concordance=TRUE

Does Partisanship Affect Fed Inflation Forecasts?

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Abstract

Very Early draft version. Comments welcome.[1]

Recent work argues that the Federal Reserve is not politically indifferent (**?**). The Fed tends to choose looser monetary policies during Republican administrations, possibly in order to ensure the (re)election of ideologically preferred administrations. This model excludes an essential aspect of monetary policy decision-making: expectations about future inflation. We use the Fed's Green Book forecasts to test whether the partisanship of a government shape the estimates of future economic performance that influence FOMC policies. We find that Federal Reserve staff probably do not bias their forecasts to influence Fed governors around elections. However, they do systematically overestimate inflation during Democratic presidencies and underestimate inflation during Republican ones. This suggests that while not electorally motivated, Fed staff have a partisan bias when making inflation forecasts.

Keywords: forecast bias, Federal Reserve, rational partisan cycle,

Recent work argues that the Federal Reserve is not politically indifferent (**?**). The Fed tends to choose looser monetary policies during Republican administrations, possibly in order to ensure the (re)election of ideologically preferred administrations. This bias is assumed by Clark and Arel-Bundock to arise from a Board of Governors that prefer rightist presidents to leftist ones and so set interest rates to help Republican incumbents and hinder Democratic ones.

Does this partisan preference also permeate the Federal Reserve staff's forecasts? If economists at the Federal Reserve hold such preferences, then they would have an incentive to produce upward biased inflation estimates under Democratic administrations and downward biased inflation estimates under Republican administrations.

Alternatively, Federal Reserve staff may believe that inflation will be much higher under Democratic presidents. Employees within the Federal Reserve Banks may expect that Democratic presidents produce

[1] The paper is written with `knitr` (**?**) and is fully reproducible. Please contact us for the replication files.

policies that increase inflation and Republican presidents produce policies that limit inflation. However, Republican and Democratic administrations both engage in largely expansionary fiscal policies. We argue that this set of beliefs would also lead to large overestimations of inflation during Democratic presidencies and a significant underestimation of inflation during Republican ones.

In this paper we first provide a brief discussion of what Green Book inflation forecasts and forecast errors are, including their importance for monetary policy making and our current understanding of how they are made. As we demonstrate in this first section, academic scholarship up till now has not examined possible partisan causes of forecast errors. We then introduce the issues of inflation forecast partisan biases and posit a number of ways that Green Book forecasting may be influenced by them. We test these theories with a series of regression models using both unmatched and matched data on Green Book inflation forecast errors from the 1970s through 2005. The models suggest that, even when controlling for a number of important economic and political factors, Green Book forecasts show a distinct presidential partisan bias.

1 Forecasting Inflation at the Fed & Inflation Forecast Errors

In this section we briefly describe what Green Book inflation forecasts and forecast errors are, why they are an important part of monetary policymaking in the United States, and the current understanding of how Federal Reserve inflation forecasts were made since the late 1960s.

1.1 Forecasting & Forecasting Errors

[2]

Federal Reserve staff create a document called the "Current Economic and Financial Conditions" or "Green Book" that contains information on recent behavior and forecasts of various macroeconomic aggregates [3] before each meeting of the Federal Open Markets Committee (FOMC), the Federal Reserve's primary decision-making body. The Federal Reserve staff produces forecasts of various elements of the US and global economies in order to that the FOMC can produce policies appropriate to fulfill the Fed's dual mandate of maintaining output growth and price stability. We focus on GNP/GDP price index forecasts in our study.[4] Green Book forecasts are available for each quarter from the fourth quarter of 1964 through the end of 2005[5]. It is important to note that finalized forecasts of macroeconomic aggregates

[2]This section draws heavily on Brayton et al.'s (1997) detailed description of the changes to Federal Reserve forecasting models that took place in 1996. See Brayton et al. 1997 for further details.

[3]Green Book data can be found at http://www.phil.frb.org/research-and-data/real-time-center/greenbook-data/philadelphia-data-set.cfm. Accessed December 2011.

[4]Note: GNP was used through 1991 (inclusive) and GDP was used from 1992 onward. Furthermore, the implicit deflator was used before the second quarter of 1996 and chain-weighted price index was used from the second quarter of 1996 onwards.

[5]There is a five year lagged release schedule

are a combination of both these econometric models and the professional opinions of forecasters about likely changes in the economy's trajectory not necessarily picked up in these models **??**. The forecasts contained in the Green Book are the "consensus" forecasts combining both econometric models and judgmental forecasts under a continuation of current monetary policies.

