Essays in Applied Macroeconomics: Dynamic Effects of Monetary and Financial Shocks

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Introduction

This thesis consists of three self-contained chapters in the field of applied macroeconomics. The first two chapters use nonlinear time series models to investigate asymmetries in the macroeconomic effects of monetary policy and financial shocks. The third chapter empirically analyses the determinants of the decline in the natural rate of interest.

In Chapter 1, I analyse how the response of the United Kingdom (UK) economy to monetary policy shocks depends on the state of the economy, or the sign or size of the shock. Monetary policy shocks are identified by extending the Cloyne and Hürtgen (2016) approach to allow for time-variation in the central bank reaction function. Crucially, this extension results in a shock series that distinguishes between variations in the reaction function (for example, as a result of evolving monetary policy regimes) and innovations to the reaction function. The new shock series is used to estimate impulse responses by nonlinear local projections following Tenreyro and Thwaites (2016) to provide novel empirical evidence of the asymmetric effects of monetary policy in the UK. The main result is that shocks that occur during economic expansions have significantly larger effects than those that occur during recessions. This is consistent with evidence for the United States (US) in Tenreyro and Thwaites (2016) and the cross-country study by Jordà et al. (2020). In addition, I find that expansionary shocks are more powerful than contractionary shocks, and that large shocks have a proportionally weaker effect on output than small shocks. The results are robust to alternative monetary policy shock identification methods and variations in the empirical specification.

In Chapter 2, I investigate if the effects of financial and monetary policy shocks differ between high and low credit regimes in Australia. I estimate a factor-augmented smooth-transition vector autoregression model to estimate the state-dependent effects of financial and monetary shocks. The factor is a broad indicator of aggregate financial conditions extracted from a large set of financial variables, while the transition between credit regimes is determined by the deviation of household credit-to-GDP from its long-run equilibrium. The main result is that the adverse effects of an unanticipated tightening in financial conditions on output are far more pronounced when the shock occurs in a high credit regime than in a low credit regime. Sectoral models indicate that the asymmetric output response is largely driven by the state-dependent responses in the construction and manufacturing industries. In addition, financial shocks are found to be a significant source of business cycle fluctuations, especially in a high credit regime. The results are consistent with high credit regimes coinciding with periods of increased macroeconomic vulnerability where the economy is more prone to adverse financial shocks. I also find that monetary policy shocks lead to significantly larger and more persistent output and inflation responses in a low credit regime, consistent with the idea that monetary policy is most potent when households are credit constrained. The results are robust to alternative recursive identification orderings, controlling for foreign financial shocks and a range of alternative empirical specifications.

Taken together, the first two chapters extend the empirical literature by highlighting the importance of allowing for nonlinearities in the transmission of monetary and financial shocks. The first chapter shows that the effects of monetary policy shocks depend nonlinearly on the business cycle, the sign and size of the monetary shock, while the second chapter shows that the effects of both financial and monetary shocks differ over the credit cycle. Overall, the results suggest that existing empirical estimates of the effects of monetary policy and financial shocks that rely on linear models are masking important nonlinearities in the transmission mechanism. Macroeconomic theory and policy should seek to incorporate these nonlinearities into structural models and the policymaking process.

In Chapter 3, I analyse the determinants of the decline in the natural rate of interest (NRI) – the short-term real interest rate consistent with a zero output gap and stable inflation – over 1984 to 2016. To empirically analyse the determinants, I estimate the NRI for the US and the UK using three different approaches: a semi-structural model, a time-varying parameter vector autoregression, and a novel financial market-based approach. These estimates are used to analyse long-run equilibrium determinants of the NRI by estimating country-level dynamic regressions using a general-to-specific model selection algorithm. In comparison to the existing empirical literature, the model includes a larger set of NRI determinants than many studies and incorporates economic uncertainty and the demand for safe assets which have typically been overlooked in previous empirical studies. Most notably, I find evidence of a negative relationship between the NRI and economic uncertainty in both the US and the UK, while both productivity growth and the relative price of capital are positively related to the NRI. The decline in the NRI over 1984 to 2016 has predominantly been associated with a persistent decline in the relative price of capital in the US and an increase in population growth in the UK. Since the 2007–2008 financial crisis, the 1.5–2 percentage point fall in the NRI in both economies was largely associated with a decline in productivity growth and heightened economic uncertainty.

Chapter 1

The Asymmetric Effects of Monetary Policy: Evidence from the United Kingdom

Abstract

In this chapter, I analyse how the response of the United Kingdom economy to monetary policy shocks depends on the state of the economy, or the sign or size of the shock. Monetary policy shocks are identified by extending the Cloyne and Hürtgen (2016) approach to allow for time-variation in the central bank reaction function. These shocks are used to estimate impulse responses by local projections to investigate asymmetries in the transmission mechanism. The main result is that shocks that occur during economic expansions have significantly larger effects than those that occur during recessions. In addition, I find that expansionary shocks are more powerful than contractionary shocks, and that large shocks have a proportionally weaker effect on output than small shocks. The results are robust to alternative monetary policy shock identification methods and variations in the empirical specification.

1.1 Introduction

A central question in macroeconomics is how the economy responds to monetary policy. The vast empirical literature estimating the effects of monetary policy typically employs linear models which, by construction, mask any asymmetries in the monetary policy transmission mechanism. However, since at least Keynes (1936), economists have debated whether the economic response to shocks may vary over the business cycle, or depend on the sign or size of the shock. Numerous empirical investigations, beginning with a seminal study of the unemployment rate by Neftçi (1984), and more recently studies relating to fiscal policy (Auerbach and Gorodnichenko 2013; Ghassibe and Zanetti 2020; Glocker et al. 2019; Ramey and Zubairy 2018) and the labour market (Pizzinelli et al., 2020), document that macroeconomic fluctuations differ over various phases of the business cycle. Nevertheless, empirical evidence on the asymmetric effects of monetary policy is relatively thin and inconclusive. This chapter provides novel evidence of the asymmetric effects of monetary policy in the United Kingdom (UK) by investigating the following three questions:

1. Do the effects of monetary policy vary over the business cycle?
2. Do contractionary and expansionary shocks have asymmetric effects?
3. Do the effects of monetary shocks depend nonlinearly on the size of the shock?

To analyse the asymmetric effects of monetary policy, I first construct a series of monetary policy shocks by extending the Cloyne and Hürtgen (2016) narrative identification approach to allow for time-variation in the central bank reaction function. Crucially, this extension results in a shock series that distinguishes between variations in the reaction function (for example, as a result of evolving monetary policy regimes) and innovations to the reaction function. The new shock series is used to estimate impulse responses by local projections following Tenreyro and Thwaites (2016) to provide novel empirical evidence of the asymmetric effects of monetary policy in the UK.

The main result is that shocks to monetary policy are more powerful during economic expansions than during recessions. In particular, the decline in output following a contractionary shock in a linear model is almost entirely attributable to the effect during expansions. Moreover, the unemployment rate, gross fixed capital formation, aggregate household consumption, and durable goods consumption all respond by significantly more during expansions, consistent with the response of aggregate output. Standard empirical estimates that do not allow the response to a monetary policy shock to vary over the business cycle mask these differential effects. The state-dependence results are consistent with models where the Phillips curve flattens during expansions and steepens during recessions (e.g. Vavra 2014) or where durable goods consumption is more responsive to monetary policy during expansions (e.g. McKay and Wieland 2019; Berger and Vavra 2015). In addition, I find that expansionary shocks are more powerful than contractionary shocks. Lastly, large shocks have a proportionally weaker effect on output than small shocks, consistent with the implications of models that include state-dependent price rigidities. The results are robust to variations in the empirical specification, including alternative monetary policy shock identification methods, and are not driven by differences in the statistical properties of the shocks across states.

This work contributes to the empirical literature on the asymmetric effects of monetary policy by providing, to my knowledge, the first evidence of the asymmetric effects of monetary policy in the UK. This chapter is closest to Tenreyro and Thwaites (2016), who use Romer and Romer (2004) monetary policy shocks and local projections to analyse the asymmetric effects of monetary policy in the United States (US).[1] Consistent with the results presented in this chapter, Tenreyro and Thwaites find that monetary policy shocks have a greater effect on both output and prices during expansions than during recessions. In particular, they also find that durable household expenditure responds very strongly to shocks during expansions and that large shocks have a proportionally weaker effect on output. However, in contrast to the results presented in this chapter, they find that contractionary shocks have more powerful effects than expansionary shocks.

A number of other empirical studies have also investigated the asymmetric effects of

[1]Specifically, Tenreyro and Thwaites (2016) use a smooth transition analogue of the original Romer and Romer (2004) regression to identify monetary policy shocks.

monetary policy.[2] In general, the empirical literature on the state-dependent effects of monetary policy presents mixed results. For example, Tenreyro and Thwaites (2016) and Jordà et al. (2020) find that monetary policy is more powerful in expansions than recessions, whereas Garcia and Schaller (2002), Peersman and Smets (2001) and Lo and Piger (2005) reach the opposite conclusion. On balance, the evidence seems to suggest that contractionary shocks are more powerful than expansionary shocks (e.g., Angrist et al. 2018), while there is limited evidence as to whether the effects of monetary policy vary nonlinearly with the size of the shock.

This chapter also contributes to the literature on identifying monetary policy shocks in the UK. Cloyne and Hürtgen (2016) apply the Romer and Romer (2004) narrative identification approach to construct a novel series of monetary policy shocks for the UK. Their identification relies on the constant-parameter first-stage regression accurately capturing the central bank's reaction to forecasts of inflation and output. However, I provide very strong evidence of time-variation in the central bank's reaction function. To account for this, I follow Boivin (2006) and Coibion (2012) and estimate a time-varying parameter (TVP) first-stage regression. The TVP reaction function documents important but gradual changes in the systematic conduct of monetary policy that are broadly consistent with evolving UK monetary regimes. This results in a new series of monetary policy shocks that extends Cloyne and Hürtgen (2016) to distinguish between changes in the reaction function and innovations to the reaction function. I use the new series of monetary policy shocks to estimate the effects of monetary policy in the UK. The linear estimates are broadly in line with the previous literature for the UK (e.g., Ellis et al. 2014; Zanetti and Li 2016; Gerko and Rey 2017; Cesa-Bianchi et al. 2020), however I differ from these studies by focusing on the *asymmetric* effects of monetary policy.[3]

The rest of the chapter is organised as follows. Section 1.2 outlines the monetary policy

[2] Appendix A.1 provides an overview of different theoretical mechanisms that explain why an economy may respond asymmetrically to monetary policy shocks.

[3] Ellis et al. (2014) study how the monetary transmission mechanism in the UK changes over time, but do not consider how the time-variation depends on the state of the economy.

shock identification approach. Section 1.3 describes the specification and data used to investigate asymmetries in the transmission mechanism. Section 1.4 presents the results. Section 1.5 provides extensions and robustness checks. Section 1.6 concludes.

1.2 Identification of Monetary Policy Shocks

1.2.1 Cloyne and Hürtgen (2016) first-stage regression

In order to estimate the effects of monetary policy on the economy, identification requires the isolation of the unanticipated and exogenous component of monetary policy actions. Cloyne and Hürtgen (2016) (hereafter, CH) construct an extensive real-time forecast dataset for the UK covering 235 Bank Rate decisions over the period 1975–2007 and use the Romer and Romer (2004) narrative identification approach to identify a series of monetary policy shocks. This approach identifies shocks by purging the target policy rate of the central bank's endogenous response to information about the economy. Specifically, CH estimate the following first-stage regression:

$$\begin{aligned}\Delta i_m = \alpha + \beta i_{t-d14} + \sum_{j=-1}^{2} \gamma_j \hat{y}^F_{m,j} + \sum_{j=-1}^{2} \varphi_j \hat{\pi}^F_{m,j} + \sum_{j=1}^{3} \rho_j u_{t-j} \\ + \sum_{j=-1}^{2} \delta_j (\hat{y}^F_{m,j} - \hat{y}^F_{m-1,j}) + \sum_{j=-1}^{2} \vartheta_j (\hat{\pi}^F_{m,j} - \hat{\pi}^F_{m-1,j}) + \varepsilon_m\end{aligned} \tag{1.1}$$

where Δi_m is the change in the policy target rate (the Bank of England Bank Rate) at meeting m. The change in the Bank Rate is regressed on real-time data from the previous period, the forecast for the current period, forecasts up to two quarters ahead of real GDP $\hat{y}^F_{m,j}$ and inflation $\hat{\pi}^F_{m,j}$, and revisions of the forecasts relative to the previous meeting $(\hat{y}^F_{m,j} - \hat{y}^F_{m-1,j})$ and $(\hat{\pi}^F_{m,j} - \hat{\pi}^F_{m-1,j})$. The Bank Rate two weeks before the meeting (i_{t-d14}) and lags of the unemployment rate (u_{t-j}) are included to control for recent economic conditions. The subscript j denotes the quarter of the forecast relative to the meeting. The shocks are defined as the regression residuals, ε_m, as these capture changes in the policy target that are not the result of the central bank's systematic response to expected economic conditions.

The CH first-stage regression in (1.1) assumes constant coefficients over the full sample (1975–2007), which implies that the central bank reaction function has been stable.[4] However, there is good reason to think that the central bank's reaction function has changed over time. There have been periods when the government has publicly emphasised targeting money supply or exchange rates, and the Bank of England started explicitly targeting inflation in October 1992 and gained operational independence from the UK Treasury in 1997. Indeed, Nelson (2000) estimates interest rate reaction functions for different UK monetary policy regimes over the period 1972–1997 and concludes that it is "untenable to treat the monetary policy rule as relatively constant" over this period (Nelson, 2000, p. 30). If the reaction function has changed over time, a constant-coefficient first-stage regression would result in a shock series that includes the evolution of the reaction function as well as random shocks to policy. The potential problem with conflating these factors is that variations in the reaction function may lead to different dynamics than innovations to the reaction function (Coibion, 2012).

I test for parameter stability in (1.1) using a heteroskedasticity-robust version of the Quandt (1960) likelihood ratio (QLR) test. This tests the null hypothesis of parameter stability against the alternative of a structural break at an unknown date by conducting a series of Chow tests over a range of eligible break dates.[5] Panel A of Figure 1.1 plots the Chow F-statistics for the CH first-stage regression specification over the middle 70% of the sample. The QLR test does not indicate whether there is a single break, multiple discrete breaks, or a slow evolution of the parameters.[6] However, the figure shows that there is

[4]As a robustness exercise (Section 4.E), CH consider two different scenarios to analyse parameter stability in the first-stage regression. First, they split the sample in 1992 to coincide with the Bank of England officially targeting inflation, and second they split the sample in 1997 to coincide with operational independence for the Bank. CH run the first-stage regression on each subsample and splice together the resulting shock series. They do not report or comment on the subsample first-stage regression results but show that the estimated effects from the resulting shocks are similar to the baseline model.

[5]The QLR test statistic is the maximum Chow $F(\tau)$ statistic over a range of eligible break dates given by $\tau_{min} \leq \tau \leq \tau_{max}$: QLR $= \max\{F(\tau_{min}), F(\tau_{min}+1), ..., F(\tau_{max})\}$. The distribution of the test statistic depends on the number of restrictions being tested and the range over which the test is applied (given by τ_{min} and τ_{max}). Critical values are given in Stock and Watson (2012).

[6]As a robustness exercise, the Bai and Perron (1998, 2003) multiple structural break test also provides strong evidence of multiple structural breaks in both the real GDP and inflation coefficients. Results available upon request.

strong evidence against parameter stability until the late 1980s and no evidence against parameter stability from around 1990 onwards. Table 1.1 reports QLR test statistics for a range of different reaction function specifications. There is very strong evidence against parameter stability for all these reaction function combinations. These results suggest that the response to forecasts and forecast revisions of real GDP and inflation has changed significantly over the sample. As a consequence, a simple sample split in 1992 or 1997 will not adequately account for the parameter instability, and the time variation appears more complex than a one-time discrete break.

Table 1.1: Quandt Likelihood Ratio Tests

Reaction function specification	QLR test statistic	Break date	Critical values 1%	5%
CH specification	9.23***	1981Q4	2.43	2.13
Equation (1.2) with constant coefficients	7.18***	1981Q3	2.58	2.25
Forward-looking reaction function $\{\alpha, \beta, \gamma_1, \gamma_2, \varphi_1, \varphi_2, \rho_1, \rho_2, \rho_3, \delta_1, \delta_2, \vartheta_1, \vartheta_2\}$	3.89***	1982Q2	2.87	2.46
Inflation-only reaction function $\{\alpha, \beta, \varphi_{-1}, ..., \varphi_2, \rho_1, \rho_2, \rho_3, \vartheta_{-1}, ..., \vartheta_2\}$	2.88***	1983Q1	2.87	2.46
GDP-only reaction function $\{\alpha, \beta, \gamma_{-1}, ..., \gamma_2, \rho_1, \rho_2, \rho_3, \delta_{-1}, ..., \delta_2\}$	8.38***	1981Q4	2.87	2.46
Forward-looking (no revisions) rule $\{\alpha, \beta, \gamma_2, \varphi_2, \rho_1\}$	4.38**	1981Q3	4.53	3.66

Notes: In each case the test is applied jointly to all the coefficients. Critical values are taken from Stock and Watson (2012). ***, **, and * denote statistical significance at the 1, 5 and 10 per cent levels, respectively.

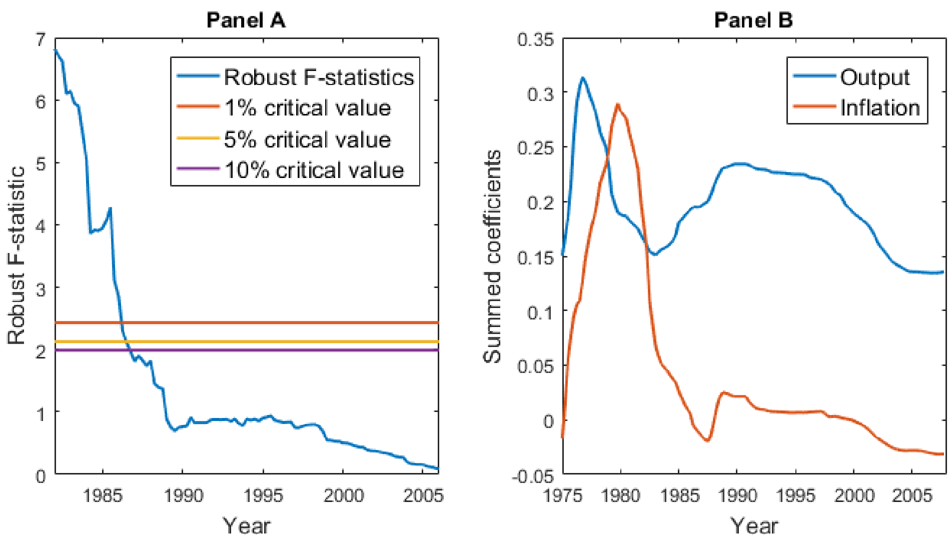
1.2.2 Time-varying parameter first-stage regression

To address parameter instability, I follow Boivin (2006) and Coibion (2012) and estimate a time-varying parameter (TVP) first-stage regression to extract monetary policy shocks that distinguish between changes in the reaction function and innovations to the reaction function. Specifically, I estimate a restricted version of the CH first-stage regression with time-varying parameters:

$$\Delta i_m = \alpha_m + \beta_m i_{t-d14} + \sum_{j=-1}^{1} \gamma_{m,j}\hat{y}^F_{m,j} + \sum_{j=-1}^{1} \varphi_{m,j}\hat{\pi}^F_{m,j} + \sum_{j=1}^{2} \rho_{m,j}u_{t-j} + \sum_{j=-1}^{1} \delta_{m,j}(\hat{y}^F_{m,j} - \hat{y}^F_{m-1,j}) + \sum_{j=-1}^{1} \vartheta_{m,j}(\hat{\pi}^F_{m,j} - \hat{\pi}^F_{m-1,j}) + \varepsilon_m. \tag{1.2}$$

Equation (1.2) is estimated at the Bank Rate meeting frequency m, and the estimated residuals, $\hat{\varepsilon}_m$, are defined as the monetary policy shocks. However, unlike CH, the coefficients are not constant over time but are assumed to follow a random walk. In addition, I account for the presence of heteroskedasticity in the policy shocks by allowing for a shift in the variance in 1993Q1 (to coincide with the introduction of inflation targeting in the UK and the shift in variance apparent in the CH shock series).[7] This approach has the advantage that policy changes that are the result of a regime change will not be classified as monetary policy shocks. Moreover, the time-varying intercept will account for any changes in the central bank's target for inflation or GDP growth (Coibion, 2012).

