AN EMPIRICAL INVESTIGATION OF THE TRANSMISSION AND EFFECTS OF MONETARY AND FISCAL POLICIES

by

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Abstract

Using statistical models, this dissertation investigates the transmission and effects of monetary and fiscal policies in the context of new challenges and environments that emerged following the 2008 global financial crisis. Chapter 2 analyzes an important step in the transmission of monetary policy—the interest rate pass-through from money market rates to consumer retail loan and deposit rates—in Canada from 1983 to 2015 using a nonlinear vector error-correction model. I find that pass-through was complete for all rates before the financial crisis but since the end of the 2008–09 recession, it has significantly declined for deposit rates. Chapter 3, co-authored with Margaux MacDonald, investigates the effects of unconventional monetary policy in Canada. We use recently proposed methods to construct a shadow interest rate that captures monetary policy at the zero lower bound and estimate a small open economy Bayesian structural vector autoregressive model. Controlling for the US macroeconomic and monetary policy variables, we find that Canadian unconventional monetary policy had expansionary effects on the Canadian economy. Chapter 4 shifts focus to fiscal policy. The rise in US partisan conflict following the Great Recession led to a popular belief that uncertainty about fiscal policy was impeding output growth. I explore this hypothesis by nesting it in a standard structural vector autoregression model traditionally used for estimating fiscal multipliers. I augment the model with stochastic volatility (a measure of uncertainty) and allow that to interact with the endogenous variables. I consider various trend assumptions, subsamples, information sets and estimation methods and find that the evidence does not support
this hypothesis. The results reveal that there is no systematic relationship between fiscal policy uncertainty and output. Moreover, a time-varying parameter version of the model shows that the lack of consistency across specifications is not driven by changes in the transmission of uncertainty shocks over time.
Dedication

To my parents, Marek and Krystyna Popiel, for their encouragement and to my wife, Émilie-Claude Leroux, for her patience and unwavering support.
Co-Authorship

Chapter 3, *Unconventional monetary policy in a small open economy*, is co-authored with Margaux MacDonald.
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# Contents

Abstract i
Dedication iii
Co-Authorship iv
Acknowledgments v
Contents vi
List of Tables viii
List of Figures xi

Chapter 1: Introduction 1

Chapter 2: Interest rate pass-through: 5
a nonlinear vector error-correction approach

2.1 Introduction 5
2.2 Interest rate pass-through and market frictions 9
2.3 Data and empirical model 11
  2.3.1 Description and timing 12
  2.3.2 Empirical model 15
2.4 Results 19
  2.4.1 Deposit rates 22
  2.4.2 Mortgage rates 28
2.5 Robustness 33
2.6 Conclusion 36

Chapter 3: Unconventional monetary policy in a small open economy 39

3.1 Introduction 39
3.2 Measuring unconventional monetary policy 45
  3.2.1 Shadow rates 46
  3.2.2 Event study 52
3.3 Small open economy B-SVAR model 55
3.4 Results 58
3.4.1 Effects of unconventional monetary policy . . . . . . . . . . . . . . 61
3.5 Robustness . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 66
3.5.1 Alternative current account measure . . . . . . . . . . . . . . . . . 67
3.5.2 Government spending . . . . . . . . . . . . . . . . . . . . . . . . . . . 70
3.6 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 75

Chapter 4: Fiscal policy uncertainty and US output 77
4.1 Introduction . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 78
4.2 Measuring fiscal policy uncertainty and its effect on output . . . . . . . 82
4.3 Time-varying effects of fiscal policy uncertainty . . . . . . . . . . . . . 97
4.4 Estimating uncertainty with maximum likelihood . . . . . . . . . . . . . 104
4.5 Sensitivity to monetary policy and anticipation effects . . . . . . . . . . 110
4.6 Revisiting the results from FGKR . . . . . . . . . . . . . . . . . . . . . . 116
4.7 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 120

Chapter 5: Conclusion 123

Appendix A: Interest rate pass-through:
   a nonlinear vector error-correction approach 139
   A.1 Additional tables . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 139

Appendix B: Unconventional monetary policy in a small open economy 144
   B.1 Data . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 145

Appendix C: Fiscal policy uncertainty and US output 146
   C.1 Data sources and definitions . . . . . . . . . . . . . . . . . . . . . . . . . 146
   C.2 SVAR-SV-M model estimation . . . . . . . . . . . . . . . . . . . . . . . . 148
      C.2.1 Prior distributions . . . . . . . . . . . . . . . . . . . . . . . . . . . . 148
      C.2.2 Initial values and estimation algorithm . . . . . . . . . . . . . . . . 151
   C.3 TVP-SVAR-SV-M model estimation . . . . . . . . . . . . . . . . . . . . 155
      C.3.1 Prior distributions . . . . . . . . . . . . . . . . . . . . . . . . . . . . 156
      C.3.2 Initial values and estimation algorithm . . . . . . . . . . . . . . . . 157
   C.4 Additional figures for the SVAR-SV-M model . . . . . . . . . . . . . . 162
   C.5 Additional figures for TVP-SVAR-SV-M . . . . . . . . . . . . . . . . . . 165
   C.6 Additional tables for SVAR-MGARCH-M model . . . . . . . . . . . . . 172
   C.7 Additional figures for model with broader information set . . . . . . . 174
List of Tables

2.1 Summary statistics ....................................................... 14
2.2 Summary statistics of interest rate spreads: retail over market ........ 16
2.3 Rank test results ......................................................... 21
2.4 Hypothesis test results for deposit rates ................................ 23
2.5 Coefficient estimates for deposit rates ................................ 25
2.6 Hypothesis test results for mortgage rates ............................. 30
2.7 Coefficient estimates for mortgage rates ................................ 31
2.8 Rank test results with interest rate swaps as proxy for bank funding costs 34
2.9 Hypothesis test results for mortgage rates with swaps ................. 34
2.10 Coefficient estimates for mortgage rates with swaps ................... 35

3.1 Bank of Canada announcements and shadow short rate changes ........ 53
3.2 Effect of Bank of Canada Announcements on Shadow Short Rate ....... 54
3.3 Average percent difference between data series and counterfactual path (full sample) ................................................... 64
3.4 Average percent difference between data series and counterfactual path (full sample) ................................................... 71
3.5 Average percent difference between data series and counterfactual path (full sample) ................................................... 73

4.1 Parameter estimates for stochastic volatility equations ................. 88
4.2 Correlations with EPU, PCI and FGKR .................................. 91
C.7  SVAR-MGARCH-M model fit (1960Q1–2015Q4) using federal government
data in levels with a deterministic trend .......................... 174
List of Figures

2.1 Interest rates 1983–2015 ........................................... 12
2.2 Mortgage rate spreads in 1996-2007 ............................... 29
2.3 Spreads of 3 month swaps over matching maturity market rates in 1996-2015 33

3.2 Response to domestic (Canadian) expansionary monetary policy shock (July 1994 – July 2015) ........................................... 59
3.3 Response to foreign (US) expansionary monetary policy shock (July 1994 – July 2015) .................................................. 60
3.4 Counterfactual paths: Canadian ZLB imposed ................. 63
3.5 Counterfactual paths: US ZLB imposed ......................... 65
4.1 SVAR-SV-M model impulse response to first moment shocks .......... 87
4.2 Square-root of stochastic volatility ........................................... 89
4.3 Square-root of stochastic volatility and comparison to indices ............ 92
4.4 SVAR-SV-M model impulse response to second moment shocks ......... 93
4.5 SVAR-SV-M model impulse response of output to revenue uncertainty shocks under various specifications .............................. 94
4.6 SVAR-SV-M model impulse response of output to spending uncertainty shocks under various specifications .............................. 96
4.7 Time-varying output response to first moment fiscal shocks ............. 101
4.8 Time-varying output response to second moment fiscal shocks .......... 102
4.9 Estimates of fiscal policy uncertainty for consolidated government data .... 107
4.10 Estimates of fiscal policy uncertainty for federal government data ........ 108
4.11 SVAR-SV-M model impulse responses to first moment shocks controlling for monetary policy and fiscal foresight ......................... 112
4.12 SVAR-SV-M model impulse responses to second moment shocks controlling for monetary policy and fiscal foresight ......................... 113
4.13 Impulse response functions to a two-standard-deviation innovation in capital tax volatility (replication of Figure 3 in FGKR) ..................... 117
4.14 FGKR result comparison with 1-step and 2-step estimation ............... 119
C.1 Square-root of stochastic volatility for model estimated with federal data 162
C.2 SVAR-SV-M model impulse response of output to revenue shocks under various specifications ........................................... 163

C.3 SVAR-SV-M model impulse response of output to spending shocks under various specifications ........................................... 164

C.4 Square-root of stochastic volatility ........................................... 165

C.5 Time-varying output response to first moment fiscal shocks with federal data in growth rates ........................................... 166

C.6 Time-varying output response to second moment fiscal shocks with federal data in growth rates ........................................... 167

C.7 Time-varying output response to first moment fiscal shocks with consolidated government data in levels ........................................... 168

C.8 Time-varying output response to second moment fiscal shocks with consolidated government data in levels ........................................... 169

C.9 Time-varying output response to first moment fiscal shocks with federal data in levels ........................................... 170

C.10 Time-varying output response to second moment fiscal shocks with federal data in levels ........................................... 171

C.11 Shadow short rate ........................................... 174

C.12 SVAR-SV-M model impulse responses to first moment shocks controlling for monetary policy and fiscal foresight with data specified in levels ........................................... 175

C.13 SVAR-SV-M model impulse responses to second moment shocks controlling for monetary policy and fiscal foresight with data specified in levels ........................................... 176
Chapter 1

Introduction

The 2008 global financial crisis led to one of the deepest recessions and slowest recoveries in recent history. Its severity presented new challenges to our understanding of business cycles and set off a critical debate about the appropriate policy response both during the crisis and in its aftermath. This dissertation contributes to that discussion by providing empirical evidence on various aspects of the transmission and effects of monetary and fiscal policy.

In Chapter 2, I estimate the interest rate pass-through from money market rates to consumer retail loan and deposit rates in Canada from 1983 to 2015. Typically, money markets are competitive and thus the interest rates for treasury bills and government bonds adjust quickly and completely in response to changes in the target interest rate set by the central bank. Commercial banks, on the other hand, often have significant market power and, as a result, retail loan and deposit rates can adjust sluggishly, potentially impeding the transmission of monetary policy.

Many recent studies (e.g. Karagiannis et al., 2014; Aristei and Gallo, 2014; Illes and Lombardi, 2013; Mora, 2014; Hristov et al., 2014) document a decline in pass-through in the US and in several countries across Europe since the financial crisis. Is this decline occurring in parts of the world that experienced the most severe turmoil or is it a global phenomena? To shed light on this question, I study the case of Canada because, in
contrast to the countries analyzed in previous studies, it has a relatively stronger banking sector and experienced no bank failures or bailouts.

To estimate the relationship between Canadian money market rates and consumer retail loan and deposit rates, I propose using the nonlinear vector error-correction model. Since the asymptotic distributions for conducting inference in this framework were only recently derived by Kristensen and Rahbek (2013), this framework has yet to be used in the pass-through literature. This model permits estimation of long-run pass-through coefficients while simultaneously accounting for asymmetric adjustments and short-run dynamics. In contrast to empirical frameworks used in previous studies, it also allows testing of commonly made assumptions such as exogeneity of the market rate, making inference more robust. I find that pass-through was complete for all rates before the financial crisis although only after the mid 1990s for the 1 year mortgage rate. Since the end of the 2008–09 recession, pass-through remains complete in the mortgage market but has significantly declined for deposit rates. Furthermore, many rates adjust asymmetrically but the direction of rigidity differs among rates and time periods.

Chapter 3 explores the effects of unconventional monetary policies on real variables in a small-open economy. Once central banks lowered their nominal target interest rate to zero, they turned to unconventional measures—including large scale asset purchases and forward guidance—to continue to stimulate the economy. While a substantial part of the literature has looked at the effects of these policies on financial variables, relatively few have evaluated their effects on the real economy. Moreover, the focus of much of the previous work has been on large open economies such as the US. Thus, Chapter 3 contributes to filling these two gaps in the literature by quantifying the effects of the Bank of Canada’s unconventional monetary policies on the real Canadian economy.
We estimate a Bayesian structural vector autoregressive model and include both Canadian and US variables. To model the small-open economy feature, we impose a block-exogeneity structure à la Cushman and Zha (1997), allowing Canadian variables to respond to foreign shocks, but not the other way around. Since the nominal rate has no variation at the zero lower bound, we follow the method recently developed by Wu and Xia (2016) and estimate shadow rates to capture the stance of monetary policy. Their approach uses information from the entire term structure of interest rates to back out a shadow rate: what the short rate would be if it were not restricted below by zero. Although the shadow rate cannot distinguish between types of unconventional monetary policy actions, it has the advantage of giving us a measure that is consistent for both countries. Moreover, since the shadow rate is simply a continuation of the short rate that is uninterrupted by the zero lower bound, we can extend our sample to many years before the zero lower bound episode and obtain more precise estimates.

In a series of counterfactual experiments, we find that Canadian unconventional monetary policy increased Canadian output by 0.23% per month on average between April 2009 and June 2010. Our empirical framework also allows us to quantify the effects of US unconventional monetary policy, which raised US and Canadian output by 1.21% and 1.94% per month, respectively, on average over the 2008–2015 period.

Chapter 4 shifts focus to US fiscal policy. Following the financial crisis, partisan politics and severe gridlock in Washington led to the emergence of the hypothesis that uncertainty about the future path of fiscal policy was impeding the recovery. However, despite the popularity of this belief and the importance of its potential implications for policymakers and researchers, there is a dearth of empirical evidence supporting the existence of a link between fiscal policy uncertainty and macroeconomic activity. I explore this relationship by nesting it in a standard structural vector autoregression model à la Blanchard and Perotti (2002) traditionally used for estimating fiscal multipliers.

The main advantages of this framework are that the model identifies fiscal shocks and
controls for them in estimating both fiscal policy uncertainty and its effect on output. My measure of uncertainty is the variance of the one-step-ahead forecast errors of the fiscal variables: the higher the variance of the forecast error, the more difficult it is to predict future outcomes. The uncertainty measure evolves stochastically and enters the level equation as an explanatory variable, thus capturing the relationship between fiscal policy uncertainty and output.

I subject the model to the same sensitivity analysis that is standard in the fiscal multiplier literature and find that the empirical evidence does not support the hypothesis that fiscal policy uncertainty has a detrimental effect on output. In fact, there is no systematic relationship between fiscal policy uncertainty and output. Using a time-varying parameter version of the model, I also show that the relationship between fiscal policy uncertainty and output has been stable and insignificant over the entire sample period. This result challenges some recent theoretical papers (Johannsen, 2014; Fernández-Villaverde et al., 2015) that argue that the effects of fiscal policy uncertainty become more pronounced when monetary policy is restricted by the zero lower bound. Finally, I revisit Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015) who find a significant negative relationship between fiscal policy uncertainty and output. I show that when their estimation is modified to incorporate the uncertainty around the estimate of uncertainty, their empirical result falls in line with my findings.
Chapter 2

Interest rate pass-through:
a nonlinear vector error-correction approach

2.1 Introduction

Banks play a critical role in the interest-rate channel of monetary policy transmission. Most central banks’ main policy instrument is the target for the overnight rate, which directly affects only the shortest term interest rate. In competitive money markets, rates of securities of longer maturities usually respond quickly and completely to changes in the policy rate through the term structure of interest rates. However, consumer retail rates on loans and deposits are set by commercial banks that often have significant market power. As a result, the speed and degree of adjustment in this second step, known as the interest rate pass-through (IRPT), is subject to market frictions.

The recent global financial crisis exposed the fragility of banking sectors across the world and heightened concerns about IRPT as central banks embarked on aggressive monetary policy easing. Not surprisingly, several studies (e.g. Karagiannis et al., 2014; Aristei and Gallo, 2014; Illes and Lombardi, 2013; Mora, 2014; Hristov et al., 2014) find evidence of a decline in pass-through across Europe and the US and associate it with changes in risk appetites, the size and structure of macroeconomic shocks, or funding
uncertainty. In light of this evidence, an important question is whether this decline in pass-through is a global problem or one that is tied to areas that experienced the most severe turmoil. This chapter contributes to this question by analyzing IRPT in Canada, a country with a relatively resilient banking sector that, in contrast to Europe and the US, experienced no bank failures or bailouts.\(^1\)

Moreover, this chapter also tackles another important issue. Despite its prominent role in the transmission process, there is no consensus in the literature on the appropriate model for estimating IRPT. Choosing an econometric model is complicated by the need to simultaneously account for several key features, such as cointegration and asymmetric movements, of retail interest rates and their relationship to market rates. While different models can account for different features of the data, this chapter proposes using a flexible, nonlinear, vector error-correction model that can account for all of them in a unified framework. Other studies\(^2\) have tried to capture these features using error-correction models with asymmetric adjustments, but they have done so in single-equation frameworks under the assumption of weak exogeneity of the market rate — an assumption that can lead to incorrect inference if it is not satisfied. In contrast, the nonlinear vector error-correction model permits explicit testing of this assumption and thus allows for more robust inference.

This model is applied to Canadian weekly data from 1983 to 2015 on five deposit rates and three loan rates of maturities ranging from three months to five years. The sample is long enough to consider three distinct periods. In 1996, the Bank of Canada officially dropped the Bank Rate peg to the 3 month treasury bill and set it to the top of the operating band for the overnight target rate.\(^3\) Thus, the first two periods are divided by

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\(^1\)Canadian banks were not immune to the financial crisis and benefited from increased liquidity provisions and from a government funded mortgage buyback program (Zorn et al., 2009). Nevertheless, their losses were relatively low compared to those experienced in other countries (Crawford et al., 2013).

\(^2\)See for example Becker et al. (2012), Belke et al. (2013), Sander and Kleimeier (2004), Kleimeier and Sander (2006), among others.

\(^3\)The Bank Rate is the rate that the Bank of Canada charges on overnight loans.
a shift in the way that monetary policy was conducted, allowing for a comparison across regimes. The third period begins in 2009 after the end of the recession that followed the global financial crisis. Analysis of this period looks at whether the transmission mechanism has weakened.

For each of the rates I test two main hypotheses. First, tests of the *completeness hypothesis* reveal whether or not pass-through is complete, *i.e.* if retail rates fully adjust to changes in the market rate in the long-run. Second, tests of the *symmetry hypothesis* reveal whether retail rates respond in the same way to upward and downward movements in the market rate. I find that pass-through was complete among all of the deposit and loan rates in the first two periods (with the exception of the 1 year mortgage rate, for which pass-through was incomplete before 1996) but has noticeably declined for deposit rates since the financial crisis. Furthermore, I find evidence of asymmetric adjustment for several rates across various periods. Interestingly, the asymmetry in adjustment of deposit rates favours the consumer in the first period, *i.e.* quick to increase and slow to decrease, but then switches to favour the bank in the second period. Meanwhile, all mortgage rates are downward rigid in the first period and become either upward rigid or adjust symmetrically — depending on the specification of the market rate — in the second period. In the last period, both the 3 and 5 year mortgage rates exhibit downward rigidity, although the evidence is stronger for the 5 year rate. Thus, the recent decline of pass-through to deposit rates and reemergence of rigidity in mortgage rates suggest that a weakened transmission through the interest rate channel may indeed be a global problem.

This chapter relates to a large and growing literature on IRPT. Some of the more notable studies include the work of Cottarelli and Kourelis (1994), which ties differences in the degree of pass-through across countries to characteristics of their financial structures, and De Bondt (2005), which provides a comprehensive review of literature on individual European countries and performs a cross-country analysis to measure the impact of the
monetary union on IRPT. Another strand of literature focuses entirely on the adjustment process. For example, Berger and Hannan (1991) and Neumark and Sharpe (1992) find evidence of upward rigidity in US banking retail deposit rates and associate it with high levels of market concentration. Driscoll and Judson (2013) confirm this result with updated data.

Relatively few studies consider IRPT in Canada. Clinton and Howard (1994) provide a discussion of transmission from market rates to long-term retail rates, but they impose complete pass-through in their empirical specification. Scholnick (1999) considers a wider variety of interest rates over a longer horizon and tests for adjustment asymmetries. He finds that despite the high degree of market concentration in Canadian banking, only car loans and savings deposits exhibit adjustment asymmetries that favour the banks. Finally, Allen and McVanel (2009) examine individual bank mortgage rate data for a later period and find evidence of asymmetric adjustment favouring banks in the 3 and 5 year mortgage rates as well as complete pass-through.

This study makes three main contributions. The first is methodological: empirical analysis is conducted using a nonlinear vector error-correction model which generalizes previously used models and estimates pass-through while simultaneously allowing for asymmetric adjustments and short-run dynamics under less restrictive conditions. It also allows for explicit tests of some commonly made assumptions such as exogeneity of the market rate. Since the asymptotic distributions for conducting inference in this framework were only recently derived by Kristensen and Rahbek (2013), this framework has yet to be used in the IRPT literature. Second, this chapter extends the work of Scholnick (1999) and Allen and McVanel (2009) on Canadian retail rates by looking at the most recent time period since the financial crisis. It is also the first to test for completeness of pass-through to Canadian deposit rates. Third, it contributes to the recent literature on post-financial-crisis IRPT by showing that although Canadian financial markets were relatively resilient, Canada was not immune to a potential weakening of the transmission
mechanism of monetary policy.

This chapter is structured as follows. The next section discusses IRPT and various market frictions that can affect completeness and symmetry. Section 2.3 describes the data and empirical model, Section 2.4 presents the results and Section 2.5 contains some robustness analysis. Section 2.6 concludes.

2.2 Interest rate pass-through and market frictions

Analysis of IRPT is based on the Monti-Klein model of banking, which treats banks as profit maximizing firms that take deposits, give loans, and put the balance on the inter-bank market (Monti, 1972; Klein, 1971). Thus, in addition to the costs of managing loans and deposits, the optimal retail rates are also influenced by the exogenously determined market rates. The main pass-through equation, which is derived from maximizing the bank’s profit function, is specified as follows

\[ r_t = \rho + \beta m_t, \]

where \( m_t \) is the market rate, \( r_t \) is the retail rate, \( \rho \) is the markup\(^4\) and \( \beta \) determines the degree of pass-through. Since monetary policy through the interest channel has the ultimate goal of influencing consumer spending and savings decisions, the pass-through parameter \( \beta \) plays a critical role in determining the efficiency of transmission.

The pass-through equation represents an equilibrium outcome that is best modeled as a long-run relationship. Market rates fluctuate daily, but since it would be too costly for banks to respond to every one of these changes, short-run equilibrium deviations are likely to arise. The short-run dynamics around adjustments to the long-run equilibrium contain

\[^4\text{The IRPT literature often refers to } \rho \text{ as the markup over marginal cost, but this ignores the fact that the marginal cost of handling loans and deposits is contained in } \rho. \text{ More accurately, } \rho \text{ represents the markup over the market rate, which can be approximated by } \rho - (1 - \beta)\bar{m} \text{ when } \beta \neq 1 \text{ (Allen and McVanel, 2009).} \]
important information about banking behaviour. For instance, a finding of complete pass-through does not necessarily imply that the market is free of frictions. Banks could, for example, be slower to respond to fluctuations in market rates that are less favourable to their profit margins. This is the case for US retail deposits rates which exhibit upward rigidity as confirmed by several studies (Neumark and Sharpe, 1992; Berger and Hannan, 1991; Driscoll and Judson, 2013).

Incomplete pass-through and asymmetric adjustments that favour banks are most often associated with market power and an inelastic demand. Consumers may be irresponsive to changes in retail banking rates if, for instance, switching costs are high. This situation may arise in the presence of information and search costs, which are likely to appear in markets where repeated transactions lead to long-term relationships (Sharpe, 1997). If search and switching costs are sufficiently high, consumers may be less inclined to look for better rates or change banks even if they find them. Allen et al. (2012) estimate these costs for consumers in the Canadian mortgage market and find that they are non-negligible. Furthermore, for the same market, Allen et al. (2014b) find evidence of price discrimination and Allen et al. (2014a) show that a decline in competition leads to an increase in mortgage rates. Both studies also discuss the presence of heterogeneity among consumers in their search efforts or negotiation abilities and how this can lead to price dispersion. Therefore, if average bargaining power is low, pass-through is likely to be incomplete or adjust in a way that favours the banks.

Retail rate movements may also adjust to favour the consumer. Berger and Hannan (1991) discuss the case of negative consumer reactions to unstable prices and that they may be more pronounced when price fluctuations are unfavourable. If the banking sector is competitive, banks may adjust their retail rates to minimize negative reactions and maintain their consumers. This behaviour would manifest itself with upward rigidity of

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5However, high concentration can also be associated with more competitive pricing if it arises from more efficient banks replacing less efficient ones. These opposing views are referred to as the *structure-performance* and *efficient-structure* hypotheses, respectively (see for e.g. Berger and Hannan, 1989).
rates in the loan market and downward rigidity of rates in the deposit market.

On the loan side, upward rigidity can also arise because of asymmetric information. When interest rates rise banks can encounter problems of adverse selection and moral hazard (Stiglitz and Weiss, 1981). Higher rates can attract riskier individuals and more speculative projects. In response, banks may be driven by a credit rationing motive that makes them slow to increase lending rates and quick to decrease them.

More recently, Ritz and Walther (2015) argue that the increased rigidity and decline in pass-through observed during the 2007–08 financial crisis can be explained by a rise in funding uncertainty. Competitiveness for deposit rates can increase sharply in the presence of funding uncertainty and if banks are highly risk averse, deposit rates can even be driven above their cost of funding. Furthermore, they show that retail rates become less responsive to changes in market rates and pass-through is dampened.

In summary, completeness of pass-through implies that banks fully adjust their retail rates to changes in the market rate in the long-run. The presence of asymmetries affects how quickly this adjustment takes place in different directions. Both completeness and symmetry may be violated in the presence of various market imperfections and the direction of asymmetry can shed light on the type of imperfection that is present in the market.

2.3 Data and empirical model

This section describes the data on the interest rates and the selection of dates that split the sample into three main periods. It also discusses the empirical framework and how each of the research questions can be represented by testable hypotheses within the model.
2.3.1 Description and timing

The data contain weekly observations of several consumer loan and deposit rates: fixed rate mortgages and Guaranteed Investment Certificates (GICs) of 1, 3, and 5 year maturities, as well as fixed term deposits of 90 day and 5 year maturities. Each loan and deposit rate is matched with an equal maturity government bond or treasury bill to proxy for banks’ cost of funding. Figure 2.1 plots the rates and shows that they move closely together over the entire sample, with loan rates mostly above and deposit rates mostly below the market rate. Vertical lines are added at dates separating subsamples under consideration.

All data are taken from Statistics Canada and are available from June 1982 for all rates. However, since this date is very close to the end of a severe recession with large

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6In general, fixed term deposits are redeemable before maturity at a penalty while GICs are not.
7CANSIM Table 176-0078: Financial market statistics, as at Wednesday, Bank of Canada. Each series represents the most typical rate of those offered by major Canadian chartered banks.
market fluctuations, the first period is set to begin in January 1983, the first quarter of recovery. In the 1990s, the way that the Bank of Canada conducted monetary policy underwent several significant changes (Lundrigan and Toll, 1998). Most notably, the Bank of Canada phased out reserve requirements from 1992 to 1994 and adopted the corridor system in 1994. The corridor system establishes a 50 basis point operating band target for the overnight rate. In February 1996, the Bank of Canada officially set the Bank Rate to the upper bound of the corridor. Prior to this period, the Bank Rate had been pegged to the 3 month treasury bill plus 25 basis points. The Bank of Canada often intervened in the treasury bill market to influence the Bank Rate, but following this change it stopped open market operations and focused entirely on targeting the overnight rate. Since this marked a major shift in monetary policy it comes as a natural break point to start the second period. The second break point is set for the end of July 2007, the onset of the financial crisis. At this point, ratings agencies downgraded mortgage backed securities, Bear Stearns filed for bankruptcy, and markets began to slide. The last period starts in May 2009, at the beginning of the recovery.

For a closer look at the data, Table 2.1 provides summary statistics for each of the rates across the three main time periods. In addition to means and standard deviations, the table contains two unit root test statistics: Augmented Dickey Fuller (ADF) and the Jansson-Nielsen (JN) nearly efficient likelihood ratio test (Jansson and Nielsen, 2012). Both the means and standard deviations of all rates decline over time. The decline from the first period to the second period reflects the change in the Bank of Canada’s stance on inflation targeting whereas the very low means and volatility in the third period correspond to a new era of near zero interest rates following the financial crisis.

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8Recession dates are obtained from Cross and Bergevin (2012).
9Although other studies have tested for unknown breakpoints (e.g. Marotta, 2009), such tests have not been developed for the nonlinear model used in this chapter and I rely on known events to select subsamples.
10The Bank of Canada began targeting inflation in 1991. By the mid 1990s inflation was successfully reduced to the target of 2% and inflation expectations fell in line soon after (Dodge, 2002). Thus, compared to the 1980’s, the second period had lower and less volatile inflation.
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>sd</td>
<td>ADF</td>
</tr>
<tr>
<td>FTD</td>
<td>3m</td>
<td>6.50</td>
<td>2.16</td>
</tr>
<tr>
<td>TB</td>
<td>3m</td>
<td>8.74</td>
<td>2.44</td>
</tr>
<tr>
<td>GIC</td>
<td>1y</td>
<td>8.12</td>
<td>2.20</td>
</tr>
<tr>
<td>MR</td>
<td>1y</td>
<td>10.10</td>
<td>2.06</td>
</tr>
<tr>
<td>TB</td>
<td>1y</td>
<td>9.10</td>
<td>2.26</td>
</tr>
<tr>
<td>GIC</td>
<td>3y</td>
<td>8.85</td>
<td>1.99</td>
</tr>
<tr>
<td>MR</td>
<td>3y</td>
<td>10.87</td>
<td>1.83</td>
</tr>
<tr>
<td>GB</td>
<td>3y</td>
<td>9.09</td>
<td>1.78</td>
</tr>
<tr>
<td>GIC</td>
<td>5y</td>
<td>9.26</td>
<td>1.85</td>
</tr>
<tr>
<td>FTD</td>
<td>5y</td>
<td>8.13</td>
<td>1.72</td>
</tr>
<tr>
<td>MR</td>
<td>5y</td>
<td>11.25</td>
<td>1.71</td>
</tr>
<tr>
<td>GB</td>
<td>5y</td>
<td>9.29</td>
<td>1.67</td>
</tr>
</tbody>
</table>

Note: The table shows the mean and standard deviation in each period for each interest rate: fixed term deposit (FTD), treasury bill (TB), Guaranteed Investment Certificate (GIC), mortgage (MR), and government bond (GB). In addition, the Augmented Dickey-Fuller (ADF) is reported as well as the JN statistic, each with lag \(k = 1\). The sample sizes are \(N = 683\) for 1983–1996, \(N = 600\) for 1996–2007, and \(N = 330\) for 2009–2015. Statistical significance at the 5%, 1%, and 0.1% level is denoted by *, **, and ***, respectively.
Furthermore, the rates fail to reject the presence of a unit root with only one exception.\textsuperscript{11}

Another series of interest is the difference between market and retail rates. If retail rates react to market rates with complete pass-through, then their difference should be stationary. Table 2.2 reports the summary statistics for the spreads of retail over market rates of matching maturities. These results should be interpreted with caution because analyzing the spreads and their properties abstracts from a lot of short and long-run dynamics that are critical for an accurate description of the relationship among the variables. In general, the spreads appear to be stationary in the first two periods, which is suggestive of complete pass-through. However, in the period following the financial crisis several rates, in particular those with longer maturities, appear to have non-stationary spreads. The means of the spreads also exhibit some patterns. For instance, mortgage rates show that the markup over cost has been on the rise across the three periods. Deposit rates, on the other hand, show a steady decrease in spreads for fixed terms and an increase followed by a decrease for GICs. An accurate analysis of these trends requires an appropriate econometric model, which is described in the next section.

\subsection*{2.3.2 Empirical model}

To estimate the pass-through equation, the empirical model must account for several key dynamics of the data. Most importantly, as discussed in Section 2.2, since the pass-through equation represents an equilibrium outcome, it is necessary to allow for short-run deviation. The way that these short-run dynamics are specified is important for other research questions such as whether retail rates respond to market rates in the first place and, if they do, is their adjustment asymmetric. Estimation is further complicated by the fact that interest rates are non-stationary (see Table 2.1).