It is the accuracy of these forecasts that is of interest in this study. We measure accuracy as the difference between realized inflation rate for quarter Q_t from the forecast generated by Fed staffers in Q_{t-2}. One would hope that forecasts would be unbiased (a mean error of zero)

We have 161 forecast quarters in our data set, spanning the first Green Book's production in June 1964 through the end of 2005. During this period the econometric models used to generate the consensus forecast has undergone a single large change. Forecasts correspond to the FOMC meeting closest to the middle of the quarter. For a given quarter the data includes forecasts made in the present quarter and up to 5 quarters before. Actual inflation corresponding to each of these quarters[6] was found using data from the Federal Reserve Economic Data website.[7] Indicators comparable to the forecasted quantity are used, e.g. from the second quarter of 1996 we use the chain-weighted GDP price index. Absolute actual inflation for each quarter and inflation forecasts made two quarters before are compared in Figure **??**. In general we use forecasts made two quarters before.[8]

We calculate **forecast error** E as the difference between the Green Book inflation forecast F for a given quarter q and actual inflation I as a proportion of actual inflation

$$E_q = \frac{F_q - I_q}{I_q} \tag{1}$$

We put the error in terms of actual inflation to control for the fact that mean actual inflation varies considerably across different periods (see Figure **??**).

1.2 Forecasting & Monetary Policymaking

1.3 Our Current Understanding of Fed Inflation Forecasting

The Federal Reserve produces forecasts of various elements of the US and global economies in order to formulate policies appropriate to fulfill the Fed's dual mandate of maintaining output and price stability.[9] There have been two essential sets of models used during our observation period. This section describes these two models and their importance for our BLAH BLAH BLAH. It is important to note that finalized

[6] Inflation was calculated by comparing quarters year-on-year.

[7] http://research.stlouisfed.org/fred2/

[8] Using these two quarter forecasts constricts our observations so to 150 since, apart from the first quater of 1968, they are not included in the Green Book data before the fourth quarter of 1968.

[9] This subsection draws heavily on Brayton et al.'s (1997) detailed description of the changes to Federal Reserve forecasting models that took place in 1996. See Brayton et al. 1997 for further details.

Figure 1: Green Book Inflation Forecasts and Actual Quarterly Inflation

¡¡BaseInflation, warning=FALSE, echo=FALSE, message=FALSE, fig.width=7, fig.height=4, out.width='0.8
linewidth'¿¿=
library(RCurl) library(reshape2) library(ggplot2)
Load data
Load data from GitHub url ¡-
"https://raw.github.com/christophergandrud/GreenBook/master/Data/GB$_F RED_c pi.csv" cpi.data < -getURL(url) cpi.data < -read.csv(textConnection(cpi.data))$
Other data loading options cpi.data ¡-
read.csv("/git$_r epositories/GreenBook/Data/GB_F RED_c pi.csv") Loaddatalocally from Christopher's computer cpi.data -read.dta("http : //dl.dropbox.com/u/12581470/code/Replicability_c ode/GreenBook/GB_F RED_c pi.dta") Loaddata from Dropbox$
Melt data, i.e. reshape cpi.abs ¡- melt(cpi.data, id = "Quarter", measure = c("GB$_C PI_Q TR2", "deflator"))$
Rename variables cpi.abs$variable < -gsub("GB_C PI_Q TR2", "Forecast", cpi.abs$variable)
cpi.abs$variable < -gsub("deflator", "Actual", cpi.abs$variable)
Colours absolute.colors ¡- c("Forecast" = "B35B40", "Actual" = "000000")
Create line graph absInflation ¡- qplot(Quarter, value, geom = "line", data = cpi.abs, color = variable, linetype = variable) + xlab("") + ylab("Inflation") +
scale$_c olor_m anual(values = absolute.colors, name = "") + scale_l inetype(name = "") + geom_v line(aes(xintercept = 1996), linetype = "dotted", colour = "grey50") + annotate("text", x = 2001, y = 8.5, label = "FRB/Global", colour = "grey50") + geom_v line(aes(xintercept = 1975), linetype = "dotted", colour = "grey50") + annotate("text", x = 1978, y = 1.5, label = "SEM", colour = "grey50") + theme_b w() + opts(axis.title.x = theme_t ext(size = 12, vjust = 0))$
print(absInflation)
@

Forecasts were made two quarters beforehand.
The grey dotted lines indicate the *approximate* years that the Simultaneous Equation Models (SEM) and Federal Reserve Board Global (FRB/Global) forecasting models were fully implemented.

forecasts of macroeconomic aggregates are a combination of both these mathematical models *and* the professional opinions of forecasters about likely changes in the economy's trajectory not necessarily picked up in these models (FIND THE CITE FOR THIS!!!). The most significant change with the move to the Federal Reserve Board (FRB) Models in the mid-1990s was the incorporation of rational, as opposed to adaptive, expectations by market actors. We discuss the early and current models followed by the implications each has for predicted forecast errors.

Early models of the economy The first simultaneous equation model of the US economy was developed and adopted by the Federal Reserve between 1966 and 1975. The model, originally developed in conjunction between MIT, University of Pittsburg, and the Social Science Research Council (MPS), was based on a neo-classical growth model of production and factor demands and embraced the IS/LM/Phillip's Curve paradigm. This model was composed of more than XYZ equations modelling various interdependent aspects of the American economy in a simultaneous equations framework. Homogeneity assumptions ensured neutrality of money in the long-run–that is, EXPLAIN WHAT THIS

MEANS WHEN YOU AREN'T SO SLEEPY.