Figure 1.1: Time-variation in the First-stage Regression



Notes: Panel A shows heteroskedasticity-robust F-statistics for Equation (1.2). The test is applied jointly to all the coefficients. Critical values are taken from Stock and Watson (2012). In Panel B, the blue line shows the response to a 1 percentage point increase in expected GDP, calculated by summing the TVP coefficients on GDP growth forecasts and forecast revisions at each meeting. The orange line shows the response to a 1 percentage point increase in expected inflation, calculated using the same approach.

[7]See Cogley and Sargent (2005) and Boivin (2006) for further information about accounting for heteroskedasticity in the policy shocks when estimating time-varying monetary policy rules.

I estimate (1.2) to obtain a shock series over 1975 to 2007. I end the sample in 2007 to exclude the following years when the policy rate was around its effective lower bound (ELB) and the Bank of England employed unconventional policy tools (CH end their sample in 2007 for the same reason).[8] As a robustness exercise, in Section 1.5.3 I use shadow rates from Wu and Xia (2016, 2017) and forecasts from the Bank of England Inflation Report to estimate a shock series over 1975 to 2015 and confirm that my main state-dependent results hold over this extended sample.[9]

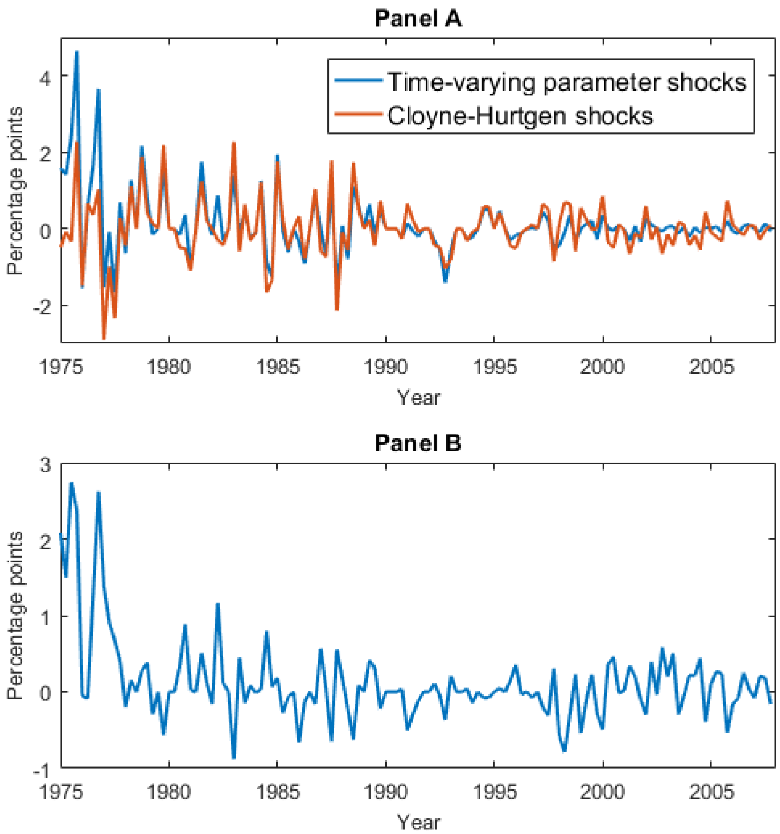
Estimation of (1.2) follows the procedure outlined in Boivin (2006) and is explained in detail in Appendix A.2. In short, the estimation consists of two key steps. First, an estimate of the variance of the parameters is obtained using the median-unbiased estimator approach proposed by Stock and Watson (1998). Second, conditional on the estimated variance, the time-varying parameters are estimated using the Kalman smoother and allowing for a shift in the variance of the policy shock in 1993Q1.

Panel B of Figure 1.1 plots the estimates of the cumulative time-varying coefficients for real GDP and inflation forecasts. The coefficients show the time-varying response to a 1 percentage point increase in either the real GDP growth or inflation forecast. The figure provides clear evidence of changes in the systematic conduct of monetary policy over the sample. The response to GDP growth varies between 0.14 and 0.31 while the response to inflation varies between -0.04 and 0.29. The response to GDP growth peaked in 1976Q4 and subsequently declined, on average, over the sample. Similarly, the response to inflation peaked in 1979Q4 following the election of the Conservative government in 1979Q2 that emphasised control of inflation (Nelson, 2000) and declined throughout the 1980s. During the inflation targeting period (1993Q1–2007Q4) the Bank Rate was lowered, on average, 1 basis point in response to a 1 percentage point increase in the inflation forecast (by comparison,

[8] Liu et al. (2019) provide empirical evidence that macroeconomic dynamics shift at the ELB.

[9] There is no consensus on the most accurate measure of the (unobservable) shadow rate and Krippner (2020) shows that both the level and profile of shadow rate estimates are very sensitive to model specification. Consequently, minor changes in the assumptions used when estimating shadow rates may lead to material changes in the resulting identified monetary policy shocks. For this reason, I use the shock series calculated using shadow rates as a robustness exercise and do not use shadow rates in the baseline analysis.

Figure 1.2: Monetary Policy Shocks



Notes: The top panel displays the TVP shocks obtained from the residuals from equation (1.2) (blue line) against the original Cloyne and Hürtgen (2016) shock series. The bottom panel shows the difference between these two series.

Table A.3 in Appendix A.3 shows the CH constant-coefficient first-stage regression (1.1) estimated over 1993Q1–2007Q4 yields a cumulative coefficient on inflation of –0.02).[10] The magnitude of changes in both the real GDP and inflation response declined throughout the sample, consistent with the move towards a more stable and transparent monetary policy framework in the UK. In summary, the TVP coefficients document important time-variation in the central bank reaction function that is broadly consistent with evolving UK monetary regimes and not captured in the CH constant-coefficient first-stage regression.

[10]The cumulative coefficient on inflation over 1993Q1-2007Q4 remains negative even if I estimate the reaction function without GDP growth forecasts (columns 5 and 6 in Table A.3). In addition, in Section 1.5.3 I use shadow rates to estimate the reaction function over 1975Q1–2015Q1 and once again find a negative response to inflation over the inflation targeting period.

1.2.3 Properties of the new shock series

Equation (1.2) is estimated at the meeting frequency, and a quarterly series of shocks is constructed by summing the shocks within each quarter over 1975Q1–2007Q4. In a quarter with no Bank Rate decision, the shock is set equal to zero. Panel A of Figure 1.2 displays the resulting shocks alongside the original CH shocks. Most notably, the shock series is less volatile over the second half of the sample, which largely coincides with the Great Moderation and a period of relative stability in the reaction function. The low volatility has occurred over the period during which the Bank of England began to target inflation (October 1992) and increased transparency through the publication of the Inflation Report (since 1993) and the Monetary Policy Committee Minutes (since 1997) (Cloyne and Hürtgen, 2016). The correlation between the two series is reasonably high at 0.76. Panel B plots the difference between the two series and shows that there are some large differences, particularly around 1975–1976, where the TVP shock series indicates two large contractionary shocks. This was a period during which the UK government targeted the M3 monetary aggregate and exchange rates. To the extent that the tightening in policy over this period was not the result of information about expected inflation and output, we should expect large contractionary shocks.[11]

Monetary policy shocks should, in principle, only capture unanticipated movements in the policy rate. However, Miranda-Agrippino and Ricco (2020) show that popular monetary policy shock identification methods that do not account for informational rigidities can lead to shocks that capture both exogenous monetary shocks and information shocks.[12] If the identified shocks are contaminated by the information effect of central bank announcements, the shocks will be autocorrelated and predictable based on past information (see the model in Miranda-Agrippino and Ricco 2020).

[11] The Bank Rate was raised by 600 basis points (from 9 to 15 per cent) between 8 March and 7 October 1976. Nelson (2000) notes that the depreciation of the exchange rate in 1976 was a major factor driving the tightening monetary policy.

[12] Information shocks occur when the public revises their information about the state of the economy based on the information disclosed through the central bank policy action (assuming there are informational asymmetries between the public and the central bank).

To test whether the identified shocks are predictable from movements in ex post revised data, I regress the shock series on a set of lagged macroeconomic variables:

$$\varepsilon_t = c + \sum_{j=1}^{4} \beta_j x_{t-j} + u_t, \tag{1.3}$$

where ε_t are the monetary policy shocks, c is a constant and x_t is a macroeconomic variable.[13] The macroeconomic variables considered are real GDP growth, inflation, M4 growth, the unemployment rate, the real exchange rate and the real oil price. Table 1.2 shows F-statistics and p-values for the null hypothesis that the shock series is not predictable from lags of these macroeconomic variables. The results confirm that the new monetary policy shock series is not predictable based on past information. Furthermore, in Section 1.3.3 I provide evidence against the hypothesis that the shocks are autocorrelated. Therefore, I conclude that the identified shocks capture unanticipated movements in the policy rate and are not contaminated by informational rigidities of the type discussed in Miranda-Agrippino and Ricco (2020).

Table 1.2: Monetary Policy Shock Predictability

Variable	F-statistic	p-values
GDP (quarterly growth)	0.79	0.54
Inflation (quarterly)	1.83	0.13
Money growth (M4)	1.22	0.31
Unemployment rate	0.29	0.88
Real exchange rate	1.00	0.41
Real oil price	0.47	0.76

Notes: The null hypothesis is that the shock series is not predictable from lags of these macroeconomic variables. Heteroskedasticity and autocorrelation-robust (HAC) standard errors are used.

[13]Cloyne and Hürtgen (2016) conduct similar tests in Section 2.C for their monthly shock series and show that their series is not predictable based on past information. Miranda-Agrippino and Ricco (2020) test for shock predictability using lagged factors extracted from a set of over 130 macroeconomic and financial variables.

1.3 Econometric Specification and Data

1.3.1 Specification

I use local projection methods to investigate the asymmetric effects of monetary policy following Tenreyro and Thwaites (2016).

State-dependent effects. I estimate the state-dependent effects of monetary policy using a smooth-transition local projection model (STLPM) that combines the standard local projection method proposed by Jordà (2005) with the smooth-transition regression methodology of Granger and Teräsvirta (1993). Specifically, the impulse response of variable y_t at horizon $h \in \{0, H\}$ in state $j \in \{e, r\}$ to a monetary policy shock ε_t is estimated as the coefficient β_h^j in the following regression:

$$y_{t+h} = \tau t + F(z_t)(\alpha_h^e + \beta_h^e \varepsilon_t + \gamma_h^e(L)\mathbf{x_{t-1}}) + (1 - F(z_t))(\alpha_h^r + \beta_h^r \varepsilon_t + \gamma_h^r(L)\mathbf{x_{t-1}}) + u_{t+h}, \quad (1.4)$$

where τ is a linear time trend, α_h^j is a constant, and $\mathbf{x_{t-1}}$ is a vector of lagged controls. Thus, each impulse response function (IRF) is a sequence of β_h^j values estimated from a series of single regressions for each horizon. $F(\cdot)$ is a smooth increasing function that varies between 0 and 1 based on an indicator of the state of the economy, z_t. I employ the logistic function

$$F(z_t) = \frac{\exp(\theta \frac{z_t - c}{\sigma_z})}{1 + \exp(\theta \frac{z_t - c}{\sigma_z})}, \quad (1.5)$$

where c determines what proportion of the sample period the economy spends in either state, σ_z is the standard deviation of the state variable z and θ determines the speed at which the economy moves between recession and expansion when z_t changes. The controls $\mathbf{x_{t-1}}$ are set to one lag of the log-level of real GDP, US real GDP and the real oil price, the level of the CPI, the Bank Rate and the dependent variable (in cases where the dependent variable is not GDP, the CPI or the Bank Rate). As the UK is a small open economy, the controls are chosen to capture the state of both domestic and global economic conditions.[14]

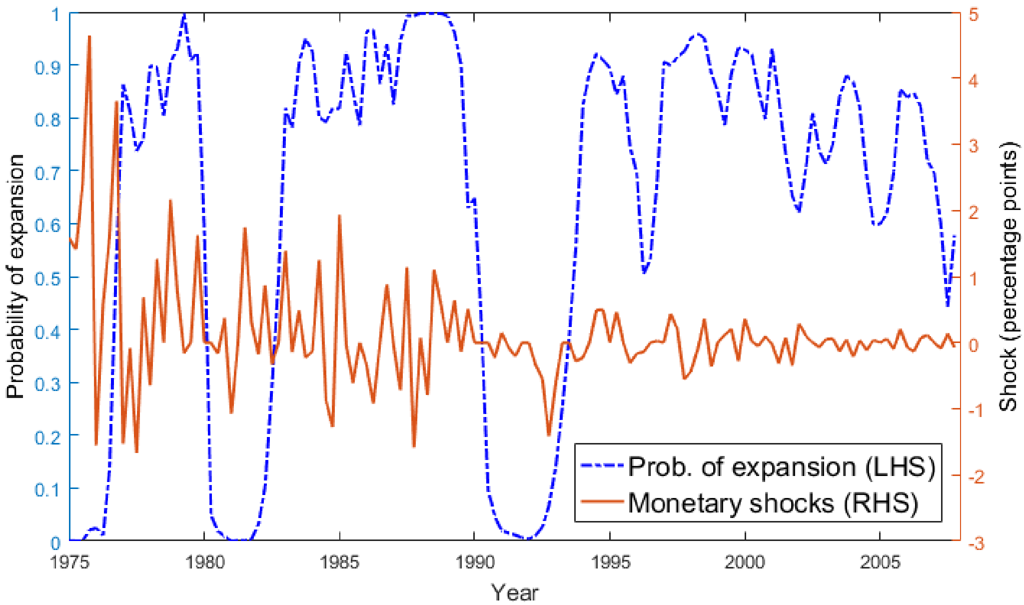
[14] The results are not sensitive to increasing the lag length. In addition, I obtain qualitatively similar, although less efficient, results when I include only one lag of the Bank Rate and the dependent variable as controls.

The STLPM is a flexible single-equation approach that can incorporate nonlinearities in the IRF. In (1.4), the set of regressors does not vary with the horizon h, and the impulse response incorporates the average transition of the economy between states. Thus, if monetary shocks impact the state of the economy, this will be reflected in $\{\beta_h^j\}_{h=0}^H$ for $j \in \{e, r\}$, and it is not necessary to model the dynamics of z. In addition, the smooth transition between states allows the effects to vary flexibly with the state of the economy. In contrast to a discrete regime-switching framework wherein the economy may spend little time in recession, the model utilises more information by exploiting variations in the extent to which the economy is in a particular regime. Therefore, estimation and inference for each regime use a larger set of observations (Auerbach and Gorodnichenko, 2012). This flexibility is not without its drawbacks. As there are no restrictions linking the IRFs between horizons h and $h + 1$, the IRFs are often erratic as a result of the loss of efficiency, and sometimes display oscillations at longer horizons (this is discussed further in Ramey and Zubairy 2018).

There is no clear theoretical prescription for the state variable z_t that defines the state of the business cycle. I follow Tenreyro and Thwaites (2016) and use a lagged seven-quarter moving average of real quarterly GDP growth (i.e., $z_t = \frac{1}{7}\sum_{i=1}^{7} \Delta y_{t-i}$ where Δy_t is quarterly GDP growth). Using a lagged moving average instead of a centred moving average as in Auerbach and Gorodnichenko (2013) ensures that future values of the response variables do not appear on the right-hand side of the regression. An additional advantage of using lagged GDP growth is that it is a coincident indicator, whereas the unemployment gap often lags the business cycle, which may lead to an incorrect assessment of the state of the economy (Auerbach and Gorodnichenko, 2013). Nevertheless, the robustness of the results to the use of alternative indicators of the business cycle is investigated in Section 1.5.

The value of θ determines the smoothness of the transition function. As θ increases, $F(z_t)$ approaches a discrete regime-switching framework and spends more time near the $\{0, 1\}$ bounds. Auerbach and Gorodnichenko (2013) argue in favour of calibrating rather than estimating θ, as it is difficult to identify the location and curvature of the transition function in the data. I follow them in setting $\theta = 3$ to allow an intermediate degree of regime-switching intensity. I set c to be consistent with defining a recession as the worst 25% of the periods in the sample. The resulting state variable $F(z_t)$ is shown in Figure 1.3 alongside the monetary policy shocks. The UK recessions of the mid-1970s, early 1980s and early 1990s are all clearly reflected in the state variable, and $F(z_t)$ also indicates a non-trivial probability of a recession in the mid-2000s. The sensitivity of the results to the choices of θ and c is analysed in Section 1.5.

Figure 1.3: State of the Economy



Notes: The blue line shows the transition function $F(z)$ computed with $\theta = 3$ and c set to define a recession as the worst 25% of the periods in the sample. The orange line shows the baseline monetary policy shocks.

Asymmetries as a result of the sign or size of the shock. To investigate whether positive or negative shocks (i.e., contractionary or expansionary shocks) are proportionally more powerful, I follow the specification used in Tenreyro and Thwaites (2016) and estimate the following equation:

$$y_{t+h} = \tau t + \alpha_h + \beta_h^{pos} \max[0, \varepsilon_t] + \beta_h^{neg} \min[0, \varepsilon_t] + \gamma_h(L)\mathbf{x_{t-1}} + u_{t+h} \tag{1.6}$$

for $h \in \{0, H\}$, where the variables are defined as in (1.4). The coefficient β_h^{pos} represents the response of y at time $t+h$ to a positive shock at time t. Similarly, β_h^{neg} represents the response to negative shocks. Throughout, I often refer to positive shocks as "contractionary" and negative shocks as "expansionary". For ease of comparison, in the figures, I scale β so that the shock raises the Bank Rate by 1 percentage point on impact for both positive and negative shocks.

To investigate whether smaller or larger shocks are proportionally more powerful, I estimate the following equation:

$$y_{t+h} = \tau t + \alpha_h + \beta_h^{small}\varepsilon_t + \beta_h^{large}\varepsilon_t^3 + \gamma_h(L)\mathbf{x_{t-1}} + u_{t+h} \tag{1.7}$$

for $h \in \{0, H\}$, where the variables are defined as in the baseline. That is, I add a cubed value of the shock to the standard linear model to distinguish between large and small shocks of either sign. If the parameter of interest, β_h^{large}, has the same sign as (opposite sign to) β_h^{small}, large shocks have a proportionally greater (smaller) effect.

Inference. I follow Tenreyro and Thwaites (2016) and Ascari and Haber (2019) and use two approaches to conduct inference on the estimated impulse responses. First, I use the Driscoll and Kraay (1998) method to calculate standard errors that are robust to heteroskedasticity, autocorrelation and spatial correlation. This method adjusts standard errors for the possibility of serial correlation both within and across equations. Second, I bootstrap the key statistics of interest (e.g., when testing for state dependence, the statistic of interest is $\beta_h^e - \beta_h^r = 0$). This provides a non-parametric measure for coefficient confidence and accounts for any estimation uncertainty arising through the first-stage regression used to identify the shocks and various forms of dependence among the residuals. I construct 10,000 samples with replacement of size T and calculate the percentage of instances in which the null hypothesis does not hold. To account for temporal dependence, the samples are constructed using adjacent blocks of observations of size H.

1.3.2 Data

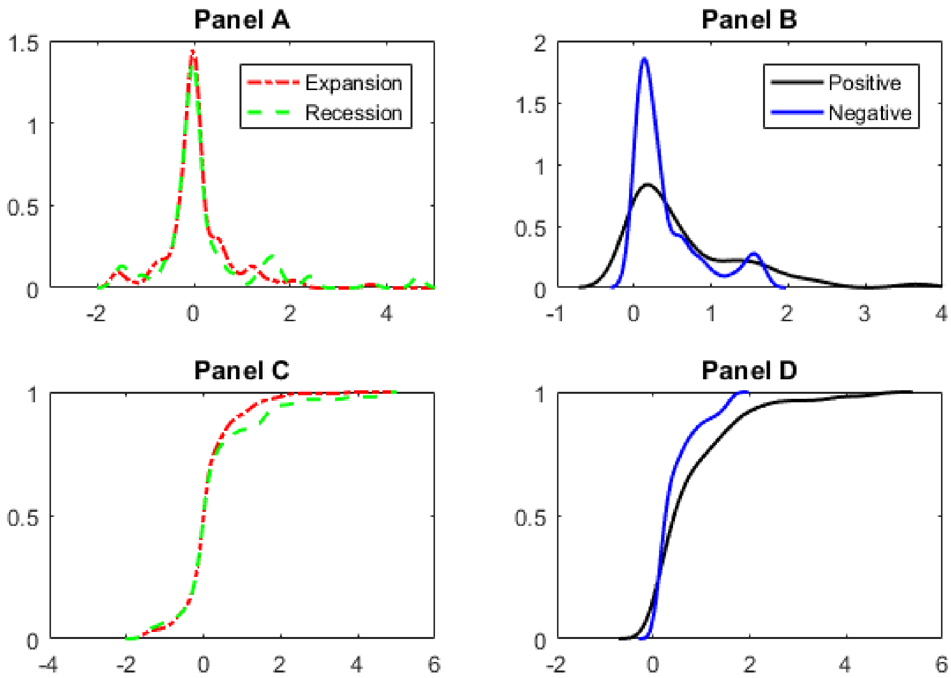
The baseline sample period includes shocks occurring in 1975Q1–2007Q4, with the response variables measured up to 2012Q4 (as the IRF horizon is $H = 20$). The response variables analysed are real GDP, the consumer price index (CPI), the unemployment rate, gross fixed capital formation (GFCF), and government and household consumption. See Table A.1 (in Appendix A.3) for a detailed list of sources.

