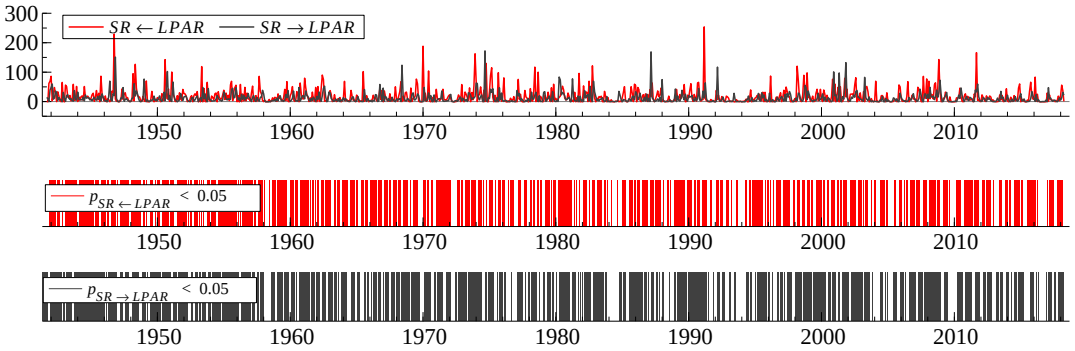
Recently, Engle et al., (2013), and earlier to that Engle and Rangel (2008), have highlighted the role played by macroeconomic variables in predicting stock market volatility. Given that presidential approval rating is affected by macroeconomic

[5] We were also able to detect five breaks (1953:01, 1957:03, 1974:06, 1981:02, and 2009:01) when the same test was applied to the LPAR equation of the VAR(3) model.

[6] Complete details of these results have been presented in Table A2 of the Appendix.

[7] Figure 1 also shows that, in general, SR causes LPAR, except for 92 months, i.e., 10 percent of total cases. Note that the VAR(3) model had a $\chi^2(3)$ statistic of 3.2164 with a p-value of 0.3595, i.e., we could not reject the null that SR predicted LPAR.

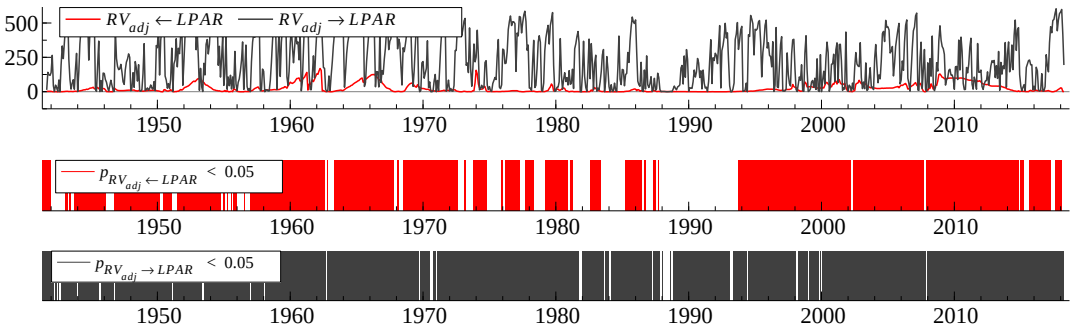
Figure 1: Time-varying Granger causality between stock returns and presidential approval ratings



Notes: The Figure at the top plots the time-varying DCC-MGARCH Hong test statistic. Figures with shaded regions below show the month during which the corresponding test is statistically significant at the 5% level.

movements, as discussed in the introduction, it is highly likely that LPAR can also predict the volatility of the S&P 500. Since daily data on the S&P 500 index is available since 17th March, 1936 from the GFD, we computed monthly realized volatility (RV) as a measure of model-free estimate of volatility. Following Andersen and Bollerslev (1998), we computed RV as the sum of squared daily log-returns over a month. Realizing that RV has long-memory, we fit a Heterogeneous Autoregressive (HAR) model of the form: $RV_t = \alpha_0 + \alpha_1 RV_{t-1} + \alpha_2 RV_{t-1,\varpi_1} + \alpha_3 RV_{t-1,\varpi_2} + \varepsilon_t$, where $RV_{t-1,\varpi_i} = (RV_{t-1} .... + RV_{t-\varpi_i-1})/\varpi_i$, $i = 1, 2$, with $\varpi_1 = 3$, and $\varpi_2 = 12$ corresponding to a quarter and a year respectively. We then use the residuals from the model in the DCC-MGARCH as the persistence-adjusted measure of RV_{adj}.

Figure 2: Time-varying Granger causality between realized volatility and presidential approval ratings



Notes: See notes for Figure 1.