The collapse of Bretton Woods spurred a number of changes to the model. First, following the introduction of floating exchange rates the trade and exchange rate sections of the domestic economy were expanded significantly. Second, and more significantly, an explicit model of the global economy was developed. The Multi-Country Model (MCM) introduced in 1975 originally included estimates of macroeconomic performance in the US, Canada, Germany, Japan, the UK, and "the rest of the world sector." This model, which included both estimates of American consumption and production but then fed into equations of American consumption and production. This model was again based on the short-run dynamics of of the IS/LM/Phillip's Curve and long-run neo-classical growth model.

Both the MPS and MCM models were tweaked during the 1980s, with about one-third of the equations in the MPS model changed during this time. For instance, the second oil shock led to the inclusion of oil prices and consumption in the MCM. The MCM was also expanded to include a larger set of major trading partners.[10] However, the basic assumptions of the models, specifically the adaptive expectations assumptions, remained unchanged. The exclusive use of VAR models (solely backwards looking actors) meant that the models failed to account for actors concerns about future outcomes explicitly in these models. The rational expectations revolution in economics in the 1970s and 1980s made this assumption an increasingly controversial one. Thus, the development of new models began in earnest in 1991.

Current models of the economy New models of the American economy's near-term trajectory replaced the MPS in 19XY. The Federal Reserve Board US model (FRB/US) is composed of approximately 40 behavioral equations, estimated with single-equation techniques. This model explicitly considers the role of economic expectations in economic behavior. In these models, prices are sticky and aggregate demand determines short-run output. Further, monetary policy's effects on the economy are extensively modeled.

The Federal Reserve Board Global (FRB/Global) model's development began in 1993 and had replaced the MCM by 1996. The FRB/Global model links the behavioral equations of FRB/US with approximately 200 behavioral equations representing the other 11 regions of the model. Anticipated values of future variables directly influence interest and exchange rates, components of aggregate demand, and wages and prices.

Models and their effects on predicted forecast errors The innovations in how the Federal Reserve Board generates estimates of future economic performance (including changes to how they incorporated the effects of expected Fed interest rate policies has XYZ implications for forecast errors. Most notably,

[10]The post-1992 model included each of the G-7 countries individually as well as Mexico, and blocks representing the OECD, newly industrialized countries, OPEC, and the rest of the world.

the move to rational expectations ought to shrink errors relative to the earlier period. The goal of incorporating forward looking actors into the models was to account for an important source of endogeneity in the earlier models that would lead to overestimates of important economic indicators under some circumstances and underestimates of those same indicators under others. Thus, we may expect that forecast errors' absolute magnitude will be smaller after 1996 than in the earlier era.

2 Partisan Biases in Fed Inflation Forecasts?

In this section we first describe what a partisan inflation forecast error would be and briefly demonstrate that it is plausible that such biases exist. We then draw on the political economy literature to predict what may cause these biases.

2.1 Partisan Forecast Errors

Ideally forecasts should be unbiassed in that they have a mean error of zero (**?**, 5). Using this criteria, forecasts errors should be the same–ideally with a mean of 0–regardless of the incumbent president's party identification. To determine what Federal Reserve inflation forecasts errors were we created a variable comparing forecasts to actual inflation.

Looking only at forecast errors and the United States president's partisan identity, is it plausible that there is a partisan bias to Green Book inflation forecasts? Figure **??** plots forecast errors across our sample. We've shaded out errors made between $+/-10$ percent of actual inflation. These could be considered largely random errors.

The first thing to note is that inflation was almost never underestimated during the three Democratic presidential terms in our sample. Also, the largest overestimates were made during Clinton's (Democratic) presidency. All of the major inflation underestimates were made during Republican presidencies, particularly during Nixon's, Ford's, and George W. Bush's presidencies. Inflation was often overestimated during the second part of Reagan's first term, his second term and George H.W. Bush's term. Though it is important to note that over this period–often referred to as the Volker Revolution (see **?**)–inflation was much lower than before, as we can see in Figure **??**.

This summary examination of inflation forecast errors suggests that there might be partisan biases. Before jumping into a further empirical investigation of these errors, why might Green Book forecasts have partisan biases?

Figure 2: Inflation Forecast Errors (1969 - 2005)