1.3.3 Statistical properties of the shock series

It is important to analyse whether the statistical properties of the shocks, such as their distribution or persistence, depend on the state of the economy, or the sign or size of the shock. For example, assume that the effects of monetary policy do not depend on the state of the economy or the sign of the shock, but that large shocks are proportionally more powerful than small shocks. Under these assumptions, in a sample where large shocks are more common in expansions than in recessions, we would expect to find that monetary policy is more powerful in expansions. However, this conclusion is driven by the distribution of shocks differing across the state of the economy and is not the result of structural economic forces. In addition, monetary policy shocks should capture unanticipated movements in the policy rate and should therefore not display any significant persistence.

Figure 1.4 shows estimates of the probability distribution function (PDF) and cumulative distribution function (CDF) of the shocks depending on the state of the economy (Panels A and C) and the sign of the shocks (Panels B and D). Panel A shows that the regime-dependent distributions are very similar in shape, suggesting that neither the size nor the frequency of positive and negative shocks depend on the state of the economy. This is also apparent by viewing a time series of the shocks alongside $F(z_t)$ in Figure 1.3. Panel B shows that there is little difference between the central tendencies of the distribution of positive and (the absolute value of) negative shocks, but positive shocks are more variable than negative shocks. However, in both cases the Kolmogorov-Smirnov test[15] provides no evidence against the hypothesis that the two samples are drawn from populations with the same distribution (see Table A.2 in Appendix A.3). Therefore, any state- or sign-dependent asymmetric effects cannot be explained by asymmetries related to either the size or sign of the shock.

Figure 1.4: Shock Distribution



Notes: Panels A and C show the PDFs and CDFs of the shocks in the different states of the economy. The dashed red and green lines show the distributions during an expansion and a recession, respectively. Panels B and D show the PDFs and CDFs of the positive (black) and the absolute value of the negative (blue) shocks. The shocks are smoothed with a normally distributed kernel (ksdensity function in MATLAB) and the expansion and recession regimes are generated by weighting the kernel function with $F(z_t)$ and $1-F(z_t)$, respectively.

To test whether the identified shocks are autocorrelated and if the shock persistence differs across different regimes or types of shocks, I estimate the following model:

$$\varepsilon_t = c + \sum_{j=1}^{4} \rho_j \varepsilon_{t-j} + \sum_{j=1}^{4} \gamma_j D_t \cdot \varepsilon_{t-j} + u_t, \tag{1.8}$$

[15]The Kolmogorov-Smirnov (KS) test is a nonparametric test that analyses the probability that two sample distributions are drawn from populations with the same distribution. The KS statistic quantifies the distance between the two empirical distribution functions, and the distribution of this statistic is calculated under the null hypothesis that the two samples are drawn the same distribution.

where c is a constant, ε_t are the monetary policy shocks, and D_t is a dummy variable used to identify certain types of shocks. The lag length is chosen by the lag order that minimises the Akaike information criterion (AIC) in a model with no interaction term (i.e., $D_t = 0 \quad \forall\ t$). First, I test for autocorrelation in a linear model with no interaction terms. Second, I run three separate models setting D_t equal to $F(z_t)$, an indicator variable for positive shocks (denoted by $\mathbf{1}\{\varepsilon_t > 0\}$), or include ε_t^3 instead of the interaction term. I conduct partial F-tests to compare each of these interacted models with the model with no interaction terms to analyse whether the persistence of shocks depends on the state of the economy, or the sign or size of the shock.

The first column of Table A.2 (in Appendix A.3) indicates that in a linear model with no interaction terms there is no evidence at the 5 per cent level that the shocks are serially correlated. In addition, the partial F-tests in columns two and four indicate that there is no strong statistical evidence that the interaction terms for either the state of the economy or large shocks improve the fit of the model. However, the results of the F-test provide some evidence that positive shocks are more persistent than negative shocks. Overall, I find no strong statistical evidence that the shocks are autocorrelated or that the shocks are serially correlated across different states of the economy or shock sizes, however there is evidence that positive shocks are more persistent than negative shocks.

1.4 Results

1.4.1 State-dependent effects

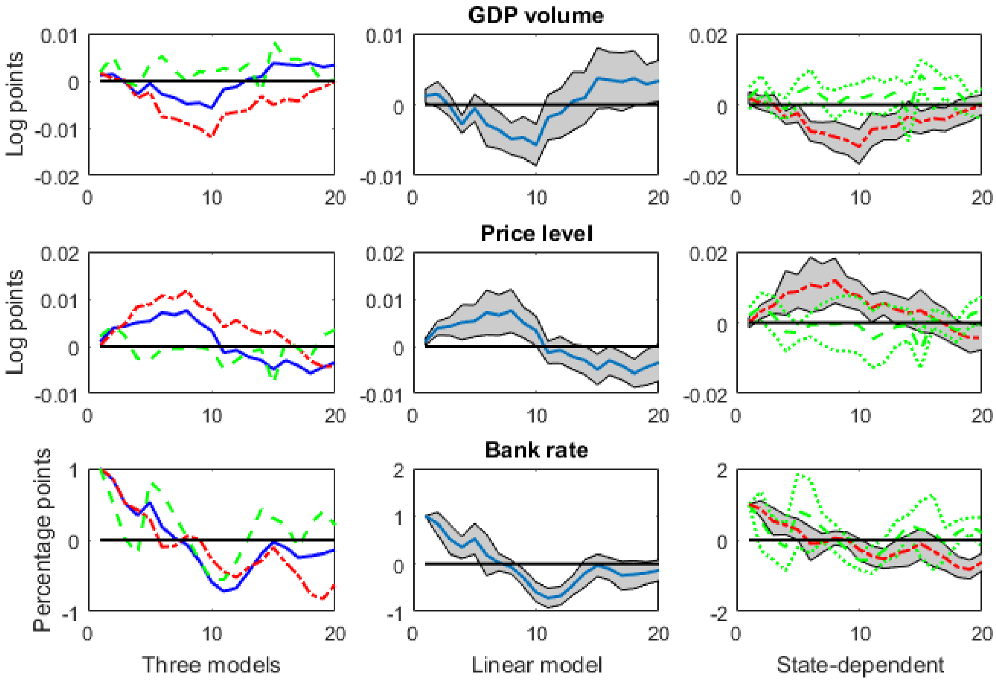
Figure 1.5 displays the IRF of the log-level of real GDP, the CPI and the level of the Bank Rate in response to a monetary policy shock that increases the Bank Rate by 1 percentage point. The first column shows the central estimate of the IRF for a linear, state-independent model (solid blue line) and the state-dependent model (expansions are represented by the dash-dot red line and recessions by the dashed green line). The second and third columns show the 90 per cent confidence intervals around the central tendencies. The IRFs are scaled so that the shock leads to a 1 percentage point increase in the Bank Rate in each regime as in Tenreyro and Thwaites (2016).

The results for the linear model are consistent with those of previous studies for the UK. In response to a contractionary monetary policy shock, the level of GDP declines to a minimum of 0.6 per cent below the baseline nine quarters after the shock, after which GDP begins to recover. The price level initially rises (commonly referred to as a "price puzzle"), although it eventually falls below zero after ten quarters and reaches a maximum decline of 0.6 per cent. The price puzzle is discussed further in Section 1.4.3. The Bank Rate declines persistently following the contractionary shock and falls below the conditional mean after eight quarters.

The left-hand column of Figure 1.5 clearly shows how the effects differ in expansions and recessions. In an expansion, output reaches a maximum decline of 1.2 per cent – approximately twice the magnitude of the response in the linear model – following a contractionary shock. In contrast, during a recessionary regime, output responds very little to the shock. There is a sustained price puzzle following a contractionary shock during an expansion. However, during a recession, prices briefly rise following the shock before falling below zero after three quarters. The right-hand column shows that the effects during a recession are typically statistically insignificant, while during expansions, a contractionary shock leads to a statistically significant fall in output and increase in prices. In Section 1.5, I show that these results are robust to alternative monetary policy identification methods and variations in the empirical specification.

The asymmetric price response may be explained by the cost channel of monetary transmission (proposed in a linear framework by Barth and Ramey 2000), which posits that the price puzzle can be explained by short-run cost-push inflation brought on by a contractionary shock. It may be that during expansions, firms are more willing to pass on increases in costs to prices, as they deem households more able to absorb the increase because of the expansionary economic conditions, whereas in recessions, firms choose to absorb the

Figure 1.5: State-dependent Impulse Responses to a Monetary Policy Shock



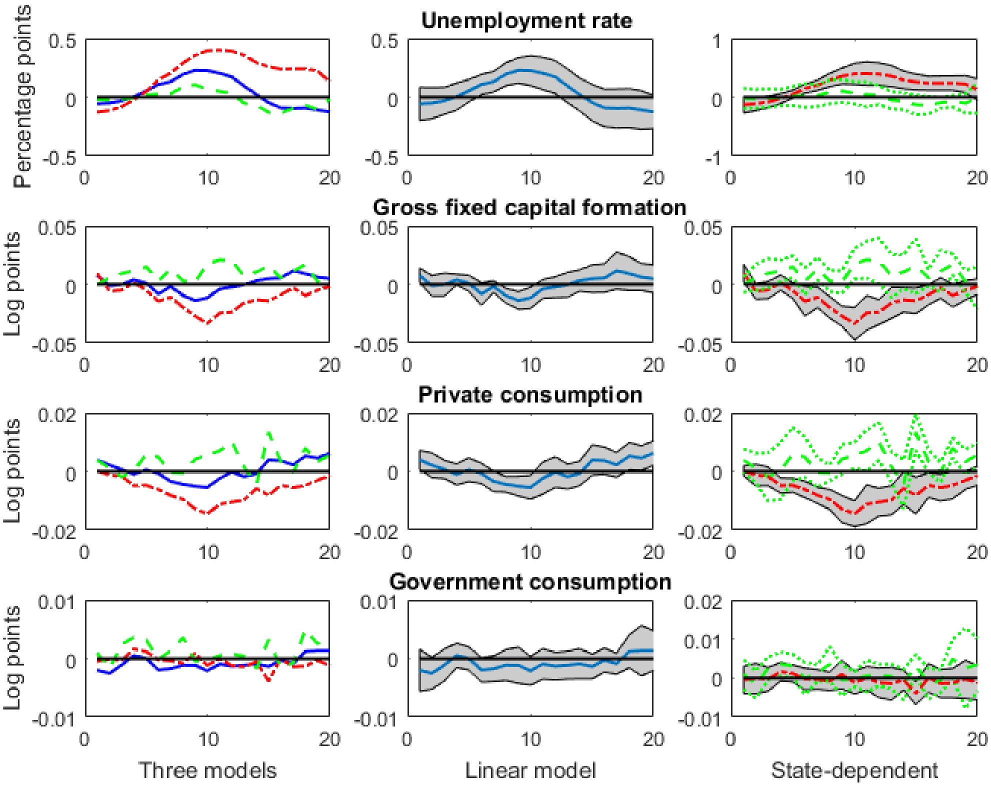
Notes: Response of the log-level of real GDP, the consumer price index, and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion, and the green dashed line shows the response in a recession. The second column shows the 90 percent confidence interval around the state-independent response. The third column shows the same interval around the state-dependent responses.

increases in costs. Alternatively, expansionary shocks may lead to a fall in prices if firms are more willing to pass on the decreases in costs to customers in the form of lower prices during expansions.

Figure 1.6 displays the IRF of the level of the unemployment rate and the log-level of GFCF and real household and government consumption in response to the same shock as before. The top row shows that the unemployment rate rises by up to 0.2 percentage points eight quarters after a shock in the linear model, and by up to 0.4 percentage points during an expansion. However, the unemployment rate does not respond significantly to the shock during a recession. The responses of both GFCF and household consumption are consistent with the response of aggregate output.

To further investigate the asymmetric household consumption response, Figure A.1 (in

Figure 1.6: State-dependent Impulse Responses to a Monetary Policy Shock – Additional Variables



Notes: Response of the unemployment rate, the log-level of gross fixed capital formation and private and government consumption to a monetary policy shock that increases the Bank Rate by 1 percentage point. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-independent response. The third column shows the same interval around the state-dependent responses.

Appendix A.3) shows the IRF of durable, semi-durable and non-durable goods consumption.[16] Due to data constraints, the IRFs are estimated from a smaller sample with shocks occurring during 1985Q1–2007Q4. The smaller sample does not include the recessions in the mid 1970s and early 1980s which leads to imprecise estimates in the recession regime. Nevertheless, consumption of durable goods declines by up to 4 per cent following a contractionary shock in an expansion but does not respond significantly during a recession. Durable goods consumption declines by approximately twice the magnitude of aggregate

[16]Empirical evidence suggests that the response of aggregate activity to monetary policy is largely driven by the durable goods sector (Sterk and Tenreyro, 2018).

household consumption in both the linear model and during expansions. The responses of semi-durable and non-durable goods are not significantly different during expansions and recessions. Therefore, the asymmetric household consumption response is primarily driven by durable goods consumption.

Table 1.3 shows the cumulated impulse responses for the baseline variables discussed above. The final two columns show the significance of the difference between the responses in each regime based on Driscoll and Kraay (1998) and bootstrapped standard errors. There is statistical evidence that there are economically significant asymmetries in the response of all variables except government consumption, although the level of significance depends on how the standard errors are calculated. In general, the evidence for an asymmetric output response is very strong, but there are only a few instances where I find statistically significant asymmetric responses in the price level when bootstrapped standard errors are used.

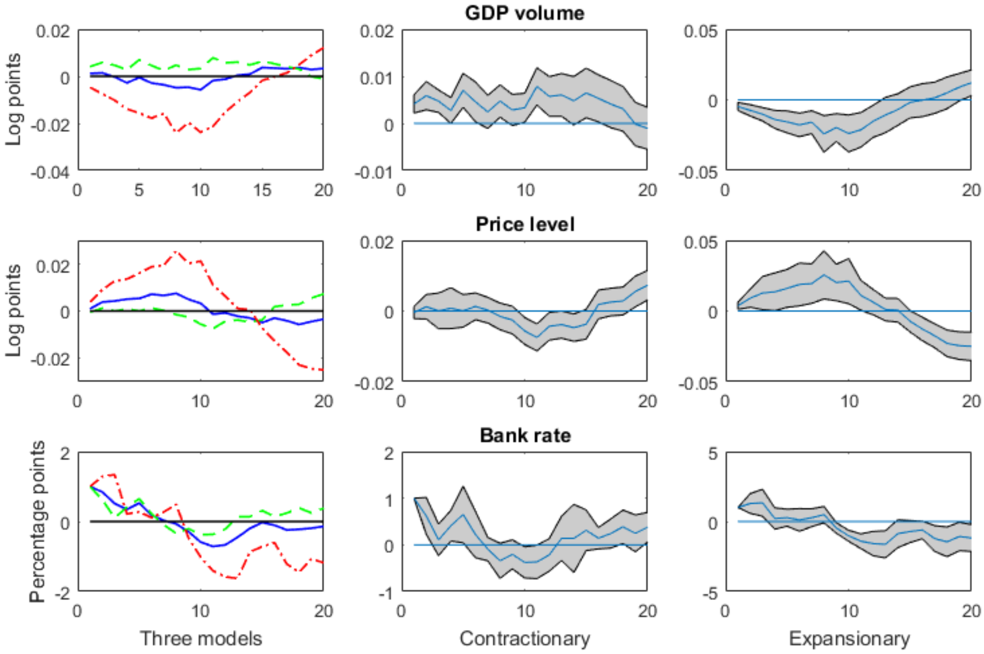
1.4.2 Asymmetries as a result of the sign or size of the shock

Figure 1.7 shows the IRFs estimated from equation (1.6) for real GDP, prices and the Bank Rate, as well as the associated 90 per cent confidence intervals. The IRFs are scaled so that the shock raises the Bank Rate by 1 percentage point on impact. Table 1.4 shows the cumulated impulse responses.

Figure 1.7 shows that GDP responds significantly to expansionary shocks, whereas contractionary shocks do not lead to a notable output response. The price level does not respond initially following a contractionary shock, but there is a significant price puzzle following expansionary shocks (β_h^{neg} is scaled so that the shock raises the Bank Rate by 1 percentage point). This suggests that the price puzzle in the linear model is solely driven by expansionary shocks. Table 1.4 shows that these differences are statistically significant when Driscoll and Kraay (1998) standard errors are used.[17] Note that the frequency of

[17] I reach the same qualitative conclusion estimating the equation $y_{t+h} = \tau t + \alpha_h + \beta_h \varepsilon_t + \beta_h^{pos} \mathbf{1}\{\varepsilon_t > 0\} \cdot \varepsilon_t + \boldsymbol{\gamma} \mathbf{x_t} + u_{t+h}$ and testing whether β_h^{pos} is statistically different from zero. In this specification, $\mathbf{1}\{\varepsilon_t > 0\}$ is a dummy variable equal to 1 for positive shocks and zero otherwise.

Figure 1.7: Impulse Responses for Positive and Negative Shocks



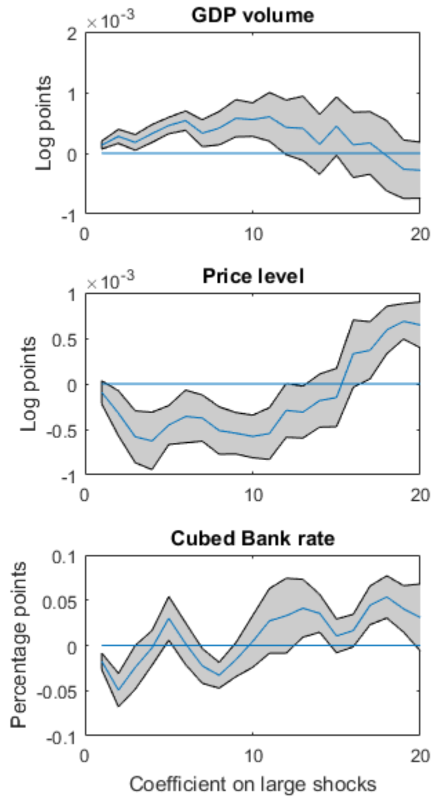
Notes: All columns show the impulse response to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the linear model, the dashed green line shows the response for positive/contractionary shocks, and the dashed red line shows the response for negative/expansionary shocks. The second and third columns show the 90 per cent confidence interval around the positive and negative shock IRFs, respectively.

expansionary and contractionary shocks does not depend on the state of the economy (see Figure 1.4), so this finding cannot explain the main result that monetary policy shocks have more powerful effects during expansions.

Figure 1.8 shows $\hat{\beta}_h^{large}$ estimated from equation (1.7) for GDP, prices, and the Bank Rate, as well as the associated 90 per cent confidence intervals.[18] Table 1.5 reports the corresponding cumulative impulses and estimates of significance. Large shocks lead to a weaker effect on both prices and GDP than small shocks. The GDP response is consistent with the menu cost literature, whereby a large shock induces a change in prices, and this attenuates the impact on output. However, the next section shows that the price level responses from equation (1.7) are sensitive to the method of monetary policy shock iden-

[18] I also estimated a model wherein the impact of policy is allowed to depend on both the state of the economy and the sign of the shock. However, estimating a four-regime model incurs a large loss of degrees of freedom, and consequently there was considerable uncertainty around the central estimates and no statistically significant asymmetries.

Figure 1.8: Impulse Response to Cubed Shocks



Notes: Impulse response of the coefficient on the cubed monetary policy shocks β_h^{large} and the 90 per cent confidence interval.

tification. Therefore, I conclude that large shocks have a proportionally weaker effect on output, but there is not robust evidence that the price level response depends nonlinearly on the size of the shock.

1.4.3 Discussion

The key results can be summarised as follows:

- Monetary policy shocks that occur during economic expansions have significantly larger effects than those that occur during recessions.
- Expansionary shocks have greater effects than contractionary shocks.
- Large shocks have a proportionally weaker effect on output than small shocks.