The typical approach in the literature takes one of three main forms. The simplest method is a regression of the change in market rates on the change in retail rates (see for

\textsuperscript{11}The ADF test rejects the unit root for the 3 year GIC in the last period, but the JN test suggests a unit root is present.
Table 2.2: Summary statistics of interest rate spreads: retail over market

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>sd</td>
<td>ADF</td>
</tr>
<tr>
<td>3m†</td>
<td>−2.24</td>
<td>0.68</td>
<td>−4.26***</td>
</tr>
<tr>
<td>1y</td>
<td>−0.98</td>
<td>0.48</td>
<td>−8.17***</td>
</tr>
<tr>
<td>3y</td>
<td>−0.24</td>
<td>0.56</td>
<td>−5.17***</td>
</tr>
<tr>
<td>5y</td>
<td>−0.02</td>
<td>0.53</td>
<td>−4.94***</td>
</tr>
<tr>
<td>5y‡</td>
<td>−1.15</td>
<td>0.71</td>
<td>−4.18***</td>
</tr>
</tbody>
</table>

1y‡  1.00     0.58     −6.62***  0.98     1.87     0.35     −3.82**    4.33     2.34     0.39     −2.97*      0.01
3y‡  1.78     0.55     −5.62***  0.57     2.09     0.39     −3.78**    2.95     2.60     0.25     −3.60**    6.02***
5y‡  1.96     0.51     −5.74***  0.36     2.20     0.39     −3.59**    0.80     3.45     0.40     −2.34       1.82

Note: The table shows the mean and standard deviation for each of the interest rate spreads for the three periods. In addition, the Augmented Dickey-Fuller (ADF) is reported as well as the JN statistic, each with lag \( k = 1 \). The sample sizes are \( N = 683 \) for 1983–1996, \( N = 600 \) for 1996–2007, and \( N = 330 \) for 2009–2015. Statistical significance at the 5%, 1%, and 0.1% level is denoted by *, **, and *** respectively. † denotes term deposit spreads, and ‡ denotes mortgage spreads.
example Mora, 2014). Although this accounts for non-stationarity, it abstracts from all of the other features. Some authors, for example Scholnick (1999), use the cointegrated VAR (CVAR) model which is capable of estimating the long-run equilibrium between the two variables while simultaneously accounting for short-run dynamics. This framework, however, does not allow for nonlinearities such as asymmetric adjustments. To deal with this problem, others use single equation error-correction models (ECMs) with dummy variables (or smooth transition functions) for positive and negative movements in the market rate. They either estimate them with non-linear least squares (Karagiannis et al., 2010) or in two steps with OLS (Allen and McVanel, 2009). However, inference is only valid in single equation analysis under a condition that is implicitly imposed but left untested: the weak exogeneity of the market rate (see Theorem 8.1 in Johansen, 1995).

To deal with these empirical issues, I use the nonlinear vector error-correction model (VECM). This model specifies a long-run equilibrium relationship with nonlinear adjustment coefficients without the assumption of exogeneity of the market rate. In fact, exogeneity of the market rate is a testable hypothesis within the model. Estimation and analysis is based on Kristensen and Rahbek (2013), who provide a rigorous discussion of testing and inference — as well as the asymptotic distributions for the relevant test statistics — within a general class of nonlinear VECMs.

Letting $X_t = [r_t, m_t]'$ be a vector containing a retail and market rate, the nonlinear VECM is specified as follows,

$$\Delta X_t = g(\beta' \tilde{X}_{t-1}) + \sum_{i=1}^{k} \Gamma_i \Delta X_{t-i} + \varepsilon_t,$$  \hspace{1cm} (2.1)

where $\varepsilon_t$ is i.i.d. with $E[\varepsilon_t] = 0$ and $E[\varepsilon_t \varepsilon_t'] = \Omega$. The long-run stationary equilibrium
corresponds to the pass-through equation and is given by,

$$\beta' \tilde{X}_{t-1} = \begin{bmatrix} 1 & \beta & \rho \\ m_t & 1 \end{bmatrix} \begin{bmatrix} r_t \\ m_t \end{bmatrix} = r_t + \beta m_t + \rho. \quad (2.2)$$

The $\Gamma$'s determine the short run dynamics while the function $g(\cdot)$ captures the adjustment to equilibrium fluctuations. In contrast to the CVAR, this model allows for both linear and nonlinear adjustment coefficients,

$$g(\beta' \tilde{X}_{t-1}) = \alpha \beta' \tilde{X}_{t-1} + \delta \underbrace{f(\beta' \tilde{X}_{t-1}; \psi)}_{\text{nonlinear}} \beta' \tilde{X}_{t-1}. \quad (2.3)$$

That is, both $\alpha$ and $\delta f(\beta' \tilde{X}_{t-1}; \psi)$ determine how the variables in the system respond to equilibrium shocks (movements in $\beta' \tilde{X}_{t-1}$). The nonlinear adjustment is specified using a logistic function which can account for asymmetry in a general way,

$$f(\beta' \tilde{X}_{t-1}; \psi) = \left[1 + \exp(\psi(\beta' \tilde{X}_{t-1}))\right]^{-1}. \quad (2.4)$$

If $\psi > 0$, as the deviation from equilibrium becomes large and negative, $f(\cdot)$ approaches 1 and as it becomes large and positive, $f(\cdot)$ approaches 0. When $\psi$ is large, $f(\cdot)$ behaves similarly to an indicator function and when $\psi$ is small, the size of the asymmetric adjustment depends on the size of the deviation from equilibrium. This could arise if, for example, banks adjust their retail rates only in response to large changes in the market rate.

Several hypotheses of interest can be tested within this framework. First, note that the CVAR is nested within model (2.1) as a special case when $\delta = 0$. Thus the hypothesis $\mathcal{H}_{1,2}^{\delta} : \delta_1 = \delta_2 = 0$ tests for the presence of asymmetric adjustments in the error-correction.
Failing to reject this hypothesis implies that adjustments are symmetric (symmetry hypothesis). Second, the null hypothesis of complete pass-through is specified as a test on the long-run coefficients in $\beta$, namely $H_{\beta}: \beta = -1$. This hypothesis implies that a change in the market rate is fully transmitted to the retail rate in the long-run equilibrium (completeness hypothesis). Third, the hypothesis $H_{\alpha,\delta}: \alpha_i = \delta_i = 0$, for $i \in \{1, 2\}$, tests for weak exogeneity. If a variable does not respond to fluctuations in the long-run equilibrium then it is weakly exogenous. Fourth, the hypothesis $H_{\alpha,\delta,\Gamma}: \alpha_i = \delta_i = \Gamma_{s,ij} = 0$, for $s = 1, \ldots, k$ and $i, j \in \{1, 2\}$ with $i \neq j$, tests whether the variable is strongly exogenous, i.e. driven entirely by its own dynamics, and can establish Granger causality. For example, if only the market rate is strongly exogenous then changes in the market rate Granger-cause changes in the retail rate.

2.4 Results

Each of the retail rates is estimated in a bivariate system with the market rate of matching maturity. Before conducting inference on the parameters of interest the model needs to be correctly specified with an appropriate lag augmentation and cointegrating rank. With a slight abuse of notation, the rank $r$ determines the number of stationary cointegrating relations. If the rank is 0, then the two interest rates are not cointegrated. A rank of 1 implies that the market rate and retail rate form a long-run stationary equilibrium and a rank of 2 implies that they are both stationary.

The lag order $k$ is selected using a combination of Bayes information criteria (BIC) and serial correlation tests on the residuals. I start with the lag augmentation that minimizes the BIC for models estimated with $k = 0, \ldots, 5$ lags and, if needed, increase $k$ until

\[12 \text{ More generally, the hypothesis is specified as } H_{\beta}: \beta_1 = -\beta_2, \text{ but since the cointegrating vector is normalized on the retail rate for identification, these two specifications are equivalent.} \]

\[13 \text{ This weak form of exogeneity — the variable can still respond to short-run fluctuations — is required for valid inference on the long-run parameters } (\beta, \rho, \alpha, \delta, \psi) \text{ in single-equation ECMs. However, inference on the short-run coefficients } \{\Gamma_i\}_{i=1}^k \text{ requires an additional assumption of } \Omega \text{ being diagonal (Urbain, 1992).} \]
residuals fail to reject the null of no serial correlation.

Rank selection follows the procedure outlined in Johansen (1995). Testing is done sequentially, starting with the null of no cointegration $\mathcal{H}_0^r : r = 0$. If this hypothesis is rejected, then the null of one cointegrating vector $\mathcal{H}_1^r : r = 1$ is tested. In both cases the alternative is the model with full rank $\mathcal{H}_2^r : r = 2$.

Rank and lag selection follow a general-to-specific testing procedure. Lags are chosen based on bivariate estimates of full rank models and then once a lag is chosen it is fixed for the rank tests. Rank tests are conducted within the CVAR model because inference in nonlinear VECMs requires the long-run coefficient $\beta$ to be identified under the null (Kristensen and Rahbek, 2013). For consistency, the CVAR is also used for lag selection.

Table 2.3 reports the results of rank tests for all of the bivariate systems.⁴ These results must be interpreted with caution since the estimated models abstract from potential nonlinearities ignored by the CVAR. Nevertheless, with the exception of very few cases, the models reject the null of no cointegration and fail to reject the null of 1 cointegrating vector. In three cases, the test fails to reject the null of no cointegration but since the test statistics are still relatively large this is likely due to the fact that the rank test has low power against the null, especially in smaller samples. In one case (3yr mortgage in 2000–2007), the null of one cointegrating vector is rejected but the test statistic (7.56) is just on the edge of significance with a $P$-value of 0.0995. Moreover, if rejection of cointegration occurs, it is never for the same rates in multiple periods. As a result, the rank tests provide strong enough evidence to proceed with estimating the bivariate systems in the nonlinear VECM with one cointegrating vector.

The rest of the hypothesis test results are discussed in detail for deposit rates in Section 2.4.1 and mortgage rates in Section 2.4.2. For each bivariate model, the testing procedure is conducted as follows. Using the rank and lag from Table 2.3, model (2.1)
<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$k$</td>
<td>$r = 0$</td>
<td>$r = 1$</td>
<td>$k$</td>
<td>$r = 0$</td>
<td>$r = 1$</td>
<td>$k$</td>
<td>$r = 0$</td>
</tr>
<tr>
<td>FTD 3m, TB 3m</td>
<td>2</td>
<td>21.29**</td>
<td>1.68</td>
<td>1</td>
<td>33.41***</td>
<td>2.81</td>
<td>1</td>
<td>15.13</td>
</tr>
<tr>
<td>GIC 1y, TB 1y</td>
<td>2</td>
<td>104.70***</td>
<td>1.64</td>
<td>1</td>
<td>82.49***</td>
<td>2.75</td>
<td>0</td>
<td>28.80***</td>
</tr>
<tr>
<td>GIC 3y, GB 3y</td>
<td>2</td>
<td>41.15***</td>
<td>1.94</td>
<td>1</td>
<td>85.68***</td>
<td>3.51</td>
<td>0</td>
<td>25.10***</td>
</tr>
<tr>
<td>GIC 5y, GB 5y</td>
<td>2</td>
<td>31.53***</td>
<td>2.18</td>
<td>1</td>
<td>89.63***</td>
<td>4.38</td>
<td>0</td>
<td>26.48***</td>
</tr>
<tr>
<td>FTD 5y, GB 5y</td>
<td>2</td>
<td>28.19***</td>
<td>2.45</td>
<td>1</td>
<td>82.48***</td>
<td>4.34</td>
<td>0</td>
<td>30.29***</td>
</tr>
<tr>
<td>MR 1y, TB 1y</td>
<td>1</td>
<td>95.60***</td>
<td>2.12</td>
<td>2</td>
<td>19.38*</td>
<td>3.63</td>
<td>0</td>
<td>13.11</td>
</tr>
<tr>
<td>MR 3y, GB 3y</td>
<td>2</td>
<td>50.15***</td>
<td>2.55</td>
<td>1</td>
<td>28.90***</td>
<td>5.39</td>
<td>0</td>
<td>30.84***</td>
</tr>
<tr>
<td>MR 5y, GB 5y</td>
<td>3</td>
<td>28.92***</td>
<td>2.86</td>
<td>3</td>
<td>16.93</td>
<td>6.79</td>
<td>0</td>
<td>24.13**</td>
</tr>
</tbody>
</table>

Note: LR statistics are reported against the alternative of full rank, $r = 2$. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.
is estimated. The first test is for asymmetry, $H_{1,2}$, and if it is rejected then the rest of the hypotheses — completeness and exogeneity — are tested within the linear CVAR model.\footnote{Estimation and inference for the CVAR uses software developed by Nielsen and Popiel (2014).} The test statistic used for all tests is the likelihood ratio and $P$-values are generated using the wild bootstrap. Although critical values are known for the CVAR and can be simulated for the nonlinear VECM, the bootstrap procedure is robust to heteroskedasticity (Boswijk et al., 2013). In general the bootstrap samples are generated using the residuals obtained under the null, but for the hypothesis of linearity this can be problematic (for details, see Kristensen and Rahbek, 2013) and therefore, the residuals under the alternative are used instead.\footnote{Kristensen and Rahbek (2013) also discuss an issue of obtaining negative likelihood ratio statistics for some samples. To get around this problem, the restricted likelihood is estimated first and the coefficients are used as starting values for maximizing the unrestricted likelihood. I thank Dennis Kristensen for providing me with the code for the simulation study in Kristensen and Rahbek (2013).} If the roots of the characteristic polynomial for the coefficients specified under the null are inside the unit circle the hypothesis is rejected because these coefficients would generate explosive bootstrap samples. The number of bootstrap samples is 4999.

### 2.4.1 Deposit rates

The hypothesis test results for all of the deposit rates and each time period are shown in Table 2.4 and the coefficient estimates for the final restricted models are shown in Table 2.5. Due to the difference in asymptotic convergence rates of the adjustment coefficients and the coefficients of the cointegrating vector (Johansen, 1995), conditional hypotheses are also reported. In particular, hypotheses on the adjustment coefficients are nested in the model with restrictions imposed on the super-consistent long-run coefficients and complete pass-through is nested in the model of exogeneity of the market rate. The latter conditioning is reported since exogeneity restrictions can be considered as part of the model selection and based on this reasoning should be imposed before testing restrictions on other parameters. The ability to test both conditional and unconditional hypotheses
Table 2.4: Hypothesis test results for deposit rates

<table>
<thead>
<tr>
<th>Rate</th>
<th>Time</th>
<th>$H_{1,2}$</th>
<th>Unconditional</th>
<th>Conditional</th>
<th>Joint</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$H_1^\delta$</td>
<td>$H_2^\beta$</td>
<td>$H_3^{\alpha,\delta}$</td>
<td>$H_4^{\alpha,\Gamma}$</td>
</tr>
<tr>
<td>FTD 3m</td>
<td>'83-'96</td>
<td>11.24</td>
<td>3.49</td>
<td>17.62***</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>8.97</td>
<td>2.87</td>
<td>–</td>
<td>7.47*</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>137.14</td>
<td>3.04</td>
<td>8.10**</td>
<td>0.09</td>
</tr>
<tr>
<td>GIC 1y</td>
<td>'83-'96</td>
<td>3.89</td>
<td>0.28</td>
<td>97.54***</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>5.46</td>
<td>0.69</td>
<td>75.81***</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>20.69**</td>
<td>15.04**</td>
<td>–</td>
<td>3.90</td>
</tr>
<tr>
<td>GIC 3y</td>
<td>'83-'96</td>
<td>61.65***</td>
<td>–</td>
<td>–</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>27.44***</td>
<td>–</td>
<td>–</td>
<td>0.73</td>
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<tr>
<td></td>
<td>'09-'15</td>
<td>1.79</td>
<td>–</td>
<td>20.17***</td>
<td>0.92</td>
</tr>
<tr>
<td>GIC 5y</td>
<td>'83-'96</td>
<td>16.56**</td>
<td>2.85</td>
<td>40.68***</td>
<td>1.74</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>10.17*</td>
<td>4.41*</td>
<td>85.28***</td>
<td>3.86</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>44.08</td>
<td>17.54***</td>
<td>21.55**</td>
<td>1.11</td>
</tr>
<tr>
<td>FTD 5y</td>
<td>'83-'96</td>
<td>16.24***</td>
<td>–</td>
<td>31.22***</td>
<td>7.23*</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>13.14**</td>
<td>7.60**</td>
<td>–</td>
<td>2.32</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>21.34*</td>
<td>–</td>
<td>–</td>
<td>5.42</td>
</tr>
</tbody>
</table>

Notes: This table reports the likelihood ratio test statistics for each of the hypotheses of interest in the following order: (1) $H_{1,2}^\delta$ tests for the presence of asymmetric adjustments in the error-correction; (2) $H_2^\beta$ tests for complete pass-through; (3)–(4) $H_i^{\alpha,\delta}$ for $i \in \{1, 2\}$ tests for weak exogeneity of the market rate and retail rate, respectively; (5) $H_2^{\alpha,\delta,\Gamma}$ tests for strong exogeneity of the market rate; (6) $H_2^{\alpha,\delta,\Gamma}$ tests for strong exogeneity conditional on complete pass-through; (7) $H_7^{\beta}$ tests for complete pass-through conditional on strong exogeneity of the market rate; and (8) $H_2^{\alpha,\delta,\Gamma} \cap H_7^{\beta}$ tests the joint hypothesis of complete pass-through and strong exogeneity of the market rate. Results are based on 4,999 bootstrap samples. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ****, respectively. If the roots of the characteristic polynomial are inside the unit circle for a given hypothesis, the LR statistic is not reported.
is another major advantage over the single-equation ECM — in fact, in three cases the results from the unconditional and conditional hypotheses are different. In addition, the joint test of complete pass-through and exogeneity of the market rate is reported in the last column because it is the model that is selected most often. Missing test statistics imply that the null hypothesis generated explosive roots.

As expected, for all terms and time periods, $H_{1,\alpha,\delta}$ is strongly rejected while $H_{2,\alpha,\delta,\Gamma}$ fails rejection, implying that the market rate is strongly-exogenous and the retail rate responds to fluctuations in the long-run equilibrium as well as short-run dynamics of the market rate. In two cases, weak exogeneity of the market rate $H_{2,\alpha,\delta}$ is rejected but since the conclusions from both the conditional and unconditional hypotheses are the same for these two cases, the strong exogeneity restriction is imposed.

For the shortest term rate, both the completeness and symmetry hypotheses fail rejection for all time periods.\(^17\) Although completeness conditional on strong exogeneity of the market rate is rejected at a low level of significance in period one, the joint hypothesis test matches the result from the unconditional hypothesis, suggesting that pass-through is indeed complete. Although a similar situation arises for the 5 year GIC in the first period, the coefficient estimate of $\beta$ in that case is actually greater than 1. Nevertheless, these two instances demonstrate the importance of using a flexible model that can allow for unconditional tests of completeness.\(^18\) The additional joint and unconditional hypotheses can provide more information and sometimes even lead to different conclusions than those that would be obtained from a single-equation ECM.

The rest of the rates strongly reject both completeness and symmetry in at least one period. Table 2.5 allows for a better analysis of the implications of these findings. Although the hypothesis of complete pass-through is rejected for the 3 year GIC in period

\(^17\)Although the LR statistic for the symmetry hypothesis is very large in magnitude (137.14) for the 3 month term deposit in the last period, the nonlinear model under the alternative has explosive roots and the bootstrap distribution has a very fat tail. The same occurs for the 5 year GIC in the last period.

\(^18\)For the 3 month term deposit, completeness is also rejected conditional on weak exogeneity. For details see Table A.1 in Appendix A.1.
Table 2.5: Coefficient estimates for deposit rates

<table>
<thead>
<tr>
<th>Rate</th>
<th>Time</th>
<th>$\beta$</th>
<th>$\rho$</th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\delta_1$</th>
<th>$\delta_2$</th>
<th>$\psi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTD 3m</td>
<td>'83-'96</td>
<td>-1.000</td>
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<tr>
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<tr>
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</tr>
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<td>0.470</td>
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</table>

Notes: This table reports the coefficient estimates from the final restricted models: $\beta$ and $\rho$ are the coefficients for pass-through and markup presented in (2.2); $\alpha_i$ and $\delta_i$ are the linear and nonlinear adjustment coefficients, respectively, presented in (2.3) — subscript 1 is for the retail rate and 2 is for the market rate — and $\psi$ is the parameter determining the behaviour of the logistic function in (2.4).

1 and for the 5 year fixed term in periods 1 and 2, the coefficient estimates in the cointegrating relation actually imply a pass-through that is greater than 1. Therefore, even though the stronger two-sided hypothesis is rejected, it is clear from the coefficient estimates that pass-through is still complete for these two rates in the first two periods. The unconditional hypothesis of completeness is also rejected for the 5 year GIC in period 1, but the unrestricted coefficient estimate of $\beta$ is above 1 and not significantly different from 1 according to the conditional and joint hypothesis test results. The same cannot be said about the last period. For all of the deposit rates with maturities of 1 year and greater, pass-through has significantly declined since the financial crisis.

Sluggish behaviour for these deposit rates appears to be common throughout the
entire sample. Even though pass-through was complete in the first two periods, several of these rates responded differently to equilibrium fluctuations based on the direction of the movement in the market rate. According to the functional form of the nonlinear adjustment shown in (2.4), the signs on the coefficients of $\psi$ and $\delta_1$ reveal the direction of the asymmetry in response to an equilibrium shock. The equilibrium relation, $\beta' \tilde{X}_t = r_t + \beta m_t + \rho$, becomes positive when the market rate $m_t$ decreases and negative when it increases. As a result, when $\psi > 0$, $f(\beta' \tilde{X}_{t-1}; \psi) \to 1$ as $m_t$ declines and $f(\beta' \tilde{X}_{t-1}; \psi) \to 0$ as $m_t$ rises.

When both $\psi > 0$ and $\delta_1 > 0$, the retail deposit rate responds more strongly to a market rate decrease than to an increase. This type of asymmetry is consistent with a profit motive on the side of the bank since it implies that they are reluctant to pay more for deposits when their cost of funding decreases, but are quick to pay less when it increases. If $\psi$ and $\delta_1$ have opposite signs, then the dynamic is reversed and the adjustment asymmetry favours the consumer.\(^{19}\)

Surprisingly, we observe both of these cases for the 3 and 5 year GICs. Consider a 100 basis point increase in the 3 year government bond in the first period at time $t$. The nonlinear adjustment function $f(\beta' \tilde{X}_t; \psi)$, evaluated with the coefficient estimates for this deviation is

$$f(-1; 135.063) = [1 + \exp(135.063(-1))]^{-1} \approx 1.$$  

Thus the short-run adjustment to equilibrium for the retail rate in period $t+1$ is,

$$[\hat{\alpha}_1 + \hat{\delta}_1 f(\beta' \tilde{X}_t; \hat{\psi})] \hat{\beta}' \tilde{X}_t = (-0.019 - 0.930)(-1) = 0.949.$$  

For a 100 basis point movement of the market rate in the other direction, the reaction of

\(^{19}\)Note that if $\alpha_i$ and $\delta_i$ have the opposite sign then $\delta_i$ must be smaller in magnitude than $\alpha_i$ for variable $i$ to adjust toward equilibrium following a shock. Otherwise, it may diverge.
the retail rate is significantly different. Now $\hat{\beta}' \tilde{X}_t = 1, f(\hat{\beta}' \tilde{X}_t; \hat{\psi}) \approx 0$ and

$$[\hat{\alpha}_1 + \hat{\delta}_1 f(\hat{\beta}' \tilde{X}_t; \hat{\psi})] \hat{\beta}' \tilde{X}_t = (-0.019)(1) = -0.019.$$

In each of the cases, the equilibrium correction is in the right direction, i.e. retail rates follow movements in market rates, but the magnitude is greatly reduced when the retail rate decreases. In the next period, the exact opposite behaviour takes place: for a 100 basis point increase in the retail rate, the 3 year GIC adjusts by 0.071 and for a decrease by −0.558.

This change in the direction of rigidity across periods 1 and 2 is also present in the 5 year GIC. The 5 year fixed term deposit, however, has maintained upward rigidity for all three periods and the 1 year GIC began exhibiting downward rigidity following the financial crisis. As discussed in Section 2.2, downward rigidity in deposit rates is consistent with banks trying to keep consumers content in the face of higher levels of competition. GICs are an important source of funding for mortgages because they match them in term (Clinton and Howard, 1994). However, the second period saw a significant rise in securitization of mortgages and the growth of mortgage-backed securities (Traclet, 2005, 2010; Crawford et al., 2013). The fact that banks became less reliant on GICs could explain this transition from asymmetric adjustment that favours the consumer to one that favours the bank.

In 2005, the Canadian Deposit Insurance Corporation raised the limit on insurable deposits from $60,000 to $100,000.\(^{20}\) This change made retail deposits more popular and could have increased banks’ market power as a result. To explore whether this change had an impact on the observed upward rigidity in deposit rates in the second period, I repeat the analysis with the period ending at the end of 2004. The conclusions from the

\(^{20}\)The change was passed in Part 15 of the 2005 Federal Budget as an amendment to paragraph 12(c) of the Canadian Deposit Insurance Act (for details see http://laws-lois.justice.gc.ca/eng/annualstatutes/2005_30/page-26.html).
hypothesis as well as the parameter estimates are very similar to those obtained from the full subsample.\textsuperscript{21} This suggests that the change in the deposit insurance limit was not a major factor in the presence of rigidities.

In the period following the financial crisis, deposit rates became substantially more sluggish. However, even though a decline in pass-through is most often associated with banks exploiting their pricing power for higher profits, the coefficient estimates in the last period suggest a different dynamic. Using the mean values for the market rate from Table 2.1, the markups, approximated by \( \rho - (1 - \beta) \bar{m} \), for the 1, 2, and 3 year GIC and 5 year fixed term deposit are \(-0.302, 0.113, 0.016, \) and \(0.038\), respectively. These markups are very low relative to the other time periods and even negative in the case of the 1 year GIC. As a result, it is likely that the sluggish behaviour is driven by a response to funding uncertainty as described by Ritz and Walther (2015).

Moreover, the upward pressure on long-term deposit rates may explain the failure to reject symmetry for the 3 and 5 year GICs in this period. These rates have generally been quick to fall and slow to rise but given this additional force preventing them from adjusting downward they are now rigid in both directions. This lack of movement results in an incomplete pass-through and a drastically reduced markup. For the 1 year GIC and 5 year fixed term, however, even though pass-through is incomplete, upward rigidity appears to dominate the adjustment process.

\textbf{2.4.2 Mortgage rates}

Turning to the loan side of the market, this section considers mortgage rates. Before discussing the results, I first provide some relevant historical context. In the 1990s Canadian chartered banks started facing increasing competition in the mortgage market from virtual banks and mortgage brokers (Traclet, 2005). While these competitors offered their lowest rate upfront, chartered banks adopted a different strategy, namely discounting.

\textsuperscript{21}The results are reported in Tables A.2 and A.3 in Appendix A.1.
Note: Mortgage rate spread is the difference between the mortgage rate and the matching maturity government bond. The vertical black line indicates the subsample breakpoint. Source: CANSIM Table 176-0078.

Banks would offer their customers a mortgage rate below the posted rate. This practice grew steadily over time and by the early 2000s it was common for consumers to expect discounts when taking on a mortgage from a chartered bank. Day and Tkacz (2005) point out that while discounts steadily increased, so did posted rates, so that the actual transaction rate remained steady over the time period. Although the market share of these competitors remained modest at only a few percent, the discounting in the early part of the second period poses some potential problems for estimation.

Since the data contain posted rates and not transaction rates, there is a positive trend in the spread between market and retail rates in the late 1990s, which corresponds to the first part of the second sample period. This spread is plotted in Figure 2.2. As discussed by Day and Tkacz (2005) and as can be seen from the figure, this trend stabilized in late 2000. Although this trend is not very strong, tests are also performed using a smaller sub-period that begins in December 2000 (denoted by the vertical black line in Figure 2.2).

Table 2.6 presents the results from the hypothesis tests. As was the case for deposit rates, the retail loan rates are endogenous while their market counterparts are exogenous for almost all maturities and time periods. For the 1 year mortgage, even though weak
<table>
<thead>
<tr>
<th>Rate</th>
<th>Time</th>
<th>$H_{1,2}^\delta$</th>
<th>$H_1^\beta$</th>
<th>$H_2^{\alpha,\delta}$</th>
<th>$H_2^{\alpha,\delta,\Gamma}$</th>
<th>$H_2^{\alpha,\delta,\Gamma}$</th>
<th>$H_3^\beta$</th>
<th>$H_2^{\alpha,\delta,\Gamma} \cap H_3^\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>MR 1y '83-'96</td>
<td>43.65***</td>
<td>48.70***</td>
<td>8.52**</td>
<td>8.53</td>
<td>2.52</td>
<td>42.70***</td>
<td>51.23***</td>
<td></td>
</tr>
<tr>
<td>'96-'07</td>
<td>9.82</td>
<td>0.06</td>
<td>10.91**</td>
<td>0.04</td>
<td>0.61</td>
<td>0.57</td>
<td>0.03</td>
<td>0.63</td>
</tr>
<tr>
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<td>0.14</td>
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<td>2.96</td>
<td>2.54</td>
<td>0.03</td>
<td>2.99</td>
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<tr>
<td>MR 3y '83-'96</td>
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<td>78.45***</td>
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<td>1.34</td>
<td>0.10</td>
<td>2.71</td>
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</tr>
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<td>4.44</td>
<td>53.60***</td>
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<td>1.20</td>
<td>0.88</td>
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<tr>
<td>MR 5y '83-'96</td>
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<td>39.43***</td>
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<td>0.38</td>
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<td>4.60</td>
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<td>'09-'15</td>
<td>61.71***</td>
<td>17.93***</td>
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<td>0.27</td>
<td>0.19</td>
<td>17.59**</td>
<td>18.12*</td>
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Notes: This table reports the likelihood ratio test statistics for each of the hypotheses of interest in the following order: (1) $H_{1,2}^\delta$ tests for the presence of asymmetric adjustments in the error-correction; (2) $H_1^\beta$ tests for complete pass-through; (3)-(4) $H_2^{\alpha,\delta}$ for $i \in \{1, 2\}$ tests for weak exogeneity of the market rate and retail rate, respectively; (5) $H_2^{\alpha,\delta,\Gamma}$ tests for strong exogeneity of the market rate; (6) $H_2^{\alpha,\delta,\Gamma}$ tests for strong exogeneity conditional on complete pass-through; (7) $H_3^\beta$ tests for complete pass-through conditional on strong exogeneity of the market rate; and (8) $H_2^{\alpha,\delta,\Gamma} \cap H_3^\beta$ tests the joint hypothesis of complete pass-through and strong exogeneity of the market rate. Results are based on 4,999 bootstrap samples. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. If the roots of the characteristic polynomial are inside the unit circle for a given hypothesis, the LR statistic is not reported.
Table 2.7: Coefficient estimates for mortgage rates

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<th>Rate</th>
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<th>( \rho )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>( \delta_1 )</th>
<th>( \delta_2 )</th>
<th>( \psi )</th>
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<td></td>
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<tr>
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<td>0.000</td>
<td>-0.786</td>
<td>0.000</td>
<td>29.326</td>
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</table>

Notes: This table reports the coefficient estimates from the final restricted models: \( \beta \) and \( \rho \) are the coefficients for pass-through and markup presented in (2.2); \( \alpha_i \) and \( \delta_i \) are the linear and nonlinear adjustment coefficients, respectively, presented in (2.3) — subscript 1 is for the retail rate and 2 is for the market rate — and \( \psi \) is the parameter determining the behaviour of the logistic function in (2.4).

Exogeneity is rejected for the market rate, strong exogeneity is not rejected and therefore imposed. However, the conditional hypothesis test for completeness yields the same result as the unconditional one. For the 5 year mortgage rate, the retail rate fails to reject weak exogeneity. However, this hypothesis is rejected conditional on complete pass-through and therefore not imposed.\(^{22}\)

In contrast to deposit rates, mortgage rates had complete pass-through before the crisis and have maintained it since the end of the recession. Moreover, the 1 year mortgage rate was the only rate to exhibit incomplete pass-through in the earliest period. This product saw a large level of activity in the first period, but as inflation and interest rates fell in the mid 1990s the longer term mortgages gained more popularity (Clinton and Howard, 1994). Thus, the finding of incomplete pass-through could be tied to the fact that it was a popular product and banks were yet to face the steeper competition that arrived in the

\(^{22}\)The test statistics for the hypothesis \( \mathcal{H}_1^{\alpha, \delta} \cap \mathcal{H}_{\beta} | \mathcal{H}_{\beta} \) are reported in Table A.4 in Appendix A.1.

31
late 1990s.

Perhaps not surprisingly, linear adjustment is also strongly rejected for the 1 year mortgage in the earliest period. Likewise, the 3 and 5 year mortgage rates exhibit asymmetric adjustments in the earliest period. The sign on the impact coefficient is negative implying that rates responded more strongly to market rate increases than decreases. This downward rigidity is consistent with the presence of switching costs discussed in Section 2.2. However, banks may also be slow to decrease rates because of the way that the mortgage contracts are formed. There is often a significant time lag between when the loan is approved and when it is actually issued. During this time the bank is committed to the interest rate, but the consumer is not committed to the loan (Clinton and Howard, 1994). If rates decline before the mortgage is issued, the bank can renegotiate a new rate with the consumer. But if rates increase, the bank must still offer the lower rate agreed upon approval. Therefore, the presence of downward rigidity in the mortgage market could be a symptom of higher risk for delaying a rate increase.

In the middle period, there is only one case where the conclusions differ for the shorter stable subsample 2000–2007. Although completeness is not rejected in both subsamples for the 1 year mortgage, symmetry is rejected in the shorter subsample. Interestingly, the adjustment process exhibits upward rigidity. This could be either due to asymmetric information and the banks’ reluctance to increase rates for fear of attracting riskier projects, or competitive behaviour aimed to attract more consumers. Since the other mortgage rates adjust symmetrically in this period, the latter explanation is more likely.

Although pass-through is complete for all rates in the final period, downward rigidity reappears in the 3 and 5 year mortgage rates. Therefore, the adjustment of mortgage rates has also become more sluggish since the financial crisis but, unlike the deposit rates, we can expect them to fully adjust in the long run to movements in the market rates.
Figure 2.3: Spreads of 3 month swaps over matching maturity market rates in 1996-2015

Note: Vertical black lines indicate subsample breakpoints. Source: Datastream.

2.5 Robustness

In this section I consider alternative interest rates as proxies for banks’ cost of funding in the decision to set mortgage rates. Since banks face a maturity mismatch between these assets and their mostly short-term liabilities (deposits), they may want to hedge their positions by exchanging the cash-flow from a fixed rate contract (mortgage) to one based on a floating rate, i.e. by entering a swap agreement. Therefore, I re-estimate the models matching each of the mortgage rates with the same maturity swap rate which converts the fixed rate into a floating 3 month rate. Since data is not available for the full first period, I focus only on the two most recent periods. The spreads are shown in Figure 2.3 and the estimation results are in Tables 2.8–2.10.