¡¡PartisanError, warning=FALSE, echo=FALSE, fig.width=7, fig.height=4, out.width='0.8 linewidth'¿¿=
Clean up data and create forecast error variable cpi.data$pres_party_name <- factor(cpi.data$pres$_party, label = c("Rep", "Dem"))cpi.data$error.prop.deflator.q2 ¡- (cpi.data$GB_CPI_QTR2 - cpi.data$deflator)/cpi.data$deflator$
Create FRB/Global Model Variable cpi.data$GlobalModel[cpi.data$Quarter ¿ 1995.4] ¡- "1" cpi.data$GlobalModel[cpi.data$Quarter ¡ 1996.1] ¡- "0" cpi.data$GlobalModel <- factor(cpi.data$GlobalModel, labels = c("Before 1996", "After 1996"))
Partisan colours partisan.colors = c("Rep" = "C42B00", "Dem" = "2259B3")
Remove 2 quarters from Johnson presidency cpi.data ¡- subset(cpi.data, president != "Johnson") cpi.data$president <- as.factor(cpi.data$presTerm)
Error region +/- 10 percent rect.time ¡- data.frame(xmin = 1968, xmax = 2006, ymin = -0.1, ymax = 0.1)
Create graph errors.time ¡- ggplot(cpi.data, aes(x = Quarter, y = error.prop.deflator.q2)) + geom$_point(aes(color = pres_party_name)) + stat_smooth(method = "lm", aes(group = presTerm, color = pres_party_name, fill = pres_party_name)) + geom_rect(data = rect.time, aes(xmin = xmin, xmax = xmax, ymin = ymin, ymax = ymax), color = "grey20", alpha = 0.5, inherit.aes = FALSE) + scale_color_manual(values = partisan.colors, name = "") + scale_fill_manual(values = partisan.colors, name = "") + xlab("") + ylab("StandardizedForecastError") + scale_x_continuous(limits = c(1968, 2006)) + theme_bw() + opts(axis.title.x = theme_text(size = 12, vjust = 0)) + opts(axis.title.y = theme_text(angle = 90, size = 12, vjust = 0.3))print(errors.time)$@

Note: An error of 0 indicates that inflation was perfectly forecasted.
The grey shaded box indicates minimal error, i.e. $+/-0.1$.

2.2 How Might Partisanship and/or Elections Affect Forecast Biases

3 Research Methods

We use matched and non-matched data sets with a number of parametric models (see **?**) to assess whether or not there are partisan biases in Green Book forecasts. This section discusses the choice of methods and variables. The following section lays out our results.

3.1 Matching & Models

We are interested in disentangling the effects of presidential party and elections from the many background factors, such as economic shocks, that might lead to inflation forecast errors E. We treat these presidential partisan identification and elections as 'treatments'. Democratic presidencies are considered to be treatments. Republican presidencies are 'controls'. Similarly, we considered the election quarter and the quarter before as treated and all other quarters as controls. Of course, given that we are working with observational data, other variables that have an impact on forecast errors may have different distributions across the treatment and control groups (**??**). This makes it difficult to isolate the relationship between presidential party identification, elections and errors from all of the confounding background variables.

To address this issue we follow the advice of ? to use nonparametric matching to preprocess our data–so that the distributions of confounding variables is more even across treatment and control groups. Then we run our parametric analyses. We used the `R` package `MatchIt` (?) to create the matched data sets. This created two data sets where the non-treatment covariates in the control groups closely matched with those in the treatment groups. Doing this helps us isolate the effects of these two 'treatments' from that of the background covariates.

Formally, each unit i in the data set is 'assigned' to either the treatment group ($t_i = 1$) or the control group ($t_i = 0$). $y_i(1)$ is the potential outcome for unit i of being in the treatment group, regardless of whether or not it was observed to be in this group. $y_i(0)$ is the potential outcome if i was not in the treatment group, regardless of its observed assignment. It is impossible to observe both $y_i(1)$ and $y_i(0)$ at the same time. Instead we observe one version of $y_i = t_i y_i(1) - (1 - t_i)y_i 0$. For each i there is a fixed vector of exogenous confounders X_i. Ideally t_i and X_i are independent. However, this is not necessarily the case. The point of matching is to reduce or eliminate the relationship between t_i and X_i by selecting, dropping, and/or duplicating data. Ideally this process matches one treated unit with one controlled unit that has the same values of X_i, i.e. the distribution of covariates is the same in the treated and control groups (?). This is know as "covariate balance" (?, 1). Using matching to balance a data set "break[s] the link between the treatment variables and the pre-treatment controls", effectively replicating the conditions of a randomized experiment with observational data (?, 2–3).

Balance is usually achieved in matching through propensity scores; the probabilities that unit were assigned the treatment given the covariates. The propensity score model is generally unknown (?, 1). The particular matching model we use is Diamond and Sekhon's (?) genetic matching (GenMatch).[11] GenMatch uses an evolutionary search algorithm to automate the search for the propensity score model that will create maximum balance.

We then used standard parametric analysis–normal linear regression and Bayesian normal linear regression–to estimate the effect of our treatments on forecast errors.[12] Because we used nonparametric matching methods, not only do we better isolate the treatments' effect from those of the background variables, but we also reduce our estimated causal effects' dependence on the type of model we choose (?, 200–201).

The general parametric model we used is given by

$$E_q = \alpha + \beta T_q + \beta X_q + \epsilon, \tag{2}$$

[11] The model was implemented with `MatchIt`.

[12] All parametric analyses were conducted using the `R` package `Zelig` (?). See also ? for a discussion of how to combine nonparametric matching and parametric analysis in one research process.

where T_q is the treatment for quarter q and X is a vector of covariates.