The finding that monetary policy shocks have more powerful effects on output during expansions is consistent with Tenreyro and Thwaites (2016) and the cross-country study of Jordà et al. (2020). However, Garcia and Schaller (2002), Lo and Piger (2005) and Peersman and Smets (2001) reach the opposite conclusion in their empirical studies of the US and the Euro area. To my knowledge, this the first empirical investigation of the state-dependent effects of monetary policy in the UK. Consequently, it is interesting to see how closely these results line-up with estimates for the US. I replicate the baseline results from Tenreyro and Thwaites (2016) for the US, but to make the results as comparable as possible, I set c to ensure that 25% of the periods in the sample are defined as a recession, and use the largest sample period of shocks that is common to both studies, 1975Q1–2002Q4.[19]

Figure A.2 (in Appendix A.3) shows the state-dependent results for the UK and the US (blue line with crosses) of a 1 percentage point contractionary monetary policy shock. Interestingly, the output results for the US and the UK are broadly similar, with slightly stronger evidence of an asymmetric response for the UK. However, the price responses are notably different between the two countries. In an expansion, the price level is initially sticky in the US, but eventually falls by about 3 per cent, whereas there is a notable price puzzle in the UK. During a recession, the price response is reasonably similar in the US and the UK. Overall, the state-dependent output responses in the UK and the US are qualitatively similar, but the state-dependent price responses are markedly different, largely as a result of the price puzzle in the UK during expansions.

In general, the state-dependent effects of monetary policy over the business cycle has not received much attention in the theoretical literature.[20] The main empirical result that output responds more to shocks during expansions is consistent with a framework where the Phillips curve flattens during expansions and steepens during recessions. Vavra (2014) argues that recessions are characterised by high volatility, which leads to increased aggregate

[19]Tenreyro and Thwaites (2016) use a sample of shocks occurring in 1969Q1–2002Q4 and define a recession as the worst 20% of periods in the sample.

[20]See Appendix A.1 for an overview of different theoretical mechanisms that explain why an economy may respond asymmetrically to monetary policy shocks.

price flexibility and a steepening of the Phillips curve. He constructs price-setting models with "volatility shocks" that imply that monetary policy is more powerful during periods of low volatility, such as expansions, whereas in periods of high volatility, such as recessions, monetary policy will fail to stimulate output. Alternatively, Berger and Vavra (2015) and McKay and Wieland (2019) develop heterogeneous agent models where households' willingness to hold durable goods declines during recessions, and this implies that households are less sensitive to monetary stimulus during recessions.[21] The results in this chapter show that monetary policy is more powerful during economic expansions and durable goods consumption exhibits notable state-dependence, consistent with the implications of the models in Vavra (2014), McKay and Wieland (2019) and Berger and Vavra (2015).

The finding that expansionary shocks are more powerful than contractionary shocks is inconsistent with the findings of Tenreyro and Thwaites (2016) and Angrist et al. (2018) for the US. Barnichon and Matthes (2018) find that contractionary shocks lead to larger effects on unemployment, but expansionary shocks lead to larger price responses in the US. The findings for the UK would be consistent with a framework where the external finance premium declines by more following expansionary shocks than it increases following contractionary shocks. In this case, the interest rates at which households and firms can borrow would move by proportionally more following expansionary shocks than contractionary shocks. However, the UK results are not consistent with sign asymmetries arising through downward nominal wage rigidities as emphasized in relation to fiscal policy shocks in Barnichon et al. (2020). The finding that expansionary shocks are more powerful than contractionary shocks in the UK is interesting in its own right. However, given this result is inconsistent with previous evidence for the US, future research that assesses the robustness of the UK results to using the propensity score weighting approach developed in Angrist

[21]These models are consistent with empirical evidence that suggests the response of aggregate activity to monetary policy is largely driven by the durable goods sector (Sterk and Tenreyro, 2018). In addition to time-variation in the frequency of durable adjustment, the Berger and Vavra (2015) model also displays time-variation in the strength of selection effects. That is, the aggregate durable response also depends on which households choose to adjust, not just on how many households adjust, and these selection effects are more important during expansions.

et al. (2018) and the functional approximation of impulse responses approach in Barnichon and Matthes (2018) would be useful.

The result that large shocks have a proportionally weaker effect on output is consistent with Tenreyro and Thwaites (2016) and Ascari and Haber (2019). Ascari and Haber (2019) also provide evidence that large shocks have a proportionally greater effect on prices. Taken together, the results are consistent with the menu costs literature where sufficiently large shocks are needed to shift firms far enough from their optimal price that they are willing to pay the fixed cost to change prices, and this tempers the impact on output. This supports the use of models that include state-dependent price rigidities over time-dependent models.[22] State-dependent pricing models are also able match the empirical distribution of price changes in micro data (Ascari and Haber, 2019).

What explains the price puzzle in the linear model? The price puzzle in the linear model is slightly larger than that found in Dedola and Lippi (2005) but smaller than the price puzzle in Gerko and Rey (2017). CH claim to solve the price puzzle for the UK. However, their shock series does not allow for time-variation in the central bank reaction function, and their baseline analysis uses a linear VAR which Ramey (2016) argues is less robust than local projections to model misspecification. I replicated the CH baseline VAR results and plotted them alongside IRFs estimated from the CH VAR with my TVP shock series (see Figure A.23 in Appendix A.3). This figure clearly shows the implications for CH's VAR results of allowing for time-variation in the first-stage regression. Most notably, the price puzzle reemerges once I allow for time-variation in the first-stage regression. The price puzzle is discussed further in Section 1.5.

These results have important policy implications. Policymakers in the UK are able to stimulate the economy through lower interest rates during expansions, but may need

[22] In state-dependent pricing models with positive trend inflation, inflation leads to firms' relative prices declining over time, and consequently firms are more likely to adjust prices and pay the fixed cost when trend inflation is high. Therefore, a monetary policy shock in a high-inflation regime should lead to a faster but less persistent price response. Ascari and Haber (2019) find empirical support for this prediction in the US.

to consider alternative policy measures, such as fiscal policy or unconventional tools, to stimulate the economy during a recession. This is particularly relevant when coupled with recent research (e.g., Glocker et al. 2019; Auerbach and Gorodnichenko 2013) suggesting that fiscal multipliers are larger during recessions. Taken together, pursuing fiscal austerity and relying on expansionary monetary policy to stimulate an economy in a recessionary or low-growth regime appears to be a particularly harmful policy mix.

1.5 Extensions and Robustness

This section presents a number of exercises which show the robustness of the results. All tables and figures associated with the robustness exercises are reported in Appendix A.3.

1.5.1 Nonlinearities in the slope of the Phillips Curve

The main result that output responds more to shocks during expansions is consistent with a theoretical framework where the Phillips curve flattens during expansions and steepens during recessions (e.g. Vavra 2014). To investigate this empirically, I follow Coibion and Gorodnichenko (2015) and estimate reduced form expectations-augmented Phillips curve regressions of the form

$$\pi_t - E_t\pi_{t+1} = c + \kappa_1 x_t + \kappa_2 I_t \cdot x_t + \theta I_t + v_t, \tag{1.9}$$

where π_t is the quarterly annualised rate of CPI inflation, $E_t\pi_{t+1}$ is the expectation of inflation one year ahead, c is a constant, x_t is the output gap,[23] and I_t is a dummy variable that is equal to one when the output gap is positive and zero when it is negative. Inflation expectations are calculated as the one-year-ahead forecast from an AR(3) model estimated over the 40 quarters prior to expectations being formed, as in Laubach and Williams (2003).[24] The coefficient of interest is κ_2, and assuming the Phillips curve is positively sloped $\kappa_1 > 0$,

[23] The output gap is calculated using the Hodrick and Prescott (1997) (hereafter HP) filter based on a sample period from 1975Q1 to 2012Q4 and $\lambda = 1600$.

[24] Unfortunately, no survey- or financial-market-based measures of inflation expectations are available for the UK from 1975 onwards, therefore I am limited to using a backward-looking univariate measure. This is an unavoidable limitation of the analysis.

$\kappa_2 < 0$ indicates that the Phillips curve flattens during periods in which the output gap is positive.

I estimate (1.9) by both OLS and instrumental variables (IV) using one lag of the output gap and the interaction term as instruments. The empirical challenges involved in estimating reduced-form Phillips curves are well-documented.[25] However, assuming that the instruments are uncorrelated with the current period cost-push shock and that cost-push shocks are not autocorrelated, McLeay and Tenreyro (2020) show that the IV estimates will identify the Phillips curve.

Table A.10 reports the OLS and IV results. As expected, the Phillips curve slope $\kappa_1 > 0$, indicating that periods in which output growth is in excess of its trend rate have, on average, been associated with inflation exceeding expectations. Interestingly, I also find $\kappa_2 < 0$, which is consistent with the Phillips curve flattening during periods of economic expansion. However, I can only reject the null at the 10 per cent level for the OLS specification. Taken together, and noting the limitations as a result of the lack of alternative measures of inflation expectations, these findings provide suggestive evidence that the Phillips curve flattens during economic expansions in the UK. The results are robust to using the unemployment gap instead of the output gap as the measure of economic slack, and measuring inflation expectations as the four-quarter moving average of realised inflation.[26] These results support the development of models that lead to state-dependent effects of monetary policy due to a flattening of the Phillips curve during expansions (e.g. Vavra 2014).

1.5.2 Alternative identification of monetary policy shocks

Cloyne and Hürtgen (2016) shocks. The baseline analysis used monetary policy shocks identified by extending the original CH approach to allow for time variation in the first-stage regression. As an alternative, I use the original CH shocks (shown in Figure 1.2) that are identified based on the assumption of a constant-coefficient first-stage regression. The

[25] For an analysis of the empirical literature on the role of inflation expectations in the New Keynesian Phillips curve, see Mavroeidis et al. (2014) and Coibion et al. (2018).

[26] Results available upon request.

main findings are robust to the use of the original CH shocks, which suggests that they are not driven by allowing for time variation in the first-stage regression (see Figures A.3, A.4 and A.5 and Table A.4). The state-dependent results are similar to the baseline results, with the CH shocks resulting in slightly larger peak effects during expansions. There is evidence that expansionary shocks are more powerful than contractionary shocks, and that large shocks lead to a proportionally weaker effect on output but a larger price response.[27]

The original CH paper claimed to solve the price puzzle for the UK using a VAR, and they confirm their results hold in a local projection framework (see Section 4.G in CH). However, Figure A.3 shows a price puzzle in the linear model when using the original CH shocks. The difference is due to two reasons: lags of the shocks and recursive identification. I use quarterly data and do not include lags of the shock, whereas the CH local projections use monthly data and 48 months of lags of the shocks. By replicating the CH local projections exercise I find that their results are very sensitive to the number of lags of shocks. For example, there is a notable price puzzle in the CH local projections when I include 12 months of lags of the shocks. This is consistent with results for the US, where Coibion (2012) finds that the Romer and Romer (2004) single equation results are very sensitive to the number of lags of shocks. In addition, after identifying the exogenous monetary policy shock series and confirming it is unpredictable from movements in macroeconomic data, CH order the shock series last in their VAR and impose a recursiveness assumption to estimate the effects of monetary policy. However, the recursiveness assumption is not needed if one believes that the forecasts used in the first-stage regression incorporate all relevant information used by the central bank (Ramey, 2016). I do not impose a recursiveness assumption in my STLPM.[28]

[27]The results are also robust to an alternative approach of mapping meetings to quarters. In the baseline situation, to obtain a quarterly series, the shocks associated with each meeting within a given quarter were simply summed. As an alternative, I follow the aggregation approach proposed by Bluedorn and Bowdler (2010) and obtain qualitatively similar results.

[28]It is possible to impose a recursiveness assumption in a local projection framework through the appropriate choice of contemporaneous control variables (see Ramey 2016).

Recursive identification. I estimate monetary policy shocks using a Cholesky identification scheme on a linear VAR that includes four lags of the log-level of GDP, the price level, commodity prices and the Bank Rate (in that order).[29] This common identification approach assumes that shocks to the Bank Rate affect the other variables with a lag.

The state-dependent results are similar to those for the baseline (see Figure A.6 and Table A.6). The maximum decline in GDP during an expansion is approximately twice that of the linear model, while GDP does not respond significantly during a recession. There is a sustained price puzzle following the shock in the linear model and during expansions, but prices do not respond significantly during recessions. In addition, Figure A.7 shows that expansionary shocks are more powerful than contractionary shocks. I find evidence that large shocks have proportionally weaker effects on output, but there is no evidence that the price response depends significantly on the size of the shock (see Figure A.8).

Cochrane (2004) critique of the Romer–Romer identification. In his discussion of the Romer and Romer (2004) identification, Cochrane (2004) argues that if the forecast of, for example, future GDP growth contains all the information that the central bank uses to make its decision, then that forecast is a "sufficient statistic" to measure the effects of monetary policy on GDP. He states that movements in the target policy rate that are orthogonal to the GDP forecasts can be used to identify the causal effect of monetary policy on GDP.[30] To implement Cochrane's method, I estimate the following regression to obtain a shock, ε_m^x, to the variable x:[31]

$$\Delta i_m = \alpha + \beta i_{t-d14} + \sum_{j=-1}^{2} \gamma_j \hat{x}_{m,j}^F + \sum_{j=-1}^{2} \delta_j (\hat{x}_{m,j}^F - \hat{x}_{m-1,j}^F) + \sum_{j=1}^{3} \rho_j u_{t-j} + \varepsilon_m^x. \qquad (1.10)$$

Shocks using the Cochrane (2004) method lead to slightly larger absolute effects of monetary policy.[32] This result is consistent with Cochrane's (2004) findings for the US

[29] The correlation between the baseline shock series and the recursively identified shock series is equal to 0.50.

[30] Ramey (2016) notes that Cochrane's notion of a shock is not what we typically think of as a structural shock, but rather an instrument for estimating the causal effect of monetary policy.

[31] Cochrane (2004) argues that it is best to estimate as few parameters as possible to obtain the shocks, thus I follow Cochrane (2004) and opt for a constant-coefficient regression.

[32] The correlations between the baseline shock series and shocks used to identify the effects on inflation and GDP equal 0.74 and 0.75, respectively.

compared with the original Romer and Romer (2004) results. Nevertheless, the state-dependent results are qualitatively similar to those of the baseline and the findings are robust to this alternative identification approach (see Figure A.9 and Table A.5). In addition, Figure A.10 shows that expansionary shocks are more powerful than contractionary shocks. However, large shocks have a stronger effect on both prices and GDP, which is inconsistent with the baseline result (see Figure A.11).

1.5.3 Extending the shock series to 2015

The baseline sample uses shocks occurring during the period 1975Q1–2007Q4, with IRFs calculated using data up to 2012Q4. The sample ended in 2007Q4 to exclude the period where the policy rate approached the ELB and the Bank of England employed a range of unconventional policy measures. During periods of unconventional monetary policy the Bank Rate may not appropriately capture the Bank of England's intended policy target when estimating a narrative shock series. To address this concern, I use shadow rates estimated by Wu and Xia (2016, 2017) to approximate the policy rate over 2008Q1–2015Q4 and compute a shock series over 1975Q1–2015Q1. The shadow rate is the short-term interest rate obtained from a term structure model that relaxes the ELB constraint. Consequently, the shadow rate corresponds to the policy rate in periods where the ELB is not binding, but can freely evolve to negative values during periods where the ELB is binding to capture the effects of unconventional monetary policy on long-term interest rates (see Wu and Xia (2016, 2017) for further details). Forecasts and forecast revisions for GDP and inflation are taken from the Bank of England Inflation Report.

Panel A of Figure A.12 shows monetary policy shocks over 1975–2015 estimated by the TVP first-stage regression (1.2), where the policy target rate is the Bank Rate over 1975–2007 and the Wu and Xia (2016, 2017) shadow rate over 2008–2015. Over the common sample 1975–2007, the correlation with the baseline shock series is high at 0.89. The vertical line on the figure occurs at 2008Q1. There is a large expansionary shock of 2.2

percentage points in 2008Q4, but the main Bank of England quantitative easing announcements over 2009 are not associated with notable expansionary shocks.[33] This suggests that the announcements did not lead to a fall in the shadow rate materially greater than that implied by the central bank's systematic reaction to the forecasts of GDP and inflation.

Panel B of Figure A.12 shows the cumulative time-varying coefficients for real GDP growth and inflation forecasts. Most notably, the response to inflation is negative over the inflation targeting period, indicating that the policy rate was lowered, on average, in response to increases in the inflation forecast. For comparison, estimating the CH constant-coefficient first-stage regression (1.1) over 1993Q1–2015Q4 yields a cumulative coefficient on inflation of –0.08. The response to expected output has been relatively constant over the sample.

Figure A.13 shows that the state-dependence results for output and inflation are robust to extending the sample of shocks to 2015Q4 (IRFs are calculated using data up to 2019Q4). However, Figures A.14 and A.15 show that there is no statistical evidence that expansionary shocks are more powerful than contractionary shocks or that the output response depends nonlinearly on the size of the shock.

1.5.4 The transition function

The state variable. There is no clear theoretical prescription on the state variable that should be used to define the stage of the business cycle. In the baseline analysis, I used a lagged moving average of the real GDP growth rate to measure the state of the business cycle. However, Keynesian theories typically interpret the notion of slack in an economy as relating to a disequilibrium measure, such as the output gap, rather than a flow variable, such as GDP growth (Auerbach and Gorodnichenko, 2013). Consequently, I investigate the robustness of the results to the use of the output gap and the unemployment gap as state

[33] See Joyce et al. (2011) for a study of the impact of the Bank of England's quantitative easing policy on UK. Table 1 in Joyce et al. (2011) lists the major quantitative easing announcement dates.

variables in the STLPM.[34]

The top panel of Figure A.16 shows the transition between regimes when the output and unemployment gaps are used as state variables. Figures A.17 and A.18 show the state-dependent IRFs and Table A.7 shows the cumulated IRFs and tests of significance. The result that output falls significantly following the shock in an expansion but does not respond significantly during a recession is very robust. The price response when the unemployment gap is used as the state variable is qualitatively similar to that in the baseline, although there is no clear asymmetric price response when the output gap is the state variable and no statistical evidence of asymmetric price responses in either case. In conclusion, the finding that monetary policy has a more powerful effect on output during expansions is robust across a range of variables measuring the stage of the business cycle.

I also estimated a model whereby the economy is deemed to be in expansion (recession) when real GDP is above (below) its HP-filtered trend. This differs from the baseline situation, as there is now a discrete movement between states (i.e., there is no smooth transition) and the economy spends approximately 50 per cent of the overall sample in each regime. Nevertheless, the overriding conclusions concerning state-dependent effects remain under this alternative specification.

Proportion of time spent in recession. In the baseline analysis, I define a recession as the worst 25 per cent of periods in the sample. The bottom panel of Figure A.16 shows how the transition between regimes differs when the proportion of the sample judged to be in recession is increased to 50 per cent. There is stronger statistical evidence of state-dependent asymmetries when the proportion of the sample judged to be in recession is increased to 50 per cent (Table A.8). The response of output is even larger in an expansion, falling by up to 1.4 per cent, while the price puzzle during an expansion is also slightly larger (Figure A.21). This confirms that the statistically insignificant effect of monetary

[34] The output and unemployment gaps are calculated using the HP filter. I use the smoothing parameter $\lambda = 1600$ in both cases, as is standard for quarterly data, and estimate over the period 1975Q1–2012Q4 to avoid any end-point bias.

policy during recessions is not driven by a small number of observations.

Intensity of regime switching. The θ parameter controls the speed at which the economy switches between expansion and recession. In the baseline, I set $\theta = 3$ to give a moderate degree of regime-switching intensity following Auerbach and Gorodnichenko (2013). The middle panel of Figure A.16 shows how the transition between regimes differs under different choices of θ. If $\theta = 10$ the economy moves very quickly between different states, whereas when $\theta = 1$ the economy transitions slowly between regimes. The state-dependent results are robust to these alternative calibrations of the transition function (see Figures A.19 and A.20 and Table A.9).

1.5.5 Monthly frequency

I construct a monthly shock series over 1975M1–2007M12 and use industrial production as the measure of output to analyse the sensitivity of the state-dependent results to estimation at a monthly frequency. The shock series is constructed as in the baseline, except I sum the shocks occurring within each month. In a month with no Bank Rate decision, the shock is set to equal zero.[35]

The state-dependent results are robust to estimation at a monthly frequency and the use of industrial production as the measure of output (Figure A.22). In response to a 1 per cent contractionary shock, the level of industrial production declines by up to 1.3 per cent during expansions, but eventually increases following the shock during a recession. The rise in industrial production towards the end of the IRF horizon is not significantly different from zero and may be partly due to the large decline in the policy rate. Prices increase by up to 0.5 per cent in the linear model and 0.8 per cent when the shock occurs during an expansion before falling, while during a recession prices increase briefly before falling by around 1 per cent. In both cases the peak responses during expansions are statistically significant whereas the responses during recessions are not statistically different from zero.

[35] The correlation between the baseline and original CH shock series is equal to 0.81 over 1975M1–2007M12.