In general, the rank test results, shown in Table 2.8, and hypothesis test results, shown in Table 2.9, are very similar to what was found in the main analysis in Section 2.4. Once

\[23\] Note that this balance sheet risk is not present for long-term deposit rates and as a result matching maturity government bonds or treasury bills are appropriate proxies for the opportunity cost of these products.

\[24\] Data is obtained from Datastream, series codes: S93116, S06551, and S06553.

\[25\] Additionally, there are missing values for the 1 year swap spread for 9/15/1999–3/5/2000. As a result, for this rate, I only report estimates for the smaller subperiod 12/2000–7/2007 and the final period.
Table 2.8: Rank test results with interest rate swaps as proxy for bank funding costs

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$k$</td>
<td>$r = 0$</td>
<td>$r = 1$</td>
</tr>
<tr>
<td>MR 1y, TB 1y</td>
<td>1</td>
<td>44.58***</td>
<td>4.72</td>
</tr>
<tr>
<td>MR 3y, GB 3y</td>
<td>2</td>
<td>24.46*</td>
<td>7.25</td>
</tr>
<tr>
<td>MR 5y, GB 5y</td>
<td>2</td>
<td>22.34*</td>
<td>8.11*</td>
</tr>
</tbody>
</table>

Note: LR statistics are reported against the alternative of full rank, $r = 2$. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

Table 2.9: Hypothesis test results for mortgage rates with swaps

<table>
<thead>
<tr>
<th>Term</th>
<th>Time</th>
<th>Unconditional</th>
<th>Conditional</th>
<th>Joint</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\mathcal{H}_{1,2}$</td>
<td>$\mathcal{H}^\beta$</td>
<td>$\mathcal{H}_{1,2}^{\alpha,\delta}$</td>
</tr>
<tr>
<td>MR 1</td>
<td>'00-'07</td>
<td>5.78</td>
<td>2.67</td>
<td>32.43***</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>7.86</td>
<td>0.50</td>
<td>5.81*</td>
</tr>
<tr>
<td>MR 3</td>
<td>'96-'07</td>
<td>5.87</td>
<td>2.79</td>
<td>9.94*</td>
</tr>
<tr>
<td></td>
<td>'00-'07</td>
<td>10.90***</td>
<td>1.41</td>
<td>32.22***</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>15.05</td>
<td>0.36</td>
<td>17.19***</td>
</tr>
<tr>
<td>MR 5</td>
<td>'96-'07</td>
<td>3.19</td>
<td>2.71</td>
<td>6.06</td>
</tr>
<tr>
<td></td>
<td>'00-'07</td>
<td>0.75</td>
<td>0.01</td>
<td>50.48***</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>67.37***</td>
<td>–</td>
<td>85.60***</td>
</tr>
</tbody>
</table>

Notes: This table reports the likelihood ratio test statistics for each of the hypotheses of interest in the following order: (1) $\mathcal{H}_{1,2}^\delta$ tests for the presence of asymmetric adjustments in the error-correction; (2) $\mathcal{H}^\beta$ tests for complete pass-through; (3)–(4) $\mathcal{H}_{i}^{\alpha,\delta}$ for $i \in \{1,2\}$ tests for weak exogeneity of the market rate and retail rate, respectively; (5) $\mathcal{H}_{2,3}^{\alpha,\delta,\Gamma}$ tests for strong exogeneity of the market rate; (6) $\mathcal{H}_{2,3}^{\alpha,\delta,\Gamma}$ tests for strong exogeneity conditional on complete pass-through; (7) $\mathcal{H}^\beta$ tests for complete pass-through conditional on strong exogeneity of the market rate; and (8) $\mathcal{H}_{2,3}^{\alpha,\delta,\Gamma} \cap \mathcal{H}^\beta$ tests the joint hypothesis of complete pass-through and strong exogeneity of the market rate. Results are based on 4,999 bootstrap samples. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. If the roots of the characteristic polynomial are inside the unit circle for a given hypothesis, the LR statistic is not reported.
Table 2.10: Coefficient estimates for mortgage rates with swaps

<table>
<thead>
<tr>
<th>Rate</th>
<th>Time</th>
<th>β</th>
<th>ρ</th>
<th>α₁</th>
<th>α₂</th>
<th>δ₁</th>
<th>δ₂</th>
<th>ψ</th>
</tr>
</thead>
<tbody>
<tr>
<td>MR 1y</td>
<td>'00-'07</td>
<td>-1.000</td>
<td>-1.977</td>
<td>-0.128</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>-1.000</td>
<td>-1.864</td>
<td>-0.012</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MR 3y</td>
<td>'96-'07</td>
<td>-1.000</td>
<td>-1.931</td>
<td>-0.041</td>
<td>0.000</td>
<td></td>
<td></td>
<td>2339.855</td>
</tr>
<tr>
<td></td>
<td>'00-'07</td>
<td>-1.000</td>
<td>-2.285</td>
<td>-0.489</td>
<td>0.000</td>
<td>0.406</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>-1.000</td>
<td>-2.289</td>
<td>-0.057</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MR 5y</td>
<td>'96-'07</td>
<td>-1.000</td>
<td>-1.981</td>
<td>-0.033</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>'00-'07</td>
<td>-1.000</td>
<td>-2.186</td>
<td>-0.253</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>-1.407</td>
<td>-1.354</td>
<td>-0.007</td>
<td>0.001</td>
<td>-2.057</td>
<td>-0.278</td>
<td>165.865</td>
</tr>
</tbody>
</table>

Notes: This table reports the coefficient estimates from the final restricted models: β and ρ are the coefficients for pass-through and markup presented in (2.2); α and δ are the linear and nonlinear adjustment coefficients, respectively, presented in (2.3) — subscript 1 is for the retail rate and 2 is for the market rate — and ψ is the parameter determining the behaviour of the logistic function in (2.4).

Again the weak exogeneity of the retail rate is rejected for all rates and time periods. Meanwhile, the market rate is strongly exogenous for all rates and time periods with the exception of the 5 year mortgage rate in the last period. With the same exception, pass-through is also complete for all rates and time periods. Although completeness and strong exogeneity are rejected conditionally for the 1 year mortgage separately in two different periods, the unconditional and joint hypothesis test results suggest that these restrictions should be imposed. The most striking differences are for the results on the symmetry hypothesis. The 1 year mortgage adjusts symmetrically in both periods and the 3 year mortgage rate adjusts symmetrically in the last period but not in 2000–2007.

Table 2.10 contains the coefficient estimates for the restricted models and reveals the direction of the asymmetry. The 3 year mortgage rate exhibits upward rigidity in 2000–2007. As mentioned in Section 2.4.2, since this asymmetry is not present in all of the rates, it is likely driven by competitive pricing behaviour as opposed to aversion to riskier loans that become more prevalent when rates increase. In the last period, the 3 year mortgage...
mortgage rate adjusts symmetrically although the likelihood-ratio test statistic for this hypothesis is large and the unrestricted coefficient estimate is $\hat{\delta}_1 = -0.408$, suggesting downward rigidity. Nevertheless, although the evidence for downward rigidity in the 3 year mortgage rate in the last period is weaker when using the swap rate as the relevant market rate, there is evidence of a switch in asymmetry suggesting less competitive pricing behaviour.

Since the majority of the hypotheses for the 5 year mortgage in the last period are rejected because of explosive roots, the coefficient estimates are left unrestricted. Although completeness is rejected, the pass-through coefficient is greater than 1, suggesting that it is indeed complete. Moreover, the sign on the impact coefficient is negative, which implies that the mortgage rate responds more quickly to a rate rise than a rate fall.

Despite the different proxy for banks’ cost of funding, the coefficient estimates are very similar to the ones in Table 2.7. The estimates of the mark-up are lower with the swap rates, which is due to the fact that the swap spreads are positive on average, but pass-through is complete for all rates and time periods. The downward rigidity found in the 5 year mortgage rate in Section 2.4.2 is robust to this different specification, but the conclusions on the adjustments of the 1 and 3 year mortgage rates are not. Upward rigidity for the 1 year rate mortgage in 2000–2007 and downward rigidity for the 3 year rate mortgage in the last period are no longer significant. Meanwhile the 3 year mortgage rate adjusts more quickly for a swap rate decline than for a rate increase in 2000–2007.

2.6 Conclusion

This chapter provides a comprehensive analysis of the transmission process from market rates to retail loan and deposit rates in Canada. In contrast to previous studies on Canadian retail rates, it is the first to test completeness and symmetry for both deposit and loan rates. Furthermore, the empirical model used for estimation and inference encompasses commonly used models in the IRPT literature. The nonlinear VECM estimates
the long-run equilibrium pass-through equation while accounting for short-run dynamics and asymmetric adjustments. In addition, the model allows for explicit testing of commonly made assumptions of exogeneity and reveals that the conclusions based on tests conditional on these assumptions can differ from those based on unconditional tests.

The results identify incomplete pass-through and asymmetric adjustment for various loan and deposit rates in different time periods. In the period 1983–1996, before the Bank of Canada set the Bank Rate to the upper bound of the corridor for managing the overnight rate, pass-through was incomplete only for the 1 year mortgage rate, however, all mortgage rates were rigid downwards. On the deposit side, asymmetries were present in rates of longer maturities but the direction of rigidity differed across products. Changes in GICs favoured the consumer while changes in the fixed term deposit favoured the bank. Before the onset of the financial crisis, in the period 1996–2007, pass-through was complete for all rates and asymmetric adjustment — in the form of downward rigidity — only appeared in the movements of long-term deposits and the 1 year mortgage (or the 3 year mortgage when swap rates are used). Finally, in the most recent period 2009–2015, pass-through has significantly declined for longer term deposits and asymmetric adjustment has reappeared for mortgage rates — although the presence of downward rigidity is only robust for the 5 year mortgage rate.

These results provide important information that is relevant for a better understanding of the transmission mechanism of monetary policy through the interest rate channel. If the Bank of Canada moves to increase rates in the future, we can expect mortgage rates to respond quickly and fully and deposit rates to adjust partially and sluggishly.

In contrast to the US and Europe, the pass-through from market to retail loan rates in Canada was resilient to the financial crisis. However, the presence of asymmetries and the decline in pass-through to deposit rates suggest that overall the transmission between money market rates and retail loan and deposit rates has weakened. The decline in pass-through is consistent with the effects of increased competitiveness in the face of funding
uncertainty (Ritz and Walther, 2015) and could be exacerbated by regulatory pressures. Thus, disentangling these channels as well as extending the analysis to other countries are natural next steps for future research.
Chapter 3

Unconventional monetary policy in a small open economy

3.1 Introduction

Following the 2008 global financial crisis, many central banks quickly exhausted their ability to stimulate economic activity as policy rates reached the zero lower bound (ZLB).\(^1\) To continue to encourage lending, they turned to unconventional measures including direct market interventions through large scale asset purchases and forward guidance to influence expectations of the future short rate. A focus of much of the recent literature has been to quantify the effects of these policies on long term rates, asset prices, credit costs and,

\(^1\)The ZLB, also called the effective lower bound, refers to the rate at which households and firms began to prefer to hold physical currency over bank deposits. Although this bound could potentially be negative (\textit{e.g.} due to convenience costs) we define it as 25 basis points (bps) to be consistent with central bank definitions at the time. At a target rate of 25 bps, banks earn zero interest on overnight loans but still pay a positive rate when they borrow. Note that if depository institutions are required to hold a certain level of balances at the central bank above the required reserves level, or if they simply desire to do so, then the policy rate can be set below zero. The Swiss National Bank, the Danish National Bank, the Swedish Riskbank, and the European Central Bank (ECB) were able to lower their policy rates below zero in 2014 and 2015 because of such requirements and desires for excess reserves. The Bank of Canada has recently indicated it would be willing to implement negative rates as well.
to a lesser extent, the real economy.\footnote{See, for example, Hamilton and Wu (2012), Swanson and Williams (2014), D’Amico and King (2013), Krishnamurthy and Vissing-Jorgensen (2011), and Gagnon, Raskin, Remache, and Sack (2010), among others, for studies that look at the impact on interest rates, term spreads, asset prices, and credit costs, and Dahlhaus, Hess, and Reza (2014) and Gambacorta, Hofmann, and Peersman (2014) for studies that look at the impact on the real economy.} Moreover, a majority of these studies have focused on the domestic effects of such policies in large open economies, most notably the US. In contrast, this chapter analyzes the effects of unconventional monetary policy measures in a small open economy, a topic which has hitherto received relatively little attention.\footnote{Note that there is a large literature on Japanese unconventional monetary policy from the early 2000s, which is separate from the literature we refer to here on US or small open economy unconventional monetary policies. See Bernanke and Reinhart (2004) for an overview of the state of the literature at that time.} Specifically, we measure the effects of the Bank of Canada’s actions while at the ZLB on the real Canadian economy.

There are two main challenges that we face in conducting our analysis. First, small open economies often respond strongly to foreign shocks. Therefore, to gain meaningful insight into the role of domestic monetary policy we must control for international variables. This motivates our selection of Canada, among several candidate small open economies that engaged in unconventional monetary policy following the global financial crisis, since international effects can be mostly captured by US variables. This greatly simplifies our analysis. Moreover, since the Canadian economy is relatively small, we can assume that its domestic shocks have little impact on the US, which also reduces the complexity of our study. In fact there is evidence that the direction of monetary spillovers globally is generally from the US to non-US markets, with limited evidence that there are spillovers in the reverse direction, even from other large open economies.\footnote{Rogers, Scotti, and Wright (2014) find this result for unconventional monetary policy, Ehrmann and Fratzscher (2005) find a similar result for conventional monetary policy.} We impose these assumptions via block-exogeneity restrictions à la Cushman and Zha (1997) in a two-country Bayesian structural vector autoregressive (B-SVAR) model. More recently SVAR models with block-exogeneity restrictions have been used to study the impact of...
U.S. monetary policy shocks on the Euro Area (Neri and Nobili, 2010), on Latin American countries (Canova, 2005), on a range of emerging markets (Maćkowiak, 2007), and on Canada (in an alternative model characterization) (Bhuiyan, 2012). Block-exogeneity assumptions have also been used in non-monetary policy spillover models, such as models of global commodity shocks on small open economies (Charnavoki and Dolado, 2014).

Second, capturing the stance of monetary policy is complicated by the fact that there is no variation in the target interest rate — the standard choice for a policy variable — at the ZLB. To get around this problem, the literature provides two alternatives: event study methods or standard SVAR models with a different policy variable such as the central bank balance sheet (Gambacorta et al., 2014; Dahlhaus et al., 2014; MacDonald, 2016), the term spread (Baumeister and Benati, 2013) or a shadow rate (Krippner, 2013; Wu and Xia, 2016). Event studies measure the response of financial variables, such as long term yields and asset prices, to monetary policy announcements. By focusing on the response around a very short time interval (typically 30 minutes), they are able to isolate monetary policy shocks that are not contaminated by any other important events. While insightful on the immediate response of financial variables, event studies are unable to capture the effects of monetary policy shocks on real variables, such as prices and output, because their response is much slower. Additionally, the event study captures only changes in market expectations that occur within the specified time interval, which itself may be misspecified. Using the central bank balance sheet as a policy variable in an otherwise standard SVAR directly tackles this issue. However, the balance sheet only captures the effects of large scale asset purchases and does not reflect other policies such as forward guidance.\footnote{Importantly, the balance sheet only reflects the actual implementation of LSAPs and not their announcements, which have been shown to have a significant stimulating effect on the economy. Krishnamurthy and Vissing-Jorgensen (2011) and Gagnon et al. (2010), among others, show unconventional monetary policy announcements had significant impacts on US financial markets. Neely (2015), Chen, Filaro, He, and Zhu (2015), and Bowman, Londono, and Sapriza (2015), among others, show that unconventional monetary policy announcements had significant impacts on foreign country financial markets. Eichengreen and Gupta (2014), and Dahlhaus and Vasishtha (2014) show the same is true for unconventional monetary policy tapering announcements.}
term spread captures the effect of both announcements and large scale asset purchases but by measuring these effects through the compression of the yield curve it cannot be constructed as an uninterrupted variable through conventional and unconventional episodes, as is also the case with the balance sheet. Moreover, counterfactuals using the term spread rely on outside estimates of the effects of large scale asset purchases on the spread. The alternative that we adopt in this study is to define the policy variable using an estimated shadow interest rate, which uses the term structure of interest rates to predict the level of the short-term rate as if it were not bounded below by zero.

Although the use of shadow rates comes at a cost of not being able to disentangle the effects of specific policies, it has several distinct advantages. The shadow rate provides a consistent measure of monetary policy stance for both central banks in our empirical model. Since the Bank of Canada’s unconventional monetary policy measures did not include large scale asset purchases, the shadow rate is more appropriate than the balance sheet as a policy variable. Furthermore, its flexibility also makes it appropriate as a policy variable for the Federal Reserve (the Fed) because it captures the effects of both forward guidance and large scale asset purchases. Moreover, since the shadow rate can be viewed as an extension of the traditional policy variable uninterrupted by the ZLB, we are able to begin our sample long before the ZLB episode and use the additional observations to improve the precision of our results.

We estimate our model for the period 1994–2015 and quantify the impact of unconventional monetary policies through counterfactual experiments that restrict the shadow rate to the ZLB. Our main finding is that Canadian unconventional monetary policy had expansionary effects on the Canadian economy, boosting output by approximately 0.23 percent per month on average during the ZLB episode. This result is robust to several different specifications. Our setup also allows us to investigate the effects of US unconventional monetary policies on the Canadian economy. We find that Canadian output would have been approximately 1.21 percent lower per month on average without US
unconventional monetary policies.

This chapter is most closely related to other studies seeking to quantify the effects of unconventional monetary policy measures in Canada. An early effort to assess the impact of forward guidance on Canadian interest rates by He (2010) considers the relationship between interest rates, inflation and unemployment, and shows that the Bank of Canada’s conditional commitment on interest rates effectively reduced yields, albeit not statistically significantly. Chang and Feunou (2013) study changes in implied and realized volatility around important Bank of Canada announcement days, and find that forward guidance, the expansion of liquidity, and policy rate cuts successfully reduce market volatility. Gambacorta, Hofmann, and Peersman (2014) use central bank balance sheets to assess the effectiveness of monetary policy at the ZLB domestically. For Canada, as well as 7 other countries, the authors find that a positive shock to the balance sheet increased economic activity and consumer prices but, compared to conventional times, the effect on inflation was weaker and less persistent. There are two important distinctions between these studies and ours. First, they do not control for potential spillovers from the US and second, they do not evaluate the total effect of all unconventional monetary policies on the economy.

Including the US in our analysis ties our work to a strand of literature that measures the effects of US unconventional monetary policy spillovers. Fratzscher, Lo Duca, and Straub (2013) analyze the impact of 12 key quantitative easing (QE) announcements by the Fed and their impact on net inflows of bonds and equities, equity price returns, long-term bond yields, and exchange rate returns of 65 advanced- and emerging-market-economy countries (including Canada) in a panel regression. They find that QE 1 and 2 lowered sovereign yields and raised equity prices but that there was substantial heterogeneity in spillover effects between emerging market economies and advanced economies.

\footnote{Fratzscher, Lo Duca, and Straub (2014) perform a similar analysis but for European Central Bank QE announcements.}
Bauer and Neely (2014) use an event study within a dynamic term structure framework to identify the transmission channels for unconventional US monetary policy. According to their results, the LSAP programs had a large effect on Canadian long-term yields, bringing them down significantly through a signalling and portfolio balance channels. Neely (2015) also uses an event-study and finds large effects on Canadian yields and the exchange rate. Dahlhaus et al. (2014) evaluate the spillovers from QE on the Canadian economy with quarterly data from 2008Q4 to 2013Q3. Using a factor-augmented VAR (FAVAR) model and the Fed’s balance sheet as the policy instrument, they compare the impact of QE on Canadian variables to a counterfactual scenario in which the balance sheet continues to grow at the pre-crisis rate. They find that QE had a positive impact on Canadian output and that Canadian asset prices and interest rates move in tandem with their US counterparts. Our study is distinct from these because we carefully model the domestic monetary policy in the spillover country, and, by using the shadow rate, we incorporate both announcement and balance sheet spillovers.

Recent concerns about the large adverse cross-border spillovers of unconventional monetary policies have rekindled the discussion of international coordination of monetary policy (Taylor, 2013; Engel, 2015). It has been argued that countries who are responsible for substantial international monetary policy spillovers need to acknowledge their role in influencing foreign economies, and to consider feasible remedies to limit such spillovers (Blanchard, Ostry, and Ghosh, 2013; Mishra and Rajan, 2016). Our work contributes to an alternative perspective on unconventional monetary policy spillovers, and shows that under certain circumstances they can be favourable.

This chapter is structured as follows. The next section describes our measure of unconventional monetary policy. Section 3.3 presents the data and method. Our main analysis, which studies the effect of Canadian and US monetary policy on the Canadian economy, closely follows Charnavoki and Dolado (2014) who analyze the effects of commodity price shocks on Canada using a structural dynamic factor model.
economy from 1994–2015, is discussed in Section 3.4. We conduct several robustness exercises, by considering alternative model specifications. Results for these exercises are reported in Section 3.5. Section 3.6 concludes.

### 3.2 Measuring unconventional monetary policy

This section briefly discusses the scope of unconventional monetary policies enacted by the Bank of Canada and the Fed and presents the shadow rate as an appropriate proxy for capturing their effects.

The Bank of Canada targets inflation by influencing its target for the overnight rate (the “target rate”). There are eight fixed announcement dates annually, upon which it reports whether or not it will adjust the target rate. It also has an explicit policy not to intervene in the Canadian currency market. On April 21, 2009, in coordination with other central banks, the Bank of Canada lowered the target rate from 50 bps to 25 bps, considered at the time its effective lower bound. Along with the rate cut, the Bank of Canada reduced the operating band from 50 bps to 25 bps and set the target rate to the lower bound of this range (25 bps). Aiming to reduce uncertainty in Canadian financial markets, the Bank of Canada committed to keep the target rate unchanged until the end of the second quarter of 2010, conditional on inflation expectations. The Bank of Canada further reinforced the upper bound on the operating band (at 50 bps) through its standing liquidity facility (SLF), which provided access to overdraft loans at the bank rate for the Bank’s Large Value Transfer System (LVTS) participants, and by prorating access to new standing purchase and resale agreements (PRAs) at the bank rate for Canadian primary dealers.\(^8\) The Bank of Canada reinforced the lower bound on the operating band by providing LVTS participants with access to a standing deposit facility on which they could earn the deposit rate and by conducting sale and repurchase agreements (SRAs)

---

\(^8\)The Bank of Canada targets the overnight rate in the LVTS, which allows transfers of large payments with a guarantee of settlement.
intraday at 25 bps with primary dealers, if required. Finally, the Bank of Canada targeted daily settlement balance levels at $3 billion, a dramatic increase from the small positive balance target during conventional times (Bank of Canada, 2010). With market conditions improving, the statement of this commitment was removed on April 20, 2010. On June 1, 2010 the target rate was raised to 50 bps, and the standard operating framework was reestablished.

The federal funds rate reached the ZLB in December 2008 at which point the Fed began engaging in unconventional monetary policies, including LSAP purchases and announcing commitments to remaining at the ZLB and continue the LSAP program. LSAPs involved purchases of asset with medium- and long-term maturities, including US Treasuries, mortgage-backed securities, Federal agency debt, and currency swaps. These purchases were meant to lower the cost of long-term private borrowing, or flatten yield curves. The Fed conducted several rounds of LSAPs: QE1 (December 2008–March 2010), QE2 (November 2010–June 2011), and QE3 (September 2012–October 2014). The Fed’s commitment to LSAPs and the 0 to 0.25 bps rate range was meant to reduce uncertainty in US financial markets and stimulate the economy. Importantly, the central bank target rates do not reflect any of these actions because of the ZLB.

3.2.1 Shadow rates

The shadow rate term structure model (SRTSM), first proposed by Black (1995), confronts the issue of modelling interest rates at the ZLB. Since economic agents have the option to hold physical currency for a rate of return of zero, deposit rates are bounded below by this constraint. However, standard term-structure (Gaussian affine term-structure or GATSM) models are linear in factors and thus allow for the possibility of estimating

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9The Fed also conducted Operation Twist in September 2011, which involved purchases of bonds with long-term maturities and sales of bonds with short-term maturities. This operation left the overall size of the Fed’s balance sheet unchanged.
negative yields.\textsuperscript{10} Black (1995) proposed thinking of the observed nominal rate, \( r_t \), as the sum of an unobserved and unrestricted shadow rate, \( sr_t \), which can go negative and the option value of holding physical currency that is exercised at the effective lower bound, \( r \). Specifically,

\[
    r_t = \max\{sr_t, r\} = sr_t + \max\{0, r - sr_t\}.
\]

Note that when the shadow rate is above the ZLB, the option value of holding currency is zero. However, when the shadow rate begins to dip below the ZLB, the currency option begins to have an effect. Fitting this model to the data allows us to back out an estimate of the shadow rate process.

There are several benefits to using the shadow rate as a measure of unconventional monetary policy. First, the shadow rate captures both the signalling and portfolio balance channels of central banks actions. While the Fed’s LSAPs were meant to flatten yield curves, Fed announcements were meant to reduce both future rate expectations and uncertainty in financial markets. Measuring monetary policy by either the balance sheet or Fed announcements alone would then only capture one of the two channels. By taking information from the entire yield curve, the shadow rate captures both channels as well as forward guidance and other actions. Second, the shadow rate provides us with an uninterrupted measure of monetary policy through conventional and unconventional-ZLB episodes. This allows for more precise estimation as we can extend the time series beyond the ZLB period. The nature of the variable also allows us to study whether there are significant differences in the effects of monetary policy at or away from the ZLB.

Despite its many advantages, estimating the SRTSM is significantly more involved

\textsuperscript{10}Some models specify the short-rate diffusion process as quadratic or square-root to avoid negative rates. However, these specifications do not have theoretically consistent assumptions as they treat the ZLB as a reflecting barrier rather than an absorbing one. See Christensen and Rudebusch (2014) for a detailed discussion.
than estimating a short rate in a standard term structure model. The main difference between the shadow rate defined by a SRTSM and a traditional short rate defined by a GATSM model is the non-linearity that the max operator introduces. This non-linearity implies that there is no analytical solution to the model. While Krippner (2012, 2013) and Bauer and Rudebusch (2013) use numerical simulation methods to solve for the rate, Wu and Xia (2016) take an alternative approach and derive an approximate solution to the shadow rate as a function of the yield curve and the probability that the shadow rate will fall below the effective lower bound.\footnote{Specifically, they solve the shadow rate by defining it in a nonlinear state space model, where the shadow forward rate depends on the probability of the short rate being at its ZLB and a vector of state variables. The model is solved using the extended Kalman filter. The observed state variables are the forward rates associated with the 3 month, 6 month, 1, 2, 5, 7, and 10 year yields on zero coupon bonds from the Gürkaynak, Sack, and Wright (2007) dataset.} This method provides a tractable analytical approximation of the shadow rate, and does not require numerical simulation.

We take the estimate of the US shadow rate directly from Wu and Xia (2016), and we adopt their method to estimate a Canadian shadow rate which is briefly outlined here.\footnote{See Wu and Xia (2016) for the complete derivation of the state space model for the SRTSM.} The Canadian SRTSM is constructed as a nonlinear state space model estimated with the extended Kalman filter. The Canadian shadow rate is assumed to be an affine function of state variables, \( X_t \):

\[
\text{sr}_t = \delta_0 + \delta_1' X_t.
\]  

(3.2)

Our state variables are the forward rates derived from the Bank of Canada’s zero-coupon bond yield data for 3 month, 6 month, 1, 2, 5, 7, and 10 year maturities (Bolder, Johnson, and Metzler, 2004). We assume the state variables follow a first order vector autoregressive (VAR(1)) process under the physical measure \( \mathbb{P} \),

\[
X_{t+1} = \mu + \rho X_t + \Sigma \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim N(0, I),
\]  

(3.3)
which is the transition equation. The log stochastic discount factor is essentially affine

\[ M_{t+1} = \exp \left( -r_t - \frac{1}{2} \lambda_t' \lambda_t - \lambda_t' \varepsilon_{t+1} \right), \]  

(3.4)

where the price of risk \( \lambda_t \) is linear in the factors: \( \lambda_t = \lambda_0 + \lambda_1 X_t \). The dynamics under the risk neutral measure \( Q \) also follow a VAR(1)

\[ X_{t+1} = \mu^Q + \rho^Q X_t + \Sigma \varepsilon_{t+1}^Q, \quad \varepsilon_{t+1}^Q \sim Q N(0, I). \]  

(3.5)

The parameters under the \( P \) and \( Q \) measures are related as follows: \( \mu - \mu^Q = \Sigma \lambda_0 \) and \( \rho - \rho^Q = \Sigma \lambda_1 \).

An analytical approximation of the forward rate in the SRTSM is generated by defining a forward rate, \( f_{n,n+t,t} \), as the rate at time \( t \) for a loan starting at \( t + n \) and maturing at \( t + n + 1 \). The forward rate is a linear function of the yields on risk-free \( n \) and \( n + 1 \) period pure discount bonds \( q \)

\[ f_{n,n+t,t} = (n + 1) q_{n+t,t} - n q_{nt}. \]  

(3.6)

The forward rate in the SRTSM described in equations (3.2)–(3.5) is approximated by

\[ f^{SRTSM}_{n,n+t,t} = r + \sigma_n^Q g \left( \frac{a_n + b_n' X_t - r}{\sigma_n^Q} \right) \]  

(3.7)
where
\[ a_n = \delta_0 + \delta'_1 + \left( \sum_{j=0}^{n-1} (\rho^Q)^j \right) \mu^Q - \frac{1}{2} \delta'_1 \left( \sum_{j=0}^{n-1} (\rho^Q)^j \right) \Sigma \left( \sum_{j=0}^{n-1} (\rho^Q)^j \right)' \delta_1, \]
\[ b'_n = \delta'_1 (\rho^Q)^n, \text{ and} \]
\[ \text{Var}_t(Q_{s+n}) \equiv (\sigma^Q_n)^2 = \sum_{j=0}^{n-1} \delta'_1 (\rho^Q)^j \Sigma \Sigma' (\rho^Q)^j \delta_1. \]

The function \( g(z) \equiv z \Phi(z) + \phi(z) \) consists of a normal cumulative distribution function \( \Phi(\cdot) \) and a normal probability density function \( \phi(\cdot) \). Its non-linearity comes from the moments of the truncated normal distribution.\(^{13}\)

Finally, we define a measurement equation that relates the observed forward rate, \( f_{n,n+t,t} \), to the factors, based on equation (3.7), as follows
\[ f_{n,n+t,t} = r + \sigma^Q_n g \left( \frac{a_n + b'_n X_t - r}{\sigma^Q_n} \right) + \eta_{nt}, \tag{3.8} \]
where the measurement error \( \eta_{nt} \) is i.i.d. normal, \( \eta_{nt} \sim N(0, \omega) \). Finally, using the same identification assumptions as Wu and Xia (2016), we assume a three factor model and impose normalizing restrictions on the \( Q \) parameters: \( \delta = [1, 1, 0]' \); \( \mu^Q = 0 \); and \( \Sigma \) is lower triangular. We also assume \( \rho^Q \) is real Jordan form with eigenvalues in descending order: \( \rho^Q = [\rho^Q_1 \ 0 \ 0; 0 \ \rho^Q_2 \ 0; 0 \ 0 \ \rho^Q_3] \). The model is estimated using the extended Kalman filter with equation (3.8).

Figure 3.1 plots our estimated Canadian shadow rate and the US shadow rate, spliced with the Bank of Canada target rate and federal funds target rate when these policy rates were at the ZLB. The Canadian shadow rate reached its lowest point of approximately \(-0.34\%\) in November 2009, at which point the Bank of Canada was midway through its conditional commitment mandate and was actively engaging in liquidity provision

\(^{13}\)For details of the derivation of (3.7), see the appendix in Wu and Xia (2016).
Figure 3.1: Canadian and U.S. Policy Rates (1994–2015)

(a) Canadian Policy Rate

(b) US Policy Rate

Source: FRED, Statistics Canada CANSIM, Bank of Canada, Wu and Xia (2016), and authors’ own calculations. Note: The federal funds rate is the target federal funds rate before November 2008 and the upper bound of the federal funds rate from November 2008 onwards.

activities. The US shadow rate was decreasing from 2008 through 2014, reaching a low of −2.99 percent. Throughout this period the Fed engaged in three rounds of QE and made numerous statements regarding continued policy easing.
3.2.2 Event study

Since we are the first to estimate a shadow rate for Canada, we begin by assessing whether its movements are consistent with the actions taken by the Bank of Canada during the ZLB.\textsuperscript{14} Specifically, we conduct an event study around Bank of Canada policy announcements. We note, however, that an event study is not ideal. Our shadow rate can be estimated at a daily frequency at most, which is often considered too low to identify any effects from central bank announcements.\textsuperscript{15} Furthermore, the ZLB episode was relatively short for Canada and thus the number of monetary policy events is limited. As a result, we are cautious when interpreting our results and treat the event study more as a consistency check than a careful empirical exercise.