3.2 Variables

We have already discussed our dependent variable of interests–inflation forecast errors. We are interested in seeing how US presidents' partisan identity and the existence of an upcoming presidential election affect these errors. A **president's party identification** was straightforward to observe. The variable is 1 when the president is a Democrat and 0 when they are a Republican. Since forecast error data is released on a quarterly basis, we consider a president to be sitting from the first quarter after the election.[13] We consider quarters to be **election period** either if the presidential election is held in that quarter or the quarter before.[14]

To further examine whether or not Federal Reserve staff were taking into consideration an electoral business cycle, we included a variable of **quarters until the presidential election**.This simply counted down from the quarter after the previous election.[15] The quarters that included presidential elections were coded as 0.

The United States president does not set the level of government expenditure alone. Instead, the president is constrained by the two houses of Congress. To examine whether or not Federal Reserve staff are taking into consideration the partisan composition of Congress as well as the president's party identification, we include variables of **Democratic legislators as a proportion of Republican legislators** in the House of Representatives and the Senate. Data on the number of legislators with Republican and Democratic party IDs was found at infoplease.[16] If the Presidency and the Senate and/or the House is controlled by Democrats we would expect Federal Reserve staff with partisan inflation forecast biases to expect even more increases in government spending. This would lead them to further overestimate inflation. We consider this possible interaction in a number of models.

If biases are largely the result of misspecified economic forecasting models we would expect errors to decrease overtime as the models improved. In particular, we would expect this fall in errors to occur specifically around 1996 when the Federal Reserve Board's new Global behavioral equation model was introduced. To examine this we include a **FRB/Global Model** dummy variable. It equals one for all quarters from and including the first quarter of 1996. It is zero otherwise.

To examine if Federal Reserve inflation forecaster errors are affected by levels of government expenditure, which may be correlated with the president's party, we included the percentage of **current government expenditure to GDP** and **government debt to GDP**. We include **GDP output**

[13]Elections are held almost at the midpoint–early November–of an election year's fourth quarter. Presidents are sworn into office near the beginning–20 January–of the following year's first quarter.

[14]If q_e is a quarter with an election then we code quarters q_e and q_{e-1} election quarters.

[15]There are 15 quarters before an United States presidential election quarter.

[16]See http://www.infoplease.com/ipa/A0774721.html. Accessed May 2012.

gaps. This is simply potential GDP as a percentage of real GDP. Finally, we include a dummy variable for whether or not the United States was in **recession**. All of these variables are from the FRED database at the St. Louis Federal Reserve[17] and are in nominal terms.

3.3 Models

We chose two types of parametric models to examine the effects of our treatment variable on the continuous inflation forecast error. The first was ordinary linear regression (i.e. OLS).[18] The other type was Bayesian normal linear regression.[19] Please see the `Zelig` manual for details about Bayesian normal linear regression (**?**).

In all of the Bayesian regressions we used the `Zelig` default 1,000 MCMC burnin iterations and 10,000 iterations after burnin. We used the Heidelberger-Welch diagnostic to examine whether or not the Markov Chains converged to their stationary distributions.

We ran all model specifications with both the matched and unmatched datasets. We used visual methods to determine if the covariates in the matched data sets were balanced. We were unable to achieve covariate balance for government debt as a percentage of GDP. This variable was not included in the models using the matched data set.

All models used inflation forecast error data–as defined earlier–from the start of Richard Nixon's first presidency through the fourth quarter of 2005.

4 Results

In this section we present results from multiple regression model specifications with both matched and unmatched data sets. We graphically present the key results in this section. Coefficient estimate tables for the models are given in the Appendix (see tables **??**, **??**, **??**, **??**, and **??**).

In general there is very little difference in the coefficients estimated using OLS and Bayesian linear regression (see Figure **??**). Usually more variables were 'statistically significant'[20] in models from the unmatched data set compared to estimates from both matched data sets.

¡¡MainAnalysis, warning=FALSE, echo=FALSE, message=FALSE, results='hide'¿¿= library(devtools)

Run main analysis source code AnalysisURL ¡- "https://raw.github.com/christophergandrud/GreenBook/master/Ana

source$_{u}rl(AnalysisURL)$

Local source("/git$_{r}epositories/GreenBook/Analysis/MainAnalysis2.R$")@

[17]See: http://research.stlouisfed.org/fred2/. Accessed June 2012.
[18]In `Zelig` this is the `ls` model.
[19]In `Zelig` this is the `normal.bayes` model.
[20]At the standard 0.05 significance level.

Figure 3: 95% Confidence Bands for Coefficients from a Variety of Matching and Parametric Model Specifications

¡¡CoefComparePlots, warning=FALSE, echo=FALSE, message=FALSE, results='hide', fig.height=4, out.width='0.95
linewidth'¿¿=
source("/git$_repositories/GreenBook/Analysis/BasicAnalysisCoefPlots.R$")
Create plots CoefPlotsURL ¡-
"https://raw.github.com/christophergandrud/GreenBook/master/Analysis/BasicAnalysisCoefPlots.R"
source$_url(CoefPlotsURL)$
@

Intercept values are not shown to maintain a reasonable scale for comparing covariate estimates.

FRB Global Forecasting Model The introduction of the FRB/Global behavioral equation forecasting model does not seem to have begun an era of significantly lower inflation forecasting error. In fact, across all of our matching and parametric model specifications, forecasts made after the introduction of this approach are not significantly different than those made before it.