1.6 Conclusion

The literature on the effects of monetary policy in the UK typically uses linear models that mask any asymmetries in the monetary policy transmission mechanism. In addition, empirical evidence of the asymmetric effects of monetary policy in other countries is mixed. In this chapter, I first construct a new monetary policy shock series by extending the Cloyne and Hürtgen (2016) approach to allow for time-variation in the central bank reaction function. Secondly, these shocks are used to estimate impulse responses by local projections to provide novel evidence of the asymmetric effects of monetary policy in the UK.

The main result is that monetary policy shocks are more powerful during economic expansions than during recessions. In particular, the decline in output following a contractionary shock in a linear model is almost entirely attributable to the effect during expansions. Moreover, the unemployment rate, gross fixed capital formation, aggregate household consumption, and durable goods consumption all respond by significantly more during expansions. Standard empirical estimates that do not allow the response to a monetary policy shock to vary over the business cycle mask these different effects. I also find that expansionary shocks are more powerful than contractionary shocks, and that large shocks have a proportionally weaker effect on output than small shocks. These findings are robust to alternative monetary policy shock identification methods and a number of variations in the empirical specification. In addition, the results are not driven by differences in the statistical properties of the shocks themselves, but rather suggest that the economic response to a given shock depends on the state of the economy, and the sign and size of the shock.

The robust empirical results in this chapter call for the development of structural models that incorporate nonlinearities in the transmission of monetary policy. In particular, developing monetary models that generate larger effects from monetary policy shocks during expansions due to a flattening of the Phillips curve and higher sensitivity in the response of durable goods is warranted. Further, the results support the use of models that incorporate state-dependent price rigidities to allow the economic response to a shock to depend nonlinearly on the size of the shock. Lastly, policymakers may need to consider alternative policy measures to interest rate cuts, such as fiscal policy or unconventional tools, to stimulate the economy during a recession.

Table 1.3: Cumulative Impulse Responses

Cumulative impact on	Horizon	State of economy		$H_0 : \hat{\beta}^b - \hat{\beta}^r = 0$	
		Expansion	Recession	Driscoll-Kraay	Bootstrap
GDP volume	4	-0.004	0.009	0.116	0.338
	8	-0.038	0.019	0.000	0.083
	12	-0.070	0.028	0.001	0.081
	16	-0.087	0.043	0.001	0.059
	20	-0.087	0.044	0.000	0.085
Price level	4	0.025	0.003	0.066	0.523
	8	0.066	0.002	0.001	0.839
	12	0.087	-0.008	0.005	0.839
	16	0.094	-0.016	0.003	0.870
	20	0.078	-0.010	0.019	0.829
Unemployment rate	4	-0.294	-0.049	0.358	0.259
	8	0.711	0.204	0.338	0.411
	12	2.267	0.306	0.131	0.610
	16	3.303	-0.125	0.043	0.606
	20	3.947	-0.264	0.033	0.677
Gross fixed capital formation	4	-0.005	0.041	0.031	0.361
	8	-0.077	0.062	0.003	0.137
	12	-0.175	0.128	0.001	0.056
	16	-0.214	0.171	0.001	0.051
	20	-0.228	0.193	0.000	0.054
Household consumption	4	-0.012	0.009	0.179	0.701
	8	-0.049	0.017	0.009	0.345
	12	-0.095	0.042	0.000	0.140
	16	-0.119	0.054	0.000	0.122
	20	-0.126	0.069	0.000	0.116
Government consumption	4	0.002	0.008	0.299	0.459
	8	0.001	0.013	0.301	0.449
	12	-0.002	0.014	0.293	0.441
	16	-0.008	0.014	0.277	0.439
	20	-0.011	0.026	0.237	0.357

Table 1.4: Cumulative Impulse Responses for the Positive and Negative Shocks

Cumulative impact on	At horizon	Positive shock	Negative shock	$H_0 : \hat{\beta}^{pos} - \hat{\beta}^{neg} = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	0.024	-0.052	0.000	0.978
	8	0.039	-0.129	0.000	0.988
	12	0.062	-0.200	0.000	0.974
	16	0.083	-0.208	0.000	0.916
	20	0.083	-0.166	0.003	0.846
Prices	4	0.002	0.055	0.069	0.182
	8	-0.001	0.139	0.021	0.145
	12	-0.022	0.179	0.016	0.230
	16	-0.026	0.142	0.048	0.338
	20	-0.004	0.045	0.323	0.469

Table 1.5: Cumulative Impulse Responses for Cubed Shocks

Cumulative impact on	At horizon	Cubed shock	$H_0 : \hat{\beta}^{large} = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	0.001	0.000	0.554
	8	0.003	0.000	0.557
	12	0.005	0.000	0.634
	16	0.006	0.006	0.754
	20	-0.002	0.001	0.555
Prices	4	-0.004	0.000	0.322
	8	-0.006	0.000	0.273
	12	-0.005	0.000	0.256
	16	-0.026	0.142	0.048
	20	-0.004	0.045	0.323

Chapter 2

Credit, Financial Conditions and Monetary Policy in Australia

Abstract

In this chapter, I investigate if the effects of financial and monetary policy shocks differ between high and low credit regimes in Australia. I estimate a factor-augmented smooth-transition vector autoregression model to estimate the state-dependent effects of financial and monetary shocks. The factor is a broad indicator of aggregate financial conditions extracted from a large set of financial variables, while the transition between credit regimes is determined by the deviation of household credit-to-GDP from its long-run equilibrium. The main result is that the adverse effects of an unanticipated tightening in financial conditions are far more pronounced when the shock occurs in a high credit regime than in a low credit regime. This is consistent with high credit regimes coinciding with periods of increased macroeconomic vulnerability where the economy is more prone to adverse financial shocks. I also find that monetary policy shocks lead to significantly larger and more persistent output and inflation responses in a low credit regime, consistent with the idea that monetary policy is most potent when households are credit constrained. The results are robust to alternative recursive identification orderings, controlling for foreign financial shocks and a range of alternative empirical specifications.

2.1 Introduction

Understanding the relationship between monetary policy, financial conditions, and credit is central to macroeconomics. Notable economists such as Fisher (1933) and Keynes (1936) attributed the severity of the Great Depression to the failure of financial markets. More recently, the global financial crisis was a stark reminder of the importance of credit growth and the financial sector for business cycles. Evidence suggests that rapid credit growth often precedes financial crises and recessions (Schularick and Taylor 2012; Jordà et al. 2013) and that high levels of household credit have contributed to the severity of the Great Recession (Mian and Sufi, 2014). Indeed, in periods where credit is above its equilibrium level, the economy may be more vulnerable to an adverse financial shock than when credit is below its equilibrium level. Consequently, policymakers often analyse credit growth to gauge the level of macroeconomic vulnerability in an economy (see BIS 2010; Drehmann et al. 2010). In this chapter, I investigate if the effects of financial and monetary policy shocks differ between high and low credit regimes in Australia.

The empirical approach consists of three steps. First, I specify an error correction model (ECM) to estimate high and low credit regimes. The long-run equilibrium household credit-to-GDP ratio is estimated as a function of economic fundamentals, and the credit gap is defined as the ECM disequilibrium. A positive (negative) credit gap (also referred to as a high (low) credit regime) occurs when household credit-to-GDP is above (below) its estimated equilibrium level. Throughout the chapter, I primarily focus on household credit, rather than business credit, to analyse the role that the household sector plays in the transmission of financial and monetary shocks. I focus on the credit *gap*, rather than credit *growth*, as I define shifts in macroeconomic vulnerability as deviations of credit-to-GDP from economic fundamentals.[1] Consequently, the credit gap is used as a time-varying measure of the level of macroeconomic vulnerability in the economy.

[1]Rapid credit growth alone may not necessarily indicate a rise in macroeconomic vulnerability. For example, strong growth in credit may be justified by a shift in economic fundamentals (such as structurally lower debt service costs), while low credit growth may imply rising vulnerabilities if economic fundamentals indicate a decline in the level of sustainable credit-to-GDP.

Second, I estimate a financial conditions index (FCI) for Australia to capture the state of financial markets and analyse the effects of financial shocks. The FCI is a factor extracted from a large set of financial variables that summarises agents' willingness to accept risk and the ease with which borrowers can access credit. Consequently, it represents a broad indicator of aggregate financial conditions that may have an important impact on business cycles. Financial shocks are identified as movements in the FCI that are orthogonal to macroeconomic conditions and the policy rate. Therefore, financial shocks can be interpreted as shocks to overall financial conditions in Australia. For example, shocks may reflect exogenous shifts in the external finance premium due to bank capital quality shifts (e.g. Gertler et al. 2020) or endogenous reactions by banks to episodes of low or high volatility (e.g. Brunnermeier and Sannikov 2014).[2] Overall, the term "financial shock" is used in a very broad sense in this chapter which differs from the literature that analyses specific types of financial shocks (e.g. housing shocks or financial uncertainty shocks).

Third, I include the credit gap and the FCI in a smooth-transition vector autoregression (STVAR) model to estimate the state-dependent effects of financial and monetary policy shocks. The model allows for a smooth transition between high and low credit regimes for the endogenous domestic variables, where the regime is determined by the credit gap. The FCI captures the endogenous nonlinear relationship between financial conditions and the macroeconomy. Including the FCI effectively turns the STVAR into a factor-augmented STVAR (FASTVAR) which is based on a large information set, thereby minimising the risk that the results are overly influenced by the idiosyncratic behaviour of specific variables in specific periods.[3] Foreign variables enter the model as exogenous variables to estimate the parameters from the viewpoint of a small open economy. In addition, I endogenously

[2]Gertler et al. (2020) focus on a "capital quality" shock to banks that is an exogenous source of variation in the market value of bank assets. In their model, this reduces the expected return to capital, reducing investment and aggregate demand which is amplified by a Bernanke et al. (1999) financial accelerator mechanism.

[3]Previous VAR studies that have incorporated FCIs to capture the state of financial markets include (among others): Adrian et al. (2019), Alessandri and Mumtaz (2017), Aikman et al. (2020), and Abbate et al. (2016).

account for potential regime switches due to financial and monetary shocks by computing generalised impulse response functions (GIRFs) following Koop et al. (1996).

The main result is that the adverse effects of an unanticipated tightening in financial conditions are far more pronounced when the shock occurs in a high credit regime than in a low credit regime. In particular, output, inflation, the credit gap, and the policy rate all decline significantly following the shock in a high credit regime. In contrast, when the shock occurs during a low credit regime, output doesn't initially respond before eventually increasing, and the credit gap declines by significantly less. Sectoral models indicate that the asymmetric output response is largely driven by the state-dependent responses in the construction and manufacturing industries. In addition, financial shocks are found to be a significant source of business cycle fluctuations, especially in a high credit regime. The results are robust to alternative recursive identification orderings, controlling for foreign financial shocks and a range of alternative FASTVAR specifications. Overall, the results are consistent with high credit regimes coinciding with periods of increased macroeconomic vulnerability where the economy is more prone to adverse financial shocks.

The results also suggest that monetary policy shocks lead to significantly larger and more persistent output and inflation responses in a low credit regime. This is consistent with credit constraints binding in a low credit regime, and credit constrained borrowers substantially adjusting their spending in response to monetary policy shocks. However, in a high credit regime when borrowers are unconstrained, agents may base consumption decisions on their permanent income and be less sensitive to shifts in income. In addition, the central bank systematically lowers the cash rate in response to a financial shock, and this is both larger and more persistent in the low credit regime. The more aggressive monetary policy response during periods where monetary policy is more powerful may, at least in part, explain the asymmetric output response to a financial shock.

Related literature. This work relates to the literature examining the state-dependence of financial and monetary policy shocks. The vast majority of this literature focuses on measuring the effects of monetary policy over the business cycle (e.g., Tenreyro and Thwaites 2016), while in contrast, this chapter focuses primarily on the effects of financial shocks over the credit cycle.[4] In the paper that is most closely related to this work, Aikman et al. (2020) study how the effects of financial and monetary policy shocks in the United States (US) economy depend nonlinearly on the private non-financial sector credit gap. The authors use a threshold VAR (TVAR) and find that an expansionary impulse to financial conditions leads to an economic expansion during periods of a negative credit gap. However, when the credit gap is positive, an expansionary impulse to financial conditions leads to an economic expansion in the near term, but a recession further out the impulse response horizon. This chapter differs from Aikman et al. (2020) in a number of key dimensions – such as the measures of credit, financial conditions, and the nonlinear VAR specification – however their overriding conclusion that a positive credit gap is a sign of macroeconomic vulnerability that indicates the economy is more prone to a financial shock is consistent with my findings for Australia. Aikman et al. (2020) also find that monetary policy is more powerful when the credit gap is negative. The findings relating to the state-dependence of monetary policy are consistent with those of Alpanda and Zubairy (2019), who use state-dependent local projections and consider the household credit gap in the US.

The literature analysing the state-dependent effects of shocks in Australia is scarce. Jääskelä (2007) uses a TVAR to analyse if the effects of monetary policy in Australia vary with the rate of credit growth over 1978Q4 to 2006Q1. The TVAR model includes GDP growth, inflation, the policy rate, and real credit growth and the sample is divided into high and low real credit growth regimes.[5] Consistent with the results in this chapter, Jääskelä finds that monetary shocks have a larger impact on output in a low credit regime. The results suggest that time-variation in credit growth may indicate the extent to which credit

[4]In Section 2.6, I discuss the relationship between the business and credit cycles and show that positive credit gap periods in my sample do not necessarily coincide with a positive output gap. Therefore, I am capturing a nonlinearity relating to the credit cycle, which differs from the business cycle (see Figure B.14).

[5]The threshold variable is a moving average of quarterly growth in real credit. The moving average is allowed to vary across different specifications from 2 to 4 quarters, and is employed to avoid an implausible frequency of regime-switching. In the baseline, Jääskelä (2007) uses a 4-quarter moving average with 3 lags.

constraints are binding. In a low credit regime, credit constrained borrowers substantially adjust their spending in response to an increase in income via an expansionary monetary policy shock. In contrast, unconstrained borrowers may base consumption decisions on their permanent income and be less sensitive to shifts in income. In contrast to this chapter, Jääskelä's model uses credit growth to determine regimes (rather than the credit gap), does not consider the role of financial conditions or the effects of financial shocks, and models Australia as a closed economy. Overall, my results with respect to the state-dependent effects of monetary policy over the credit cycle largely align with those in Jääskelä (2007) for Australia and both Alpanda and Zubairy (2019) and Aikman et al. (2020) for the US.

The literature examining the state-dependence of financial shocks is a subset of a wider empirical literature that assesses the transmission of financial shocks to the real economy. These studies typically find that identified financial shocks explain a significant proportion of macroeconomic volatility and highlight the importance of accounting for macro-financial linkages. Previous empirical studies have focused on the international transmission of financial shocks (Abbate et al. 2016; Cesa-Bianchi and Sokol 2017), assessing how domestic and foreign shocks impact small open economies (Finlay and Jääskelä, 2014), cross-country evidence (Fornari and Stracca, 2013), disentangling different types of financial shocks (Furlanetto et al., 2017), and distinguishing between financial and economic uncertainty shocks (Caldara et al., 2016). The focus of this chapter differs from these studies by focusing on how the transmission of financial shocks to the real economy depends nonlinearly on the credit gap. In addition, the literature focuses on the US and the euro area, whereas I focus solely on Australia.

A separate line of research largely established by the Bank for International Settlements (BIS) focuses on the credit cycle as a single indicator of the level of macroeconomic vulnerability in an economy. Schularick and Taylor (2012) and Jordà et al. (2013) draw on a cross-country sample over 1870 to 2008 and find that credit growth is a powerful predictor of financial crises, and expansions that are largely credit-driven tend to be followed by deeper recessions and slower recoveries. In addition, a number of recent studies suggest that high levels of household credit have been a key contributing factor to the severity of the Great Recession (e.g. Mian and Sufi 2014). In an influential paper, Borio and Lowe (2002) identified a financial cycle that differed to the traditional business cycle and argued that, in some cases, a monetary response to developments in credit markets may be necessary to preserve financial and monetary stability. In response to this evidence, the Basel Committee for Banking Supervision has proposed the use of the credit gap as a guide for setting countercyclical capital buffers (see Drehmann and Tsatsaronis 2014; BIS 2010).[6]

From a theoretical viewpoint, incorporating financial frictions in business cycle models is not new (see the survey by Brunnermeier et al. 2012). For example, the financial accelerator framework proposed by Bernanke et al. (1999) gives financial frictions a key role in the monetary transmission mechanism. These models assume that asymmetric information between lenders and borrowers leads to an external finance premium that is negatively correlated with the borrowers' net worth. The dependence of the external finance premium on the borrowers' net worth gives rise to a 'financial accelerator' propagation mechanism. A contractionary monetary policy shock reduces profits and asset values, which lowers borrowers' net worth. The results in this chapter suggest that the financial accelerator is stronger during low credit regimes than in high credit regimes. This is consistent with a framework where firms have strong balance sheets and have the ability to finance themselves via retained earnings during high credit regimes, which leads to a low external finance premium and mitigates the financial accelerator mechanism. In contrast, in a low credit regime when borrowing constraints are binding, firms are more dependent on external finance, and monetary policy shocks may have larger effects. However, in the existing literature, models of the financial accelerator are not estimated conditional on the credit gap.

There is a vast literature on the credit channel of monetary policy, which emphasises the role that frictions play in the demand for credit (see the overview by Bernanke and Gertler

[6] In Appendix B, I provide further details on the BIS credit gap and compare the univariate HP filter approach with the ECM approach used in this chapter.

1995). However, in standard dynamic stochastic general equilibrium (DSGE) implementations of the credit channel, macroeconomic vulnerability does not play a role in equilibrium as models are typically solved up to a first-order. In models that focus on the role that financial conditions play in the supply of credit (e.g., Brunnermeier and Sannikov 2014), an increase in the vulnerability of the financial sector decreases the supply of credit to the economy, which can lead to a downturn in output growth (Adrian et al., 2019). However, to my knowledge, models of financial intermediation do not account for a nonlinear interaction between financial conditions and the level of macroeconomic vulnerability in the household sector.

Contribution. This chapter contributes to the strands of literature above. Most notably, I provide novel evidence at both the sectoral and aggregate level that the effects of financial and monetary policy shocks in Australia depend on the credit gap. This implies that empirical estimates of the effects of financial and monetary shocks that do not condition on the credit gap are masking important nonlinearities in the transmission mechanism. In addition, financial shocks are found to be a significant source of business cycle fluctuations in Australia, especially in a high credit regime. The findings also contribute to the literature that focuses on the credit gap as an indicator of macroeconomic vulnerability. The credit gap estimates provide important information on the credit cycle in Australia that complements the univariate measures of the credit gap published by the BIS.

These results have important implications for macroeconomic theory and policy. First, accurately identifying periods of excessive household credit growth appear crucial in accounting for state-dependence in the effects of financial and monetary shocks. The results point to the benefit of research that evaluates how macroprudential policies can reduce excessive credit growth and contain macroeconomic vulnerability. Second, the results suggest that financial shocks are a significant source of macroeconomic fluctuations in Australia. However, existing models of the Australian economy – such as the DSGE model (Rees et al., 2016) and macroeconometric model MARTIN (Ballantyne et al., 2019) used by the

Reserve Bank of Australia – do not account for the financial intermediation process. Third, I find strong evidence that the central bank eases the policy rate significantly in response to an unanticipated tightening of financial conditions. Therefore, central banks may need to consider alternative sources of policy accommodation to respond to financial shocks at the effective lower bound. Taken together, the results suggest that macroeconomic theory and policy should account for the role of the credit gap in the transmission of financial conditions and monetary policy.

The remainder of the chapter is organised as follows. Section 2.2 outlines the method to estimate the credit gap. Section 2.3 describes the approach taken to measure financial conditions. Section 2.4 outlines the FASTVAR model of the Australian economy. Section 2.5 presents the results and Section 2.6 considers their robustness. Section 2.7 concludes.

2.2 The Equilibrium and Cycle in Credit-to-GDP

The household credit-to-GDP ratio in Australia increased from around 40% in 1984 to 120% in 2018 (see Figure 2.1).[7] Distinguishing between the equilibrium and cycle in household credit-to-GDP is difficult as the equilibrium level is likely to vary over time in line with economic fundamentals. For example, structural shifts in the economy, such as a secular decline in debt servicing costs, may increase the equilibrium level of credit-to-GDP. The credit-to-GDP ratio will also exhibit cyclical fluctuations around its equilibrium (defined in this chapter as the "credit gap"). In this section, I outline the approach taken to estimate the equilibrium and cycle in the household credit-to-GDP ratio.