The Bank of Canada made several announcements during the ZLB period, three of which were particularly important: the announcement that the short rate was being lowered to 25 bps and would remain there until the second quarter of 2010 (April 21, 2009), the announcement that the Bank of Canada’s conditional commitment to the ZLB was being removed (April 20, 2010), and the announcement that the short rate was being raised to 50 bps (June 1, 2010). We include several other announcements in our event study that relate to the Bank of Canada’s extraordinary liquidity operations during the ZLB, but we suspect, \textit{a priori}, that these events may have a lesser impact on the shadow rate than the others as they were less widely reported or known outside of the traditional banking sector.

First, we look at the one-day changes in the shadow rate on announcement dates. We define the change in the shadow rate on announcement days as tail events if there was a statistically significant change in the shadow rate, based on standard errors calculated

\textsuperscript{14}In their paper, Wu and Xia (2016) show that there was no substantive difference in the response of US macroeconomic variables to the US shadow rate at and away from the ZLB. We do not repeat that exercise here.

\textsuperscript{15}This is because the Bank of Canada’s zero coupon bond yield curve data, which is the observed data used in the state space model to estimate the shadow rate, is available only at the daily frequency.
Table 3.1: Bank of Canada announcements and shadow short rate changes

<table>
<thead>
<tr>
<th>Date</th>
<th>$\Delta sr_t$</th>
<th>Event Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 21, 2009</td>
<td>−0.0964***</td>
<td>BoC announces operating framework for the implementation of monetary policy at the effective lower bound for the target rate, lowers target rate target to 1/4 percent, introduces conditional commitment to hold current policy rate until the end of the second quarter of 2010 and announces term PRA transaction schedule.</td>
</tr>
<tr>
<td>April 24, 2009</td>
<td>−0.0408</td>
<td>BoC announces term PRA, term PRA for private sector instruments, and TLF transaction schedules.</td>
</tr>
<tr>
<td>June 25, 2009</td>
<td>−0.0097</td>
<td>BoC announces extension of TLF and expanded swap facility with the Fed as well as temporary reciprocal currency arrangements (swap lines) between the Fed and other central banks extended to 1 February 2010.</td>
</tr>
<tr>
<td>July 21, 2009</td>
<td>−0.0014</td>
<td>BoC announces term PRA, term PRA for private sector instruments, and TLF transaction schedules.</td>
</tr>
<tr>
<td>September 23, 2009†</td>
<td>−0.0124</td>
<td>Reflecting the improved conditions in funding markets the BoC announced term PRA Facility for private sector instruments (after a final operation on October 27, 2009) and TLF (after a final operation on October 28, 2009) will expire at the end of October 2009.</td>
</tr>
<tr>
<td>October 20, 2009</td>
<td>−0.0914***</td>
<td>BoC announces another term PRA transaction schedule.</td>
</tr>
<tr>
<td>November 6, 2009†</td>
<td>−0.0056</td>
<td>Given improved conditions in funding markets the BoC announces that temporary measure of allowing LVTS participants to assign their non-mortgage loan portfolios as eligible collateral for LVTS and SLF purposes will be gradually reduced from 100 per cent to 20 per cent of each participant’s total pledged collateral starting February 2, 2010.</td>
</tr>
<tr>
<td>December 16, 2009†</td>
<td>0.0282</td>
<td>Given improved conditions in funding markets the BoC announces term PRA operations will be held on a monthly basis, rather than bi-weekly, and that only Canadian dollar securities eligible as collateral under the BoC’s SLF will be eligible for term PRAs effective January 19, 2010. Affiliated-dealer bank-sponsored ABCP, and BBB corporate bonds will no longer be eligible.</td>
</tr>
<tr>
<td>April 20, 2010</td>
<td>0.1110***</td>
<td>BoC maintains target rate at 1/4 per cent and removes conditional commitment.</td>
</tr>
<tr>
<td>May 10, 2010†</td>
<td>0.0873**</td>
<td>BoC and the Fed reestablish US$30 billion swap facility (reciprocal currency arrangement) that had expired on February 1, 2010.</td>
</tr>
<tr>
<td>June 1, 2010</td>
<td>−0.0478</td>
<td>BoC increases target rate to 1/2 per cent and reestablishes normal functioning of the overnight market as well as the standard operating framework for the implementation of monetary policy. The target for the target rate is set to the midpoint of the operating band and the width of the operating band to 50 bps.</td>
</tr>
</tbody>
</table>

Notes: This table contains a list of major policy events and the corresponding changes in the shadow rate. *, **, and *** represent tail events with respect to a normal distribution at the standard 10, 5, and 1 percent confidence levels. † marks announcement dates that were made the day before but after markets closed.

assuming a normal distribution (following Bowman et al., 2015). On several occasions the Bank of Canada made their announcements late in the day, either near to or after financial market closing. In these cases we look at the next-day change in the shadow rate for our analysis. The dates, event descriptions and one-day changes in the shadow short rate are reported in Table 3.1. We see that two of the three main ZLB announcements
Table 3.2: Effect of Bank of Canada Announcements on Shadow Short Rate

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta sr_t$</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansionary Announcement</td>
<td>$-0.025^*$</td>
<td>$-0.019$</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Contractionary Announcement</td>
<td>0.015</td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>FAD</td>
<td></td>
<td>$-0.014$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>MPR</td>
<td></td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
</tr>
<tr>
<td>N</td>
<td>280</td>
<td>280</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses. Data frequency is daily. Period is April 20, 2009 – June 1, 2010, corresponding to the Canadian ZLB period when the Bank of Canada Bank Rate was at 25 basis points. Expansionary announcements include all PRA announcements, TLF announcements, and SLF announcements. Contractionary announcements include announcements regarding the end or reduction of the PRA, TLF, or SLF operations. FAD and MPR dummy variables are equal to one on dates that the Bank of Canada released FAD document or the monetary policy report.

by the Bank of Canada were associated with tail events in changes in the shadow short rate — the April 21, 2009 announcement of the shift to the ZLB and the April 20, 2010 removal of conditional commitment. The announcement of exit from the ZLB on June 1, 2010 was not associated with a significant shift in the ZLB, we suspect because after the removal of conditional commitment the increase in the interest rate was widely expected.

We also estimate an event study regression to verify the robustness of the results. We regress the daily change in the estimated shadow rate on a set of dummy variables for expansionary and contractionary announcements. Results are reported in Table 3.2, column (1). As expected, we see that expansionary announcements were associated with a significant fall in the shadow rate and contractionary announcements were associated with a rise (albeit not statistically significant). The signs on the coefficient estimates are robust to including dummy variables for the Bank of Canada’s fixed announcement dates (FADs) and monetary policy report releases (MPR), reported in column (2), which we
include to control for market reaction on anticipated announcement days.

Both the magnitude and direction of the change in the shadow rate in response to policy announcements are consistent with the behaviour of the Bank rate during conventional times. Therefore, we proceed with our empirical analysis and use the shadow rate as our policy indicator during the ZLB.

3.3 Small open economy B-SVAR model

We model the dynamic interaction of the variables in the two countries using a structural vector autoregression,

$$AY_t = C + \sum_{l=1}^{p} B_l Y_{t-l} + \varepsilon_t,$$

where $Y_t$ is an $n \times 1$ vector of endogenous variables, $A$ and $B_l$ are $n \times n$ parameter matrices, $\varepsilon_t$ is an $n \times 1$ vector of structural shocks with $E(\varepsilon_t|Y_1, ..., Y_{t-1}) = 0$ and $E(\varepsilon_t\varepsilon_t'|Y_1, ..., Y_{t-1}) = I_n$.

Introducing the small open economy assumption that Canada cannot influence US variables involves imposing block exogeneity restrictions on the parameters $A$ and $B_l$. This greatly reduces the number of parameters to be estimated, despite the number of overall parameters increasing with the inclusion of US variables, which are meant to capture international influence on Canadian variables. We follow Cushman and Zha (1997) and assume that the endogenous variable vector $Y_t$ comprises two blocks: a Canadian block $Y_{t,\text{CAN}}$ and a US block $Y_{t,\text{US}}$. We allow the Canadian block to respond to the US variables both contemporaneously and with a lag, but restrict the US block to be self contained and not influenced by the dynamics in the Canadian variables. Specifically, we impose the restrictions in the following way

$$\begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix} \begin{bmatrix} Y_{t,\text{CAN}} \\ Y_{t,\text{US}} \end{bmatrix} = \begin{bmatrix} F_{11} & F_{12} \\ 0 & F_{22} \end{bmatrix} \begin{bmatrix} Z_{t,\text{CAN}} \\ Z_{t,\text{US}} \end{bmatrix} + \begin{bmatrix} \varepsilon_{t,\text{CAN}} \\ \varepsilon_{t,\text{US}} \end{bmatrix},$$
where $F = [C, B_1, \ldots, B_p]$ and $Z_i = [I, Y_{t-1}^i, \ldots, Y_{t-p}^i]'$ for $i = \{\text{CAN, US}\}$.

For the Canadian block, our main specification includes the Canadian policy rate, $r$; seasonally-adjusted real Canadian industrial production, $y$; the Canadian consumer price index, $p$; the Canadian/US dollar exchange rate, $s$; and the Canadian current account balance, $CA$. For the US block, we include seasonally-adjusted real US industrial production, $y^*$; the US consumer price index, $p^*$; commodity export prices, $wpx$; the implied volatility of the S&P 500 index, $VIX$; and the US policy rate, $r^*$. Detailed data definition and sources are provided in Table B.1 of Appendix B.1.

All variables are in logs except for the two policy rates, which we construct using (3.1), i.e. splicing the Bank of Canada target rate and the federal funds rate with their respective shadow rates whenever the shadow rates are below the 25 bps ZLB. The Canadian shadow rate is calculated as described in Section 3.2.1, using Canadian zero coupon bond yield curve data derived by Bolder, Johnson, and Metzler (2004).\footnote{Data is available at http://www.bankofcanada.ca/rates/interest-rates/bond-yield-curves/.

We use the US shadow rate provided by Wu and Xia (2016). Using the policy rate, as defined in (3.1), allows us to extend the data much farther and treat both central banks as if they have a constant reaction function but a varying set of policy instruments at the ZLB. Including multiple business cycles gives our estimates more precision. The data is monthly and covers July 1994 to October 2015. The beginning of our sample coincides with a notable shift in the Bank of Canada’s operating procedure as it adopted a corridor system and shifted to targeting the overnight rate as its key monetary policy instrument.\footnote{The corridor system establishes a 50bp operating band target around the target rate.} This change was part of a broader transition in the 1990s to targeting two percent inflation and improving both the clarity and efficiency of monetary policy.\footnote{The Bank of Canada officially began targeting inflation in 1991, introduced the LVTS in 1999 and adopted eight annual fixed announcement days in 2001.}

Our identification is based on exclusion restrictions in the contemporaneous coefficient matrix $A$. We assume that the Bank of Canada reacts contemporaneously to the exchange
rate, the US policy rate, the VIX and commodity prices, but not to any other variables because information on output, prices and current account balances arrives with a delay. Including commodity prices is particularly important for decision making by the Bank of Canada for two reasons. First, commodity prices adjust very quickly to market conditions and hence they control for future price expectations, i.e. they help mitigate the price puzzle often found in similar SVAR analyses, and second, since Canada is a commodity exporter, commodity prices have a large impact on Canadian output as well as the value of the Canadian dollar. Following Gambacorta et al. (2014), we include the VIX as a proxy for financial turmoil, economic risk, and uncertainty, which played a critical role in the latter part of our sample. We control for current account balances to capture both the trade balance as well as international receipts and payments of income. From 1994–2015 receipts of income from abroad accounted for 9 percent of all current account receipts, and payments of income from abroad account for 15 percent of current account payments, on average, in Canada. By simply looking at the trade balance we miss a substantial component of Canadian international borrowing and lending.\footnote{Secondary income (transfers) accounts for only one percent of current account credits and 2 percent of current account debits, on average.} We let the exchange rate react contemporaneously to all variables, domestic and foreign, in the model and assume that the production sector of the Canadian economy takes an upper triangular form with the variables ordered \((CA, p, y)\).\footnote{Results are robust to ordering \(CA\) last, and are available upon request.} The US block takes an upper triangular form, ordered \((r^\ast, VIX, wxp, p^\ast, y^\ast)\), so that output and prices cannot respond to a monetary policy shock within the same month.

The total number of restrictions on the contemporaneous coefficient matrix is 64. However, since we need only \(n(n-1)/2 = 45\) restrictions for exact identification, the model is overidentified. Although overidentification permits a more sensible set of restrictions than a recursive ordering, it imposes restrictions on the reduced-form covariance matrix, \(A^{-1}A^{-1}' = \Omega\), which complicates the estimation. The posterior distribution of \(\Omega\) does
not have a convenient form and regular Monte Carlo integration methods cannot be used. Cushman and Zha (1997) use the importance sampler, but Waggoner and Zha (2003) show that it is inefficient in the presence of overidentifying restrictions. They propose a Gibbs sampler which yields more accurate results. We follow this method, and use 2000 draws, discarding the first 1000 to ensure that the initial values do not affect the posterior distribution. We use the Sims and Zha (1998) prior and set loose values for all hyper-parameters except for the lag decay.\footnote{We set $\mu_i = 10$ for $i = 1, \ldots, 6$.} We estimate the model with 12 lags and report 68\% error bands as well as the medians of the posterior distribution.

Prior to estimation, we check the validity of the overidentifying restrictions. Since the contemporaneous coefficient matrix is overidentified, we cannot directly test block exogeneity in the reduced form VAR. Similarly, we cannot directly test overidentifying restrictions because of block exogeneity imposed in the contemporaneous coefficient matrix. As a result, we follow Cushman and Zha (1995, 1997) and perform a joint likelihood ratio test for overidentification and block exogeneity in the contemporaneous coefficient matrix and block exogeneity in the lagged coefficient matrices (a total of 319 restrictions). This test rejects the null hypothesis, but we nevertheless choose to keep the model as specified.

We have explored a variety of different models based on alternative variables (including deterministic trends), lag selections, and time periods and did not find any specification that resulted in a sufficiently large increase in the $p$-value of the likelihood ratio test, while also satisfying the underlying small open economy theory. We suspect this result could be driven by an omitted variable or poor small sample properties of this non-standard test. We plan to explore these possibilities in future research.

3.4 Results

We first consider the dynamic response of the variables in our system to both domestic and foreign expansionary monetary policy shocks and then use the estimated system to
The impulse response functions from a 25 bps expansionary shock to Canadian monetary policy are shown in Figure 3.2. Prices, output, and the exchange rate respond to this shock in accordance with theoretical models and existing empirical evidence. That is, an expansionary monetary policy shock raises output and prices significantly on impact, and for approximately 24 months after the initial shock. The currency depreciates on impact, and appreciates as the interest rate rises. While the Canadian dollar is weaker, a fall in the current account is consistent with a fall in the trade balance driven by rising Canadian income increasing demand for imports. This suggests an income effect is outweighing any exchange rate effect on the current account balance.\footnote{One would also expect that as Canadian interest rates fall, net investment income payments to foreigners would also fall, which would imply a rise in the current account balance. However, as net exports make up approximately 90 percent of the Canadian current account balance, it is likely that the income effect on net exports outweighs any change in investment income payments due to lower interest rates.}

The impulse response functions from a 25 bps expansionary shock to US monetary
policy for both Canadian and US variables are shown in Figure 3.3. Though our primary focus is on the impact to Canadian variables, we find the response of US variables in Figures 3.3(a)–3.3(e) is generally consistent with theoretical and empirical literature.\footnote{The impact on the US economy has been studied extensively, as discussed in Section 3.1. We have not attempted to model the US economy explicitly here, but rather include those US variables which are important to Canadian spillovers.}
Following the US monetary policy shock, US equity market volatility falls significantly, output rises significantly, and prices fall significantly (this price puzzle is commonly found in the recursive SVAR literature), all with a delay of approximately 1–2 years.

Figure 3.3(f) shows a strong response from the Canadian policy rate both on impact and for over two years following the initial shock. The Canadian dollar depreciates, as shown in Figure 3.3(g), along with a fall in the policy rate. Both variables reach their minimum after approximately 18 months. Canadian output, shown in Figure 3.3(j), rises in response to the US monetary policy shock and exhibits the same delay as US output, demonstrating the strong spillover effects from US monetary policy. Canadian prices fall in the first month and then rise albeit not significantly. The current account balance rises on impact, briefly falls after approximately eight months, and then falls again after three years. This pattern is consistent with an initial fall in investment income payments as the Canadian interest rate falls, followed by a fall in net exports as Canadian output rises and the income effect becomes more important.

In summary, we find that a Canadian expansionary monetary policy shock boosts domestic prices and output and depreciates the Canadian dollar. A US expansionary monetary policy shock increases US output, and has strong spillover effects on Canada, operating through both the exchange rate and the endogenous response of the Bank of Canada.

3.4.1 Effects of unconventional monetary policy

In order to quantify the effects of unconventional monetary policy we conduct a counterfactual experiment proposed by Wu and Xia (2016), where we simulate a scenario in which the shadow rate remains at 25 bps (the ZLB) while the other variables remain unrestricted. We assume that, since the nominal rate is bounded by 25 bps, any movement in the policy rate below this bound is driven by unconventional monetary policies. As a result, our estimates can be considered an upper bound on the effect of unconventional
monetary policy.

We begin with the historical decomposition, which decomposes each variable in $Y_t$ into the contribution from the initial value, the constant term and the structural shocks,

$$Y_t = G^t Y_0 + \sum_{i=1}^{t} G^t C + \sum_{i=1}^{t} \Psi_{i-1} \varepsilon_{t-i+1},$$

(3.9)

where $G = A^{-1} F$ and $\Psi_i$ is the set of coefficients for the impulse response function in period $i$. We use this equation to calculate the paths of the variables under different scenarios by manipulating the set of contributing structural shocks. The scenarios we are interested in are those that restrict the shadow rate to 25 bps for Canada and the US.

For Canada, the counterfactual is implemented by replacing the realized monetary policy shock, $\varepsilon_{t}^{MP\text{\text{CAN}}}$ in (3.9), with a counterfactual shock, $\tilde{\varepsilon}_{t}^{MP\text{\text{CAN}}}$, such that the shadow rate respects the lower bound, $\tilde{s}_t = 0.25$ when the actual target rate was at 25 bps. Similarly for the US, the counterfactual is implemented by replacing replace $\varepsilon_{t}^{MP\text{\text{US}}}$ in (3.9) with $\tilde{\varepsilon}_{t}^{MP\text{\text{US}}}$, such that $\tilde{s}_t^* = 0.25$ when the federal funds rate was at the ZLB. The path of each variable is then simulated under these two scenarios.

**Restricted monetary policy in Canada**

Figure 3.4 reports the results for our first experiment which restricts Canadian unconventional monetary policy. We show each original series with its counterfactual path, which we interpret as what the state of the economy would have been had the Bank of Canada been unable to provide any additional stimulus beyond lowering the target rate to 25 bps.

Figure 3.4(a) visually demonstrates how the counterfactual scenario is constructed:

---

24 We have also conducted a third counterfactual experiment that replaces both the Canadian and US monetary policy shocks with their counterfactual shock so as to make both the Canadian and US shadow rates constrained at $\tilde{s}_t = \tilde{s}_t^* = 0.25$. Because the impact of US unconventional monetary policy is so large relative to Canadian unconventional policy (as reported in this section), the results from this experiment are essentially unchanged from the US counterfactual experiment. We thus do not report these results, but note that they are available upon request.
while the shadow rate is below 25 bps during the period 2009–2010, we restrict it to be bound by this lower limit for the counterfactual path. Figure 3.4(e) (which is zoomed-in to the ZLB period only) shows that under the counterfactual scenario Canadian output would have been significantly lower. Table 3.3 contains the average percentage difference between each series and their counterfactual paths. Output and prices would have been 0.23% and 0.14% lower on average during the Canadian ZLB period, respectively, had the Bank of Canada been unable to provide any additional stimulus.

Importantly, although output and prices are significantly lower under the counterfactual scenario, they would have returned to their observed path within two years. This means the unconventional monetary policy operations conducted by the Bank of Canada while the target rate was at 25 bps sped up the recovery of the Canadian economy significantly, but had relatively short term transitory effects.
### Table 3.3: Average percent difference between data series and counterfactual path (full sample)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Canadian ZLB Imposed</th>
<th>US ZLB Imposed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>Max</td>
</tr>
<tr>
<td>Canadian Interest rate</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Canadian Interest rate†</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Canadian CPI</td>
<td>−0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Canadian CPI†</td>
<td>−0.14</td>
<td>−0.07</td>
</tr>
<tr>
<td>Canadian output</td>
<td>−0.07</td>
<td>0.13</td>
</tr>
<tr>
<td>Canadian output†</td>
<td>−0.23</td>
<td>−0.15</td>
</tr>
<tr>
<td>US interest rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>US CPI</td>
<td>0.38</td>
<td>1.15</td>
</tr>
<tr>
<td>US Output</td>
<td>−1.94</td>
<td>−0.29</td>
</tr>
</tbody>
</table>

Note: This table contains the average percentage difference between the actual series and the counterfactual median as well as 68% bounds. The calculation uses the formula \( \frac{1}{T} \sum_{t \in ZLB} \frac{y_t - y_t^{CF}}{y_t} \), where \( y_t \) is the series \( y \) at time \( t \) and \( y_t^{CF} \) is the same series under the counterfactual scenario, ZLB denotes the time period for the experiment and \( T \) denotes the number of observations for the experiment. † indicates the estimates are for the Canadian ZLB period only. Also note that although the max and min bounds may include 0 this does not exclude the possibility that the paths were significantly different from zero for individual months during the experiment period.

### Restricted monetary policy in the US

Figure 3.5 reports the results from our second counterfactual experiment in which we restrict the US shadow rate to 25 bps after December 2008, while the federal funds rate was at the ZLB. As shown in Figure 3.5(a), US unconventional monetary was significantly more expansionary than Canadian unconventional monetary policy and the ZLB episode lasted much longer. As a result, the measured magnitude of the effects of US unconventional monetary policy is much larger as well. US output, shown in Figure 3.5(e), is substantially and persistently lower under the counterfactual experiment. The trajectory of output reveals that without unconventional interventions from the Fed, US output would have significantly diverted from its growth path. The summary statistics from the counterfactual experiment shown in Table 3.3 indicate that US output would have been 1.94 percent lower on average without the Fed’s unconventional monetary policy. This
**Figure 3.5: Counterfactual paths: US ZLB imposed**

(a) Policy Interest rate (US)  
(b) VIX  
(c) WPX  
(d) Price Level (US)  
(e) Output (US)  
(f) Policy Interest rate  
(g) Exchange rate  
(h) CA Balance  
(i) Price Level  
(j) Output

Notes: This figure contains the plot of each series along with its counterfactual path constructed by coming up with a set of structural shocks for the policy rate such that it is forced to respect the ZLB. Error bands are constructed based on 2000 Gibbs sampling draws from the posterior distribution.

An estimate is similar in magnitude to those found in other studies. Dahlhaus et al. (2014) find that US GDP would have been 2.3% lower on average over the period from 2008Q4 to 2013Q3 if the Fed’s balance sheet continued to grow at pre-crisis levels; Chung, Laforte, Reifschneider, and Williams (2012), find that US GDP would have been 3% lower in 2012 without the first instalment of quantitative easing (QE I); Baumeister and Benati (2013) find that QE I boosted US GDP growth by 2% in 2009; and Wu and Xia (2016) find that the US industrial production index would have been 101.0 rather than 101.8 in December 2013, a 0.78% difference. In contrast to these studies (with the exception of Wu and Xia (2016)), we consider the expansionary effects of both large scale asset purchases and
Importantly, we find that US unconventional monetary policy had a significant impact on the Canadian economy. Figure 3.5(f) shows that the Canadian policy rate would have been much higher under this counterfactual scenario, remaining around 2 percent for much of the experiment. The higher Canadian policy rate highlights the sensitivity of the Bank of Canada’s reaction function to movements in the US policy rate. Canadian output, shown in Figure 3.5(j), clearly benefited from the US expansionary policies. Not only is it significantly lower — about 1.21 percent lower on average as shown in Table 3.3 — but it would be on a different trajectory without US policy intervention. Our estimate is smaller in magnitude compared to the only study considering a similar question; Dahlhaus et al. (2014) find that US QE alone increased Canadian GDP by 2.2 percent on average over the period from 2008Q4 to 2013Q3.

A preeminent result from this US counterfactual experiment, which can be seen clearly in Figure 3.5, is that not only would Canadian output have been lower on average during the US ZLB, but its trend would be altered for a considerable length of time. In the last period of our sample, July 2015, we estimate that Canadian output would have still been 3.56 percent lower.\footnote{This is the estimated median value, and is significantly different from zero with the 68 percent confidence band \((-7.3025, -0.7755)\).} Similarly, US output would have been on a very different path for substantially longer without the Fed’s actions. The much more persistent effect of the Fed’s unconventional monetary policy shocks stands in stark contrast to the Bank of Canada’s.

### 3.5 Robustness

In this section we assess the robustness of our main result. In Section 3.5.1 we use an alternative definition of the current account and in Section 3.5.2 we control for government expenditure. In both cases our results are robust to these different specifications.
3.5.1 Alternative current account measure

It is possible that the monthly current account balance measure we use in Section 3.4 misses some important variation because it is interpolated from quarterly data. Here we use an alternative estimation method to construct a monthly current account balance variable, and inspect the robustness of our main results. We follow Miao and Pant (2012) and construct the alternative variable as monthly Canadian net exports minus monthly changes in Canadian international reserves. This proxy is based on the accounting identity:

\[
\text{change in reserves} = \text{net exports} + \text{net income from abroad} + \text{net transfers} + \text{capital and financial flows} + \text{errors and omissions} + \text{valuation effects},
\]

and the assumption that valuation effects, transfers, and income from abroad are all small and errors and omissions are negligible. It is because of these necessarily strong assumptions, and the corresponding potential for substantial measurement error in this proxy variable, that we choose not to use it in our main analysis. The data we use is described in Table B.1 of Appendix B.1.

\[26\]Miao and Pant (2012) note that similar approaches have been used by Forbes and Warnock (2012) and Reinhart and Reinhart (2008).
Figure 3.6: Response to domestic (Canadian) expansionary monetary policy shock (July 1994 – July 2015)
Alternative CA balance

(a) Interest rate  (b) Exchange rate  (c) CA balance

(d) Price Level  (e) Output

Figure 3.7: Response to foreign (US) expansionary monetary policy shock (July 1994 – July 2015)
Alternative CA balance

(a) Interest rate  (b) Exchange rate  (c) CA balance

(d) Price Level  (e) Output

Note: See Figure 3.3 for US impulse response functions, which are unchanged when we replace exports and imports with the current account balance.

Figure 3.6 reports the impulse response functions for a 25 bps expansionary monetary policy shock in Canada, with the different measure of the current account. As in Section
3.4 both the price level and output rise, but the initial exchange rate depreciation is no longer statistically significant. Figure 3.7 reports the Canadian impulse response functions for a 25 bps expansionary monetary policy shock in the US.\textsuperscript{27} Again, the results are largely consistent with those in Section 3.4. Prices fall significantly on impact, then rise after a lag. Output rises after approximately a two year lag. Finally, the currency depreciates as the Canadian policy rate falls.

As with the impulse response functions, the counterfactual experiments using this alternative current account proxy variable produce results that are largely consistent with those presented in Section 3.4. These are reported in Figures 3.8 and 3.9 and Table 3.4. Canadian output would have been approximately 0.15 percent lower on average during the Canadian ZLB without unconventional monetary policies from the Bank of Canada and 1.28 percent lower on average had the Fed not enacted any unconventional monetary policies. The error bands from these estimates overlap the error bands from our main

\textsuperscript{27}Due to the block exogeneity assumption, the effect on US variables is identical to the main specification.
Figure 3.9: Counterfactual paths: US ZLB imposed
Alternative CA balance

(a) Policy Interest rate  (b) Exchange rate  (c) CA Balance

(d) Price Level  (e) Output

Note: See Figure 3.5 for US impulse response functions, which are unchanged when we replace exports and imports with the current account balance.

3.5.2 Government spending

Government stimulus can play an important role in economic recoveries, particularly so in the aftermath of the financial crisis. Since monetary policy easing often coincides with increased government spending, excluding this variable could lead to overestimating the effect of monetary policy on output. Therefore, in this section we adjust our main specification to control for fiscal policy, measured by federal government expenditures. Following the literature on government shocks (see e.g. Ramey, 2011, 2015), we assume that fiscal policy does not respond contemporaneously to any variables because of legislative constraints. We replace the Canadian current account balance variable with Canadian federal expenditures in the Canadian block, $Y_{t}^{\text{CAN}}$, and add US federal expenditures to the bottom of the US block, $Y_{t}^{\text{US}}$, of our original model.

Figures 3.10 and 3.11 contain the impulse response functions, which are generally
Table 3.4: Average percent difference between data series and counterfactual path (full sample)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Canadian ZLB Imposed</th>
<th>US ZLB Imposed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>Max</td>
</tr>
<tr>
<td>Canadian Interest rate</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Canadian Interest rate†</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Canadian CPI</td>
<td>−0.08</td>
<td>0.05</td>
</tr>
<tr>
<td>Canadian CPI†</td>
<td>−0.07</td>
<td>−0.01</td>
</tr>
<tr>
<td>Canadian output</td>
<td>−0.03</td>
<td>0.25</td>
</tr>
<tr>
<td>Canadian output†</td>
<td>−0.14</td>
<td>−0.05</td>
</tr>
</tbody>
</table>

Note: This table contains the average percentage difference between the actual series and the counterfactual median as well as 68% bounds. The calculation uses the formula $\frac{1}{T} \sum_{t \in ZLB} \frac{y_t - y_t^{CF}}{y_t}$, where $y_t$ is the series $y$ at time $t$ and $y_t^{CF}$ is the same series under the counterfactual scenario, ZLB denotes the time period for the experiment and $\bar{T}$ denotes the number of observations for the experiment. † indicates the estimates are for the Canadian ZLB period only. Also note that although the max and min bounds may include 0 this does not exclude the possibility that the paths were significantly different from zero for individual months during the experiment period.

Figure 3.10: Response to domestic (Canadian) expansionary monetary policy shock (July 1994 – July 2015) Control for Fiscal Policy

consistent with the main specification. Following a Canadian expansionary shock, output and prices rise, the Canadian dollar depreciates on impact and later appreciates, and government spending rises on impact and falls after approximately 6 months. In response
to a US expansionary shock, Canadian and US output rise significantly, although with a long delay and only after a small decline in the US case. Both US and Canadian spending rise initially, albeit not significantly, but then fall as output increases. This is consistent with both automatic stabilizers and discretionary expenditures falling as the economy improves.

The results of the counterfactual experiments, reported in Figures 3.12 and 3.13 and
Figure 3.12: Counterfactual paths: Canadian ZLB imposed
Control for Fiscal Policy

Table 3.5: Average percent difference between data series and counterfactual path (full sample)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Canadian ZLB Imposed</th>
<th>US ZLB Imposed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>Max</td>
</tr>
<tr>
<td>Canadian Interest rate</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Canadian Interest rate†</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Canadian CPI</td>
<td>0.00</td>
<td>0.06</td>
</tr>
<tr>
<td>Canadian CPI†</td>
<td>−0.07</td>
<td>−0.02</td>
</tr>
<tr>
<td>Canadian output</td>
<td>0.00</td>
<td>0.07</td>
</tr>
<tr>
<td>Canadian output†</td>
<td>−0.07</td>
<td>0.01</td>
</tr>
<tr>
<td>US interest rate</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>US CPI</td>
<td>−0.11</td>
<td>0.49</td>
</tr>
<tr>
<td>US Output</td>
<td>−0.17</td>
<td>1.97</td>
</tr>
</tbody>
</table>

Note: This table contains the average percentage difference between the actual series and the counterfactual median as well as 68% bounds. The calculation uses the formula \( \frac{1}{T} \sum_{t \in ZLB} \frac{y_t - y_t^{CF}}{y_t} \), where \( y_t \) is the series \( y \) at time \( t \) and \( y_t^{CF} \) is the same series under the counterfactual scenario, ZLB denotes the time period for the experiment and \( T \) denotes the number of observations for the experiment. † indicates the estimates are for the Canadian ZLB period only. Also note that although the max and min bounds may include 0 this does not exclude the possibility that the paths were significantly different from zero for individual months during the experiment period.
Table 3.5, are similar to the findings in the main specification. There does appear to be some evidence, however, that controlling for fiscal expenditures reduces the degree to which monetary policy explains changes in the real variables. We estimate that Canadian output would have been 0.14 percent lower on average during the ZLB without Canadian unconventional monetary policy. US output would have been 0.07 percent lower on average during the ZLB period, and Canadian output 0.56 percent lower on average without US unconventional monetary policy. Interestingly, without US unconventional monetary policy both Canadian and US fiscal policy would not have been any more expansionary.
3.6 Conclusion

This chapter contributes to a growing literature on the effects of unconventional monetary policy by analyzing these policies in a small open economy. There are two main challenges for quantifying the effects of unconventional policy in this setting: controlling for the outside world and finding an appropriate policy variable. To deal with these issues, we use the recently proposed shadow rates (Wu and Xia, 2016) as a proxy for monetary policy at the ZLB and construct a block-exogenous B-SVAR model to allow for international policy spillovers. The choice of Canada as a small open economy allows us to assume that the US adequately controls for the outside world. Furthermore, given our model, we are also able to explore the effects of unconventional monetary policy spillovers from the US.