Presidential Elections We also did not find any evidence that Federal Reserve staff inflation forecast errors were associated with election timing. This was true in parametric models using both unmatched data and matched data where the election period variable is the treatment. Estimates of the relationship between the quarters until election variable and forecast errors[21] also did not provide any evidence that inflation errors are related to election timing.

Data limitations make it difficult to fully examine the extension of Clark and Arel-Bundock's (**?**) election gaming theory for Federal Reserves staff. We only have three Democratic presidential terms in our data, only two of which ended in the incumbent running for reelection. Nonetheless, we attempted to examine this hypothesis with an interaction of the president's party ID variable and both the election dummy and quarters to election variables. In all cases the president's party ID variable was robust whereas the election variables and the interaction term were very statistically insignificant.

In this limited data set Fed Staff do not appear to be over estimating inflation when a Democratic president is running for reelection in an attempt to influence the FOMC to raise interest rates and lower the president's chances of winning.

These findings have clear implications for how we understand the potential causes of Green Book partisan inflation forecast biases as well as FOMC interest rate decisions around elections. Federal Reserve staff do not seem to be engaged in a signalling game with the aim of influencing elections. Given both our findings and Clark and Arel-Bundock's results, it seems that FOMC members, not their staff, are driving the increases in the Fed Funds Rate around elections when Democrats are in power.

[21] This variable was obviously omitted from the models with the election period variable because they are highly correlated.

Figure 4: Simulated Expected Inflation Forecast Error for Republican and Democratic Presidencies

¡¡ExpectValueParty, warning=FALSE, echo=FALSE, message=FALSE, results='hide', fig.width=6, fig.height=4, out.width='0.7
linewidth'¿¿=
URL ¡-
"https://raw.github.com/christophergandrud/GreenBook/master/Analysis/ExpectedValuesPlot.R"
source$_url(URL)$
@

From an OLS regression with data matched by presidential party identification. Variables included are the same as those in Model C6 from Table **??**.
The figures show 1000 simulations per fitted value.
The solid line connects the two groups' means.

Presidential Party Identification Our second treatment variable–presidential party identification–had a strong positive association with Federal Reserve staff inflation forecast errors across all model specifications. This finding is what we would expect if Federal Reserve staff have a general presidential partisan bias. The 95% confidence band around the coefficient estimate actually moves somewhat further away from 0–i.e. no relationship–when using matched data (see Figure **??**).

These analyses provide strong evidence that Federal Reserve staff overestimate the effect Democratic presidents have on inflation compared to Republican presidents.

To get a sense of approximately how big this bias might be we simulated expected standardized forecast error for democratic and republican presidencies, holding all other covariates at their means.[22] Results from these simulations can be found in Figure **??**. On we expect that on average the Fed overestimates inflation by format(mean(ModelParty.ev$value[ModelParty.ev$variable == "Dem"]*100), digits = 2) percent. This compares to an average inflation error of format(mean(ModelParty.ev$value[ModelParty.ev$variable == "Rep"]*100), digits = 2) percent during Republican presidencies. Clearly, at least between 1970 and 2005, Fed staff were overly pessimistic about Democratic presidents' effect on inflation and even more overly optimistic about Republican presidents' effect.

The estimated effects hold even when we control for actual government expenditure. This suggests that Federal Reserve staff are not simply responding to higher government expenditure that Democrats may be initiating.

Government Expenditure Nonetheless, it seems that Federal Reserve staff may also overestimate the effect of government expenditure on inflation. This is indicated by a consistently positive and significant coefficient for the government expenditure variable, even when controlling for president's party ID. Maybe Federal Reserve staff, as monetarily conservative actors, generally overestimate the effect of government

[22] 1000 simulations were run on a normal Bayesian linear regression model matched by presidential party ID and including the same variables as those in Model C6 from Table **??**.

expenditure on inflation.

Partisan Control of Congress Might Federal Reserve staff be taking into consideration not only the president's party identification, but also the partisan composition of congress? There are at least three possible ways that congressional party identification may effect forecast errors.

The first is a simple circumstance where Federal Reserve staff with rational partisan expectations paid attention to the partisan control of a chamber of Congress *independent of* the president's party identification. For example, Fed staff could predict higher spending if Democrats control one of the houses of congress even if they do not control the other house or the presidency compared to a situation where all parts of the executive and legislature were controlled by Republicans. This might lead to higher inflation error. We find no evidence for this across all of our datasets and parametric model specifications.

Though they make different predictions, both of the latter two ways that partisan control of Congress may affect inflation forecasts are through interactions with presidential party identification.

The first interaction theory is that Federal Reserve staff with simple rational partisan expectations would presumably expect that a Democratic president would be able to get policies closer to their ideal point when there is a congress with similar ideal preferences. If a Democratic president had chambers of congress controlled by Democrats, presumably Federal Reserve staff would expect even higher fiscal expenditures and therefore even higher inflation. Conversely, Republican presidents with a Republican-controlled congress may be even better at cutting spending, leading to lower inflation.