2.2.1 Error correction model

To estimate the long-run equilibrium and cycle in the credit-to-GDP ratio I specify an error correction model (ECM) for credit-to-GDP of the form:

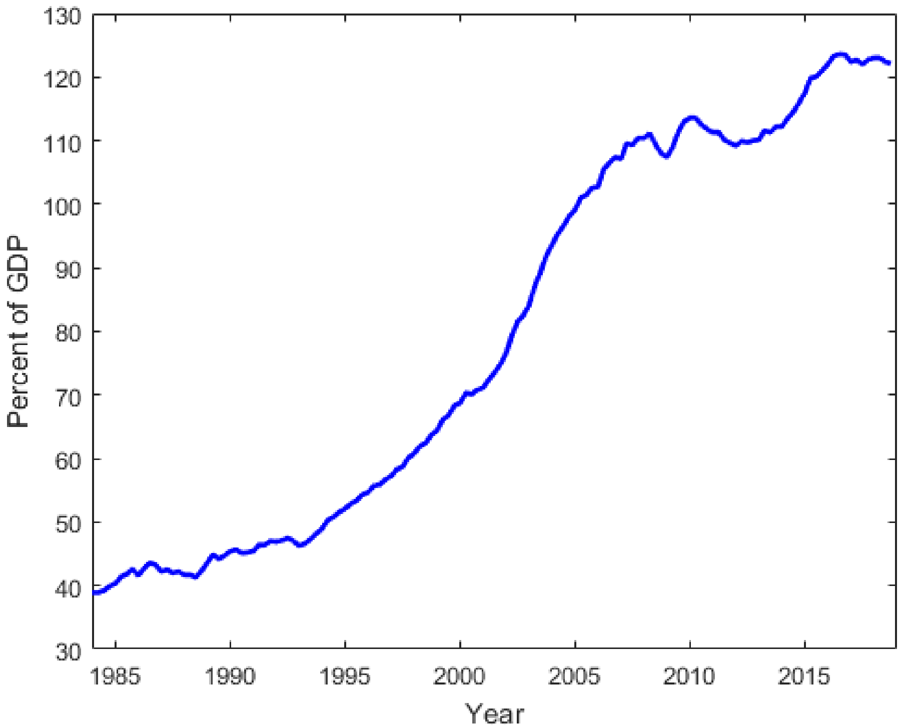
$$\text{Long run:} \quad C_t = \mu_L + \beta' X_t + cgap_t \tag{2.1}$$

[7] Figure B.2 shows the private non-financial sector (which comprises both households and non-financial corporations) credit-to-GDP ratio split between households and non-financial corporations.

$$\text{Short run:} \quad \Delta C_t = \mu_S + \alpha\{cgap_{t-1}\} + \gamma' \Delta X_t + u_t \tag{2.2}$$

where C_t is the household credit-to-GDP ratio, μ_L and μ_S are long- and short-run constants, $X_t = (i_t, r_t, u_t, dem_t, hpi_t, vol_t, s_{1t}, s_{2t})'$ is the set of explanatory variables (discussed below), β are the long-run equilibrium coefficients, γ are the short-run coefficients and α is the speed of adjustment to disequilibrium. The credit gap is the residual in the long run equation (2.1), $cgap_t$, which captures the difference between the household credit-to-GDP ratio and its long-run equilibrium.

Figure 2.1: Household Credit-to-GDP Ratio



Notes: Credit to households also includes credit to non-profit institutions serving households as defined in the System of National Accounts 2008. Credit statistics are sourced from the Bank for International Settlements.

The model is estimated over 1984Q1 to 2018Q4. This sample period is used throughout this chapter. Starting the sample in 1984Q1 is common for Australian VAR studies and follows the float of the Australian dollar in December 1983 and a period of significant financial deregulation during the 1970s which may have induced structural shifts in Australia's macro-financial relationships. Battellino (2007) summarises Australia's experience with financial deregulation and notes it was largely completed by the time of the float of the Australian dollar.

The choice of explanatory variables for determining the equilibrium credit-to-GDP ratio broadly follows previous empirical studies by Muellbauer and Williams (2011), Kent et al. (2007), Fernandez-Corugedo and Muellbauer (2006) and Albuquerque et al. (2015). In addition, I include step dummies to account for shifts in financial liberalisation and innovation that fundamentally alter the sustainable level of credit-to-GDP (see Williams 2010; Muellbauer and Williams 2011). The model assumes that the equilibrium credit-to-GDP ratio is determined by the following variables (shown in Figure B.1 and sources listed in Table B.1 in Appendix B.3):

- **Nominal mortgage rate (i)**: Lower interest rates reduce the debt service burden for a given stock of credit, allowing households to sustainably finance a higher credit stock. Around 80% of household credit in Australia is related to housing, which makes the average variable mortgage rate an important explanatory variable.[8] (–)

- **Real interest rate (r)**: In addition to the nominal mortgage rate, I use the real 10-year government bond yield, which is closely related to the natural rate of interest in an economy and provides an anchor for a range of interest rates that households face. (–)

- **Unemployment rate (u)**: The unemployment rate is included to account for both income expectations and uncertainty as suggested by Fernandez-Corugedo and Muellbauer (2006). Higher future income expectations through lower unemployment should reduce the probability of default by those who are employed and lead to increased current consumption due to consumption smoothing and increased borrowing capacity.

[8] The nominal mortgage rate is included instead of the real mortgage rate to capture the role of the disinflation in the early 1990s. In his discussion of Muellbauer and Williams (2011), Thompson (2011) notes that in Australia, mortgage lenders commonly set a maximum loan size such that initial repayments are no more than 30% of a borrower's gross income. A permanent disinflation that reduces nominal interest rates eases this credit constraint and allows greater borrowing for a given repayment ratio. The variable rate is included over the average fixed rate as over 80 per cent of home mortgages in Australia are originated at variable rates (Price et al., 2019).

In addition, lower uncertainty (associated with lower unemployment) implies less need for precautionary saving. (–)

- **Share of middle-aged people in the population (*dem*)**: Approximately 90% of household debt in Australia is held by households in which the head is between the ages of 25 and 64 (Bullock, 2018). As the share of the population in this age group rises, the sustainable level of credit-to-GDP will also rise. (+)

- **Logarithm of the house price index-to-income ratio (*hpi*)**: Increases in house prices (relative to income) leads to greater borrowing through increased consumption due to the wealth effect. Higher house prices also increase the sustainable level of debt as they are a primary form of collateral for households and small business owners. (+)

- **Macroeconomic volatility (*vol*):** A reduction in the volatility of aggregate economic activity should reduce uncertainty around income and expected firm revenue. A reduction in output volatility may also proxy for financial deepening due to its potential role in consumption smoothing (Kent et al., 2007). (–)

- **Step dummy from 1993Q1 (s_1):** Non-price credit conditions eased substantially in Australia from around 1993. Notable developments include: 1) new banks entering the market; 2) strong consumer debt product innovation, especially relating to housing (see RBA 2002); 3) widespread growth in securitisation (see Debelle 2009); 4) relaxation of bank lending standards; and 5) strong promotion and growth in home equity loans (see Muellbauer and Williams (2011) for a detailed discussion).[9] (+)

- **Step dummy from 2009Q1 (s_2):** Balances in offset and redraw accounts increased

[9] Home equity loans were first introduced by St George Building Society in late 1980s, followed by the Commonwealth Bank in late 1990 and were heavily promoted by mortgage managers from the mid 1990s (Muellbauer and Williams, 2011).

rapidly following the financial crisis (RBA, 2015).[10] These balances are not reflected in the BIS household credit statistics and effectively reduce the household sector's net debt position. (+)

2.2.2 Unit root and cointegration tests

Before turning to the estimation of the ECM, I use the augmented Dickey-Fuller (ADF) unit root test to test for the presence of a unit root in each of the explanatory variables.[11] The ADF tests support the hypothesis that all variables are $I(1)$ in levels and stationary in first differences (see Table B.2 for full results).

Given the variables are $I(1)$, I use the Engle and Granger (1987) two-step approach to test whether there is evidence of a long-run cointegrating relationship between the variables that would support my approach of modelling the relationship within a cointegrating framework. I estimate (2.1) by OLS and conduct ADF unit root tests on the disequilibrium term, $cgap_t$. The ADF test statistic in a model with 4 lags is equal to -3.74, which provides evidence at the 10% level (based on MacKinnon (2010) critical values) against a unit root and suggests that there is evidence of a cointegrating relationship between the variables.[12] Further, cointegration is implied by strongly significant coefficients on the long run variables in (2.1) and the equilibrium adjustment parameter in (2.2) (discussed below).

ECM estimation uses a single equation, rather than modelling each of the variables in a system of equations. Johansen (1992) shows that the ECM is equivalent to the system

[10] Offset accounts are at-call deposit accounts that are directly linked to a mortgage. A redraw facility enables the borrower to withdraw principal payments that they have made ahead of the required schedule. The balance deposited into an offset or redraw account reduces the borrower's net debt and the interest payable. Over recent years mortgages with offset accounts comprised around 45 per cent of the value of residential mortgage debt while around 70 per cent of the total number of residential mortgages in Australia had redraw facilities (Price et al., 2019).

[11] I also conducted tests of the null hypothesis of trend-stationarity by employing the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. In contrast to the ADF test, the presence of a unit root is not the null hypothesis but the alternative. The results provide strong evidence against the hypothesis of trend-stationarity.

[12] MacKinnon (2010) extends the critical values presented in Engle and Granger (1987) to a larger simulation and reports critical values for any finite sample size. The critical values account for the fact that, by construction, OLS effectively "chooses" the residuals to have the smallest variance, so they will appear as stationary as possible and lead to over-rejection of the null under a standard Dickey–Fuller distribution. Additionally, the distribution of the test statistic under the null depends on the number of $I(1)$ variables, so different critical values are needed as the number of $I(1)$ variables changes.

approach under the assumption that all the variables in X_t are weakly exogenous with respect to the parameters of the cointegrating relationship and that there is one unique cointegrating vector.[13] I assume that there is one unique cointegrating vector and test for weak exogeneity following Muellbauer and Williams (2011) through a series of single equation regressions for the ΔX_t variables. I find that the lagged equilibrium correction term is insignificant in these equations which suggests that the variables in X_t are weakly exogenous. Intuitively, this suggests that the variables in X_t do not error correct when there is disequilibrium in the long-run relationship.

2.2.3 Results

Table 2.1 displays the long-run equilibrium relationship for the credit-to-GDP ratio estimated in (2.1). The adjusted R^2 is 0.97 and the long-run standard error is 5.57. Estimating (2.2) shows there is a 4.7 per cent adjustment to disequilibrium in each quarter, which implies a half-life to eliminate any deviation from equilibrium of around 14 quarters. A slow adjustment speed is consistent with the notion of a long credit cycle (e.g. Drehmann and Tsatsaronis (2014) argue that credit cycles are typically about four times longer than business cycles). The estimated coefficients all have their expected signs and are statistically significant at conventional levels, except the coefficient on demographics is not significant.

The model implies that the long-run equilibrium variables explain the 80 percentage point increase in the household credit-to-GDP ratio between 1984 and 2018 in the following partial equilibrium terms.[14] The decline in unemployment and increase in house prices are associated with an increase in equilibrium credit-to-GDP of 16 and 11 percentage points, respectively. Lower nominal mortgage and real interest rates are associated with an increase in equilibrium credit-to-GDP of 12 and 5 percentage points, respectively. The decline in macroeconomic volatility correlates with an 8 percentage point rise while demographics shifted notably throughout the sample but had a negligible effect when measured from 1984

[13]See Engle et al. (1983) for formal definitions of weak, strong and super exogeneity.

[14]Note that the long run partial equilibrium impacts do not sum to the total change in the household credit-to-GDP ratio due to the unexplained variation and short-run dynamics.

Table 2.1: Credit-to-GDP Equilibrium Relationship

Variable	Parameter	Coefficient	HAC Standard error
Nominal mortgage rate	i	-1.88***	(0.36)
Real interest rate	r	-0.60**	(0.31)
Unemployment rate	u	-4.35***	(0.54)
Demographics	dem	9.65	(8.36)
House prices	hpi	63.16***	(7.06)
Macroeconomic volatility	vol	-8.78*	(4.73)
Step-dummy 1993	s_1	1.79	(2.94)
Step-dummy 2009	s_2	16.75***	(2.27)
Constant	μ_L	-218.18***	(64.34)
Short-run adjustment	α	-0.047***	(0.014)
Half-life		14.4	
ADF test statistic		-3.74*	
Long-run $\hat{\sigma}$		5.57	
Adj. R^2		0.97	

Notes: Long-run equilibrium estimated from equation (2.1). Sample 1983Q1–2018Q4. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively. ADF critical values calculated by MacKinnon (2010).

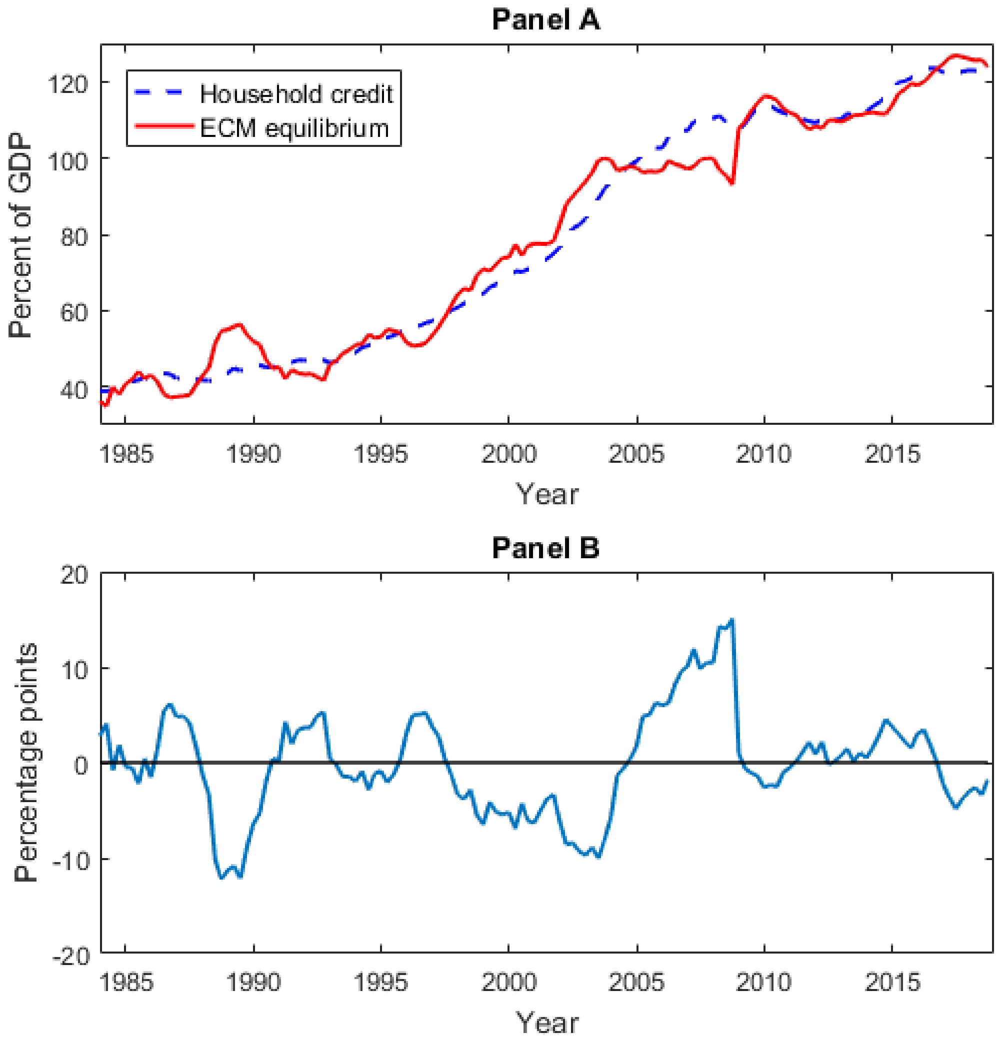
to 2018. The statistically significant step-dummies suggest that shifts in financial innovation impact the long-run equilibrium throughout the sample. The impact of financial innovation on the equilibrium will also, in part, be captured in the coefficients on macroeconomic volatility and the real interest rate.[15]

Panel A of Figure 2.2 plots the estimated equilibrium household credit-to-GDP ratio alongside the actual ratio over 1984 to 2018. The difference between the two lines is the estimated credit gap, which is shown in Panel B. Notably, the equilibrium level rose by around 15 percentage points in the late 1980s alongside sharp falls in real interest rates, unemployment and volatility, and a rise in house prices. This coincided with a negative credit gap as the credit-to-GDP ratio only rose modestly. In addition, the credit-to-GDP ratio increased strongly prior to the 2007-08 financial crisis, and this exceeded the increase in the equilibrium level by up to 15 percentage points.

The primary purpose of estimating the credit gap is to identify periods of high and low

[15] Given these effects are likely to have a nonlinear impact on different equilibrium variables, a system approach that directly models these effects as in Muellbauer and Williams (2011) would be an interesting extension.

Figure 2.2: Household Credit Equilibrium and Gap



Notes: Panel A plots the household credit-to-GDP ratio alongside the estimated long-run equilibrium from equation (2.1) described in Section 2.2. Panel B shows the estimated credit gap.

credit relative to equilibrium. This is necessary to investigate if the effects of financial and monetary shocks differ between these regimes. To my knowledge, the only other estimated credit gap for Australia is the BIS gap, which uses private non-financial sector credit and the HP filter to calculate the equilibrium (see Appendix B.2 and Figures B.3 and B.4 for a discussion of the BIS gap and comparison of the ECM-based credit gap to those calculated with the HP filter). Therefore, this section contributes to the nascent literature on credit gap estimation. In particular, methods that account for economic fundamentals in the estimation of the credit gap are likely to provide a useful complement to purely statistical measures such as the BIS gap.

2.3 Measuring Financial Conditions

To capture the state of financial markets and analyse the effects of financial shocks in Australia I estimate a financial conditions index (FCI). The FCI summarises the time-varying state of financial conditions in Australia by extracting information contained in a range of financial variables. This section outlines the method used to estimate the FCI before discussing the baseline FCI. Appendix B.2 provides a brief background on the history of FCIs and different methods used to construct FCIs.

2.3.1 Dynamic Factor Model

The FCI is an unobserved factor that summarises the time-varying state of financial conditions in Australia. The FCI is estimated using a dynamic factor model following the approach described in Brave and Butters (2011) to construct the National Financial Conditions Index (NFCI) for the US.[16] The state-space representation is given by:

$$X_t = \Gamma F_t + \varepsilon_t \tag{2.3}$$

$$F_t = AF_{t-1} + \eta_t \tag{2.4}$$

where X_t is a $N \times T$ matrix of standardised financial indicators, Γ is a $N \times 1$ vector of factor loadings, F_t is a $1 \times T$ latent factor that captures a time-varying common source of variation in X_t, A is the transition matrix describing how the latent factor evolves over time, and ε_t and η_t are measurement and transition errors. The choice of using one factor is based on the Bai and Ng (2002) information criterion and is also consistent with Brave and Butters (2011). Prior to estimation, each series is standardised to have mean zero and unit standard deviation over the sample period. This ensures that the factor is not unduly influenced by the relative magnitude and measurement units of the individual series.

[16] For a survey of the key theoretical results and applications of dynamic factor models, see Stock and Watson (2011).

The baseline FCI is estimated over 1984Q1 to 2018Q4 using the two-step approach described in Doz et al. (2011). In the first step, the parameters of the model are estimated using principal components analysis on the truncated dataset with no missing observations (i.e. a balanced panel). In the second step, the Kalman smoother is used to estimate the factor using all available information.

2.3.2 Variables included in the FCI

There are a vast range of potential price and quantity variables to include when estimating a FCI. In general, the variables in X_t are standard in the literature and similar in scope to those US variables used in Hatzius et al. (2010), but reflect Australia's status as a small open economy. Table 2.2 lists the 19 financial variables in X_t. The variables can be categorised into four main groups:

- **Risk:** Including corporate and sovereign yield spreads is standard in the literature as they are a key measure of risk in the economy. The relative share price of the financial sector is included to capture the relative performance of the financial sector. The VIX captures expectations of stock market volatility, while the gold price increases with risk aversion.

- **Collateral:** Equity and house prices are included as households and firms with high collateral will have increased borrowing power.

- **Quantity developments:** Capital issuance and credit measures contain relevant information on how easily agents can access finance.

- **External financial conditions:** Including a sovereign yield spread and US asset prices reflects global financial conditions which are important for domestic financial conditions in a small open economy. The real exchange rate is standard in FCIs and reflects the relative price of goods and services in Australia and is a key determinant of foreign capital flows.