We find that over the 1994–2015 period both Canadian and US expansionary monetary policy shocks are associated with increased output and prices in Canada. This result is consistent with theoretical and empirical literature based on pre-global financial crisis data. To quantify the magnitude of unconventional monetary policies in both countries, we conduct two counterfactual experiments that restrict the policy rate separately in each country to the ZLB. We find that without the Bank of Canada’s unconventional policies, output would have been 0.23 percent lower on average during the Canadian ZLB period. Although these policies had significant expansionary effects, we also show that without them, the Canadian economy would have eventually recovered to the path observed at the end of our sample. In contrast, without the Fed’s unconventional monetary policies, both Canadian and US output would be on different paths. US policies had a much larger effect in general, boosting US and Canadian output by approximately 1.21 and 1.94 percent on average over the July 2007–2015 period. Our results are robust to alternative specifications, including a different proxy for the current account balance and controlling for government spending.
Our findings reveal that unconventional monetary policy in a small open economy is effective, but also underline the importance of favourable foreign monetary policy spillovers. Recent concerns about the large adverse cross-border spillovers of unconventional monetary policies have rekindled the discussion of international coordination of monetary policy and the need to acknowledge one's role in spillovers. However, as we demonstrate, in some cases these spillovers can have beneficial effects. In future work, it would be interesting to explore other small open economies and compare the effectiveness of their unconventional monetary policies as well as the impact of international spillovers.
Chapter 4

Fiscal policy uncertainty and US output

“In the United States, the budget outlook for 2013 is highly uncertain, given the large number of expiring tax provisions and the threat of automatic spending cuts and in the context of highly polarized politics.”

International Monetary Fund (World Economic Outlook, 2012)

“The recovery in the United States continues to be held back by a number of other headwinds, including still-tight borrowing conditions for some businesses and households, and—as I will discuss in more detail shortly—the restraining effects of fiscal policy and fiscal uncertainty.”

Bernanke (Semiannual Monetary Policy Report to Congress, 2012)

“Economists sometimes belabor and measure what the rest of us find obvious. Take this assertion: When it’s unusually hard to tell where the economy and government policy are going, businesses will be reluctant to invest and hire.”

Wessel (Wall Street Journal, 2012)

“Getting back to the 2006 level of uncertainty would add 2.3 million jobs.”

Galston (Wall Street Journal, 2013)
4.1 Introduction

The weak recovery in the US following the Great Recession was accompanied by abnormally high levels of uncertainty regarding fiscal policy. Both policymakers and the media drew a link between the two and argued that fiscal policy uncertainty was impeding the recovery (e.g. see the quotations above). If this link exists and uncertainty about the future path of fiscal policy hinders output growth, then it could have important implications for policymakers and researchers. For instance, government officials would need to incorporate concerns about uncertainty in framing and announcing fiscal policies. Moreover, if uncertainty significantly affects output then it should be incorporated in quantitative fiscal analysis.

In this chapter, I explore the statistical and economic significance of this link by nesting it in a standard structural vector autoregression (SVAR) model à la Blanchard and Perotti (2002) traditionally used for estimating fiscal multipliers. I augment the model in two ways. First, I allow for the variance of the structurally identified fiscal shocks to evolve stochastically. The time-varying variance provides a measure of uncertainty: the dispersion in the one-step-ahead forecast error. Second, to estimate the relationship between fiscal policy uncertainty and aggregate output, I let the stochastic volatility enter the level equation. The evidence rejects the hypothesis that uncertainty about future government spending or revenue has a detrimental effect on the economy. I subject the model to sensitivity analysis commonly applied in the empirical fiscal literature—considering subsamples as well as different trend assumptions and information sets—and show that there is no systematic relationship between fiscal policy uncertainty and aggregate output.

The baseline model includes data on government spending, revenue and gross domestic product. It identifies structural shocks by assuming that discretionary fiscal policy does not respond to output within a quarter and that nondiscretionary policy responses are
consistent with an externally obtained cyclical elasticity parameter. Framing the research question within an empirical model for fiscal analysis has several distinct advantages. First, the model identifies fiscal shocks and controls for them both in the estimation of uncertainty and its effect on output. This feature endogenizes the estimation of uncertainty in the sense that it incorporates uncertainty surrounding the estimate of uncertainty. I show that failing to account for this uncertainty can have important consequences for inference. Second, since I am able to analyze the effects of first moment fiscal shocks within the same model, the literature provides a baseline for comparison of results as well as a list of additional issues that could affect identification.

In the first part of the analysis I find that most specifications yield an insignificant relationship between fiscal policy uncertainty and output but there is evidence of instability across subsamples. I investigate this instability further by allowing for time-varying parameters (TVP) in the model. The TVP model shows that the effect of fiscal policy uncertainty on output has been very stable across time and the instability across subsamples is likely not driven by an underlying change in the transmission mechanism.

Estimating the model with stochastic volatility has the advantage of a flexible specification. Moreover, it has the appealing characteristic that volatility can evolve independently of shocks to the level equation. However, this flexibility comes at the cost of increased complexity, which I tackle using Bayesian estimation methods. These methods raise two concerns. First, the model requires setting prior distributions that inevitably influence the results. Second, the model splits the data into a training sample (1947Q1–1959Q4) to calibrate some of the priors and an estimation sample (1960Q1–2015Q4) for which I obtain an estimate of uncertainty and its effect on output. To deal with these issues, I recast the time-varying volatility within a multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) specification and estimate the model with maximum likelihood. This model allows me to estimate fiscal policy uncertainty for the
entire available sample and thus incorporate large fluctuations in taxes and spending re-
related to the Korean War that have been shown to matter for estimating fiscal multipliers. 
The model with this alternative specification reveals no significant relationship between 
fiscal policy uncertainty and output.

Next, I augment the stochastic volatility model to control monetary policy, an impor-
tant driver of business cycle fluctuations, and anticipation effects. The latter refers to 
the idea that people may be aware of changes in fiscal policy before they come into effect 
because of implementation lags. No significant result from the first part of the analysis 
survives when the information set is broadened to control for these effects.

This chapter is most closely related to a small but growing literature on fiscal pol-
icy uncertainty. Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez 
(2015), henceforth FGKR, estimate a fiscal rule for the capital tax rate and find a consid-
erable amount of time-varying volatility in its innovation process. They use this volatility 
estimate as a proxy for fiscal policy uncertainty in an SVAR with other macroeconomic 
variables and show that shocking it leads to a significant decline in output, consumption 
and investment. They also feed the volatility series into a dynamic stochastic general 
equilibrium (DSGE) model and find that the results are in line with the empirical analy-
sis and that the effects are more pronounced when the nominal rate is at the zero lower 
bound. Born and Pfeifer (2014) estimate a very similar DSGE model and find noticeably 
smaller effects of policy risk. They attribute the difference to a larger steady-state demand 
elasticity in FGKR. Johannsen (2014) uses a theoretical model to show that the effects of 
fiscal policy uncertainty are larger when the zero lower bound is binding. Lastly, Mumtaz 
and Surico (2013) estimate a model similar to the one in the first part of this chapter. 
They find negative effects of fiscal policy uncertainty and focus their analysis on shocks 
to uncertainty of the debt-to-GDP ratio, which they interpret as uncertainty about debt 
sustainability.

This chapter contributes to this literature in several ways. I am the first to provide
empirical evidence that shows no consistent relationship between fiscal policy uncertainty and output. This finding contrasts with all previous empirical work on fiscal policy uncertainty and casts doubt on the popular claim held by the media and policymakers that the effects are contractionary. Second, I show that the relationship between fiscal policy uncertainty and output has been stable over time. This finding does not support the results from FGKR and Johannsen (2014) who argue that these effects become more pronounced at the zero lower bound. This is the first study to consider time-varying effects of an endogenously estimated fiscal policy uncertainty measure. In fact, there is only one other paper that incorporates time-varying parameters in a model with stochastic volatility entering the mean: Mumtaz and Theodoridis (2016) use a factor augmented vector autoregression to extract a measure of economic uncertainty and explore its changing effects on macroeconomic and financial variables in a model with TVP. Finally, I highlight the importance of endogenizing the estimation of uncertainty (as argued for in Carriero, Clark, and Marcellino, 2016) by showing that when the empirical model in FGKR is modified to incorporate the uncertainty around the estimate of uncertainty, their conclusion changes and falls in line with my findings.

This study also closely relates to the work of Baker, Bloom, and Davis (2016), who develop an index of economic policy uncertainty by recording the frequency of articles appearing in major newspapers with references to uncertainty in economic policy. They provide evidence on the detrimental effects of uncertainty about government spending on firms that rely heavily on government purchases. To analyze the aggregate effects of policy uncertainty, they estimate a VAR model with their index and find that an increase in economic policy uncertainty leads to a fall in output. However, they concede that these effects are not necessarily causal. My work can be seen as a closer investigation of whether the firm-level results aggregate up to have an impact on the broader economy. This chapter also complements Stock and Watson (2012) and Benati (2013), who explore the contribution of economic policy uncertainty to the Great Recession. Finally, I build
on a large literature on the empirical analysis of fiscal policy (for a recent survey, see relevant section in Ramey, 2015), which will be discussed in the sections in which it is referenced.

I introduce the baseline model and discuss my measure of uncertainty in the next section. Section 4.3 explores time-varying effects of uncertainty shocks and Section 4.4 estimates the model using maximum likelihood with the alternative MGARCH specification. Section 4.5 expands the information set to control for monetary policy and anticipation effects. Section 4.6 revisits the empirical results from FGKR and Section 4.7 concludes.

4.2 Measuring fiscal policy uncertainty and its effect on output

The first building block is the SVAR originally proposed by Blanchard and Perotti (2002). The vector of endogenous variables is $z_t = [\tau_t, g_t, y_t]'$ and it includes government revenue $\tau_t$, spending $g_t$ and gross domestic product $y_t$. These variables evolve according to

$$z_t = CD_t + \sum_{i=1}^p \Gamma_i z_{t-i} + u_t,$$

$$u_t = BH \frac{1}{2} \varepsilon_t, \quad \varepsilon_t \sim N(0, I),$$

$$H = \begin{bmatrix} \sigma^2_\tau & 0 & 0 \\ 0 & \sigma^2_g & 0 \\ 0 & 0 & \sigma^2_y \end{bmatrix},$$

where $D_t$ is a vector of deterministic terms containing a constant and, depending on the data specification, possibly a linear trend, $C$ and $\Gamma_i$ are coefficient matrices and $B$ is a matrix of coefficients describing the contemporaneous interactions among the dependent variables and their structural innovations. The matrix $H$ normalizes the structural innovations to have unit variance. All of the parameters in (4.1) can be estimated with ordinary least squares. The relationship among the reduced-form residuals
$u_t = [u_t^\tau, u_t^g, u_t^y]'$ from the OLS regression and the contemporaneous coefficient matrix is given by $E[u_t'u_t] = \Omega = BH'B'$. The reduced-form covariance matrix $\Omega$ is symmetric and contains $n(n + 1)/2$ unique coefficients, where $n$ is the number of variables. Since $n$ of these coefficients are needed to identify $H$, I must impose restrictions on all but $n(n - 1)/2$ of the elements in $B$ to identify the structural innovations. As in Blanchard and Perotti (2002), I let $B = A^{-1}B$ and define the relationship between the reduced-form residuals $u_t$ and structural shocks $\varepsilon_t$ in the following way,

$$Au_t = BH^{\frac{1}{2}}\varepsilon_t,$$

$$
\begin{bmatrix}
1 & 0 & \theta_y \\
0 & 1 & \gamma_y \\
\xi_\tau & \xi_g & 1
\end{bmatrix}
\begin{bmatrix}
u_t^\tau \\
u_t^g \\
u_t^y
\end{bmatrix}
= 
\begin{bmatrix}
1 & \theta_g & 0 \\
\gamma_\tau & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\sigma_\tau\varepsilon_{t}^\tau \\
\sigma_g\varepsilon_{t}^g \\
\sigma_y\varepsilon_{t}^y
\end{bmatrix}. \tag{4.5}
$$

where $\theta_y$ and $\gamma_y$ capture the cyclical elasticities of the revenue and spending to output, respectively, and $\xi_\tau$ and $\xi_g$ represent the response of output to changes in each of the fiscal instruments. The remaining parameters, $\theta_g$ and $\gamma_\tau$, describe the response of tax revenue to changes in spending and vice versa. Since only three of the coefficients in $A$ and $B$ can be identified, Blanchard and Perotti (2002) propose setting $\gamma_\tau = \gamma_y = 0$ and calibrating $\theta_y$ to an outside estimate. The zero restrictions are based on legislative delays and imply that spending policy cannot respond to the other variables in the model within the same quarter. I set the cyclical elasticity of tax revenue to output to $\theta_y = -3.13$, which is the value obtained by an instrumental variable approach by Mertens and Ravn (2014). This value is greater in magnitude than the $-2.08$ proposed by Blanchard and Perotti (2002), which, as argued by Mertens and Ravn (2014), suffers from downward bias arising from their empirical method. The remaining parameters $\theta_g$, $\xi_\tau$ and $\xi_g$ are estimated.

An alternative identification approach in the literature is based on constructing fiscal shocks using a historical narrative. For spending shocks, Ramey (2011) focuses on
changes related to military expenditures in response to exogenous political events and shows that these events Granger cause shocks identified by the SVAR method described above. However, this narrative approach is very restrictive since it focuses on a narrow part of government expenditures and relies only on increases in spending. Since this chapter is concerned with uncertainty about all unanticipated government spending changes, I use the SVAR model and control for potential anticipation effects in Section 4.5. On the revenue side, Romer and Romer (2010) use a narrative record for all major postwar tax policy changes and estimate a tax multiplier that is larger than the one obtained from the SVAR model. However, Mertens and Ravn (2014) reconcile the different estimates of tax multipliers based on the SVAR and the narrative approach and attribute the difference to the cyclical elasticity parameter. They estimate the cyclical elasticity using the narrative series as an instrument and show that when this value is used in the SVAR, the multipliers obtained using the two different approaches are identical. I use this updated estimate of the cyclical elasticity.

In order to nest the estimation of the effects of fiscal policy uncertainty on output in this model, I modify it in two ways. First, I allow for the variance of the structural shocks to vary over time. Second, I allow this time-varying variance to enter the VAR model as an explanatory variable. The time-varying variance measures the dispersion in the one-step ahead forecast error for each of the variables and that represents uncertainty about future outcomes. There are two competing methods for modeling the time-variation of the second moments: generalized autoregressive conditional heteroskedasticity (GARCH) and stochastic volatility (SV). SV models volatility as an autoregressive process with an innovation that is independent from the level equation. GARCH, on the other hand, restricts the evolution of volatility to be directly related to changes in levels and past volatilities. I start by augmenting the model with SV and consider GARCH in a later section. The flexibility of SV is appealing both theoretically, since innovations to uncertainty do not necessarily need to originate from innovations in levels, and empirically, since the model
clearly separates the effects of fiscal policy shocks and fiscal policy uncertainty shocks.

Next, I allow for this stochastic volatility to enter the level equation as an explanatory variable. Augmenting the model with stochastic volatility in the mean (SV-M) allows for the interaction between the endogenous variable vector and the measure of uncertainty. Recent applications of this model have shown contractionary effects of monetary policy uncertainty (Mumtaz and Zanetti, 2013) and oil price uncertainty (Jo, 2014).

The SVAR-SV-M model is specified as follows,

\[ z_t = CD_t + \sum \Gamma_i z_{t-i} + \sum \Lambda_j \log(h_{t-j}) + u_t, \quad (4.6) \]

\[ u_t = B H_t^{1/2} \varepsilon_t, \quad \varepsilon_t \sim N(0, I), \quad (4.7) \]

\[ H_t = \begin{bmatrix} h_{t}^\tau & 0 & 0 \\ 0 & h_{t}^g & 0 \\ 0 & 0 & h_{t}^y \end{bmatrix}, \quad (4.8) \]

\[ \log(h_t) = \mu + \rho \log(h_{t-1}) + \nu_t, \quad \nu_t \sim N(0, Q), \quad (4.9) \]

where \( h_t = [h_{t}^\tau, h_{t}^g, h_{t}^y]' \) is a vector of the time-varying variances of the structural shocks, \( \mu \) is a vector of intercepts, \( \rho \) is a diagonal matrix of autoregressive coefficients and \( Q \) is a diagonal matrix of variances of the second moment innovations. Although the covariance matrix for the innovations in the stochastic volatility could have non-zero off-diagonal elements, this would complicate both the estimation and interpretation of second moment shocks, which would need to be identified. Therefore, I follow the literature and assume that \( Q \) is a diagonal matrix. The main object of interest with regards to the research question is \( \{ \Lambda_j \}_{j=0}^{p_\lambda} \), since these coefficient matrices measure the effect of the fiscal policy uncertainty on the endogenous variables in \( z_t \).

I construct the data following Mertens and Ravn (2014) and provide details in Appendix C.1. I use spending and taxes of the consolidated government sector (federal, state
and local) for the main analysis. Each series is in real per capita growth rates observed at the quarterly frequency for the period 1947Q1–2015Q4.

To deal with the large number of parameters and nonlinear relationship between the residuals and unobserved volatilities, I estimate the model using Bayesian methods, which are particularly well suited for dealing with these types of complexities. In particular, I use the Gibbs sampler, which is a Markov Chain Monte Carlo (MCMC) algorithm. It breaks up the joint distribution of parameters into smaller manageable blocks of dependent conditional distributions. With enough draws from the conditional distributions, the chain converges and generates a sample from the joint distribution.

I estimate the model for the period 1960Q1–2015Q4, reserving the first 13 years of data for a training sample to calibrate the priors. I set the number of lags of the dependent variable $p$ to four, but only focus on the contemporaneous response to fiscal policy uncertainty, i.e. I set $p_\lambda = 0$. Later, I discuss the implications of relaxing this assumption. I take 20,000 draws from the Gibbs sampler. To eliminate any effects that initial conditions could have on the Markov chain, I discard the first 5,000 draws and use the remaining 15,000 for inference. Appendix C.2 provides details of the estimation, with a discussion of the priors in C.2.1 and a description of the steps in the algorithm in C.2.2.

To ensure that the model is not generating any counter-intuitive behavior for fiscal multipliers, and that the structural shocks are properly identified, I first present the impulse response functions for first moment shocks, shown in Figure 4.1. These figures also provide a first glance at whether incorporating the effects of fiscal policy uncertainty in the model affects the estimates of fiscal multipliers. Following Mertens and Ravn (2014), I normalize the fiscal shocks by their average ratio to GDP to have the interpretation of fiscal multipliers for the impulse response of output.¹ I plot the percent response of

¹Unlike Mertens and Ravn (2014), I allow for the impact response of tax revenue to incorporate the response of output to the tax shock, i.e. for a given tax shock $\varepsilon^T$, the response of output is given by $\hat{\zeta}_T \varepsilon^T$ and the response of revenue is given by $(1 - \hat{\zeta}_T)\varepsilon^T$, where $\zeta_T = \frac{-\xi_T}{1 - \phi_T \xi_T}$ as defined in (C.8) in Appendix C.2.1. This has the effect of producing smaller tax multipliers.
Figure 4.1: SVAR-SV-M model impulse response to first moment shocks

Impulse response to surprise revenue cut

(a) Revenue  (b) Spending  (c) Output

Impulse response to surprise spending increase

(d) Revenue  (e) Spending  (f) Output

Notes: This figure contains the posterior median and 68% credible sets of the cumulative impulse responses to a negative revenue shock (first row) and a positive spending shock (second row), both normalized to their average ratio to GDP over the sample period. Vertical axes are in percent growth rates. Estimates are based on the last 15k of 20k draws from the Gibbs sampler.

output to a tax cut equivalent to one percentage point of GDP in Figure 4.1(c). The blue shaded areas represent 68% credible sets, which is a standard choice for inference in the Bayesian VAR literature. Figure 4.1(f) shows the percent response of output to a surprise one percentage point of GDP increase in spending. Both shocks have expansionary effects and the shape of the impulse response functions is in line with previous studies (see e.g. Mertens and Ravn, 2014).

Before analyzing the impulse response functions to uncertainty shocks, I discuss my estimate of uncertainty and compare it other proxies used in the literature. Table 4.1 contains the estimated parameters for the equations governing the stochastic volatilities. All of the series have similar autoregressive coefficients, but the variances of the innovations differ greatly. The variance for output is more than twice as large as the one for revenue, which itself is almost four times as large as the one for spending.

These differences are apparent in Figure 4.2, which shows the estimated stochastic
Table 4.1: Parameter estimates for stochastic volatility equations

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Revenue</th>
<th>Spending</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>0.309</td>
<td>-0.097</td>
<td>-0.656</td>
</tr>
<tr>
<td></td>
<td>(0.109, 0.617)</td>
<td>(-0.276, -0.015)</td>
<td>(-1.139, -0.310)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.697</td>
<td>0.650</td>
<td>0.642</td>
</tr>
<tr>
<td></td>
<td>(0.395, 0.883)</td>
<td>(0.219, 0.894)</td>
<td>(0.453, 0.801)</td>
</tr>
<tr>
<td>$Q$</td>
<td>0.511</td>
<td>0.134</td>
<td>1.250</td>
</tr>
<tr>
<td></td>
<td>(0.195, 1.225)</td>
<td>(0.054, 0.330)</td>
<td>(0.644, 2.333)</td>
</tr>
</tbody>
</table>

Notes: This table contains the posterior median and 90% credible sets (shown in parentheses below the median) for the parameters in the stochastic volatility equation for each of the variables. Estimates are based on the last 15k of 20k draws from the Gibbs sampler.

Volatilities. Visually, the series are similar to revenue and spending volatility estimates presented by Pereira and Lopes (2014), Born and Pfeifer (2014) and Fernández-Villaverde et al. (2015). Revenue is much more volatile than spending, which is relatively flat after the mid 1980s. Several of the large spikes in revenue volatility are tied to important historical events. In the last fifteen years, uncertainty around revenue increased considerably with the passage of the Bush tax cuts in 2001Q1–2002Q2 and in 2003Q3. During the Obama administration, uncertainty rose during the financial crisis and ensuing recession and peaked in 2009Q1 with the passage of a large stimulus package (American Recovery and Reinvestment Act of 2009) that contained several tax rebates. Volatility increased again in 2013Q1–2014Q1 around the time that President Obama permanently extended some parts of the Bush tax cuts. This was also the time of the federal government shutdown, which resulted from partisan deadlock on legislation appropriating funds for 2014. Nevertheless, the largest value in the entire series occurs much earlier, in 1975Q2, when President Ford signed a large temporary tax rebate into law.

Table 4.2 contains the correlation coefficients for the estimated stochastic volatility with other measures of uncertainty. The first series is the economic policy uncertainty (EPU) index from Baker et al. (2016). They construct the EPU index by calculating the frequency of key words (e.g. uncertain, economic, congress) appearing together in
Figure 4.2: Square-root of stochastic volatility

(a) Revenue

![Graph showing revenue volatility over time with shaded regions indicating NBER recession dates.]

(b) Spending

![Graph showing spending volatility over time with shaded regions indicating NBER recession dates.]

(c) Output

![Graph showing output volatility over time with shaded regions indicating NBER recession dates.]

Notes: This figure contains the posterior median and 68% credible sets for time-varying standard deviations $\sqrt{h_t}$ of each of the structural shocks. Estimates are based on the last 15k of 20k draws from the Gibbs sampler. Shaded regions indicate NBER recession dates.

newspaper articles and combining it with a list of expiring tax code provisions from the Congressional Budget Office as well as a measure of disagreement in prediction among professional forecasters. The series is positively correlated with both volatilities, $\log(h_t^\tau)$ and $\log(h_t^g)$, but weakly and only at the 10% level of significance with the one corresponding to spending. Baker et al. (2016) also construct sub-indices for fiscal policy: $EPU(t)$ for taxes and $EPU(g)$ for government spending. These series are more relevant for comparison with my stochastic volatility estimates because, in contrast to the EPU, they
do not contain uncertainty related to other types of policy, e.g. actions conducted by the Federal Reserve. The correlation with $EPU(t)$ is stronger and more significant for revenue volatility and weaker and insignificant for spending volatility. Similarly, the correlation for $EPU(g)$ is stronger and more significant for spending volatility and weaker for revenue volatility. The co-movement between the series, despite the differences in methods in our approaches, suggests that the stochastic volatility captures important features of fiscal policy uncertainty.

The next series in Table 4.2 is the partisan conflict index (PCI) from Azzimonti (2015). The PCI is constructed using textual analysis of newspaper articles, as in Baker et al. (2016), to count the frequency of combinations of words related to political disagreement about government policy (e.g. dysfunctional, Congress). Figures 4.3(a) and 4.3(b) plot the PCI and EPU with the median volatility estimates of revenue and spending, respectively. An important distinction between the EPU and PCI series is that they move in opposite directions during times of war and national security threats. For example, after the terrorist attacks on 9/11, economic policy uncertainty as measured by EPU was very high but the PCI actually fell as politicians became more unified in the face of adversity. The PCI is not significantly correlated with either volatility estimate. This comparison suggests that even when politics become increasingly polarized, as in recent times, peoples’ abilities to forecast the path of future government spending and taxes do not necessarily fall.

The last column in Table 4.2 presents the correlations with the stochastic volatility estimated from a policy reaction function for capital tax rates from Fernández-Villaverde et al. (2015). Even though I consider consolidated government revenue and use a different information set and estimation method, my estimate of revenue volatility is very strongly and significantly correlated with that of FGKR. Figure 4.3(c) plots the two series and reveals how closely they move together. This similarity further corroborates the validity of my measure of fiscal policy uncertainty and facilitates the comparison of our results,
Table 4.2: Correlations with EPU, PCI and FGKR

<table>
<thead>
<tr>
<th></th>
<th>EPU</th>
<th>EPU((t))</th>
<th>EPU((g))</th>
<th>PCI</th>
<th>FGKR</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\log(h_{t}^{*}))</td>
<td>0.290 (0.001)</td>
<td>0.322 (0.000)</td>
<td>0.225 (0.012)</td>
<td>-0.137 (0.128)</td>
<td>0.594 (0.000)</td>
</tr>
<tr>
<td>(\log(h_{g}^{*}))</td>
<td>0.167 (0.063)</td>
<td>0.144 (0.110)</td>
<td>0.200 (0.026)</td>
<td>-0.095 (0.295)</td>
<td>-0.050 (0.507)</td>
</tr>
</tbody>
</table>

Notes: Entries are correlations (and \(P\)-values in parentheses) between the estimated log volatilities from the SVAR-SV-M model and various uncertainty measures. The volatility measures are based on estimation from the main specification (1960–2015) and each correlation is calculated using the time span for which the uncertainty measures are available. EPU is available for January 1985 through September 2014. EPU(\(t\)) refers to the EPU sub-category for taxes and EPU(\(g\)) for government spending. PCI is available from January 1981 through September 2014. The capital tax rate volatility from FGKR is available from 1970Q1–2014Q1. Monthly measures are converted to quarterly averages.

which I revisit in more detail in Section 4.6.

For each of the proxies—EPU, PCI and FGKR—the authors find that the effect of an uncertainty shock, identified by a Cholesky decomposition with the uncertainty measure ordered first in a homoskedastic VAR with macroeconomic variables, is associated with a decline in output. In contrast to this approach, the SVAR-SV-M combines the estimation of the stochastic volatility and its effect on output into one step. The advantage of this approach is two-fold. First, it captures the uncertainty surrounding the measure of uncertainty, \textit{i.e.} it does not treat it as an observable variable. Second, the model simultaneously estimates uncertainty and its effect on the endogenous variables, allowing for potential feedback between the two. For instance, if fiscal policy uncertainty has explanatory power for some of the variables in the system then their residuals will be reduced and this in turn will affect the magnitude of the structural shocks and their volatility.

Figure 4.4 shows the impulse responses to fiscal policy uncertainty shocks. The magnitude of each of the shocks is normalized to one log-point, \textit{i.e.} a doubling of uncertainty. In response to a revenue uncertainty shock, both output and revenue decline persistently and significantly with a peak loss of approximately 0.3% and 1%, respectively. A spending uncertainty shock, on the other hand, has no significant effect on any of the endogenous
Notes: This figure contains the posterior median of the logarithm of time-varying volatility \( \log h_t \) of the structural shocks for consolidated government revenue and spending along with the Economic Policy Uncertainty (EPU) index from Baker et al. (2016), the Partisan Conflict Index (PCI) from Azzimonti (2015) and the capital tax volatility series from FGKR. Shaded areas indicate NBER recessions. Estimates are based on the last 15k of 20k draws from the Gibbs sampler.

variables. The difference in the effects of uncertainty surrounding the two fiscal policy instruments reflects the fact that spending volatility is mostly flat for a large part of the sample while revenue volatility exhibits much more variation (see Figure 4.2).

At a first pass, the negative effects of fiscal policy uncertainty are consistent with previous findings in the literature as well as some pundits’ and policymakers’ concerns about the effects of recent fiscal turmoil on the recovery following the financial crisis. However,
the objective of this study is to estimate the effects of fiscal policy uncertainty on output within the empirical framework for analyzing fiscal multipliers. In this regard, previous research shows that the magnitude of the estimated multipliers are sensitive to trend assumptions, time periods and whether or not the focus is on federal or consolidated (including state and local) government data. I subject the effects of fiscal policy uncertainty to the same scrutiny and estimate the model under a variety of specifications. There is also the additional concern of including other relevant variables in the information set, which I address in Section 4.5.

Figure 4.5 contains the impulse response of output to revenue uncertainty shocks under various specifications. The main specification is for the consolidated government sector in growth rates, *i.e.* stochastic trend assumption (*st*). Figure 4.5(a) shows that when the model contains one lag in addition to the contemporaneous effect of uncertainty, the negative effect of revenue uncertainty is no longer significant. Figure 4.5(b) contains the impulse response of output to a revenue uncertainty shock when the zero restrictions in $\Lambda$ are relaxed and the endogenous variables respond to output volatility $\log(h_t^y)$ as well.
Figure 4.5: SVAR-SV-M model impulse response of output to revenue uncertainty shocks under various specifications

Main specification

(a) $p_\lambda = 1$  
(b) With $\log(h_t^y)$

1960Q1–2015Q4

(c) Cons (st)  
(d) Cons (dt)  
(e) Fed (st)  
(f) Fed (dt)

1960Q1–2006Q4

(g) Cons (st)  
(h) Cons (dt)  
(i) Fed (st)  
(j) Fed (dt)

1980Q1–2015Q4

(k) Cons (st)  
(l) Cons (dt)  
(m) Fed (st)  
(n) Fed (dt)

Notes: This figure contains the posterior median and 68% credible sets of the impulse responses to a doubling of uncertainty for revenue under various specifications. Cons means consolidated government sector data, Fed means federal government data, st means that the model is estimated under the stochastic trend assumption, i.e. growth rates and dt means that the model is estimated under the deterministic trend assumption, i.e. levels with linear trend. Impulse responses are cumulative for models specified with a stochastic trend. The vertical axis is in percent growth rates or deviations from trend. Estimates are based on the last 15k of 20k draws from the Gibbs sampler. In some cases, convergence required more draws and the results are based on the last 20k of 40k draws. Models starting estimation in 1960 use 51 observations for the training sample and those starting in 1980 use 40 observations, i.e. the previous decade.

as the two fiscal volatilities. In this case, revenue uncertainty has no significant effect on output.

Next, I estimate the model in levels with a linear trend term, i.e. deterministic trend assumption (dt) and use consolidated government sector data (cons) as well as data for
only the federal government (fed). FGKR argue that policy uncertainty after the financial crisis was high for all levels of government and as a result they use consolidated government data. However, many of the major stress events during this period, such as the fiscal cliff, expiration of Bush tax cuts and the eventual government shutdown, occurred at the federal level. Moreover, uncertainty events at the federal level are likely to have a stronger effect on aggregate output since they often attract national attention. Indeed, when I estimate the model using federal government data, the volatilities of the fiscal variables, shown in Figure C.1 in Appendix C.4, are very similar to the ones generated from including state and local government data. This similarity suggests that federal-level uncertainty is a major contributor to overall fiscal policy uncertainty.

The second row in Figure 4.5 shows the impulse response of output to revenue uncertainty shocks for models estimated using the full sample but with different data and trend specifications and including only the contemporaneous effect of uncertainty, i.e. \( p_\lambda = 0 \). Output declines significantly in all but one case. When I use federal data with a stochastic trend specification, the response of output, shown in Figure 4.5(e), is insignificant. To control for potential outliers, I drop the financial crisis and its aftermath and estimate the model for the period 1960Q1–2006Q4. The results for this time period appear in the third row of Figure 4.5. In this case, only the model with consolidated government data and a deterministic trend specification generates a significant negative response of output, as shown in Figure 4.5(h). The last row of Figure 4.5 contains the results for the models that are estimated starting the sample in 1980Q1, without the largest revenue uncertainty event (the 1975Q2 tax rebate). Once again, the negative effect of revenue uncertainty is significant only with consolidated government data and the deterministic trend assumption, as shown in Figure 4.5(l).\(^2\)

\(^2\)Although it is difficult to detect visually, the 68% credible set for the impulse response function shown in Figure 4.5(k) is \((-0.153, 0.005)\) on impact.
Figure 4.6: SVAR-SV-M model impulse response of output to spending uncertainty shocks under various specifications

Main specification

(a) $p_{\lambda} = 1$  
(b) With $\log(h_t^y)$

1960Q1–2015Q4

(c) Cons (st)  
(d) Cons (dt)  
(e) Fed (st)  
(f) Fed (dt)

1960Q1–2006Q4

(g) Cons (st)  
(h) Cons (dt)  
(i) Fed (st)  
(j) Fed (dt)

1980Q1–2015Q4

(k) Cons (st)  
(l) Cons (dt)  
(m) Fed (st)  
(n) Fed (dt)

Notes: This figure contains the posterior median and 68% credible sets of the impulse responses to a doubling of uncertainty for spending under various specifications. Cons means consolidated government sector data, Fed means federal government data, st means that the model is estimated under the stochastic trend assumption, i.e. growth rates and dt means that the model is estimated under the deterministic trend assumption, i.e. levels with linear trend. Impulse responses are cumulative for models specified with a stochastic trend. The vertical axis is in percent growth rates or deviations from trend. Estimates are based on the last 15k of 20k draws from the Gibbs sampler. In some cases, convergence required more draws and the results are based on the last 20k of 40k draws. Models starting estimation in 1960 use 51 observations for the training sample and those starting in 1980 use 40 observations, i.e. the previous decade.