As observed from Figure 2, we find that, LPAR in general can help predict RV_{adj}, with the glaring exception being the period spanning from the late 1980s to the early 1990s (specifically, 1987:08 to 1993:09), which corresponds to the relatively calmer bull period for the S&P 500 index, resulting in reduced role of the

LPAR in affecting volatility.[8] Since, financial market volatility is an important input in investment decisions, option pricing and financial market regulation (Poon and Granger, 2003), our results tend to suggest that both investors and policymakers can find the information-content of LPAR in predicting future volatility of the S&P 500 market, useful.[9]

4 Conclusion

In this paper we test the hypothesis that presidential approval ratings can predict the S&P 500 returns over the monthly period of 1941:07 to 2018:04, using a dynamic conditional correlation multivariate generalized autoregressive conditional heteroscedasticity (DCC-MGARCH) model. Our results show that, standard linear Granger causality test fail to detect any predictability emanating from presidential approval ratings to stock returns.

However, the linear framework is found to be misspecified due to structural breaks and nonlinearity, and hence, the result of no causality from presidential approval ratings to stock returns cannot be considered reliable. When we use the DCC-MGARCH model, which is robust to such misspecifications, we find that barring 284 periods out of the 922 months considered, approval ratings in fact do strongly predict the S&P 500 stock return. Moreover, using the DCC-MGARCH model we find that presidential approval rating is also a strong predictor (barring the bullish period of late 1980s to the early 1990s) of S&P 500 (realized) volatility. In sum, our results highlight the importance of information contained in US presidential approval ratings in predicting stock return and volatility, when one accounts for nonlinearity and regime changes through a robust time-varying model.

As part of future research, we could extend our analysis to check whether US presidential approval ratings can predict stock returns and volatility of other devel-

[8] Figure 2 also shows that, in general, RV_{adj} causes LPAR, and just like in the case of the SR, the predictability is stronger from RV_{adj} to LPAR, than the other way around. The ability of stock market volatility, as measured by the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), in predicting presidential approval ratings has also been confirmed by Schwartz et al., (2008) and Chong et al., (2011).

[9] Giot et al., (2010) points out that market participants care not only about the nature of volatility, but also of its level, with all traders making the distinction between good and bad volatilities. Given this, we also computed good and bad RVs based on the sum of squared daily positive returns, and the sum of squared daily negative returns over a month, respectively. Again, to filter out the long-memory, we fitted HAR models to the good (RV-Good_{adj}) and bad (RV-Bad_{adj}) Rs, as was done to overall RV. As can be seen from Figure A1 and A2 presented in the Appendix of the paper, LPAR has stronger predictability for RV-Bad_{adj} than RV-Good_{adj}. In other words, the causal result for overall volatility from the presidential approval ratings is driven by bad volatility. In addition, as observed from Figures A2 and A3, LPAR is also more strongly predicted by RV-Bad_{adj} than RV-Good_{adj}.

oped and emerging markets, given the dominance of the US in the global context, and hence its presidential ratings, as highlighted by Burden and Mughan (2003). In addition, it would also be interesting to see if our results of in-sample predictability also tend to hold out-of-sample in a full-fledged forecasting exercise, since the former does not necessarily guarantee the latter (Rapach and Zhou, 2013).

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Appendix

Table A1: Summary Statistics

	SR	LPAR
Mean	0.0061	3.9500
Median	0.0096	3.9703
Maximum	0.1135	4.5109
Minimum	-0.2280	3.0910
Std. Dev.	0.0348	0.2659
Skewness	-1.0052	-0.5886
Kurtosis	6.8453	3.1488
Jarque-Bera	723.3263***	54.0813***
ARCH(12) LM-Test	3.4119***	342.4056***
ADF^a (Constant)	-23.7671***	-5.2149***
Observations	922	922

Notes: SR: S&P 500 Stock Returns; LPAR: Natural Log of Presidential Approval Ratings; Std. Dev. symbolizes the Standard Deviation; ^{a}: the 10 percent, 5 percent and 1 percent critical values are -2.5684, -2.8645 and -3.4372, respectively; *** corresponds to the rejection of the null of normality and homoscedasticity at 1 percent level of significance.

Table A2: BDS Test

m	z-statistic - SR$^{(1)}$	p-value	z-statistic - LPAR$^{(2)}$	p-value
2	2.7299	0.0063	10.1832	0.0000
3	3.8385	0.0001	10.8087	0.0000
4	4.7712	0.0000	11.8707	0.0000
5	5.3366	0.0000	12.7412	0.0000
6	5.9713	0.0000	13.5921	0.0000

Note: m stands for the embedded dimension; (1): z-statistic of residuals of the SR equation in the VAR(3) model; (2): z-statistic of residuals of LPAR equation in the VAR(3) model; p-value corresponds to the test of i.i.d. residuals based on the z-statistic of the BDS test.