Table 2.2: Financial Variables in Financial Conditions Index

	T	Start	Loading	Rank
Interest rates				
3 month Bank Bill to OCR spread	L	1984Q1	-0.064	5
2 year AGS to OCR spread	L	1995Q1	-0.028	8
10 year AGS to OCR spread	L	1984Q1	-0.133	1
Mortgage rate to 10 year AGS spread	L	1984Q1	0.030	7
NFC A-rated bond to AGS spread	L	2005Q1	0.005	17
NFC BBB-rated Bond to AGS spread	L	2005Q1	0.005	18
Asset prices				
Real exchange rate	LD	1984Q1	-0.013	13
Residential house prices	LD	1986Q3	0.002	19
ASX 100	LD	1984Q1	-0.014	12
ASX Financials/ASX 100	LMA	1984Q1	-0.027	9
RBA commodity price index (AUD)	LD	1984Q1	-0.006	16
Gold price	LD	1984Q1	0.012	14
Quantities				
Total credit (SA)	LD	1984Q1	-0.065	4
Housing credit (SA)	LD	1984Q1	-0.022	10
Business credit (SA)	LD	1984Q1	0.070	3
M3 money supply (SA)	LD	1984Q1	0.049	6
Foreign sector				
Sovereign spread (10 year)	L	1984Q1	0.115	2
VIX	L	1990Q1	0.015	11
Wilshire 5000	LD	1984Q1	0.011	15

Notes: The column labelled "T" shows the transformation (L = level, LD = log first difference, LMA = level relative to 8-quarter moving average). The "Start" column indicates when the series begins (all series end in 2018Q4). The sovereign spread is Australia to the average of US, UK and Germany. All data sourced from the RBA statistical tables except the ASX series are from Mathews (2019), the house price data are from the ABS (cat. no. 6416), and the VIX and Wilshire 5000 are from FRED.

2.3.3 The Financial Conditions Index

Figure 2.3 shows the estimated FCI over 1984Q1 to 2018Q4. The FCI is standardised to have a mean of zero and standard deviation of one. Values of the FCI below zero are considered 'expansionary/loose' whereas values above zero are considered 'restrictive/tight'.

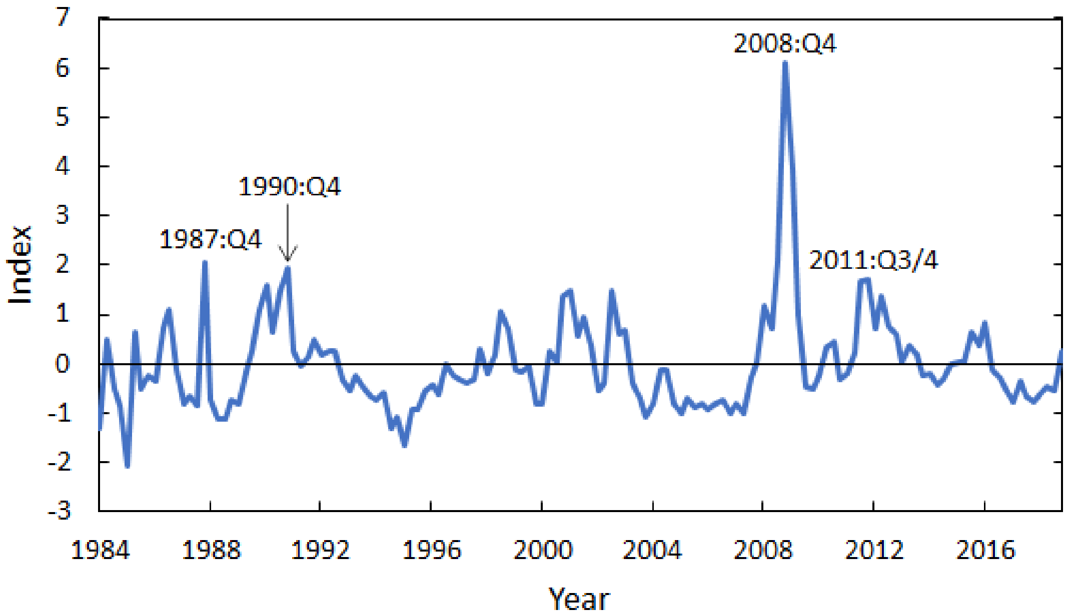
Shifts in the FCI correspond to historical events that *a priori* might be expected to move aggregate financial conditions. The FCI suggests that financial conditions were expansionary, on average, in the mid and late 1980s, consistent with strong growth in credit and asset prices over that period. Financial conditions tightened markedly in 1987Q4 (Black Monday occurred on October 19) and in the early 1990s as Australia entered a technical recession. Throughout the late 1990s and mid 2000s the FCI remained around zero amid a period of macroeconomic stability. Financial conditions tightened noticeably during the financial crisis and in late 2011 alongside European debt and US debt ceiling issues.

The sign and magnitude of the factor loadings shown in Table 2.2 indicate how each variable contributes to the FCI. Sovereign yield spreads have a large and negative relationship with the FCI, which indicates that a flattening or inversion of the yield curve is associated with tightening financial conditions (alternatively, a steepening of the yield curve, which typically indicates that future economic prospects are expected to be strong, is associated with expansionary financial conditions). Asset prices are typically negatively related to the FCI, which implies a decline in asset prices correlates with a rise in the FCI (i.e., tighter financial conditions). There is a negative relationship between financial conditions and total credit growth, suggesting that increases in credit are correlated with expansionary financial conditions. Overall, the sign and magnitude of the factor loadings on the individual variables are mostly consistent with economic theory.

The FCI summarises the time-varying state of financial conditions (both price-based and quantitative indicators) which can shift abruptly, while the credit gap estimated in the previous section captures movements in macroeconomic vulnerability which may build up over time. Indeed, the FCI and the credit gap have a correlation of only 0.14 over the sample (see Figure B.13 in Appendix B.3). Thus, while financial conditions and credit are closely related concepts, the FCI and credit gap estimated in this chapter are capturing different economic phenomena.

Foreign and Domestic Financial Conditions. As a small open economy that is closely integrated with global capital markets, shifts in foreign financial conditions may have a large impact on domestic financial conditions in Australia. Panel A of Figure 2.4 plots the FCI alongside the US NFCI produced by the Chicago Fed (both series are standardised). The figure suggests that the two series co-vary over the sample. Regressing the FCI on the

Figure 2.3: Financial Conditions Index

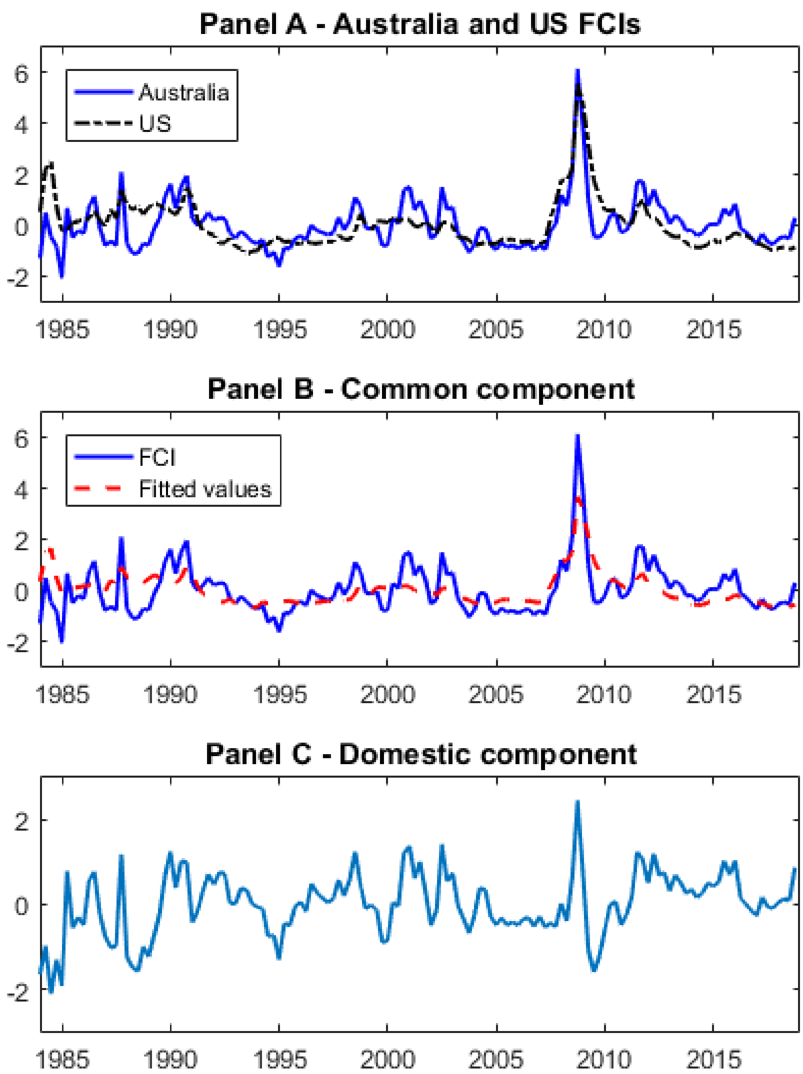


Notes: FCI estimated from the dynamic factor model described in Section 2.3. The FCI is standardised to have a mean of zero and standard deviation of one. Values below zero are considered 'expansionary/loose' whereas values above zero are considered 'restrictive/tight'. The input variables and factor loadings are listed in Table 2.2.

US NFCI provides strong evidence that the two series are positively correlated and suggests that US financial conditions explain 44 per cent of the variation in Australian financial conditions over 1984Q1 to 2018Q4.[17] The red line in Panel B plots the fitted values from this regression, which indicate what US financial conditions imply for Australian financial conditions based on their historical relationship. Panel C plots the residuals which show the domestic component of financial conditions (i.e. Australian financial conditions purged of US financial conditions). The regression suggests that much of the FCI variation in the 1980s and 1990s was driven by domestic developments, while the financial crisis is common to both economies. In Section 2.5, I investigate if domestically-sourced financial shocks affect the macroeconomy differently to foreign financial shocks.

[17]Estimating the regression over sub-samples from 1984Q1–2001Q4 and 2002Q1–2018Q4 shows the R^2 increases from 0.10 to 0.68, consistent with increased global capital market integration over the sample. As alternative measures of US financial conditions, I also considered the excess bond premium estimated by Gilchrist and Zakrajšek (2012) ($R^2 = 0.50$) and the Chicago Fed ANFCI ($R^2 = 0.25$) instead of the NFCI. The ANFCI adjusts for the state of the business cycle and the level of inflation to isolate the exogenous financial-only element of the NFCI (see Brave and Kelley 2017).

Figure 2.4: Foreign and Domestic Financial Conditions



Notes: Panel A shows the FCI (blue line) estimated in Section 2.3 alongside the US NFCI published by the Chicago Fed (black line). Both FCIs are standardised to have a mean of zero and standard deviation of one over 1984Q1–2018Q4. Panel B shows the FCI alongside the fitted values from a regression of the FCI on the US NFCI, while Panel C shows the residual from that regression.

2.4 Econometric Methodology

2.4.1 Factor-augmented Smooth-transition Vector Autoregression Model

The macroeconomic effects of financial and monetary policy shocks during low and high credit regimes are analysed using a FASTVAR framework.[18] Formally, the FASTVAR model is given by:

$$\boldsymbol{X_t} = [1 - F(z_{t-1})]\boldsymbol{\Gamma_{LC}}(L)\boldsymbol{X_t} + F(z_{t-1})\boldsymbol{\Gamma_{HC}}(L)\boldsymbol{X_t} + \boldsymbol{\beta Z_t} + \boldsymbol{\varepsilon_t} \tag{2.5}$$

$$\boldsymbol{\varepsilon_t} \sim N(0, \boldsymbol{\Omega}) \tag{2.6}$$

$$F(z_t) = \{1 + \exp[-\gamma(z_t - c)]\}^{-1} \tag{2.7}$$

where $\boldsymbol{X_t} = (y_t, \pi_t, cgap_t, ocr_t, fci_t)'$ is a set of endogenous variables (discussed below), $\boldsymbol{\Gamma_{LC}}$ and $\boldsymbol{\Gamma_{HC}}$ are the VAR coefficients capturing the dynamics of the system during low and high credit regimes respectively, $\boldsymbol{Z_t}$ is a set of exogenous variables with coefficients $\boldsymbol{\beta}$, and $\boldsymbol{\varepsilon_t}$ is the vector of reduced-form residuals with zero-mean and variance–covariance matrix $\boldsymbol{\Omega}$. $F(z_{t-1}) \in [0, 1]$ is a logistic transition function which captures the probability of being in a high credit regime. Given z_{t-1}, the model parameters in (2.5)–(2.7) are estimated jointly with conditional maximum likelihood as suggested by Teräsvirta et al. (2010).

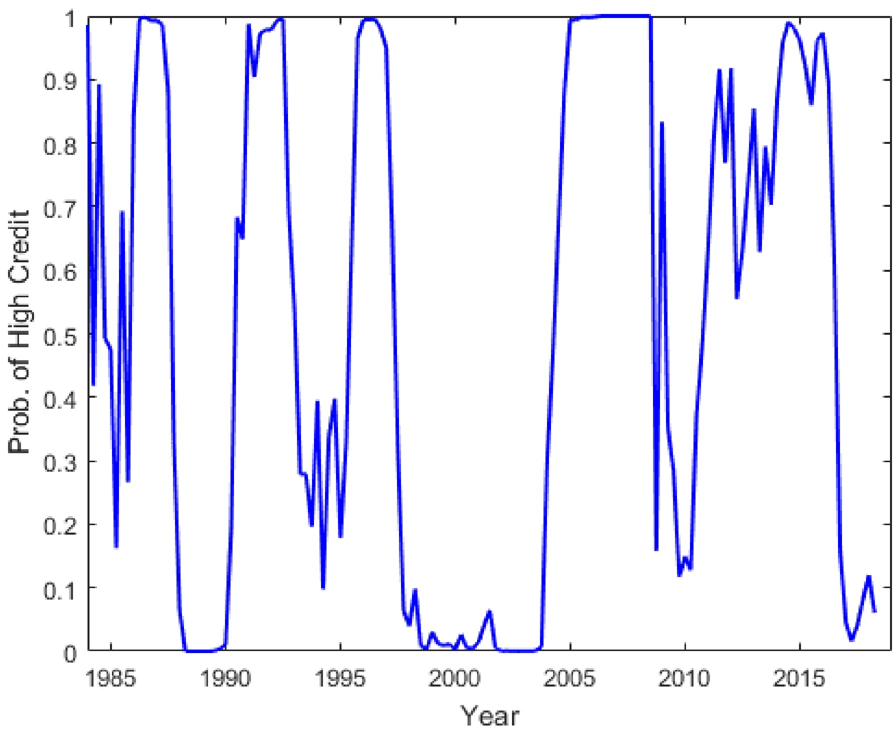
The transition variable z in the baseline is the credit gap estimated in Section 2.2 (shown in Figure 2.2). The value of γ determines the smoothness of the transition function. As γ increases, $F(z_{t-1})$ approaches a discrete regime-switching framework and spends more time near the $\{0, 1\}$ bounds. It is possible to estimate γ using the grid search method discussed in Hubrich and Teräsvirta (2013). However, it is difficult to identify the location and curvature of the transition function in the data, and previous STVAR studies typically calibrate rather than estimate γ (Auerbach and Gorodnichenko, 2013). In the baseline, I set $\gamma = 5$ to allow an intermediate degree of regime-switching intensity. I calibrate c so that 49% of the sample is in each regime which ensures that positive (negative) credit gap

[18]See Hubrich and Teräsvirta (2013) for a comprehensive survey of STVAR models.

periods coincide with high (low) credit regimes. In Section 2.6, I show that the results are robust to setting $\gamma = 10$ which implies a very abrupt shift between regimes.

Figure 2.5 shows the baseline transition function $F(z_{t-1})$. The transition function indicates that there is a high probability of being in a low credit regime in the late 1980s and between the late 1990s and mid 2000s, while the economy was in a high credit regime preceding the global financial crisis. Figure B.12 in Appendix B displays the transition function alongside the structural shocks and shows that neither the size nor the sign of monetary or financial shocks depend on the credit regime (discussed in Section 2.6).

Figure 2.5: Transition Function – Probability of High Credit Regime



Notes: Transition function $F(z)$ computed using the credit gap as the transition variable z and the logistic function (2.7) is calibrated with $\gamma = 5$ and c set to ensure positive (negative) credit gaps coincide with high (low) credit regimes.

STVAR models can be viewed as models with a continuum of states where the system dynamics change smoothly between a number of (typically two) extreme states and the transition variable determines the regime that generates the next observation. An alternative nonlinear approach would be a TVAR, where the dynamics can be modelled by defining a limited (often two) number of linear states. A primary advantage of the STVAR model relative to a TVAR model is that with a TVAR we may have relatively few observations in a given regime, which makes estimation imprecise. In contrast, estimation and inference in a STVAR is based on a larger set of observations by exploiting variation in the degree of being in a particular regime (Auerbach and Gorodnichenko, 2012). Recent applications of the STVAR model include Auerbach and Gorodnichenko (2012) and Caggiano et al. (2015) who employ it to analyse the effects of US fiscal spending shocks in expansions and recessions, and Caggiano et al. (2017) who focus on the effects of uncertainty shocks during expansions and recessions in the US.

2.4.2 Variables included in the FASTVAR

The baseline model includes one exogenous (foreign) and five endogenous (domestic) variables, reflecting the fact that Australia is a small open economy. The choice of variables reflects a trade-off between accounting for the major influences on Australian economic and financial conditions and the need to conserve degrees of freedom. The foreign variable in the baseline is the RBA real commodity price index. Foreign variables are treated as strongly exogenous following Dungey and Pagan (2009), which ensures that Australian economic developments do not affect foreign variables either contemporaneously or with a lag. The endogenous variables, $\boldsymbol{X_t} = (y_t, \pi_t, cgap_t, ocr_t, fci_t)$, are (in order): real GDP, trimmed mean inflation, the credit gap, the overnight cash rate, and the FCI. Figure B.5 (in Appendix B.3) shows the baseline variables. Overall, the choice of variables is broadly similar to other Australian VAR models (e.g. Berkelmans 2005; Dungey and Pagan 2009; Lawson and Rees 2008; Manalo et al. 2015). However, I am not aware of any Australian VAR studies that include a credit gap or an aggregate measure of financial conditions.

Real commodity prices are included as they contain information about the global business cycle which is pertinent for a commodity exporter such as Australia. Over the sample, commodity exports account for more than 50 per cent of total export values and around 10 per cent of GDP. Commodity prices are treated as exogenous as they are priced in global markets.[19]

The inclusion of Australian output and inflation is standard. Inflation is preferred over the price level as this is the target of monetary policy for over half of the sample. The inclusion of the overnight cash rate is also standard as this has been the primary instrument of monetary policy since the float of the Australian dollar in December 1983 (Berkelmans, 2005).

The household credit-to-GDP gap is included as both an endogenous variable and the transition variable z. As discussed in Section 2.2, the credit gap is informative about the level of macroeconomic vulnerability in the economy. Berkelmans (2005) and Jääskelä (2007) include measures of real credit in their Australian VAR studies. However, rapid growth in real credit may not necessarily coincide with periods of greater macroeconomic vulnerability if strong credit growth is justified by economic fundamentals. In addition, their models omit a broad measure of financial conditions, so they do not capture the endogenous relationship between credit and financial conditions. I compute GIRFs to endogenously account for potential credit regime switches due to financial and monetary shocks (discussed below).

I include the FCI estimated in Section 2.3 to capture the endogenous relationship between financial conditions and the macroeconomy. While monetary policy is captured through the inclusion of the overnight cash rate, the FCI represents movements in a broad measure (the factor is based on both price and quantity variables) of aggregate financial conditions. Modelling financial conditions alongside traditional macroeconomic variables is an important step in understanding macro-financial linkages in Australia. This allows me to estimate the dynamic response of the economy to financial shocks in high and low credit regimes, and assess the relative importance of financial shocks in each regime.

[19] This assumption may be less plausible for the prices of some bulk commodities where Australian producers account for a non-trivial share of global supply. Nevertheless, the RBA commodity price index is an export-weighted average of a wide range of commodity prices, and the results are very similar when commodity prices are modelled as an endogenous variable (ordered first in the FASTVAR).

Unit root tests suggest that commodity prices, real GDP, inflation and the cash rate are non-stationary, $I(1)$, processes (see Table B.2 in Appendix B.3). As is common in the literature, I estimate the model in levels as even with $I(1)$ variables, the inclusion of lagged levels should ensure that the residuals are stationary. Specifically, real commodity prices and real GDP enter the model in log levels, inflation enters in quarterly percentage changes (annualised) and the credit gap, cash rate and FCI enter in levels. I include two lags of both the endogenous and exogenous variables as suggested by the Akaike information criterion applied to a linear model. I estimate the FASTVAR by conditional maximum likelihood (treating the transition function parameters as known) over 1984Q1 to 2018Q4. In Section 2.6, I show that the results are robust to alternative recursive orderings, controlling for foreign financial shocks, and a range of alternative specifications.