Figure 4.6 shows the results for the same analysis but focusing on the response of output to spending uncertainty. The effects are almost always insignificant. However, in the three cases when the response of output to a spending uncertainty shock is different from zero, shown in Figures 4.6(f), 4.6(l) and 4.6(n), the effect is actually positive. Although
this result is not theoretically implausible (see e.g. discussion in Born and Pfeifer, 2014), it is likely the result of sample variation rather than an underlying economic mechanism.

For the effects of both spending and revenue uncertainty shocks, there is some variability across subsamples and specifications. This feature of the second moment shocks starkly contrasts with the relative stability of the effects of first moment shocks, shown in Figures C.2 and C.3 in Appendix C.4. Furthermore, when the effects are statistically significant, their magnitudes are relatively small, rarely exceeding half of a percent of GDP growth at the peak. For several of the specifications, especially for revenue uncertainty, the effect on output is sensitive to excluding the financial crisis or starting the estimation in the 1980s.

As argued by Johannsen (2014) and Fernández-Villaverde et al. (2015), the effects of fiscal policy uncertainty can be more pronounced when the nominal interest rate is restricted by the zero lower bound. This constraint was binding for almost the entire sample after the financial crisis. To further explore the subsample variability, the next section relaxes some assumptions in the model by allowing for time-varying parameters.

### 4.3 Time-varying effects of fiscal policy uncertainty

The results from the SVAR-SV-M model in subsamples suggest that the relationship between fiscal policy uncertainty and output is potentially unstable over time. To explore the possibility that the transmission mechanism has not been constant, I introduce time-varying parameters (TVP) into the empirical model. Although this method significantly increases the model complexity, it has two distinct advantages over simply comparing results across subsamples. First, while manually selecting potential break points is difficult and subjective, the TVP-SVAR-SV-M model detects these changes automatically. Second, changes in the transmission could occur abruptly or gradually over time and this setting can capture both types of changes.

TVP-SVAR-SV models have been applied to a variety of research contexts, ranging
from monetary policy (e.g. Cogley and Sargent, 2005; Primiceri, 2005) to demand and supply oil price elasticities (Baumeister and Peersman, 2013), and their popularity has increased with the availability of computing power. Nevertheless, there are relatively few applications to fiscal policy and uncertainty. Pereira and Lopes (2014) is the only study that considers time-varying fiscal policy in the US. They find that the effects of fiscal policy, particularly tax policy, have gradually weakened over time. This weakening in the effects of first moment shocks could influence both the estimate of uncertainty as well as its effect on output. Benati (2013) estimates the time-varying effects of economic policy uncertainty—as measured by the EPU index from Baker et al. (2016)—in the US, Euro area, Canada and the UK and finds that economic policy uncertainty shocks have been an important contributor to fluctuations in output over time and that both the volatility and the effect of these shocks became more pronounced during the financial crisis. However, these results are sensitive to the identification strategy. Finally, Mumtaz and Theodoridis (2016) investigate the time-varying effects of uncertainty shocks on the US economy. They include a large number of variables in a factor augmented VAR model to measure macroeconomic uncertainty and find that its effects on real activity have declined over time. While the focus of their paper is different, it is the only other study to estimate time-varying effects of uncertainty in a model that endogenizes the estimation of uncertainty.

The TVP-SVAR-SV-M is almost identical to the SVAR-SV-M model considered in the previous section with the important distinction that the coefficients can evolve stochastically. To simplify the notation (as in Appendix C.2), I let \( X_t = [D_t, z_{t-1}, \ldots, z_{t-p}, \log(h_t), \ldots, \log(h_{t-p})]' \) and \( \Psi_t \) be a \( 3(3p+3(p+1)+c) \times 1 \) vector of the corresponding coefficients with \( c = 1 \) for the model with only a constant and \( c = 2 \) if both a constant and a linear trend is included. Moreover, I define \( \alpha_t \) to be a vector of the free parameters in \( B_t \). With

\(^3\)Kirchner et al. (2010) explore fiscal policy in Europe in a TVP model, but focus on government spending.
this notation, the model is given by

\[ z_t = X_t'\Psi_t + u_t, \quad (4.10) \]
\[ u_t = B_t H_t^{1/2} \varepsilon_t, \quad \varepsilon_t \sim N(0, I), \quad (4.11) \]
\[ \log(h_t) = \mu + \rho \log(h_{t-1}) + v_t, \quad v_t \sim N(0, Q). \quad (4.12) \]
\[ \Psi_t = \Psi_{t-1} + \omega_t, \quad \omega_t \sim N(0, W), \quad (4.13) \]
\[ \alpha_t = \alpha_{t-1} + e_t, \quad e_t \sim N(0, S), \quad (4.14) \]

where \( S \) is block-wise diagonal with individual blocks corresponding to the variance of the coefficients in each of the identifying equations in (4.11). For parsimony, I follow Primiceri (2005) and assume that the coefficients in (4.10) and (4.11) evolve as driftless random walks. Despite the added complexity introduced by the time-varying parameters, this model can be estimated with only a few adjustments to the algorithm for the fixed-parameter version of the model. I discuss these adjustments and the prior distributions in Appendix C.3.

Introducing time-varying parameters substantially increases the number of coefficients to estimate and as a result I follow the TVP literature and specify a lower lag augmentation with \( p = 2 \) and \( p_\lambda = 0 \) and allow only the fiscal variable volatilities to enter the mean equation. Due to the higher number of coefficients and increased size and complexity of the model, I report results based on 40,000 draws after discarding the first 20,000. In the SVAR-SV-M model estimation, VAR coefficient draws that generated explosive roots were discarded, however in the TVP-SVAR-SV-M, I do not impose this restriction. This is primarily due to the fact that, when this restriction is imposed, the entire set of VAR coefficients for all time periods must be re-drawn if just one time period contains non-stationary VAR coefficients. This restriction greatly increases estimation time. However, there are also theoretical justifications for omitting the stability condition. As discussed
Table 4.3: Parameter estimates for stochastic volatility in TVP-SVAR-SV-M

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Revenue</th>
<th>Spending</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>0.127</td>
<td>$-0.010$</td>
<td>$-0.110$</td>
</tr>
<tr>
<td></td>
<td>(0.016,0.484)</td>
<td>(-0.072,-0.900)</td>
<td>(-0.337,-0.024)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.676</td>
<td>0.814</td>
<td>0.730</td>
</tr>
<tr>
<td></td>
<td>(0.382,0.883)</td>
<td>(0.406,0.936)</td>
<td>(0.535,0.866)</td>
</tr>
<tr>
<td>$Q$</td>
<td>0.299</td>
<td>0.089</td>
<td>0.439</td>
</tr>
<tr>
<td></td>
<td>(0.123,0.591)</td>
<td>(0.045,0.199)</td>
<td>(0.225,0.780)</td>
</tr>
</tbody>
</table>

Notes: This table contains the posterior median and 90% credible sets for the parameters in the stochastic volatility equation for each of the variables. Estimates are based on the last 20k of 40k draws from the Gibbs sampler.

by Kirchner et al. (2010) and Pereira and Lopes (2014), it is possible that fiscal policy might have been on unsustainable paths at certain points in history and the model should be allowed to capture this behavior. I keep track of the fraction of draws that generate non-stationary VAR coefficients for each period. This number turns out to be zero for models specified in growth rates and approximately 10-20% for models specified in levels.

Table 4.3 contains the estimates for the volatility parameters in the TVP-SVAR-SV-M model estimated with consolidated government data specified in growth rates. The intercept and autoregressive coefficients are fairly similar to the estimates from the SVAR-SV-M model (see Table 4.1), but allowing for time-varying parameters in the model tends to lower the variance of the stochastic process in the second moment equation. The lower variance is expected because some variation in the series is absorbed by changes in the coefficients. Visually, the stochastic volatilities, shown in Figure C.4 in Appendix C.5, are similar to those obtained from the fixed parameter model. The notable exception is the volatility in government spending, which, in contrast to the estimates from the SVAR-SV-M model, is more tightly estimated and exhibits some slow variation over time.

Since the coefficients in the level equation evolve over time, the TVP-SVAR-SV-M model could potentially generate a different set of impulse response functions for each time period. To explore this possibility, I calculate the impulse response functions to first and second moment shocks separately for each period, holding the parameters fixed.
Figure 4.7: Time-varying output response to first moment fiscal shocks

**Revenue shock**

(a) Response of output to surprise revenue cut on impact

(b) Response of output to surprise revenue cut after 2 years

**Spending shock**

(c) Response of output to surprise spending increase on impact

(d) Response of output to surprise spending increase after 2 years

Notes: This figure contains the time-varying response of output to first moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.

for all horizons. Figure 4.7 shows the time-varying response of output to first moment shocks. In contrast to the figures of impulse response functions in the previous section,
Figure 4.8: Time-varying output response to second moment fiscal shocks

**Revenue uncertainty shock**

(a) Response of output to revenue uncertainty shock on impact

(b) Response of output to revenue uncertainty shock after 2 years

**Spending uncertainty shock**

(c) Response of output to spending uncertainty shock on impact

(d) Response of output to spending uncertainty shock after 2 years

Notes: This figure contains the time-varying response of output to second moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.

The horizontal axis represents time and not the response horizon. Instead, the responses in different horizons are plotted separately, *i.e.* 4.7(a) and 4.7(c) contain the impact response
to a surprise revenue cut and spending increase, respectively, and 4.7(b) and 4.7(d) show
the response to the same two shocks but after eight quarters. For comparability across
time periods, the magnitude of the shocks is constant across periods. The fiscal shocks
are normalized to their average ratio to GDP across the entire sample so that, as in
Section 4.2, the impulse response of output is the percent change in output in response
to a spending increase or revenue cut of one percent of GDP. Consistent with the results
from Pereira and Lopes (2014), I find that the ability of tax policy to stimulate the
economy has weakened over time. The impact response of output to a surprise revenue
cut gradually falls from around 1% at the beginning of the sample to around 0.8% at the
end. In contrast, the effects of government spending on output are very stable across the
entire sample.

Figure 4.8 presents the time profile of the effects of fiscal policy uncertainty shocks.
A doubling of revenue uncertainty has no significant effect on output in any period and
there is essentially no variability in the impulse response function across time. Spending
uncertainty also has an insignificant effect on output, but the mass of the posterior distri-
bution is mostly in the positive region. The key feature of the plot, however, is that the
impulse response is essentially flat over the entire sample, showing no evidence of changes
in the transmission of fiscal policy uncertainty shocks.

The results are very similar when I estimate the model using federal government data
and with the alternative trend assumptions, all of which are shown in Appendix C.5. In all
cases, the effect of a surprise tax cut becomes weaker over time while the effect of a surprise
spending increase is fairly constant over the entire sample. Across all specifications,
the response of output to second moment shocks is insignificant and exhibits almost no
variation over time.

The TVP-SVAR-SV-M results thus provide no evidence to suggest that parameter
instability observed in the previous section is due to a change in the transmission of
uncertainty shocks over time. However, it supports the finding that the fiscal policy
uncertainty does not have a significant effect on output.

4.4 Estimating uncertainty with maximum likelihood

Two aspects of the estimation procedure for both the fixed and time-varying parameter models with stochastic volatility could potentially raise concerns about the results. First, even though I use the entire set of available data in the estimation, the beginning of the sample, which trains the priors for many of the parameters, is treated differently than the rest of the data. The splitting of the sample could influence the estimated effects of first moment shocks—e.g. Hall (2009) points out that estimates of government spending multipliers become more precise when the sample includes the Korean War military buildup from the early 1950s—and could also matter for the estimated effects of second moment shocks. Second, I must specify priors that, despite my guiding principle of limiting their influence, inevitably affect the outcome.

To address these two concerns, I turn to a less-flexible but simpler model that I can estimate with standard maximum likelihood methods. Instead of stochastic volatility, I model the time-varying variance using a multivariate, generalized, autoregressive, conditional heteroskedasticity (MGARCH) specification. As before, the second moment feeds back into the level equation and interacts with the endogenous variables,

\[
\begin{align*}
z_t &= C D_t + \sum_{i=1}^{p} \Gamma_i z_{t-i} + \sum_{j=0}^{p_f} \Lambda_j \log(h_{t-j}) + u_t, \\
u_t &= B \eta_t, \quad \eta_t \sim N(0, H_t), \\
H_t &= C_v + \sum_{j=1}^{p_F} F_j \text{diag}(\eta_{t-j} \eta_{t-j}'), + \sum_{i=1}^{p_G} G_i H_{t-i},
\end{align*}
\]

where \(C_v, F_j, G_i\) are diagonal matrices of coefficients, \(H_t\) is a diagonal matrix with the variance of the structural errors along the diagonal, \(h_t\) is a vector of those diagonal
elements and the \text{diag}(\cdot) operator extracts the diagonal elements of a matrix. The diagonality assumption for the coefficients in the second moment equation greatly reduces the number of parameters for estimation and is motivated by the fact that the structural shocks $\eta_t$ are uncorrelated.

Applications of versions of this model date back to Engle \textit{et al.} (1987), who explored the effects of time-varying risk premia on the term structure of interest rates. More recent studies include Jordà and Salyer (2003), who show that monetary policy uncertainty lowers nominal interest rates; Elder (2004a), who finds that inflation uncertainty has a significant negative effect on output; Elder (2004b), who shows that monetary policy uncertainty does not affect output and Elder and Serletis (2010), who establish an inverse relationship between oil price uncertainty and output.

In contrast to the SVAR-SV-M model, the SVAR-MGARCH-M model does not have an independent stochastic process governing the evolution of the second moments. Instead, any large fluctuations in the second moments originate from large level shocks. Although this specification is somewhat restrictive theoretically—uncertainty could arise independently of level shocks—it reduces the complexity of the model enough to make maximum likelihood estimation feasible.

The maximum likelihood estimator for the SVAR-MGARCH-M model does not have a closed form solution. I estimate the model by maximizing the log-likelihood via numerical optimization, adding one layer of complexity at a time and using the estimates from the previous steps as starting values in the next step. Estimating the models—(1) SVAR, (2) SVAR-MARCH, (3) SVAR-MGARCH, and (4) SVAR-MGARCH-M—separately and observing changes in information criteria also allows me to explore which features matter the most for improving model fit.

Due to the large number of parameters in the model, the specification is parsimonious but sufficient to capture important dynamics. Specifically, I set $p = 4$ and $p_A = 0$ for the level equation and $p_F = p_G = 1$ for the MGARCH equation. The model is estimated by
Table 4.4: SVAR-MGARCH-M model fit (1947Q1–2015Q4) with consolidated government data in growth rates

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>−1335.6057</td>
<td>2761.21</td>
<td>2923.31</td>
<td>45</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>−1273.5200</td>
<td>2643.04</td>
<td>2815.94</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MGARCH</td>
<td>−1251.5479</td>
<td>2603.10</td>
<td>2783.20</td>
<td>50</td>
</tr>
<tr>
<td>SVAR-MGARCH-M</td>
<td>−1251.0845</td>
<td>2606.17</td>
<td>2793.48</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2L + 2q$ and BIC = $-2L + log(T)q$, where $q$ is the number of parameters and $L = \sum_{t=1}^{T} L_t$. I only add two parameters moving from ARCH to GARCH because the GARCH term in the second moment equation for $\tau_t$ was highly insignificant.

maximizing the log-likelihood, $L = \sum_{t=1}^{T} L_t$, which is built iteratively with

$$L_t = -\frac{n}{2} \log(2\pi) - \frac{1}{2} \log |B| - \frac{1}{2} \log |H_t| + \frac{1}{2} (\eta_t' H_t^{-1} \eta_t),$$  \hspace{1cm} (4.15)

where $n$ is the number of variables. Presample values for the conditional variance matrix are set to their unconditional expectations. Assuming only one lag of the dependent variables for demonstrative purposes, the errors $\eta_t$ and their conditional variances $H_t$ are constructed as follows,

$$H_1 = |(I - G - F)^{-1} C_v|,$$
$$\eta_1 = B^{-1} (z_2 - C - \Gamma z_1 - \Lambda \log(H_1)),$$
$$H_2 = C_v + F \text{diag}(\eta_1 \eta_1') + GH_1,$$
$$\eta_3 = B^{-1} (z_3 - C - \Gamma z_2 - \Lambda \log(H_2)),$$
$$H_3 = C_v + F \text{diag}(\eta_2 \eta_2') + GH_2,$$

To ensure that $H_t$ is positive definite and that $\eta_t$ is covariance stationary, I follow Elder and Serletis (2010) and impose the following restrictions: $C_v$ is element-wise positive, $F$
Figure 4.9: Estimates of fiscal policy uncertainty for consolidated government data

(a) Government revenue volatility

(b) Government spending volatility

Notes: This figure contains the plots for the time-varying standard deviations of consolidated government revenue and spending from the SVAR-MGARCH-M model estimated with data specified in growth rates.

and $G$ are element-wise non-negative and the eigenvalues of $(F + G)$ are less than one in modulus.

I estimate only the elements in $\Lambda$ that correspond to the output response to revenue and spending uncertainty and impose zero restrictions on the remaining ones. Relaxing these restrictions greatly increases estimation time but does very little to improve the likelihood. Furthermore, in some instances adding ARCH or GARCH terms generates coefficients that are so close to zero or measured so imprecisely that it complicates numerical calculations of the Hessian. I impose zero restrictions on those coefficients as well.

As in the previous sections, I consider both federal and consolidated government data and stochastic and deterministic trend assumptions. I estimate the model using the entire sample 1947Q1–2015Q4, but also consider the 1960Q1–2015Q4 subsample for direct comparability to results from the previous sections.

Table 4.4 contains the maximized log-likelihood as well as the Akaike and Bayesian
Figure 4.10: Estimates of fiscal policy uncertainty for federal government data

(a) Government revenue volatility

(b) Government spending volatility

Notes: This figure contains the plots for the time-varying standard deviations of federal government revenue and spending from the SVAR-MGARCH-M model estimated with data specified in growth rates. Information criteria for each of the models starting with the homoskedastic SVAR and estimated using consolidated government data specified in growth rates. Both information criteria suggest that accounting for conditional heteroskedasticity is important for improving the model fit, but allowing the endogenous variables to react to it is not. The story is very similar for the other specifications, which are shown in Tables C.1–C.3 in Appendix C.6. This is also the case when I consider the 1960Q1–2015Q4 subsample, as shown in Tables C.4–C.7. Although for some data specifications there is an improvement in the AIC when the GARCH terms enter the mean, the BIC never goes down.

Figures 4.9 and 4.10 plot the estimates of fiscal policy uncertainty using the SVAR-MGARCH-M model for consolidated and federal government data, respectively. Both spending and revenue exhibit a very large spike in volatility at the onset of the Korean War near the end of 1950. In contrast to some other military buildups in US history, tax revenues increased dramatically with spending because President Truman wanted to avoid...
Table 4.5: Coefficient estimates for output response to uncertainty for various subsamples and data

<table>
<thead>
<tr>
<th>Volatility</th>
<th>Consolidated</th>
<th>Federal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1947Q1–2015Q4</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1947Q1–2015Q4</td>
</tr>
<tr>
<td>$\log(h_\tau^t)$</td>
<td>$-0.084$</td>
<td>0.086</td>
</tr>
<tr>
<td></td>
<td>(0.316)</td>
<td>(1.160)</td>
</tr>
<tr>
<td>$\log(h_0^g_t)$</td>
<td>0.130</td>
<td>0.239</td>
</tr>
<tr>
<td></td>
<td>(0.145)</td>
<td>(0.424)</td>
</tr>
<tr>
<td>$\log(h_\tau^g_t)$</td>
<td>$0.130$</td>
<td>$-0.131$</td>
</tr>
<tr>
<td></td>
<td>(0.246)</td>
<td>(0.477)</td>
</tr>
<tr>
<td>$\log(h_0^g_t)$</td>
<td>1.707</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>(2.284)</td>
<td>(7.218)</td>
</tr>
</tbody>
</table>

Notes: This table contains point estimates of the coefficients corresponding to the response of output to $\log(h_\tau^t)$ and $\log(g_\tau^t)$, i.e. revenue and spending uncertainty, respectively. Standard errors are in parentheses, $st$ refers to stochastic trend and $dt$ refers to deterministic trend. Missing values indicate that the estimated series did not exhibit conditional heteroskedasticity.

budget deficits (see e.g. the discussion in Perotti, 2007). For government spending—shown in Figures 4.9(b) and 4.10(b) for consolidated and federal government data, respectively—the rise in volatility is several orders of magnitude larger than at any other time in the sample. Moreover, the Korean War also coincides with one of the largest increases in revenue volatility, as shown in Figures 4.9(a) and 4.10(a). Besides this significant difference arising from extending the sample, the MGARCH estimates of fiscal policy uncertainty are visually similar to the ones obtained from the stochastic volatility model (see Figure 4.2).

Table 4.5 presents the coefficient estimates of the elements in $\Lambda$ corresponding to output response to fiscal policy uncertainty. Regardless of the specification, both the full

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4 The contrasting dynamics between consolidated and federal government spending volatilities arises from differences in the estimates of the autoregressive coefficient in $G$ corresponding to spending. For consolidated government spending this coefficient is large and significant whereas for federal spending it is small and insignificant.
sample and subsample results indicate that fiscal policy uncertainty has no significant effect on output. Excluding the Korean War makes the coefficient estimates even more imprecise, especially for government spending. In fact, this effect is so large that when the data is in levels and the sample starts in 1960Q1, the model is unable to reject homoskedasticity in the structural shocks to government spending.

These results reinforce the findings from the stochastic volatility models considered in the two previous sections. The SVAR-MGARCH-M model addresses potential concerns about the differential treatment of different parts of the data (training sample and estimation sample) and the influence of the priors in Bayesian estimation. Estimating fiscal policy uncertainty for the entire sample reveals that the Korean War is an influential observation, but including it does not have an important impact on the estimates of the effect of fiscal policy uncertainty on output, which are insignificant in all cases. Moreover, the evidence for the existence of a link between fiscal policy uncertainty and aggregate outcome is considerably weaker in the MGARCH specification than in the SV specification, suggesting that the influence of the priors is not driving the insignificant results found in the previous sections.

4.5 Sensitivity to monetary policy and anticipation effects

Section 4.2 shows that the effects of fiscal policy uncertainty on output are sensitive to trend assumptions and time periods. When I specify the data in growth rates, this uncertainty does not cause a significant response in output although the evidence is clearer for spending uncertainty than for revenue uncertainty since the latter exhibits much more fluctuation over time than the former. When I specify the data in levels, the significance of the response of output to uncertainty shocks differs depending on when the sample starts and ends. Section 4.3 argues that this subsample variability is not driven by an underlying change in the transmission of uncertainty shocks over time, which appear to have a stable, insignificant effect on output over the entire sample period. Moreover, the
previous section makes the case that these results are neither driven by the influence of the priors nor the omission of the Korean War—a very volatile period for fiscal policy—in the estimation of uncertainty. In this section, I tackle the issue of misspecification. Drawing on the empirical fiscal multiplier literature, I broaden the information set in the baseline trivariate SVAR-SV-M model to control for variables that could influence the estimated structural shocks. I first discuss the issues and the variables that I consider and then present the results.

As argued by Rossi and Zubairy (2011), failing to control for monetary policy may attribute some of the fluctuations in output to fiscal policy when they are actually driven by actions taken by the Federal Reserve. Moreover, if important monetary policy events occur around times of large fluctuations in the volatility of government spending or revenue, then the same could be true for the effects of fiscal policy uncertainty. To control for monetary policy, I included quarterly averages of the federal funds rate (FFR), which is available from 1954Q3. Rather than start in the middle of the 1950s, I use 1960Q1–1969Q4 for the training sample and estimate the model for the period of 1970Q1–2015Q4. The FFR is ordered last in the endogenous variable vector, allowing it to respond to all of the other variables within the same quarter.

The sample period contains several years of no variation in the FFR due to the zero lower bound. However, the Federal Reserve was very active during this period, turning to unconventional policies such as quantitative easing and forward guidance. To control for these policies, I also estimate the model using the shadow short rate (SSR) from Wu and Xia (2016). The SSR uses the entire term structure of interest rates in a nonlinear state-space model to back out an estimate of the short rate as if it were not bounded below by zero. The authors argue that this measure captures the stance of monetary policy during the time that the zero lower bound was binding. Figure C.11 in Appendix C.7 plots the SSR along with the FFR. While the FFR was stuck at the zero lower bound, the SSR dipped into negative territory and began to rise as the Federal Reserve started to unwind
Figure 4.11: SVAR-SV-M model impulse responses to first moment shocks controlling for monetary policy and fiscal foresight

Impulse response of output to a consolidated government revenue shock

(a) FFR  (b) MBS  (c) ER  (d) DN  (e) SPF

Impulse response of output to a federal government revenue shock

(f) FFR  (g) MBS  (h) ER  (i) DN  (j) SPF

Impulse response of output to a consolidated government spending shock

(k) FFR  (l) MBS  (m) ER  (n) DN  (o) SPF

Impulse response of output to a federal government spending shock

(p) FFR  (q) MBS  (r) ER  (s) DN  (t) SPF

Notes: This figure contains the posterior median and 68% credible sets of the impulse response of output to government spending and revenue shocks for various information sets with the fiscal variables and GDP specified in growth rates. The vertical axis is in percent growth rates. Estimates are based on the last 20k of 40k draws from the Gibbs sampler.

its asset purchase program. Nevertheless, the impulse response functions have the same shape and similar magnitudes whether the model is estimated with the FFR or the SSR. As a result, I only report the results for the model with the FFR.

I also augment the information set with variables that control for potential anticipation effects. Due to lags in legislation and implementation of fiscal policies, people may be aware of and adjust their behavior in response to upcoming changes in government spending or taxes before they are actually applied. When that is the case, the estimated structural shocks do not correspond to surprise innovations in fiscal policy. Ramey (2011)
Figure 4.12: SVAR-SV-M model impulse responses to second moment shocks controlling for monetary policy and fiscal foresight

Impulse response of output to a consolidated government revenue uncertainty shock

(a) FFR  (b) MBS  (c) ER  (d) DN  (e) SPF

Impulse response of output to a federal government revenue uncertainty shock

(f) FFR  (g) MBS  (h) ER  (i) DN  (j) SPF

Impulse response of output to a consolidated government spending uncertainty shock

(k) FFR  (l) MBS  (m) ER  (n) DN  (o) SPF

Impulse response of output to a federal government spending uncertainty shock

(p) FFR  (q) MBS  (r) ER  (s) DN  (t) SPF

Notes: This figure contains the posterior median and 68% credible sets of the impulse response of output to a doubling of fiscal spending and revenue uncertainty for various information sets with the fiscal variables and GDP specified in growth rates. The vertical axis is in percent growth rates. Estimates are based on the last 20k of 40k draws from the Gibbs sampler.

shows that both professional forecasts and dummy variables for dates of military conflicts Granger-cause spending shocks from SVAR models. On the revenue side, Leeper et al. (2013) discuss issues with estimating the effects of tax shocks when agents have foresight. In this case, tax shocks in the SVAR model are non-fundamental and inference is contaminated. Fiscal foresight can also affect inference on second moment shocks. If some shocks are forecastable then not only could the estimate of uncertainty be affected, but the response of output to uncertainty shocks could change as well.

I consider several variables to purge the model of predictable innovations. The first
is the implicit tax rate derived from municipal bond spreads (MBS) from Leeper et al. (2012). Since municipal bonds are exempt from federal taxes then changes in their yield spread over treasury bonds with similar maturity and risk, under efficient markets, should signal anticipated tax changes. The series is available from 1953Q2–2008Q3. I order it last, after the FFR, following the assumption in Leeper et al. (2013) that news contained in the MBS does not affect the other variables contemporaneously. I estimate the model for the period 1970Q1–2008Q3, using the first 10 years of data as a training sample for the priors.

The second variable is the accumulated excess returns of large US military contractors (ER) from Fisher and Peters (2010). In the event of a change in expected future military spending, forward looking agents will incorporate expectations of sales into the valuation of stocks of large military contractors. Thus changes in excess returns can be used to predict future federal government expenditures. The ER data is available from 1947Q2–2007Q3 and I estimate the model for the period 1970–2007Q3 with this series ordered last as in Fisher and Peters (2010).

The third variable is defense news (DN) from Ramey (2011). The series is constructed by estimating the changes in the expected present value of government spending in response to foreign political events that are mentioned in news sources. It is available from 1947Q1–2013Q4 and I estimate the model for the period 1970–2013Q4 with this series ordered first as in Ramey (2011).

The last variable that I consider is the mean of the one-quarter-ahead forecast for the growth rate of government spending from the Survey of Professional Forecasters (SPF) from the Philadelphia Federal Reserve Bank website. The data is available for both federal and consolidated government sectors from 1981Q3–2015Q4. I use the first 10 years as a training sample and estimate the model over the period 1991Q3–2015Q4. Following Auerbach and Gorodnichenko (2012), the forecast variable is lagged so that the time $t − 1$ forecast for time $t$ aligns with the time $t$ realization of the other variables. This alignment
implies that there is no contemporaneous feedback from the other variables because the forecast was made in the previous quarter. Thus, I order SPF first.

I estimate the model with each of the variables separately and the ordering and time period discussed above. Each model includes the FFR, four lags of the endogenous variable vector and only the contemporaneous effect of the uncertainty measure, \( p = 4 \) and \( p_\lambda = 0 \). Figure 4.11 plots the output response to first moment shocks in the augmented SVAR-SV-M models estimated using data in growth rates. The first two rows show the impulse responses of output to a surprise consolidated and federal government revenue cut and the last two rows show the corresponding impulse responses to spending shocks. Despite the differences in information sets and time periods, both fiscal shocks always have expansionary effects and the shape and magnitude of the impulse response functions are very similar across specifications.

However, the same is not true for the effects of the second moment shocks, shown in Figure 4.12. The impulse response of output is very sensitive to additional variables in the information set and ranges from significantly negative to significantly positive. The majority of impulse responses, however, are not statistically distinguishable from zero at any horizon. The same holds for the model estimated in levels with a linear time trend. The impulse response of output to first and second moment shocks with this specification are shown in Figures C.12 and C.13 in Appendix C.7. Once again, the first moment shocks generate fairly stable impulse responses while the second moment shocks generate positive and negative, but mostly insignificant, movements in output.

Augmenting the information set in the model from Section 4.2 reveals that there is no consistent relationship between fiscal policy uncertainty and output. Even the effects of consolidated government revenue uncertainty on output with the deterministic trend assumption, which were significantly negative across subsamples in Section 4.2, do not

\[p^5\text{The estimation follows the same steps outlined in Appendix C.2 but with additional structural equation coefficients in } \alpha. \text{ I impose a restriction on the residuals of the DN series to be homoskedastic since this variable contains mostly zeros and does not have a lot of variation over the sample.}\]
survive in a model with additional variables.

4.6 Revisiting the results from FGKR

The evidence presented in this chapter strongly suggests that fiscal policy uncertainty does not affect output in any systematic way. Therefore, in this section, I revisit the empirical results presented in FGKR that provide evidence for a significant negative relationship between output and fiscal policy uncertainty. I briefly discuss their model and the main differences between our empirical approaches and show that addressing one of these differences aligns their results with mine.

FGKR estimate the following law of motion for US capital tax rates, allowing for time-varying volatility,

\[
\tau_t^k - \tau^k = \theta(\tau_{t-1}^k - \tau^k) + \phi_y \tilde{y}_{t-1} + \phi_b \left( \frac{b_{t-1}}{y_{t-1}} - \frac{b}{y} \right) + h_t^\frac{1}{2}\varepsilon_t, \tag{4.16}
\]

\[
\log(h_t) = \mu + \rho \log(h_{t-1}) + v_t, \quad v_t \sim N(0, Q), \tag{4.17}
\]

where \(\tau_t^k\) is the capital tax rate, \(\tilde{y}_t\) is detrended log output, \(b_t\) is public debt, \(y_t\) is output and variables without \(t\) subscripts are means of variables with the same label. They then take the median of their estimate of \(\log(h_t)\) and put it into a structural VAR model, as an observed variable, to analyze the effects of fiscal policy uncertainty shocks on the economy. Their main findings, reproduced in Figure 4.13 using their data for the period 1970–2008, are that an unanticipated increase in fiscal policy uncertainty lowers output and raises markups.\(^6\) In addition to the 68% confidence interval, I also report the 90% confidence interval because that is the level of significance used in their paper.

Our empirical approaches differ among several dimensions. First, I use total government revenue instead of capital tax rates. Second, we have different information sets in

\(^6\)For inference, FGKR re-sample the residuals with replacement whereas I use a wild bootstrap procedure that multiplies the residuals by 1 or \(-1\) with equal probability but maintains their order in time. This procedure is more suitable for time series with heteroskedasticity.
Figure 4.13: Impulse response functions to a two-standard-deviation innovation in capital tax volatility (replication of Figure 3 in FGKR)

(a) Capital tax volatility

(b) Output

(c) Consumption

(d) Investment

(e) Real wage

(f) Hours worked

(g) Markup

(h) Price level

(i) Nominal rate (BPS)

Notes: This figure contains the impulse responses to a two-standard-deviation shock to capital tax volatility. The shaded areas are 90% (light blue) and 68% (dark blue) confidence intervals based on symmetric bootstrap sampling with 10,000 draws. Identification is based on recursive ordering of the variables. For details see Fernández-Villaverde et al. (2015).