The second interaction hypothesis is that more nuanced and based on largely on Krause's (**?**) work on the effect of partisan divisions and fiscal expenditures in the United Statues. Rather than seeing increasing deficits as a the result of partisan fragmentation, rather than similarity. He argued that there is a pro-deficit bias when there are divisions in the partisan control of the chambers of congress and presidency. Higher political conflict, he argues, "results in equilibrium fiscal outcomes that favor greater spending and/or a willingness to lower taxes since politicians will exhibit a greater proclivity in providing voters with program benefits and to delay its payment" (**?**, 542). Note that he is talking about deficits rather than expenditure–the latter, but not the former of which we find some evidence that Fed Staff use to overestimate inflation. Nonetheless, fragmentation, could push up not only deficits but also expenditure as politicians use both expenditure as well as tax cuts to appeal to voters. **This is weak**

To examine these two possibilities we created parametric models with two-way and three-way interactions between presidential and congressional party identification. All of the partisan interactions were generally statistically significant. To make substantive sense of these estimated interactions we use simulations, as above, to find expected inflation forecast errors at various levels of the presidential and

Figure 5: Simulated Interactions between President Party ID and Congressional Party Control

¡¡InterPlot, warning=FALSE, echo=FALSE, message=FALSE, results='hide', fig.width=6, fig.height=4, out.width='0.8
linewidth'¿¿=
InterURL ¡-
"https://raw.github.com/christophergandrud/GreenBook/master/Analysis/PresCongressInteractions.R"
source$_{u}rl(InterURL)$
@

From an OLS regression with data matched by presidential party identification. Variables included are the same as those in Model C10 from Table **??**. The figure show 1000 simulations per fitted value.
Both the House and Senate Democratic/Republican variables were set at 1.2 for Democratic congresses and 0.8 for Republican congresses.
The solid line connects the means of the congressional partisan control groups.

congressional party identification. To highlight the findings, Figure **??** shows the results of simulations where the levels of partisan convergence and divergence are at their most extreme: one party control of all bodies compared to different parties controlling the presidency and both houses of congress.[23]

The first thing we should notice in Figure **??** is how presidential partisan identification still seems to be driving the direction of the inflation forecast error: inflation is underestimated during Republican presidencies and overestimated during Democratic ones regardless of partisan control in congress. The estimated effect of congressional control is in the magnitude of the over or under estimates. In particular, inflation is very underestimated for Republican presidencies with Republican congresses. There may be an expectation among Fed Staff that these governments will cut expenditure much more than they actually do. This finding fits with the simple interaction hypothesis. Looking to the Democratic president side we have more mixed findings. Forecast error is slightly higher on average with Democratic presidencies and Republican congresses compared to when both are controlled by Democrats. This finding fits with a story where Fed Staff believe spending will be higher with a divided government. However the difference between the two means is small[24] and there is considerable overlap in the two groups of simulation results.

Despite some evidence for an interaction between congressional and presidential party identification, it is not clear at this time how these results can be consistently explained across Democratic and Republican presidencies.

[23]Both the House and Senate Democratic/Republican variables were set at 1.2 for Democratic congresses and 0.8 for Republican congresses.

[24]There is a format(mean(PL10Bound$value[PL10Bound$variable == "Democratic President" PL10Bound$Congress ==$ "$Rep.Congress$"$] * 100) - mean(PL10Bound$value[PL10Bound$variable ==$ "$DemocraticPresident$" $PL10Bound$Congress == "Dem. Congress"] * 100), digits = 2) percentage point difference between the two.

Discussion: Do Fed Forecasts Have a Partisan Bias?

FILL IN

MAYBE TALK ABOUT HOW IT IS STRANGE THAT ACTORS WITH “RATIONAL” PARTISAN EXPECTATIONS WOULD NOT UPDATE THEIR INFLATION EXPECTATIONS. I.E. WHY WOULD THEY CONTINUE TO BE WRONG ABOUT INFLATION GIVEN THE PRESIDENT’S PARTY ID?

Appendix

Replication

This paper can be entirely replicated. All data, analysis source code, and markup files can be downloaded as a `.zip` file from our GitHub page at: https://github.com/christophergandrud/GreenBook/zipball/master.

Table 1: OLS Estimation of Covariate Effects on 2 Qtr. Inflation Forecast Error (non-matched dataset)

¡¡ NLTables, warning=FALSE, echo=FALSE, message=FALSE, results='asis'¿¿=
library(apsrtable)
Model names Coefficient Names – Use A for all non-mathced models ModelNamesA ¡- c("A1", "A2", "A3", "A4", "A5", "A6", "A7", "A8", "A9", "A10", "A11") CoefNamesA ¡- c("Intercept", "Recession", "Debt/GDP", "Expenditure/GDP", "Output Gap", "Qtr. to Election", "Election Period", "Pres. Party ID", "Senate Dem/Rep", "House Dem/Rep", "FRB/GlobalModel", "Pres Party ID*House", "Pres Party ID*Senate", "House*Senate", "Pres*House*Senate")
Table of non-matched models with ls apsrtable(NL1, NL2, NL3, NL4, NL5, NL6, NL7, NL8, NL9, NL10, NL11, digits = 1, order = , Sweave = TRUE, stars = "default", model.names = ModelNamesA, coef.names = CoefNamesA)
@