Figure A1: Data Plots

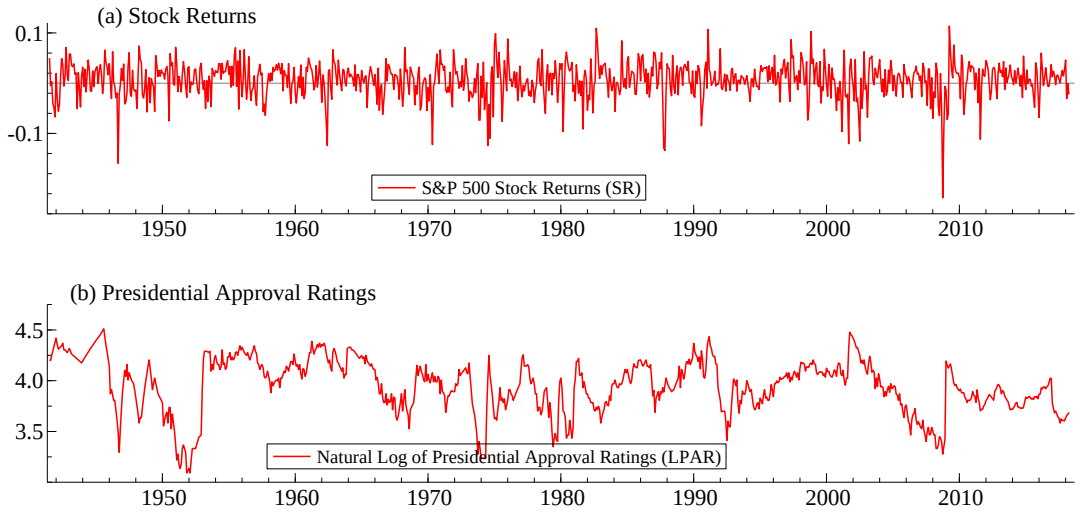
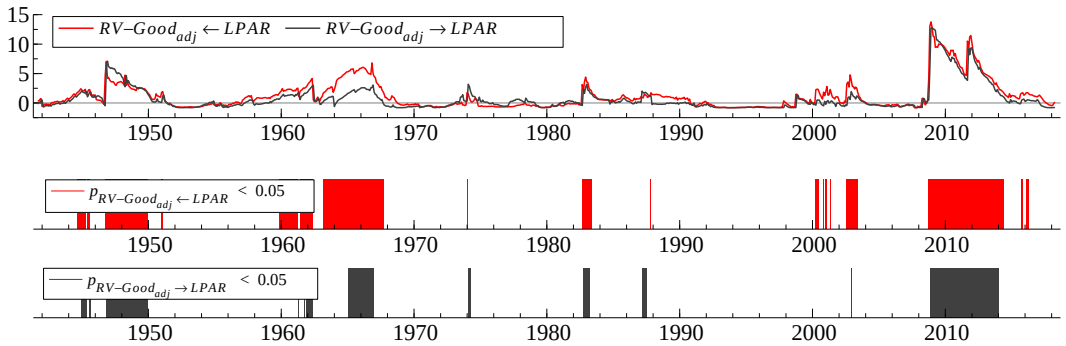
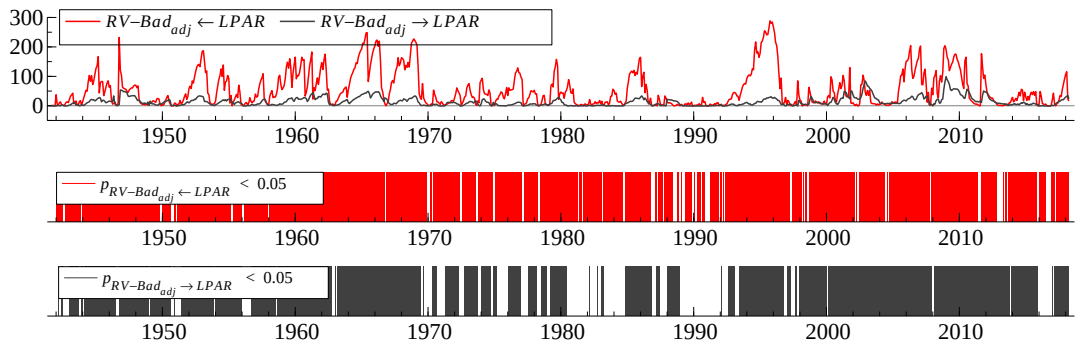


Figure A2: Time-varying Granger causality between good realized volatility and presidential approval ratings



Notes: See notes for Figure 1.

Figure A3: Time-varying Granger causality between bad realized volatility and presidential approval ratings



Notes: See notes for Figure 1.