In what follows, I revisit their results while addressing the last difference from the list, i.e. one-step versus two-step estimation. I focus on this difference because it is among the simplest modifications to implement and because it highlights the importance of endogenous estimation of uncertainty. In the two-step procedure, the volatility of the
capital tax rate is treated as an observed variable. The one-step procedure, on the other hand, takes into account the uncertainty around the estimate of the volatility in estimating its effect on output.

Let the VAR model with the endogenous variable vector $x_t$ be specified as

$$
x_t = \Theta m_t + u_t, \quad (4.18)
$$

$$
u_t = A^{-1} \varepsilon_t, \quad \varepsilon_t \sim N(0, I), \quad (4.19)
$$

with $m_t = [1, t, x_{t-1}, \ldots, x_{t-p}]'$. Let $T$ be the number of observations, $p = 4$ be the number of lags, $m = [m_1, \ldots, m_T]'$, and $x = [x_1, \ldots, x_T]'$. The covariance matrix for the reduced-form residuals $u_t$ is $\Sigma = A^{-1} A^{-1'}$, where $A$ defines the contemporaneous interactions among the endogenous variables.

To internalize the error around the estimate of volatility from (4.17) in the estimate of its effect on output in (4.18) and (4.19), I proceed with the following steps. For the coefficients in (4.16) and (4.17) as well as the stochastic volatility $h_t$, I construct the priors and draw from the posterior distributions in the same way as described in Appendix C.2. In order to compare the results from the VAR model for the entire sample, I do not split the data into observations for the training sample and observations for estimation. Instead I calibrate the priors for the coefficients in (4.16) to the OLS estimates from a homoskedastic version of that equation estimated using the entire sample. Conditional on the draw of $h^T = \{h_t\}_{t=1}^T$, I obtain VAR estimates $\hat{\Theta}$ with ordinary least squares and let $S = (x - \hat{\Theta} m)'(x - \hat{\Theta} m)$. I use diffuse priors for the VAR coefficients and the covariance matrix. I draw $\Sigma$ from an inverse Wishart distribution with scale parameter $S^{-1}$ and $T - p$ degrees of freedom, i.e. $\Sigma \sim IW (S, T - p)$. Conditional on the draw for $\Sigma$, I draw $\Theta$ from a normal distribution, i.e. vec$(\Theta) \sim N \left( \text{vec} (\hat{\Theta}), \Sigma \otimes (m'm)^{-1} \right)$. Based on the timing restrictions from FGKR, I obtain the structural coefficient matrix $A$ with a Cholesky decomposition of $\Sigma$ and use it to calculate the impulse response functions to
Figure 4.14: FGKR result comparison with 1-step and 2-step estimation

(a) Volatility estimate

(b) 2-step (original)

(c) 2-step (my estimate)

(d) 1-step

Notes: This figure contains the estimate of stochastic volatility for the policy reaction function for capital tax rates as well as the impulse response functions of output to a two-standard-deviation shock to capital tax rate volatility. The shaded areas are 90% (light blue) and 68% (dark blue) credible sets. The volatility plot only includes the 68% credible set. Estimates for Figures 4.14(a) and 4.14(d) are based on the last 10k of 15k draws from the Gibbs sampler. Figures 4.14(b) and 4.14(c) are based on symmetric bootstrap sampling with 10k draws.

Figure 4.14 presents the results from the one-step estimation procedure.\textsuperscript{7} Figure 4.14(a) plots my estimate of the capital tax rate volatility along with the median estimate from FGKR. The median of my estimate moves very closely with theirs and the two have

\textsuperscript{7}The capital tax rate series is available from 1970Q2 but I start estimation in 1970Q3 because the lagged tax rate appears on the right-hand side of the policy reaction function. For comparability, I re-estimate the original FGKR model with the same start date, as oppose to the 1970Q2 start date used in their paper and in generating the results for Figure 4.13.
a correlation of 0.9. Nevertheless, since there are noticeable differences\(^8\) in the median estimates, I present the impulse response of output to a volatility shock using my median estimate, shown in Figure 4.14(c), along with the one obtained using their estimate, shown in Figure 4.14(b). In both cases, the effect of fiscal policy uncertainty on output is significantly negative at the 90\% level of confidence. Figure 4.14(d) shows the same impulse response function estimated in one step, \emph{i.e.} incorporating the uncertainty around the volatility estimate. In this case, the effect of a capital tax rate volatility shock on output is insignificant even at the 68\% confidence level.

A simple modification in the algorithm, namely combining the estimation of uncertainty and its effect on output into one step, changes the FGKR result and makes it consistent with the findings in this chapter. This comparison also highlights the importance of endogenous estimation of uncertainty.

\section*{4.7 Conclusion}

The Great Recession was followed by one of the slowest economic recoveries in US history and many have argued that fiscal policy uncertainty contributed to the sluggish growth. I evaluate this assertion by nesting the hypothesis in a standard SVAR used for fiscal analysis. I modify the model to allow for the volatility of the variables to evolve stochastically and enter the level equation. The stochastic volatility captures the dispersion in the one-step-ahead forecast error and provides a measure of uncertainty for the fiscal variables. The key features of the model are that the fiscal shocks are identified and that the effects of fiscal policy uncertainty are jointly estimated with uncertainty itself.

I find that there is no systematic relationship between fiscal policy uncertainty and

\(^8\)The fact that the estimates are not identical stems from differences in estimation. I use the algorithm described above and used throughout this chapter, while they use a particle filter with priors that have uniform distributions over the entire support of each of the parameters (for details see Online Appendix C in Fernández-Villaverde \emph{et al.}, 2015).
output. For both fiscal policy instruments, spending and taxes, the effects of uncertainty are sensitive to the time period, trend assumptions, the information set, as well as whether or not the fiscal variables include state and local data in addition to federal data. Nevertheless, they are mostly insignificant across these various specifications.

To explore whether the instability across time periods arises from a change in the transmission of fiscal policy uncertainty shocks over time, I estimate the baseline model with the additional feature of time-varying parameters. This modified model does not provide evidence to support the argument that the fiscal policy uncertainty shocks have more pronounced effects on output at different periods in time. Instead it reveals that these effects are very stable and insignificant across the entire sample.

I also consider an alternative specification for the underlying volatility process that allows me to estimate the relationship between fiscal policy uncertainty and output over the entire sample—including the volatile Korean War period—with maximum likelihood methods. These results support the finding of insignificant effects of fiscal policy uncertainty on output and show that they are neither driven by excluding the Korean War nor by my choice of priors in the baseline model.

When I extend the information set to control for monetary policy and anticipation effects, no significant effect from the baseline model survives. In fact, the impulse response of output to fiscal policy uncertainty even changes signs depending on which control variable I include, although it is nearly always insignificant. The behavior of the output in response to second moment shocks greatly contrasts the effects of first moment shocks, which are very stable and significant across all specifications. The comparison of the stability of the effects of first and second moment shocks is another helpful outcome of nesting the research question in a standard empirical model for fiscal policy analysis.

Finally, I revisit the empirical results from Fernández-Villaverde et al. (2015) and show that when their two-step estimation is modified to incorporate the uncertainty around the estimate of uncertainty via a one-step estimation algorithm, the effect of fiscal policy
uncertainty on output is no longer significant.

This chapter thus challenges the claims that uncertainty about fiscal policy has detrimental effects on the aggregate economy. I show that there is no consistent relationship between fiscal policy uncertainty and output and that this instability is likely not the result of a change in the transmission of these shocks over time, which some have argued could arise as a result of the zero lower bound restricting monetary policy. Moreover, I highlight the importance of incorporating the uncertainty around the estimate of uncertainty in analyzing its effect on output by providing an example of how it can affect inference and alter results.
Chapter 5

Conclusion

This dissertation presents empirical evidence on various aspects of the effects and transmission of stabilization policies. That evidence supports three main findings. First, interest-rate pass through from money market rates to long-term retail deposit rates has declined in Canada since the financial crisis. Second, Canadian unconventional monetary policies had expansionary effects on the Canadian economy during the zero lower bound. Third, fiscal policy uncertainty is not an important contributor to fluctuations in US output. Each of these findings contributes to our understanding of either monetary or fiscal policy in the context of new challenges that have emerged since the financial crisis.

In Chapter 2, I use a nonlinear vector error-correction model to explore the dynamics of retail loan and deposit rates in Canada. This method is flexible and, in contrast to other approaches in the literature, it does not assume weak exogeneity of the market rate, making inference more robust. I find evidence of asymmetries in the speed of adjustment to increases and decreases in funding costs for various rates. Moreover, I show that there has been a significant decline in pass-through to long-term deposit rates in recent years. The implication of this finding is that when the Bank of Canada begins to raise the target rate, we can expect mortgage rates to respond quickly and fully and deposit rates to adjust partially and sluggishly.

In Chapter 3, we estimate a Bayesian structural vector autoregressive model with a
small-open economy structure to analyze the effects of Canadian unconventional monetary policies on the Canadian economy. Our measure of monetary policy stance is the shadow short rate, which we estimate using the term-structure model proposed by Wu and Xia (2016). Although the shadow rates are unable to distinguish between types of unconventional monetary policies, they provide a consistent measure across the two countries in our model and they allow us to extend the data to before the beginning of the zero lower bound episode. We find that Canadian unconventional monetary policy had an expansionary effect on Canadian output, suggesting that if the Bank of Canada needs to rely on these unconventional methods in the future, there is reason to believe that they are effective at stimulating the economy. We also show that the effects of US unconventional monetary policies had a positive effect on the Canadian economy.

In Chapter 4, I test the hypothesis that fiscal policy uncertainty has a detrimental effect on US output; an idea that became very popular during the Great Recession. I consider the two main fiscal policy instruments, spending and taxes, and nest this hypothesis in a standard model used for estimating fiscal multipliers. I explore the sensitivity of the relationship between fiscal policy uncertainty and output to various trend assumptions, information sets and modeling choices and find that the evidence does not support this hypothesis. While some have argued that fiscal policy uncertainty contributed to the severity of the Great Recession and the sluggishness of the recovery, I challenge this claim by showing that there is no systematic relationship between fiscal policy uncertainty and US output.
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126


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135


Appendix A

Interest rate pass-through:

a nonlinear vector error-correction approach

A.1 Additional tables
Table A.1: Hypothesis test results for deposit rates

<table>
<thead>
<tr>
<th>Term</th>
<th>Time</th>
<th>$\mathcal{H}_{1,2}^{\delta}$</th>
<th>Conditional</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\mathcal{H}_{1,2}^{\alpha,\delta} \mid \mathcal{H}^\beta$</td>
<td>$\mathcal{H}_{1,2}^{\alpha,\delta} \mid \mathcal{H}^\beta$</td>
</tr>
<tr>
<td>FTD 3m</td>
<td>'83-'96</td>
<td>11.24</td>
<td>14.62***</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>8.97</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>137.14</td>
<td>7.68**</td>
</tr>
<tr>
<td>GIC 1y</td>
<td>'83-'96</td>
<td>3.89</td>
<td>98.26***</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>5.46</td>
<td>78.15***</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>20.69**</td>
<td>-</td>
</tr>
<tr>
<td>GIC 3y</td>
<td>'83-'96</td>
<td>61.65***</td>
<td>109.19***</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>27.44***</td>
<td>102.25***</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>1.79</td>
<td>3.79*</td>
</tr>
<tr>
<td>GIC 5y</td>
<td>'83-'96</td>
<td>16.56***</td>
<td>37.55***</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>10.17*</td>
<td>59.54***</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>44.08</td>
<td>5.62**</td>
</tr>
<tr>
<td>FTD 5y</td>
<td>'83-'96</td>
<td>16.24***</td>
<td>24.41***</td>
</tr>
<tr>
<td></td>
<td>'96-'07</td>
<td>13.14**</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>'09-'15</td>
<td>21.34*</td>
<td>-</td>
</tr>
</tbody>
</table>

Notes: This table reports the likelihood ratio test statistics for each of the hypotheses of interest in the following order: (1) $\mathcal{H}_{1,2}^{\delta}$ tests for the presence of asymmetric adjustments in the error-correction; (2)–(3) $\mathcal{H}_{1}^{\alpha,\delta} \mid \mathcal{H}^\beta$ for $i \in \{1, 2\}$ tests for weak exogeneity of the market rate and retail rate, respectively, conditional on complete pass-through; and (4) $\mathcal{H}^\beta \mid \mathcal{H}_{1,2}^{\alpha,\delta}$ tests for complete pass-through conditional on weak exogeneity. Results are based on 4,999 bootstrap samples. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. If the roots of the characteristic polynomial are inside the unit circle for a given hypothesis, the LR statistic is not reported.
Table A.2: Hypothesis test results for deposit rates before change in deposit insurance limit.

<table>
<thead>
<tr>
<th>Rate</th>
<th>Time</th>
<th>Unconditional</th>
<th>Conditional</th>
<th>Joint</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$H_{1,2}$</td>
<td>$H_3$</td>
<td>$H_{1,3}$</td>
</tr>
<tr>
<td>FTD 3m</td>
<td>'96-'04</td>
<td>5.64</td>
<td>2.81</td>
<td>23.43***</td>
</tr>
<tr>
<td>GIC 1y</td>
<td>'96-'04</td>
<td>6.25</td>
<td>0.07</td>
<td>60.91***</td>
</tr>
<tr>
<td>GIC 3y</td>
<td>'96-'04</td>
<td>26.30***</td>
<td>0.42</td>
<td>–</td>
</tr>
<tr>
<td>GIC 5y</td>
<td>'96-'04</td>
<td>13.13**</td>
<td>0.94</td>
<td>68.55***</td>
</tr>
<tr>
<td>FTD 5y</td>
<td>'96-'04</td>
<td>16.43**</td>
<td>2.02</td>
<td>67.36***</td>
</tr>
</tbody>
</table>

Notes: This table reports the likelihood ratio test statistics for each of the hypotheses of interest in the following order: (1) $H_{1,2}$ tests for the presence of asymmetric adjustments in the error-correction; (2) $H_{3}$ tests for complete pass-through; (3)–(4) $H_{1,3}$ for $i \in \{1, 2\}$ tests for weak exogeneity of the market rate and retail rate, respectively; (5) $H_{2,3}$ tests for strong exogeneity of the market rate; (6) $H_{2,3}$ tests for strong exogeneity conditional on complete pass-through; (7) $H_{3}$ tests for complete pass-through conditional on strong exogeneity of the market rate; and (8) $H_{2,3} \cap H_{3}$ tests the joint hypothesis of complete pass-through and strong exogeneity of the market rate. Results are based on 4,999 bootstrap samples. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and *** respectively. If the roots of the characteristic polynomial are inside the unit circle for a given hypothesis, the LR statistic is not reported.
Table A.3: Coefficient estimates for deposit rates before change in deposit insurance limit

<table>
<thead>
<tr>
<th>Rate</th>
<th>Time</th>
<th>$\beta$</th>
<th>$\rho$</th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\delta_1$</th>
<th>$\delta_2$</th>
<th>$\psi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTD 3m</td>
<td>'96-'04</td>
<td>1.000</td>
<td>1.650</td>
<td>-0.055</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GIC 1y</td>
<td>'96-'04</td>
<td>1.000</td>
<td>1.323</td>
<td>-0.174</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GIC 3y</td>
<td>'96-'04</td>
<td>1.000</td>
<td>0.842</td>
<td>-0.613</td>
<td>0.000</td>
<td>0.543</td>
<td>0.000</td>
<td>824.678</td>
</tr>
<tr>
<td>GIC 5y</td>
<td>'96-'04</td>
<td>1.000</td>
<td>0.713</td>
<td>-0.316</td>
<td>0.000</td>
<td>0.243</td>
<td>0.000</td>
<td>5.728</td>
</tr>
<tr>
<td>FTD 5y</td>
<td>'96-'04</td>
<td>1.000</td>
<td>0.837</td>
<td>-0.343</td>
<td>0.000</td>
<td>0.271</td>
<td>0.000</td>
<td>7.916</td>
</tr>
</tbody>
</table>

Notes: This table reports the coefficient estimates from the final restricted models: $\beta$ and $\rho$ are the coefficients for pass-through and markup; $\alpha_i$ and $\delta_i$ are the linear and nonlinear adjustment coefficients, respectively — subscript 1 is for the retail rate and 2 is for the market rate — and $\psi$ is the parameter determining the behaviour of the logistic function.

Table A.4: Hypothesis test results for mortgage rates

| Term   | Time  | $H_1^\delta$ | $H_2^\alpha,\delta | H_2^\beta$ | $H_2^\alpha,\delta | H_2^\beta$ | $H_2^\beta | H_2^\alpha,\delta$ |
|--------|-------|--------------|----------------|-------------|-------------|-----------------|------------------|
| MR 1y  | '83-'96 | 43.65*** | 79.21*** | 2.52 | 42.70*** |
|        | '96-'07 | 9.82      | 13.74*** | 0.01 | 0.03    |
|        | '00-'07 | 8.94*     | 38.28*** | 0.10 | 0.20    |
|        | '09-'15 | 5.09      | 7.82**  | 2.54 | 0.03    |
| MR 3y  | '83-'96 | 34.27*** | 79.30*** | 0.54 | 0.02    |
|        | '96-'07 | 4.79      | 17.69*** | 0.01 | 2.71    |
|        | '01-'07 | 2.16      | 29.18*** | 0.01 | 0.23    |
|        | '09-'15 | 35.94*** | 56.28*** | 0.88 | 4.13    |
| MR 5y  | '83-'96 | 15.27*** | 39.65*** | 0.23 | 0.43    |
|        | '96-'07 | 6.03      | 6.37*   | 0.82 | 0.77    |
|        | '00-'07 | 1.15      | 40.56*** | 0.46 | 0.03    |
|        | '09-'15 | 61.71*** | –       | 0.19 | 17.59** |

Notes: This table reports the likelihood ratio test statistics for each of the hypotheses of interest in the following order: (1) $H_1^\delta$ tests for the presence of asymmetric adjustments in the error-correction; (2)–(3) $H_{i}^\alpha,\delta | H_2^\beta$ for $i \in \{1, 2\}$ tests for weak exogeneity of the market rate and retail rate, respectively, conditional on complete pass-through; and (4) $H_2^\beta | H_2^\alpha,\delta$ tests for complete pass-through conditional on weak exogeneity. Results are based on 4,999 bootstrap samples. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and *** respectively. If the roots of the characteristic polynomial are inside the unit circle for a given hypothesis, the LR statistic is not reported.
Table A.5: Hypothesis test results for mortgage rates with swaps

| Term | Time | $H_{1,2}^\delta$ | $H_1^{\alpha,\delta}|H_0^\beta$ | $H_2^{\alpha,\delta}|H_0^\beta$ | $H_0^\beta|H_2^{\alpha,\delta}$ |
|------|------|------------------|-------------------------------|-------------------------------|-------------------------------|
| MR 1y | '00-'07 | 5.78 | 35.90*** | 0.58 | 3.21* |
|      | '09-'15 | 7.86 | 6.62** | 3.40* | 0.00 |
| MR 3y | '96-'07 | 5.87 | 12.72*** | 0.24 | 0.65 |
|      | '00-'07 | 10.90** | 40.77*** | 0.60 | 1.52 |
|      | '09-'15 | 15.05 | 18.90*** | 1.12 | 0.07 |
| MR 5y | '96-'07 | 3.19 | 8.73** | 0.03 | 1.16 |
|      | '00-'07 | 0.75 | 56.21*** | 0.02 | 0.00 |
|      | '09-'15 | 67.37*** | 47.96*** | – | – |

Notes: This table reports the likelihood ratio test statistics for each of the hypotheses of interest in the following order: (1) $H_{1,2}^\delta$ tests for the presence of asymmetric adjustments in the error-correction; (2)–(3) $H_i^{\alpha,\delta}|H_0^\beta$ for $i \in \{1, 2\}$ tests for weak exogeneity of the market rate and retail rate, respectively, conditional on complete pass-through; and (4) $H_0^\beta|H_2^{\alpha,\delta}$ tests for complete pass-through conditional on weak exogeneity. Results are based on 4,999 bootstrap samples. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and $$, respectively. If the roots of the characteristic polynomial are inside the unit circle for a given hypothesis, the LR statistic is not reported.
Appendix B

Unconventional monetary policy in a small open economy
## B.1 Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>ca</td>
<td>CANSIM</td>
<td>Current account balance, seasonally adjusted, indexed at 2007=100. Quarterly series linearly interpolated to monthly frequency.</td>
</tr>
<tr>
<td>ca&lt;sup&gt;alt&lt;/sup&gt;</td>
<td>IFS, authors’ calculations</td>
<td>Difference between the monthly sum of Canadian exports (goods value of exports, free on board (FOB), US Dollars) and imports (goods, value of imports, FOB, national currency, converted to US dollars) and Canadian official reserve assets (US dollars), converted to Canadian dollars and indexed at 2007=100, Monthly.</td>
</tr>
<tr>
<td>g</td>
<td>CANSIM, authors’ calculations</td>
<td>General federal governments expenditure, seasonally adjusted at annual rates, indexed at 2007=100. Quarterly series linearly interpolated to monthly frequency.</td>
</tr>
<tr>
<td>g&lt;sub&gt;US&lt;/sub&gt;</td>
<td>FRED</td>
<td>Federal Reserve of St. Louis Economic Data (FRED) federal government expenditures, seasonally adjusted at annual rates, indexed at 2007=100. Quarterly series linearly interpolated to monthly frequency.</td>
</tr>
<tr>
<td>p</td>
<td>IFS</td>
<td>Consumer Price Index, All items, Index, Monthly.</td>
</tr>
<tr>
<td>p&lt;sub&gt;US&lt;/sub&gt;</td>
<td>IFS</td>
<td>Consumer Price Index, All items, Index, Monthly.</td>
</tr>
<tr>
<td>r</td>
<td>Bank of Canada, authors’ calculations</td>
<td>Bank of Canada target rate spliced with shadow rate at ZLB when shadow rate &lt; target rate = 25 bps, Monthly.</td>
</tr>
<tr>
<td>s</td>
<td>IFS</td>
<td>National Currency per U.S. Dollar, National Currency per US Dollar, Rate, Monthly average.</td>
</tr>
<tr>
<td>vix</td>
<td>CBOE</td>
<td>Chicago Board Options Exchange (CBOE) VIX index measuring market’s expectation of 30-day volatility. Constructed using the implied volatilities of a range of S&amp;P 500 index options, Monthly average.</td>
</tr>
<tr>
<td>wxp</td>
<td>IFS</td>
<td>Export Price, All Commodities, Index, Monthly average.</td>
</tr>
<tr>
<td>y</td>
<td>IFS</td>
<td>Industrial Production, Seasonally adjusted, Index, Monthly.</td>
</tr>
<tr>
<td>y&lt;sub&gt;US&lt;/sub&gt;</td>
<td>IFS</td>
<td>Industrial Production, Seasonally adjusted, Index, Monthly.</td>
</tr>
</tbody>
</table>
Appendix C

Fiscal policy uncertainty and US output

C.1 Data sources and definitions

Using NIPA tables from the BEA website,

- $y_t$ is GDP in line 1 from Table 1.1.5,

for the consolidated government sector (federal, state and local),

- $g_t$ is Government Consumption Expenditures and Gross Investment in line 22 from Table 1.1.5,

- $\tau_t$ is Government Current Tax Receipts (line 2 of Table 3.1) and Contributions for Government Social Insurance (line 7 of Table 3.1) less Corporate income taxes from Federal Reserve Banks (line 8 in Table 3.2),

and for federal government data,

- $g_t$ is Federal Government Consumption Expenditures and Gross Investment in line 9 from Table 3.9.5,

- $\tau_t$ is Federal Current Tax Receipts (line 2 of Table 3.2) and Contributions for Government Social Insurance (line 11 of Table 3.2) less Corporate income taxes from Federal Reserve Banks (line 8 in Table 3.2).
I deflate all of the above series by

- the GDP deflator in line 1 from Table 1.1.9 and
- population ages 16 and up obtained from FRED (series B230RC0Q173SBEA).

The remaining data and sources are

- the EPU index from Baker et al. (2016), obtained from FRED (series USEPUINDXM) and converted from monthly frequency to quarterly averages,
- the categorical series EPU($t$) and EPU($g$), obtained from the Policy Uncertainty website\(^1\) and converted from monthly frequency to quarterly averages,
- the PCI index from Azzimonti (2015), obtained from the Federal Reserve Bank of Philadelphia\(^2\) and converted from monthly frequency to quarterly averages,
- the quarterly average of the federal funds rate from FRED (series DFF),
- the shadow short rate, obtained from Jing Cynthia Wu’s website\(^3\) and converted from monthly frequency to quarterly averages,
- the spending forecasts from the Survey of Professional Forecasters obtained from the Federal Reserve Bank of Philadelphia website (series drfedgov3 and drslgov3),
- the defense news series obtained from Valerie Ramey’s website\(^4\) and
- the series on excess returns from Fisher and Peters (2010) and the implicit tax rate from Leeper et al. (2013) kindly given to me by Karel Mertens.

\(^1\)http://www.policyuncertainty.com/categorical_epu.html
\(^2\)https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index
\(^3\)http://faculty.chicagobooth.edu/jing.wu/research/data/WX.html
\(^4\)http://econweb.ucsd.edu/~vramey/research.html
C.2 SVAR-SV-M model estimation

I use the Gibbs sampler to estimate the SVAR-SV-M model. For discussion of the algorithm and the choice of priors, it is more convenient to rewrite the model in the following way,

\[ z_t = X_t'\Psi + u_t, \quad \text{(C.1)} \]
\[ u_t = BH_t^{1/2}\varepsilon_t, \quad \varepsilon_t \sim N(0, I), \quad \text{(C.2)} \]
\[ \log(h_t) = \mu + \rho \log(h_{t-1}) + v_t, \quad v_t \sim N(0, Q), \quad \text{(C.3)} \]

where \( X_t = [D_t, z_{t-1}, \ldots, z_{t-p}, \log(h_t), \ldots, \log(h_{t-p})]' \) and \( \Psi \) is a \( 3(3p + 3p_\lambda + 1) + c \) \times 1 \) vector of the corresponding coefficients with \( c = 1 \) if only a constant is included and \( c = 2 \) if both a constant and a linear trend is included, \textit{i.e.} the number of columns in \( D_t \).

C.2.1 Prior distributions

The parameter space is broken up into four blocks: (1) VAR coefficients \( \Psi \), (2) structural coefficients \( B \), (3) innovation equation coefficients \( \mu, \rho \) and \( Q \) and (4) the stochastic volatilities \( h_t \).

**VAR coefficients \( \Psi \)**

I assume a normal distribution for the prior of \( \Psi \). The mean and variance are calibrated based on a homoskedastic version of the model estimated with ordinary least squares using a training sample with data from 1947Q1–1959Q4.\(^5\) To account for the stochastic volatility in the mean, the estimation takes two steps. First, I estimate a homoskedastic VAR using the training sample and then I take the squared residuals as an initial guess of the stochastic volatility and re-estimate the VAR with the logarithm of this series\(^6\) (and

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\(^5\)When I consider subsamples with later start dates, I use data that begins ten years before the start date as a training sample.  
\(^6\)Following the literature I add an offset constant to the logarithm of the squared residuals to ensure that this initial guess of the stochastic volatility is well defined. I set this constant to \( 10^{-4} \).
its lags if necessary) as an additional explanatory variable. The OLS estimate of the VAR coefficients from this second step \( \hat{\Psi}_{OLS} \) and four times the estimate of its variance \( \hat{P}^\psi_{OLS} = 4 \hat{V}(\hat{\Psi}_{OLS}) \) are the mean and variance for the prior distribution, \( \Psi_0 \sim N(\hat{\Psi}_{OLS}, \hat{P}^\psi_{OLS}) \).

**Structural coefficients \( B \)**

In order to apply convenient methods from Cogley and Sargent (2005) for simulating the posterior distribution, I follow Pereira and Lopes (2014) and modify the identification equations (4.5) to ensure that only exogenous variables appear on the right-hand-side of each regression. The modification involves the equation for output. Letting \( B = \tilde{A}^{-1} \tilde{B} \), the relationship between the reduced-form residuals and structural shocks is changed to

\[
\tilde{A} u_t = \tilde{B} H_t^2 \varepsilon_t, \tag{C.4}
\]

\[
\begin{bmatrix}
1 & 0 & \theta_y \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
u_t^- \\
u_t^0 \\
u_t^y
\end{bmatrix}
= \begin{bmatrix}1 & \theta_g & 0 \\0 & 1 & 0 \\\zeta_\tau & \zeta_g & 1\end{bmatrix}
\begin{bmatrix}\sqrt{h_t^-} \varepsilon_t^- \\
\sqrt{h_t^0} \varepsilon_t^0 \\
\sqrt{h_t^y} \varepsilon_t^y
\end{bmatrix}. \tag{C.5}
\]

There is a one-to-one mapping between the coefficients in (4.5) and the ones in (C.5) and the structural shocks estimated using the two identification schemes are identical for the fiscal variables and up to a scale factor for output. The mapping of the coefficients between the identification in (4.5) and (C.5) is given by

\[
\tilde{A}^{-1} \tilde{B} = \begin{bmatrix}1 & 0 & \theta_y \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}^{-1}
\begin{bmatrix}1 & \theta_g & 0 \\0 & 1 & 0 \\\zeta_\tau & \zeta_g & 1\end{bmatrix}
= \begin{bmatrix}1 - \theta_y \zeta_\tau & \theta_g - \theta_y \zeta_g & -\theta_y \\
0 & 1 & 0 \\\zeta_\tau & \zeta_g & 1
\end{bmatrix}, \tag{C.6}
\]

\[
A^{-1} B = \begin{bmatrix}1 & 0 & \theta_y \\
0 & 1 & 0 \\
\zeta_\tau & \zeta_g & 1
\end{bmatrix}^{-1}
\begin{bmatrix}1 & \theta_g & 0 \\0 & 1 & 0 \\0 & 0 & 1
\end{bmatrix}
= \begin{bmatrix}1 - \theta_y \zeta_\tau & \theta_g + \theta_y \zeta_g & -\theta_y \\
\frac{1}{1 - \theta_y \zeta_\tau} & \frac{\theta_g + \theta_y \zeta_g}{1 - \theta_y \zeta_\tau} & \frac{-\theta_y}{1 - \theta_y \zeta_\tau} \\
\frac{-\zeta_\tau}{1 - \theta_y \zeta_\tau} & \frac{-\zeta_\tau \theta_g - \zeta_g}{1 - \theta_y \zeta_\tau} & \frac{1}{1 - \theta_y \zeta_\tau}
\end{bmatrix}, \tag{C.7}
\]

149
so that,

\[ \zeta_\tau = \frac{-\xi_\tau}{1 - \theta_y \xi_\tau} \quad \text{and} \quad \zeta_g = \frac{-\xi_g \theta_y - \xi_g y}{1 - \theta_y \xi_\tau}. \tag{C.8} \]

The prior of the free parameters in \( B \) is also normal. I set the mean to the maximum likelihood estimates—since the identification scheme is non-triangular, a Cholesky decomposition cannot be applied—of the coefficients in \( B \) based on the training sample. Let \( \alpha = [\theta_g, \zeta_\tau, \zeta_g]' \) be the vector of free parameters in \( B \). The prior is \( \alpha_0 \sim N(\hat{\alpha}_{MLE}, \hat{P}\alpha) \), where, as in Benati and Mumtaz (2007) and Baumeister and Peersman (2013), \( \hat{P}\alpha \) is a matrix with ten times the absolute value of the elements in \( \hat{\alpha}_{MLE} \) along the diagonal and zeros elsewhere. The scaling of the variance is to account for the relative magnitude of the coefficients, but otherwise arbitrary.

**Innovation equation coefficients \( \mu, \rho, Q \)**

The priors for the intercepts and autoregressive coefficients in each of the stochastic volatilities are also normal. I set \( \mu_i^0 \sim N(0, 1) \) and \( \rho_i^0 \sim N(0.9, 0.1) \), for \( i \in (\tau, g, y) \). These values reflect the traditional modeling conventions that specify the volatility process as a random walk (e.g. see Cogley and Sargent, 2005; Primiceri, 2005). The priors for the diagonal elements of \( Q \) follow inverse Gamma distributions with scale parameter 0.5 and 1 degree of freedom, i.e. \( Q_{i0}^0 \sim IG(\frac{0.5}{2}, \frac{1}{2}) \), where once again \( i \in (\tau, g, y) \) and \( Q_{i0}^0 \) is the diagonal element in \( Q_0 \) corresponding to the volatility equation for variable \( i \). The scale parameter is larger than typical choices in the literature—for example Jo (2014) and Baumeister and Peersman (2013) set it to \( 10^{-4} \)—and reflects my knowledge of estimates of similar parameters in Born and Pfeifer (2014) and Fernández-Villaverde et al. (2015).

**Stochastic volatility \( h_t \)**

The prior for the logarithm of volatility at time \( t = 0 \) is normal with the mean set to the OLS estimate of the structural shock variances based on the training sample and
the variance set to the identity matrix, i.e. \( \log(h_0) \sim N\left(\log(\hat{h}_0^{\text{OLS}}), I_3\right) \), where \( \hat{h}_0^{\text{OLS}} = [\hat{\sigma}_\tau^2, \hat{\sigma}_g^2, \hat{\sigma}_y^2]' \).