Table 2: OLS Estimation of Covariate Effects on 2 Qtr. Inflation Forecast Error (Matched by Election Period Variable)

¡¡ ELTables, warning=FALSE, echo=FALSE, message=FALSE, results='asis'¿¿=
Model names Coefficient Names – Use B for all ElectionPeriod mathced models ModelNamesB ¡- c("B1", "B2", "B3", "B4", "B5", "B6", "B7", "B8", "B9", "B10", "B11") CoefNamesB ¡- c("Intercept", "Debt/GDP", "Expenditure/GDP", "Output Gap", "Qtr. to Election", "Election Period", "Pres. Party ID", "Senate Dem/Rep", "House Dem/Rep", "FRB/GlobalModel", "Pres Party ID*House", "Pres Party ID*Senate", "House*Senate", "Pres*House*Senate")
Table of non-matched models with ls apsrtable(EL1, EL2, EL3, EL4, EL5, EL6, EL7, EL8, EL9, EL10, EL11, digits = 1, Sweave = TRUE, stars = "default", model.names = ModelNamesB, coef.names = CoefNamesB, notes = list(se.note, stars.note, "The recession variable is ommitted because there was no variation in the matched data set.", "The reason that there was no variation is because there was never a recession during an", "election period in our data set."))
@

Table 3: OLS Estimation of Covariate Effects on 2 Qtr. Inflation Forecast Error (Matched by President's Party ID variable)

¡¡ PLTables, warning=FALSE, echo=FALSE, message=FALSE, results='asis'¿¿=
Model names Coefficient Names – Use C for all ElectionPeriod mathced models ModelNamesC ¡- c("C1", "C2", "C3", "C4", "C5", "C6", "C7", "C8", "C9", "C10", "C11") CoefNamesC ¡- c("Intercept", "Recession", "Debt/GDP", "Expenditure/GDP", "Output Gap", "Qtr. to Election", "Election Period", "Pres. Party ID", "Senate Dem/Rep", "House Dem/Rep", "FRB/GlobalModel", "Pres Party ID*House", "Pres Party ID*Senate", "House*Senate", "Pres*House*Senate")
Table of non-matched models with ls apsrtable(PL1, PL2, PL3, PL4, PL5, PL6, PL7, PL8, PL9, PL10, PL11, digits = 1, Sweave = TRUE, stars = "default", model.names = ModelNamesC, coef.names = CoefNamesC)
@

¡¡ NBTables, warning=FALSE, echo=FALSE, message=FALSE, results='asis'¿¿= Load packages library(reshape) library(xtable)

Get the model summary NB1Summary ¡- summary(NB1) NB1Summary ¡- data.frame(NB1Summary*summary*)

Clean up variable names library(reshape)

NB1Summary ¡- rename(NB1Summary, c(X2.5. = ”2.5NB1Summary ¡- rename(NB1Summary, c(X50. = ”50NB1Summary ¡- rename(NB1Summary, c(X97.5. = ”97.5

Clean up Covariate Labels Variables ¡- c(”Intercept”, ”Pres. Party ID”, ”Recession”, ”Qtr. to Election”, ”Senate Dem/Rep”, ”House Dem/Rep”, ”Debt/GDP”, ”Expenditure/GDP”, ”Output Gap”, ”Global Model”, ”sigma2”)

NB1Summary ¡- cbind(Variables, NB1Summary)

print.xtable(xtable(NB1Summary, caption = ”Bayesian Normal Linear Regression Estimation of Covariate Effects on 2 Qtr. Inflation Forecast Error (non-matched data set)”, label = ”OutputNB”, align = c(”l”, ”l”, ”c”, ”c”, ”c”, ”c”, ”c”)), caption.placement=getOption(”xtable.caption.placement”, ”top”), size=getOption(”xtable.size”, ”small”), include.rownames = FALSE) @

¡¡ PBTables, warning=FALSE, echo=FALSE, message=FALSE, results='asis'¿¿= Get the model summary PB1Summary ¡- summary(PB1) PB1Summary ¡- data.frame(PB1Summary*summary*)

Clean up variable names

PB1Summary ¡- rename(PB1Summary, c(X2.5. = ”2.5PB1Summary ¡- rename(PB1Summary, c(X50. = ”50PB1Summary ¡- rename(PB1Summary, c(X97.5. = ”97.5

PB1Summary ¡- cbind(Variables, PB1Summary)

print.xtable(xtable(PB1Summary, caption = ”Bayesian Normal Linear Regression Estimation of Covariate Effects on 2 Qtr. Inflation Forecast Error (Matched by President's Party ID variable”, label = ”OutputPB”, align = c(”l”, ”l”, ”c”, ”c”, ”c”, ”c”, ”c”)), caption.placement=getOption(”xtable.caption.placement”, ”top”), size=getOption(”xtable.size”, ”small”), include.rownames = FALSE) @