**Summary of prior distributions**

To summarize, I set the prior distributions as follows

\[
\Psi_0 \sim N(\hat{\Psi}_{\text{OLS}}, \hat{P}_{\Psi_{\text{OLS}}}), \\
\alpha_0 \sim N(\hat{\alpha}_{\text{MLE}}, \hat{P}_{\alpha}), \\
\mu_i^0 \sim N(0, 1), \\
\rho_i^0 \sim N(0.9, 0.1), \\
Q_i^0 \sim IG\left(\frac{0.5}{2}, \frac{1}{2}\right), \\
\log(h_0) \sim N\left(\log(\hat{h}_0^{\text{OLS}}), I_3\right). 
\]

**C.2.2 Initial values and estimation algorithm**

I simulate the posterior distributions using the Gibbs sampler. I obtain the starting values for the algorithm by estimating a homoskedastic version of the model in the same way as for the prior distributions. I initialize the stochastic volatility using the squared residuals and set the VAR coefficients \( \Psi \) and structural coefficients \( \alpha \) to their OLS and MLE estimates. I set the remaining coefficients equal to the means of their prior distributions. I adopt the common notation of using a superscript \( T \) to refer to the entire sample. For example, \( h^T = \{h_t\}_{t=1}^T \) denotes the entire history of volatility states.
Step 1: drawing structural coefficients $\alpha$

Conditional on $\Psi$ and $h^T$, the reduced-form residuals are observable and related to the structural innovations by the following set of regression equations,

\[
\begin{align*}
    u^y_t &= \sqrt{h^y_t} \varepsilon^y_t \\
    u^\tau_t - \theta_y u^y_t &= \theta_g \sqrt{h^\tau_t} \varepsilon^\tau_t + \sqrt{h^t_t} \varepsilon^\tau_t \\
    u^\tau_t &= \zeta^\tau \sqrt{h^\tau_t} \varepsilon^\tau_t + \zeta_g \sqrt{h^\tau_t} \varepsilon^y_t + \sqrt{h^y_t} \varepsilon^\tau_t.
\end{align*}
\] (C.9) (C.10) (C.11)

Due to the identity in (C.9) and since $\theta_y$ is known, (C.10) can be rewritten as

\[
\begin{align*}
    \left( h^\tau_t \right)^{-\frac{1}{2}} (u^\tau_t - \theta_y u^y_t) = \theta_g \left( h^\tau_t \right)^{-\frac{1}{2}} u^y_t + \varepsilon^\tau_t,
\end{align*}
\]

which is a regression equation with standard normal innovations. The posterior for $\theta_g$ is also normal. Letting $R$ be the left-hand-side variable and $M$ be the right-hand-side variable, the posterior, conditional on the data and other parameters in the model, is $\theta_g \sim N(\alpha_1, P_1)$, where $P_1 = \left( \hat{P}^\alpha_i^{-1} + M' M \right)^{-1}, \alpha_1 = P_1 \left( \hat{P}^\alpha_i^{-1} \hat{\alpha}^i_{MLE} + M' R \right)$ and the index $i$ on the prior mean and variance selects the value corresponding to the revenue equation.

Once $\theta_g$ is drawn, the structural innovations $\varepsilon^\tau_t$ are identified and the same procedure is applied to (C.11), which is rewritten as

\[
( h^y_t )^{-\frac{1}{2}} u^y_t = \zeta^\tau ( h^\tau_t )^{-\frac{1}{2}} \sqrt{h^\tau_t} \varepsilon^\tau_t + \zeta_g ( h^\tau_t )^{-\frac{1}{2}} u^y_t + \varepsilon^y_t.
\]

The coefficients, conditional on the data and other parameters are drawn from $[\zeta^\tau, \zeta_g] \sim N(\alpha_1, P_1)$, where $\alpha_1$ and $P_1$ are defined in the same way as above but with values corresponding to the output equation.
Step 2: drawing VAR coefficients $\Psi$

Conditional on $h^T$ and $\alpha$, (C.1) is a linear regression with a known form of heteroskedasticity. This equation can be transformed into a state-space model,

$$z_t = X_t'\Psi_t + BH_t^{\frac{1}{2}}\epsilon_t,$$

(C.12)

$$\Psi_t = \Psi_{t-1},$$

(C.13)

where (C.12) is the observation equation and (C.13) is the transition equation. The posterior distribution for the VAR coefficients $\Psi$ is normal with mean $\Psi_{T|T} = E(\Psi_{T|h^T, X^T, \alpha})$ and variance $P_{T|T} = \text{Cov}(\Psi_{T|h^T, X^T, \alpha})$. I use the Carter and Kohn (1994) algorithm and obtain $\Psi_{T|T}$ and $P_{T|T}$ from the final iteration of a Kalman filter applied to (C.12) and (C.13). I initialize the algorithm with the prior mean and covariance and iterate on the following equations

$$\Psi_{t|t-1} = \Psi_{t-1|t-1},$$

$$P_{t|t-1} = P_{t-1|t-1},$$

$$v_{t|t-1} = z_t - X_t'\Psi_{t|t-1},$$

$$f_{t|t-1} = X_t'P_{t|t-1}X_t + BH_tB',$$

$$K_t = P_{t|t-1}X_tf_{t|t-1}^{-1},$$

$$\Psi_{t|t} = \Psi_{t|t-1} + K_tv_{t|t-1},$$

$$P_{t|t} = P_{t|t-1} - K_tX_t'P_{t|t-1}.$$  

The Kalman filter applied in this setting is equivalent to a generalized least squares transformation of the model.
Step 3: drawing innovation equation coefficients $\mu, \rho, Q$

Conditional on $h^T$, the coefficients $\mu, \rho, Q$ are drawn using the standard methods for linear regressions. For $\mu$ and $\rho$, the posterior distributions are normal with means and variances combining information from the likelihood and prior in the same way as for the structural coefficients $\alpha$ described above. The posterior for the variance of the error terms in each of the innovation equations has an inverse Gamma distribution, $Q_i \sim IG\left(\frac{\sum_{t=1}^{T} \hat{\nu}_{i,t}^2 + 0.5}{2}, \frac{T+1}{2}\right)$, where $\hat{\nu}_{i,t}$ are the residuals for the stochastic volatility equation corresponding to variable $i$ based on the posterior draws for $\mu_i$ and $\rho_i$. To prevent drawing explosive processes, I use rejection sampling to impose $|\rho_i| \leq 1$.

Step 4: drawing volatility states $h^T$

Conditional on the VAR coefficients $\Psi$, the structural coefficients $\alpha$ and the innovation equation coefficients $\mu, \rho, Q$, (C.2) and (C.3) form a nonlinear state-space model. Following Cogley and Sargent (2005), I apply the date-by-date independence Metropolis-Hastings algorithm from Jacquier et al. (1994). This is a univariate algorithm that I can apply to each equation separately due to the diagonality of $Q$, which makes the equations independent. For details on the sampling distributions and acceptance probability, see Appendix B.2.5 in Cogley and Sargent (2005).

Selecting the number of draws and monitoring convergence

Iteratively drawing from the conditional distributions from the four steps described above converges to a sample of coefficients drawn from their joint posterior distribution. To select the number of draws to discard and the number of draws to keep for inference I look at a few convergence diagnostics. A convenient method for determining the number of draws to discard is based on trace plots. These plots trace out consecutive draws for a given parameter over the simulation period. The draws often settle around a stationary mean after starting at some distant point in the parameter space. In my model, this
convergence occurs within the first few thousand draws, which I discard.

The number of draws to keep for inference is a less obvious choice because it depends on the persistence of the Markov Chain. If it takes the Gibbs sampler many draws to move from one area of the posterior to another (slow mixing), then the chain needs to run longer to obtain a sufficient amount of independent draws for inference relative to the situation in which the algorithm moves around the posterior quickly (fast mixing). The mixing speed for a given parameter can be determined by the autocorrelation function of its draws. A common practice to alleviate the problems associated with slow-mixing is thinning: keeping only every \( n \)th draw where, for example, \( n \) can be set to ten. However, as argued by Link and Eaton (2012), thinning is inefficient and—given advancements in computing (particularly for storage)—outdated. Therefore, I choose the number of draws by looking at the autocorrelation functions of a thinned sample and then use the entire sample for inference. A common criterion (e.g. see Primiceri, 2005; Pereira and Lopes, 2014) is to ensure that the 20th autocorrelation for each parameter is close to zero. For instance, if I want to have 1,000 draws for inference and thinning the sample by 15 achieves this criteria, then I set the number of draws for inference to 15,000.

C.3 TVP-SVAR-SV-M model estimation

The priors and estimation procedure for the TVP-SVAR-SV-M model have a lot of similarities to their counterparts for the fixed-parameter version of the model. I reproduce
the model equations here for reference,

\[ z_t = X'_t \Psi_t + u_t, \]  
\[ u_t = B_t H_t^\frac{1}{2} \varepsilon_t, \quad \varepsilon_t \sim N(0, I), \]  
\[ \log(h_t) = \mu + \rho \log(h_{t-1}) + v_t, \quad v_t \sim N(0, Q). \]  
\[ \Psi_t = \Psi_{t-1} + \omega_t, \quad \omega_t \sim N(0, W), \]  
\[ \alpha_t = \alpha_{t-1} + e_t, \quad e_t \sim N(0, S). \]

(C.14)  
(C.15)  
(C.16)  
(C.17)  
(C.18)

C.3.1 Prior distributions

The parameter space is broken up into the same four blocks as in Appendix C.2 and I use all of the same priors described therein. The time-varying version of the model adds only two new parameters, which are the covariance matrices for the stochastic innovations in (C.17) and (C.18). As in Primiceri (2005), I assume that the prior distributions for these matrices are inverse Wishart. The covariance matrix \( S \) is block diagonal and consists of two blocks: \( S_1 \) corresponds to the revenue equation and \( S_2 \) corresponds to the output equation. I assume the following prior distributions

\[ W \sim IW \left( k_W^2 \times T_0 \times \hat{P}_\Psi^{g \text{OLS}}, T_0 \right), \]  
\[ S_1 \sim IW \left( k_S^2 \times \hat{P}_1^\alpha, 10 \right), \]  
\[ S_2 \sim IW \left( k_S^2 \times \hat{P}_2^\alpha, 10 \right), \]

where \( T_0 \) is the number of observations in the training sample and, as before,

\[ \hat{P}_\Psi^{\text{OLS}} = 4\hat{V}(\hat{\Psi}_{\text{OLS}}), \quad \hat{P}_1^\alpha = 10|\hat{\theta}_g| \text{ and } \hat{P}_2^\alpha = 10 \begin{bmatrix} |\hat{\zeta}_\tau| & 0 \\ 0 & |\hat{\zeta}_g| \end{bmatrix} \]
where the coefficient estimates come from an estimation of a homoskedastic VAR on the training sample as in Appendix C.2. The parameters $k_W$ and $k_S$ reflect the prior belief about the amount of time-variation in the coefficients. Following Baumeister and Peersman (2013) and Benati and Mumtaz (2007), I set $k_S^2 = k_W^2 = 10^{-4}$.

As discussed by Primiceri (2005), another factor in determining the prior for the amount of time-variation in the model coefficients arises from the fact that it has a strong influence on the estimation. One the one hand, I want the data to be able to reflect changes in coefficients arising from underlying changes in the transmission mechanism. On the other hand, if the time-variation is not restricted in some way then the coefficients will adjust at each time period to reduce the residuals to as close to zero as possible. Therefore, the choice of $k_S^2$ and $k_W^2$ reflects a balance between these forces. I find that when these values are loosened the model misbehaves.\footnote{For the models estimated in levels, I set $k_W^2 = 4 \times 10^{-7}$. This is the largest value for which the time-varying coefficients do not misbehave and absorb most of the variation in the data.}

The same issue concerns the choice of the degrees of freedom. The minimum degrees of freedom required to have a proper prior distribution is equal to the number of coefficients plus one. For $W$ this value is $3(3p+3(p_\lambda+1)+c)+1$, for $S_1$ it is 2 and for $S_2$ it is 3. I set the degrees of freedom to values higher than these minimums to avert implausible behaviors of the time-varying coefficients. Primiceri (2005) also sets the degrees of freedom for the prior of $W$ to the number of observations in the training sample for the same reasons.

\subsection*{C.3.2 Initial values and estimation algorithm}

I initialize the Gibbs sampler in the same way as described in Appendix C.2.2 except that I use an estimate of $h^T$ from the SVAR-SV-M model to initialize the stochastic volatility rather than using the squared residuals from the homoskedastic regression. The estimation proceeds in the same steps as described in Appendix C.2.2 but with modifications to the procedure for drawing the VAR coefficients and structural equation coefficients to account for time-variation.
Drawing VAR coefficients $\Psi^T$ and $W$

Conditional on $h^T$, $\alpha^T$ and $W$, the VAR coefficients have a state-space representation where (C.14) is the observation equation and (C.17) is the transition equation. As in Cogley and Sargent (2005), the joint distribution for the entire history of the VAR coefficients $\Psi^T$ is given by

$$p(\Psi^T|X^T, h^T, \alpha^T) = p(\Psi_T|X^T, h^T, \alpha^T) \prod_{t=1}^{T-1} p(\Psi_t|\Psi_{t-1}, X^T, h^T, \alpha^T),$$

where all the densities on the right-hand-side are conditionally Gaussian and can be obtained by backward recursion from the terminal state of the forward Kalman filter.

I use the Carter and Kohn (1994) algorithm, set the initial values to the prior mean and covariance and iterate on the following equations

$$\Psi_{t|t-1} = \Psi_{t-1|t-1},$$
$$P_{t|t-1} = P_{t-1|t-1} + W,$$  \hspace{1cm} (C.19)
$$v_{t|t-1} = z_t - X_t'\Psi_{t|t-1},$$
$$f_{t|t-1} = X_t'P_{t|t-1}X_t + B_tH_tB_t',$$
$$K_t = P_{t|t-1}X_tf_{t|t-1}^{-1},$$
$$\Psi_{t|t} = \Psi_{t|t-1} + K_tv_{t|t-1},$$
$$P_{t|t} = P_{t|t-1} - K_tX_t'P_{t|t-1}.$$

These equations are identical to the ones for the fixed-parameter version of the model except for a key difference in (C.19), where I augment the variance to account for the stochastic evolution of the coefficients. The final iteration of the forward recursion delivers
the mean and variance for the posterior distribution of $\Psi_T$,

$$\Psi_T \sim N(\Psi_{T|T}, P_{T|T}).$$

The remaining history of $\Psi^T$ is drawn period-by-period through backward recursion where the conditional means and variances are updated to include information about $\Psi_{t+1}$ for drawing $\Psi_t$. For $t = 1, \ldots, T - 1$, the posterior distribution of $\Psi_t$ is

$$\Psi_t \sim N \left( \Psi_{t|t} + P_{t|t} P_{t+1|t}^{-1} (\Psi_{t+1} - \Psi_t), P_{t|t} - P_{t|t} P_{t+1|t}^{-1} P_{t|t} \right).$$

The algorithm generates smoothed draws for $\Psi^T$ that account for information in the entire sample.

Conditional on $\Psi^T$, the covariance for the innovation equation is drawn from an inverse Wishart distribution,

$$W \sim IW \left( k_W^2 \times T_0 \times \hat{\Phi}_{OLS}^y + (\hat{\omega}^T)'(\hat{\omega}^T), T + T_0 \right),$$

where $\hat{\omega}_t = \Psi_t - \Psi_{t-1}$ and $\hat{\omega}^T$ is the entire history of these residuals.

**Drawing structural equation coefficients $\alpha^T$ and $S$**

Drawing the structural equation coefficients follows the same procedure as described above for the VAR coefficients. Conditional on $\Psi^T$, $h^T$ and $S$, the reduced-form residuals and
structural shocks form the following set of state-space models

\[
\begin{bmatrix}
1 & 0 & \theta_y \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
u_t^y \\
u_t^g \\
u_t^y
\end{bmatrix} =
\begin{bmatrix}
1 & \theta_{g,t} & 0 \\
0 & 1 & 0 \\
\zeta_{r,t} & \zeta_{g,t} & 1
\end{bmatrix}
\begin{bmatrix}
\sqrt{h_t^r}\varepsilon_t^r \\
\sqrt{h_t^g}\varepsilon_t^g \\
\sqrt{h_t^y}\varepsilon_t^y
\end{bmatrix}, \quad \text{(C.20)}
\]

\[
\begin{bmatrix}
\theta_{g,t} \\
\zeta_{r,t} \\
\zeta_{g,t}
\end{bmatrix} =
\begin{bmatrix}
\theta_{g,t-1} \\
\zeta_{r,t-1} \\
\zeta_{g,t-1}
\end{bmatrix} + e_t, \quad \text{(C.21)}
\]

with (C.20) specifying two measurement equations and (C.21) their corresponding transition equations.

With \(u_t^g = \sqrt{h_t^g}\varepsilon_t^g\), the structural equation for tax revenue forms the following state-space model

\[
(h_t^r)^{-\frac{1}{2}}(u_t^r - \theta_y u_t^y) = \theta_{g,t}(h_t^r)^{-\frac{1}{2}}u_t^g + \varepsilon_t^r,
\]

\[
\theta_{g,t} = \theta_{g,t-1} + e_{1,t}.
\]

I use the Carter and Kohn (1994) algorithm to run the Kalman filter forward and then take draws for \(\theta_{g,T}^T\) using backward recursion form the terminal state. The draw for \(\theta_{g,T}^T\) makes \(\varepsilon_t^r\) observable in the output equation, which forms a second state-space model given by

\[
(h_t^y)^{-\frac{1}{2}}u_t^y = \zeta_{r,t}(h_t^r)^{-\frac{1}{2}}\sqrt{h_t^r}\varepsilon_t^r + \zeta_{g,t}(h_t^r)^{-\frac{1}{2}}u_t^g + \varepsilon_t^y,
\]

\[
\begin{bmatrix}
\zeta_{r,t} \\
\zeta_{g,t}
\end{bmatrix} =
\begin{bmatrix}
\zeta_{r,t-1} \\
\zeta_{g,t-1}
\end{bmatrix} + e_{2,t}.
\]

Once again, I obtain draws of the coefficients \(\zeta_{r,T}^T\) and \(\zeta_{g,T}^T\) from their posterior distributions using the Kalman filter with backward recursion.
Conditional on $\alpha^T$, the covariance matrices for each of the innovation equations are drawn from inverse Wishart distributions,

\[
S_1 \sim IW \left( k_S^2 \times \hat{P}_1^\alpha + (\hat{e}_1^T)'(\hat{e}_1^T), T + 10 \right),
\]
\[
S_2 \sim IW \left( k_S^2 \times \hat{P}_2^\alpha + (\hat{e}_2^T)'(\hat{e}_2^T), T + 10 \right),
\]

where

\[
\hat{e}_{1,t} = \theta_{g,t} - \theta_{g,t-1} \quad \text{and} \quad \hat{e}_{2,t} = \begin{bmatrix} \zeta_{\tau,t} \\ \zeta_{\tau,t-1} \\ \zeta_{g,t} \\ \zeta_{g,t-1} \end{bmatrix},
\]

and the entire histories of these residuals are given by $\hat{e}_1^T$ and $\hat{e}_2^T$, respectively.

Drawing $\mu, \rho, Q$ and $h^T$ follows exactly the same steps as in Appendix C.2.1. I also monitor convergence and determine the number of draws using the methods described in that section.
C.4 Additional figures for the SVAR-SV-M model

Figure C.1: Square-root of stochastic volatility for model estimated with federal data

(a) Revenue

(b) Spending

(c) Output

Notes: This figure contains the posterior median and 68% credible sets for time-varying standard deviations $\sqrt{\pi_t}$ of each of the structural shocks. Estimates are based on the last 15k of 20k draws from the Gibbs sampler. Shaded regions indicate NBER recession dates.
Figure C.2: SVAR-SV-M model impulse response of output to revenue shocks under various specifications

Main specification

(a) $p = 1$

(b) With log($h^Y_t$)

1960Q1–2015Q4

(c) Cons (st)

(d) Cons (dt)

(e) Fed (st)

(f) Fed (dt)

1960Q1–2006Q4

(g) Cons (st)

(h) Cons (dt)

(i) Fed (st)

(j) Fed (dt)

1980Q1–2015Q4

(k) Cons (st)

(l) Cons (dt)

(m) Fed (st)

(n) Fed (dt)

Notes: This figure contains the posterior median and 68% credible sets of the impulse responses of a revenue shock under various specifications. The shock is normalized to the average ratio of revenue to GDP for each time period. Cons means consolidated government sector data, Fed means federal government data, st means that the model is estimated under the stochastic trend assumption, i.e. growth rates, and dt means that the model is estimated under the deterministic trend assumption, i.e. levels with linear trend. Impulse responses are cumulative for models specified with a stochastic trend. The vertical axis is in percent growth rates or deviations from trend. Estimates are based on the last 15k of 20k draws from the Gibbs sampler. In some cases, convergence required more draws and the results are based on the last 20k of 40k draws. Models starting estimation in 1960 use 51 observations for the training sample and those starting in 1980 use 40 observations, i.e. the previous decade.
Figure C.3: SVAR-SV-M model impulse response of output to spending shocks under various specifications

**Main specification**

(a) $p_\lambda = 1$  
(b) With $\log(h_t^y)$

1960Q1–2015Q4

(c) Cons (st)  
(d) Cons (dt)  
(e) Fed (st)  
(f) Fed (dt)

1960Q1–2006Q4

(g) Cons (st)  
(h) Cons (dt)  
(i) Fed (st)  
(j) Fed (dt)

1980Q1–2015Q4

(k) Cons (st)  
(l) Cons (dt)  
(m) Fed (st)  
(n) Fed (dt)

Notes: This figure contains the posterior median and 68% credible sets of the impulse responses of a spending shock under various specifications. The shock is normalized to the average ratio of spending to GDP for each time period. Cons means consolidated government sector data, Fed means federal government data, st means that the model is estimated under the stochastic trend assumption, i.e. growth rates, and dt means that the model is estimated under the deterministic trend assumption, i.e. levels with linear trend. Impulse responses are cumulative for models specified with a stochastic trend. The vertical axis is in percent growth rates or deviations from trend. Estimates are based on the last 15k of 20k draws from the Gibbs sampler. In some cases, convergence required more draws and the results are based on the last 20k of 40k draws. Models starting estimation in 1960 use 51 observations for the training sample and those starting in 1980 use 40 observations, i.e. the previous decade.
C.5 Additional figures for TVP-SVAR-SV-M

Figure C.4: Square-root of stochastic volatility

(a) Revenue

(b) Spending

(c) Output

Notes: This figure contains the posterior median and 68% credible sets for time-varying standard deviations \( \sqrt{h_t} \) of each of the structural shocks estimated with the TVP-SVAR-SV-M model using consolidated government data specified in growth rates. Estimates are based on the last 20k of 40k draws from the Gibbs sampler. Shaded regions indicate NBER recession dates.
Figure C.5: Time-varying output response to first moment fiscal shocks with federal data in growth rates

Revenue shock

(a) Response of output to surprise revenue cut on impact

(b) Response of output to surprise revenue cut after 2 years

Spending shock

(c) Response of output to surprise spending increase on impact

(d) Response of output to surprise spending increase after 2 years

Notes: This figure contains the time-varying response of output to first moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.
Figure C.6: Time-varying output response to second moment fiscal shocks with federal data in growth rates

Revenue uncertainty shock
(a) Response of output to revenue uncertainty shock on impact

(b) Response of output to revenue uncertainty shock after 2 years

Spending uncertainty shock
(c) Response of output to spending uncertainty shock on impact

(d) Response of output to spending uncertainty shock after 2 years

Notes: This figure contains the time-varying response of output to second moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.
Figure C.7: Time-varying output response to first moment fiscal shocks with consolidated government data in levels

Revenue shock

(a) Response of output to surprise revenue cut on impact

(b) Response of output to surprise revenue cut after 2 years

Spending shock

(c) Response of output to surprise spending increase on impact

(d) Response of output to surprise spending increase after 2 years

Notes: This figure contains the time-varying response of output to first moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.
Figure C.8: Time-varying output response to second moment fiscal shocks with consolidated government data in levels

**Revenue uncertainty shock**

(a) Response of output to revenue uncertainty shock on impact

(b) Response of output to revenue uncertainty shock after 2 years

**Spending uncertainty shock**

(c) Response of output to spending uncertainty shock on impact

(d) Response of output to spending uncertainty shock after 2 years

Notes: This figure contains the time-varying response of output to second moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.
Figure C.9: Time-varying output response to first moment fiscal shocks with federal data in levels

**Revenue shock**

(a) Response of output to surprise revenue cut on impact

(b) Response of output to surprise revenue cut after 2 years

**Spending shock**

(c) Response of output to surprise spending increase on impact

(d) Response of output to surprise spending increase after 2 years

Notes: This figure contains the time-varying response of output to first moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.
Figure C.10: Time-varying output response to second moment fiscal shocks with federal data in levels

Revenue uncertainty shock
(a) Response of output to revenue uncertainty shock on impact

(b) Response of output to revenue uncertainty shock after 2 years

Spending uncertainty shock
(c) Response of output to spending uncertainty shock on impact

(d) Response of output to spending uncertainty shock after 2 years

Notes: This figure contains the time-varying response of output to second moment fiscal shocks. Impulse responses at various horizons are calculated holding parameters fixed at each point in time. The thick black line is the median estimate and the shaded blue region is the 68% credible set based on the last 20k of 40k draws from the Gibbs sampler. Areas shaded in gray indicate NBER recessions.
### C.6 Additional tables for SVAR-MGARCH-M model

Table C.1: SVAR-MGARCH-M model fit (1947Q1–2015Q4) using federal government data in growth rates

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>$-1579.0560$</td>
<td>3248.11</td>
<td>3410.21</td>
<td>45</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>$-1517.5010$</td>
<td>3131.00</td>
<td>3303.90</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MGARCH</td>
<td>$-1502.2266$</td>
<td>3106.45</td>
<td>3290.16</td>
<td>51</td>
</tr>
<tr>
<td>SVAR-MGARCH-M</td>
<td>$-1500.7005$</td>
<td>3107.40</td>
<td>3298.31</td>
<td>53</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2 \mathcal{L} + 2q$ and BIC = $-2 \mathcal{L} + \log(T)q$, where $q$ is the number of parameters and $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_t$.

Table C.2: SVAR-MGARCH-M model fit (1947Q1–2015Q4) using consolidated government data in levels with deterministic trend

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>$-1321.8102$</td>
<td>2739.62</td>
<td>2912.70</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>$-1282.4894$</td>
<td>2666.98</td>
<td>2850.87</td>
<td>51</td>
</tr>
<tr>
<td>SVAR-MARCH-M</td>
<td>$-1279.4400$</td>
<td>2664.88</td>
<td>2855.99</td>
<td>53</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2 \mathcal{L} + 2q$ and BIC = $-2 \mathcal{L} + \log(T)q$, where $q$ is the number of parameters and $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_t$. The MGARCH model is omitted because it generates a Hessian matrix that was not negative semi-definite.

Table C.3: SVAR-MGARCH-M model fit (1947Q1–2015Q4) using federal government data with in levels deterministic trend

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>$-1565.1704$</td>
<td>3226.34</td>
<td>3399.42</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>$-1527.7461$</td>
<td>3157.49</td>
<td>3341.39</td>
<td>51</td>
</tr>
<tr>
<td>SVAR-MARCH-M</td>
<td>$-1526.4948$</td>
<td>3158.99</td>
<td>3350.10</td>
<td>53</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2 \mathcal{L} + 2q$ and BIC = $-2 \mathcal{L} + \log(T)q$, where $q$ is the number of parameters and $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_t$. The MGARCH model is omitted because it generated a Hessian matrix that was not negative semi-definite.
Table C.4: SVAR-MGARCH-M model fit (1960Q1–2015Q4) with consolidated government data in growth rates

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>-945.7926</td>
<td>1981.59</td>
<td>2134.30</td>
<td>45</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>-932.3685</td>
<td>1960.74</td>
<td>2123.63</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MGARCH</td>
<td>-927.5638</td>
<td>1955.13</td>
<td>2124.81</td>
<td>50</td>
</tr>
<tr>
<td>SVAR-MGARCH-M</td>
<td>-926.4718</td>
<td>1956.94</td>
<td>2133.41</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2 \mathcal{L} + 2q$ and BIC = $-2 \mathcal{L} + \log(T)q$, where $q$ is the number of parameters and $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_t$. I only add two parameters moving from ARCH to GARCH because the GARCH term in the second moment equation for $g_t$ was highly insignificant.

Table C.5: SVAR-MGARCH-M model fit (1960Q1–2015Q4) using federal government data in growth rates

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>-1162.1195</td>
<td>2414.24</td>
<td>2566.95</td>
<td>45</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>-1147.3152</td>
<td>2390.63</td>
<td>2553.52</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MGARCH</td>
<td>-1141.9259</td>
<td>2381.85</td>
<td>2548.14</td>
<td>49</td>
</tr>
<tr>
<td>SVAR-MGARCH-M</td>
<td>-1138.4221</td>
<td>2378.84</td>
<td>2551.92</td>
<td>51</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2 \mathcal{L} + 2q$ and BIC = $-2 \mathcal{L} + \log(T)q$, where $q$ is the number of parameters and $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_t$. I only add 1 parameter moving from ARCH to GARCH because the GARCH terms in the second moment equations for $\tau_t$ and $g_t$ were highly insignificant.

Table C.6: SVAR-MGARCH-M model fit (1960Q1–2015Q4) using consolidated government data in levels with a deterministic trend

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>-938.7890</td>
<td>1973.58</td>
<td>2136.69</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>-930.1776</td>
<td>1960.36</td>
<td>2130.26</td>
<td>50</td>
</tr>
<tr>
<td>SVAR-MGARCH</td>
<td>-927.1480</td>
<td>1958.30</td>
<td>2135.00</td>
<td>52</td>
</tr>
<tr>
<td>SVAR-MGARCH-M</td>
<td>-926.9910</td>
<td>1959.98</td>
<td>2140.08</td>
<td>53</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2 \mathcal{L} + 2q$ and BIC = $-2 \mathcal{L} + \log(T)q$, where $q$ is the number of parameters and $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_t$. I only add 2 parameters moving from SVAR to ARCH because the ARCH term in the second moment equations for $g_t$ was highly insignificant. This also implies that only 1 parameter is added for the SVAR-MGARCH-M model because government spending is homoskedastic.
Table C.7: SVAR-MGARCH-M model fit (1960Q1–2015Q4) using federal government data in levels with a deterministic trend

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVAR</td>
<td>−1163.1889</td>
<td>2422.38</td>
<td>2585.49</td>
<td>48</td>
</tr>
<tr>
<td>SVAR-MARCH</td>
<td>−1153.1492</td>
<td>2406.30</td>
<td>2576.21</td>
<td>50</td>
</tr>
<tr>
<td>SVAR-MGARCH</td>
<td>−1147.3229</td>
<td>2396.65</td>
<td>2569.95</td>
<td>51</td>
</tr>
<tr>
<td>SVAR-MGARCH-M</td>
<td>−1144.9599</td>
<td>2393.92</td>
<td>2570.62</td>
<td>52</td>
</tr>
</tbody>
</table>

Notes: This table contains some summary statistics for the various models estimated using the consolidated government sector data. AIC = $-2\mathcal{L} + 2q$ and BIC = $-2\mathcal{L} + \log(T)q$, where $q$ is the number of parameters and $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_t$. I only add 2 parameters moving to ARCH because the equation for $g_t$ strongly rejects ARCH terms. I only add 1 parameter moving to GARCH because the equation for $\tau_t$ strongly rejects GARCH. The restrictions also imply that only 1 parameter is added for the SVAR-MGARCH-M model because government spending is homoskedastic.

C.7 Additional figures for model with broader information set

Figure C.11: Shadow short rate

Notes: This figure plots the effective federal funds rate in blue and the shadow short rate from Wu and Xia (2016) in green.
Figure C.12: SVAR-SV-M model impulse responses to first moment shocks controlling for monetary policy and fiscal foresight with data specified in levels

Impulse response of output to a consolidated government revenue shock
(a) FFR  (b) MBS  (c) ER  (d) DN  (e) SPF

Impulse response of output to a federal government revenue shock
(f) FFR  (g) MBS  (h) ER  (i) DN  (j) SPF

Impulse response of output to a consolidated government spending shock
(k) FFR  (l) MBS  (m) ER  (n) DN  (o) SPF

Impulse response of output to a federal government spending shock
(p) FFR  (q) MBS  (r) ER  (s) DN  (t) SPF

Notes: This figure contains the posterior median and 68% credible sets of the impulse response of output to government spending and revenue shocks for various information sets with the fiscal variables and GDP specified in levels. The vertical axis is in percent growth rates. Estimates are based on the last 20k of 40k draws from the Gibbs sampler.
Figure C.13: SVAR-SV-M model impulse responses to second moment shocks controlling for monetary policy and fiscal foresight with data specified in levels

Impulse response of output to a consolidated government revenue uncertainty shock

(a) FFR  (b) MBS  (c) ER  (d) DN  (e) SPF

Impulse response of output to a federal government revenue uncertainty shock

(f) FFR  (g) MBS  (h) ER  (i) DN  (j) SPF

Impulse response of output to a consolidated government spending uncertainty shock

(k) FFR  (l) MBS  (m) ER  (n) DN  (o) SPF

Impulse response of output to a federal government spending uncertainty shock

(p) FFR  (q) MBS  (r) ER  (s) DN  (t) SPF

Notes: This figure contains the posterior median and 68% credible sets of the impulse response of output to a doubling of fiscal spending and revenue uncertainty for various information sets with the fiscal variables and GDP specified in levels. The vertical axis is in percent growth rates. Estimates are based on the last 20k of 40k draws from the Gibbs sampler.