2.4.3 Identification and generalised impulse response functions

Identification. The structural shocks in the FASTVAR are identified by employing a Cholesky decomposition of the reduced-form variance-covariance matrix $\mathbf{\Omega}$. The identification of the financial shock assumes that macroeconomic shocks affect domestic financial conditions immediately, while financial shocks affect domestic macroeconomic variables with a lag. To justify the first assumption, I note that the FCI is comprised largely of forward-looking variables that readily incorporate new information and are traded in highly liquid markets. The latter assumption is consistent with the idea that it takes firms time to alter production and pricing decisions in response to changes in financial conditions.

The identification of the monetary policy shock assumes that cash rate shocks affect domestic financial conditions contemporaneously but affect domestic output, inflation and credit with a lag, while the cash rate responds to commodity, output, inflation and credit shocks contemporaneously and responds to financial shocks with a lag.[20] This is a com-

[20]The transmission of foreign shocks to the domestic economy can be very rapid. For example, an increase in global economic activity (represented by commodity prices in the model) will immediately increase the value of Australian exports and therefore domestic income. As a consequence, it is assumed that any exogenous variables affect all endogenous variables contemporaneously.

mon identification assumption and similar to the identification approach used in previous Australian VAR studies (e.g. Dungey and Pagan 2009; Manalo et al. 2015).

Imposing zero restrictions on the contemporaneous coefficients is the most commonly used identification method in macroeconomics. However, identification of financial shocks within a SVAR framework is a challenging task. The primary critique raised in this context is that zero restrictions are implausible given the presence of 'fast moving' financial variables. Nevertheless, identifying financial shocks via a recursive ordering is common in the literature (e.g. Gilchrist and Zakrajšek 2012; Gilchrist et al. 2014; Abbate et al. 2016; Mumtaz and Theodoridis 2017; Aikman et al. 2020). Alternative identification approaches involve employing sign restrictions (e.g. Cesa-Bianchi and Sokol 2017) or the penalty function approach (e.g. Caldara et al. 2016). However, a major drawback with the sign restriction approach is that financial shocks lead to similar macroeconomic dynamics as aggregate demand shocks in a wide class of models. To address the concerns associated with a recursive identification, in Section 2.6 I show that the results are not sensitive to the specific recursive ordering of variables.

GIRFs. Impulse responses measure the time profile of the effect of a shock on the behaviour of a series. In a standard linear impulse response, the effects of shocks are: 1) linear in the sense that they are proportional to the shock size; 2) independent of history; and 3) symmetric. However, Koop et al. (1996) note that in nonlinear models, the effects of shocks: 1) are nonlinear in the sense that they are not necessarily proportional to the shock size; and 2) depend on the entire history of the system up to the period when the shock occurs. To account for nonlinearities, I follow the approach proposed by Koop et al. (1996) and compute GIRFs to endogenously account for potential regime switches due to financial and monetary shocks. Using GIRFs is crucial as shocks that occur during a given regime may drive the economy into the other regime. For example, an expansionary shock to financial conditions or monetary policy that occurs in a low credit regime may lead to credit growth which pushes the economy into a high credit regime. Thus, by computing

GIRFs, the probability of being in a high credit regime $F(z_t)$ is endogenized.[21]

Following estimation of the FASTVAR model, I compute GIRFs as follows:

$$GIRF(h, \delta, \omega_{t-1}) = E\{\mathbf{X_{t+h}} | \hat{\varepsilon}_t = \delta, \varepsilon_{t+h} = \hat{\varepsilon}_{t+h}, h > 0, \omega_{t-1})$$
$$-E\{\mathbf{X_{t+h}} | \varepsilon_{t+h} = \hat{\varepsilon}_{t+h}, h > 0, \omega_{t-1})$$

where h is the horizon of the impulse responses, δ is the size of the shock, ω_{t-1} is the history identifying a particular regime in the sample, and $\hat{\varepsilon}_{t+h}$ is a set of draws of residuals from the empirical distribution $\mathbf{\Omega}$. That is, the GIRFs are computed as the difference between a stochastic simulation in which the orthogonal shock of interest (i.e., financial or monetary policy shock) takes the value δ and a stochastic simulation in which the orthogonal shock of interest takes a nil value. Appendix B.1 provides further details of the approach used to compute the GIRFs.

2.4.4 Test of linearity

Testing linearity is essential before fitting any nonlinear model. However, testing linearity is not straightforward as the FASTVAR nests a linear model and is not identified if the true data generating process is linear. Teräsvirta and Yang (2014) propose a Lagrange multiplier (LM) test of the null hypothesis of a linear FAVAR versus the alternative of a FASTVAR specification. The LM test compares the residual sum of squares of the linear model with that of a third-order approximation of the FASTVAR specification (see Appendix B.1 for test details). The test results are shown in Table 2.3. There is strong evidence against a linear model and in favour of a FASTVAR specification with the credit gap as the transition variable. This result is robust to different lag lengths and variations in the set of endogenous variables.

[21]The transition variable z_t features no stochastic elements. Therefore, I cannot estimate the FASTVAR model jointly with the evolution of z_t due to stochastic singularity. The GIRF method of Koop et al. (1996) uses simulations that take into account the link between $\boldsymbol{X_t}$ and z_t after the estimation of the model (Caggiano et al., 2015).

Table 2.3: Test of Linearity

	LM stat.	p-value
Baseline	138.8	0.000
Alternatives		
1 lag	106.3	0.000
3 lags	182.5	0.000
Model with Real Exchange Rate	175.9	0.000

Notes: Teräsvirta and Yang (2014) test of the null hypothesis of a linear model against a FASTVAR with one transition variable. The LM statistic is computed by fixing the order of the Taylor expansion at $n = 3$.

2.5 Results

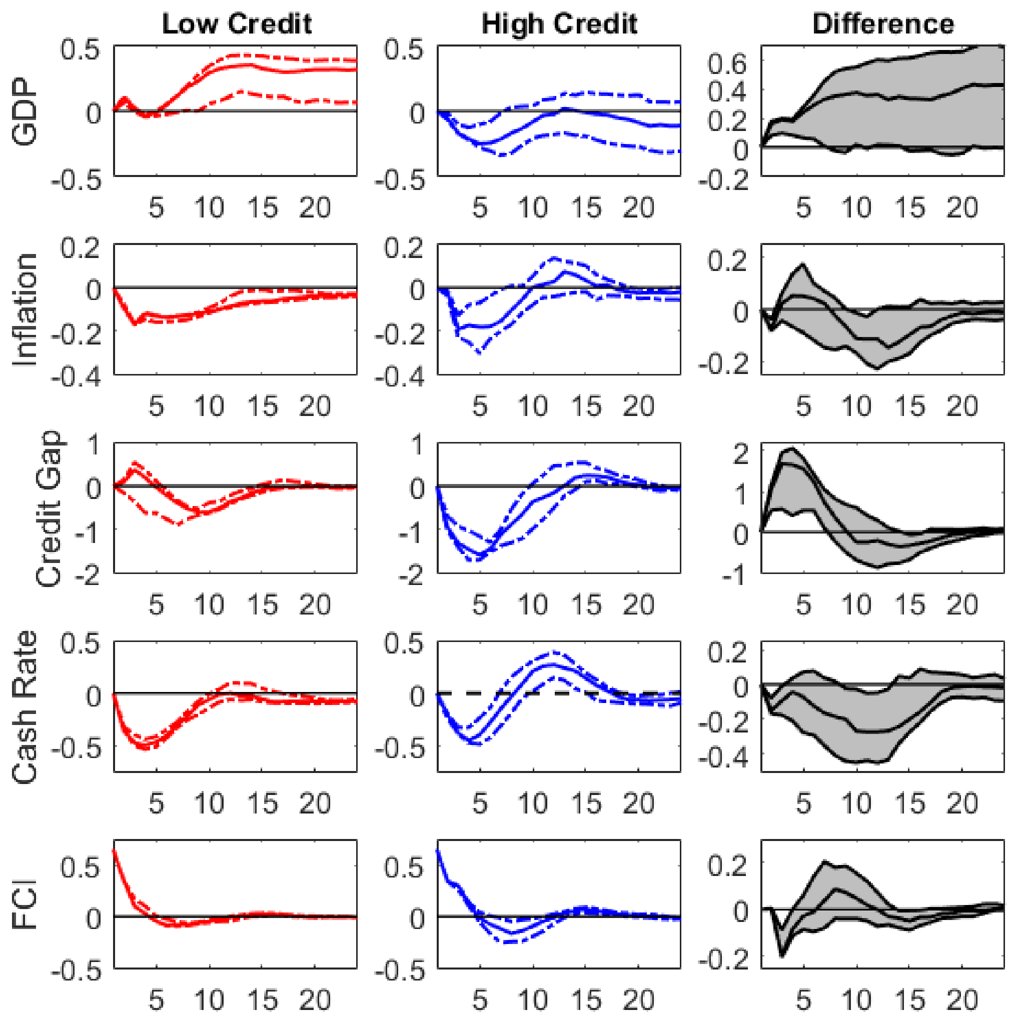
2.5.1 Baseline results

Financial Shock. Figure 2.6 displays the GIRF of the log-level of GDP, quarterly inflation, the credit gap, the level of the cash rate and the FCI to an unanticipated 1 standard deviation tightening in financial conditions.[22] The first column shows the central estimate of the GIRF and the associated 68 per cent confidence interval in a low credit regime, the second column shows the equivalent in a high credit regime and the third column shows the difference between the low and high credit regimes.

The figure shows strong evidence of asymmetries in the dynamic response to a financial shock. Most notably, when the shock occurs in a high credit regime, the unanticipated tightening of financial conditions leads to a peak fall in output of 0.25 per cent after 5 quarters, after which output recovers. In contrast, when the shock occurs in a low credit regime, output doesn't respond materially for the first 4 quarters but eventually increases to be around 0.3 per cent higher after 10 quarters. The credit gap declines by up to 1.6 per cent after 5 quarters in a high credit regime, while the credit gap doesn't initially respond in a low credit regime but eventually falls by 0.6 per cent after 9 quarters. The third column shows that the differences between the output and credit gap responses are statistically significant for approximately the first 8 quarters.

[22] In the baseline model, a 1 standard deviation financial shock causes a tightening of the FCI by 0.65 points.

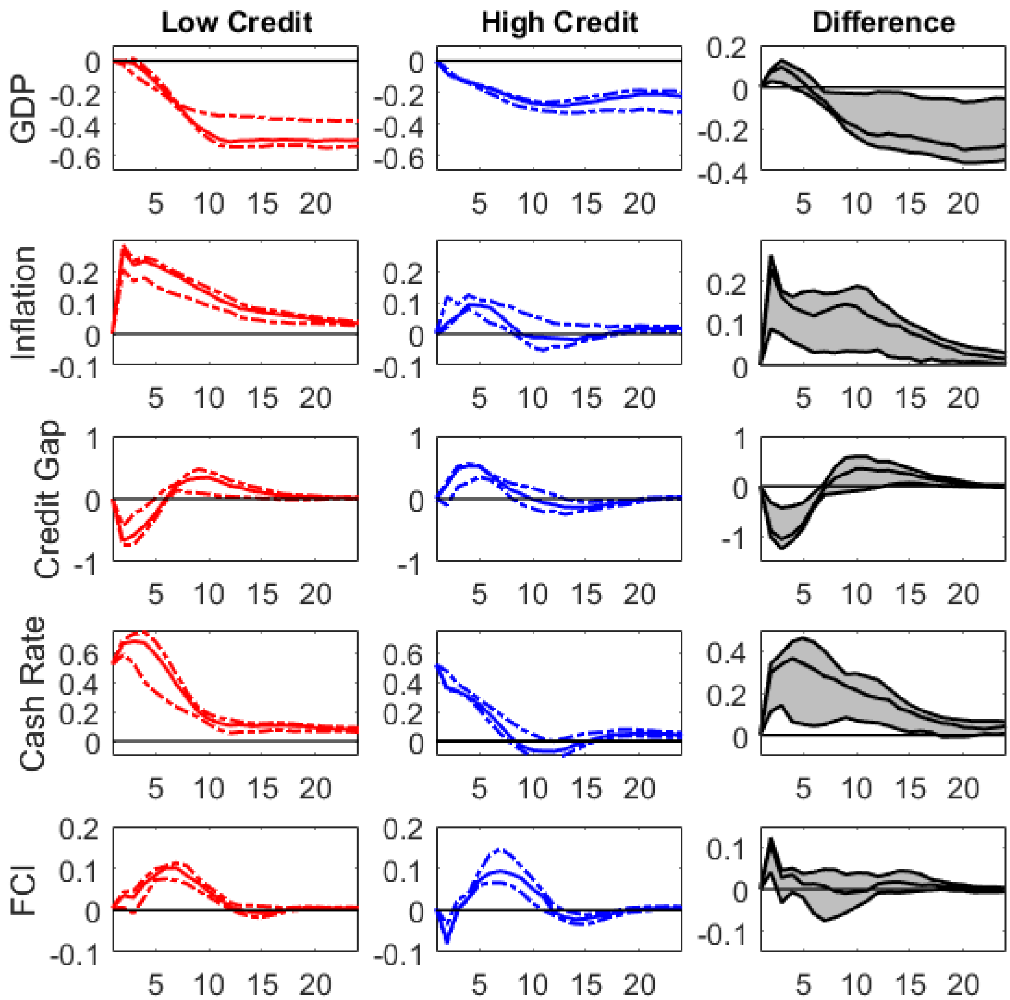
Figure 2.6: Impulse Response to a Financial Shock



Notes: Response of the log-level of real GDP, quarterly trimmed mean inflation (annualised), the credit gap, the cash rate and the FCI to an unanticipated 1 standard deviation tightening in the FCI. The first column shows the central estimate and the associated 68 per cent confidence interval in a low credit regime, the second column shows the equivalent in a high credit regime and the third column shows the difference between the low and high credit regimes.

Inflation declines significantly below zero in both regimes with a peak effect of around 0.2 per cent after 3 quarters, but there is no significant statistical evidence of an asymmetric inflation response. The cash rate decreases significantly in both regimes with a peak decline of around 50 basis points after 4 quarters, and there is statistical evidence of a larger and more persistent systematic policy reaction in the low credit regime. The FCI is allowed

Figure 2.7: Impulse Response to a Monetary Shock



Notes: Response of the log-level of real GDP, quarterly trimmed mean inflation (annualised), the credit gap, the cash rate and the FCI to an unanticipated 1 standard deviation increase in the cash rate. The first column shows the central estimate and the associated 68 per cent confidence interval in a low credit regime, the second column shows the equivalent in a high credit regime and the third column shows the difference between the low and high credit regimes.

to evolve endogenously following the shock, and the bottom row shows that the tightening in financial conditions is relatively short-lived, with the FCI returning to its initial level 5 quarters after the shock.

Monetary Policy Shock. Figure 2.7 displays the GIRF of the endogenous variables to a 1 standard deviation unanticipated increase in the cash rate.[23] In response to a contractionary monetary shock, output declines by up to 0.5 per cent when the shock occurs in a low credit regime and nearly 0.3 per cent in a high credit regime. The decline in output is persistent and the difference is statistically significant. The persistence of the output response is inconsistent with standard macroeconomic theory that suggests monetary policy has a temporary effect on output. However, Lawson and Rees (2008) and Bishop and Tulip (2017) both find persistent output responses to monetary shocks in Australia.

There is a significant increase in the inflation rate in both regimes, and this is significantly larger in the low credit regime. Bishop and Tulip (2017) consider a range of monetary policy shock identification schemes (e.g. recursive, Romer and Romer (2004) narrative identification, high frequency monetary surprises) and find that the price puzzle is pervasive in Australia. The credit gap initially declines by up to 0.7 per cent in a low credit regime. However, the credit gap increases in a high credit regime which suggests that increasing the policy rate is relatively ineffective in constraining excessive credit growth in a high credit regime. The FCI tightens significantly in each regime following the contractionary monetary shock, which suggests that the financial accelerator emphasized by Bernanke et al. (1999) operates in both regimes. The FCI increases by more, on average, when the shock occurs in the low credit regime.

Overall, the results suggest that the adverse effects of an unanticipated tightening in financial conditions are far more pronounced when the shock occurs in a high credit regime. This is consistent with high credit regimes coinciding with periods of increased macroeconomic vulnerability where the economy is more prone to adverse financial shocks. Monetary policy appears more powerful (i.e. significantly larger and more persistent output and inflation responses) in a low credit regime, which is consistent with monetary policy being more potent when there is a large share of credit constrained households. The central bank systematically lowers the cash rate in response to a financial shock, and this is both larger

[23]In the baseline model, a 1 standard deviation monetary shock causes a 52 basis point increase in the cash rate.

and more persistent in the low credit regime. Taken together, the more aggressive monetary policy response during periods where monetary policy is more powerful may, at least in part, explain the asymmetric output response to a financial shock. In Section 2.6, I show that the results are robust to alternative recursive shock identification orderings, controlling for foreign financial shocks and a range of alternative FASTVAR specifications.

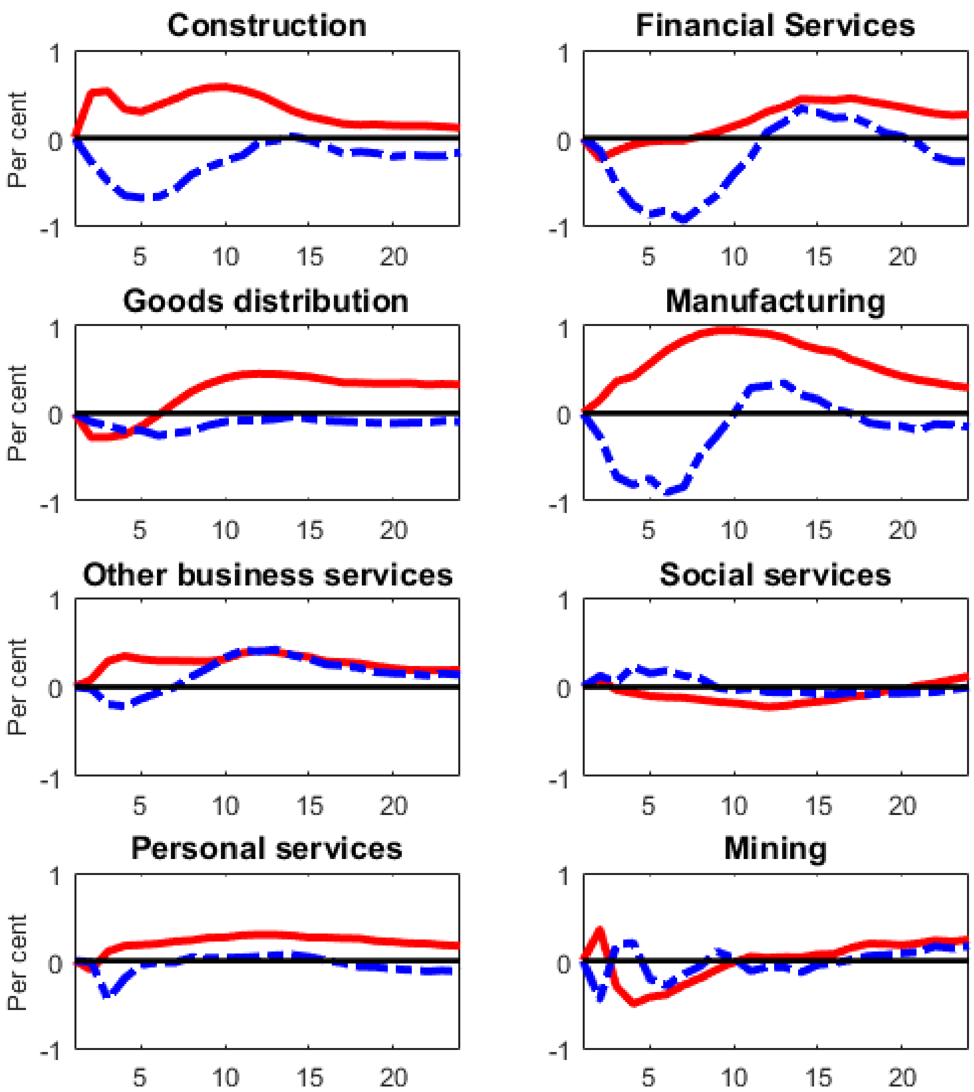
2.5.2 The sectoral effects of financial shocks

To further investigate the asymmetric output response to financial shocks, I estimate a sectoral FASTVAR to analyse the GDP component/industry implications of financial shocks during low and high credit regimes. The model is the same as the baseline FASTVAR, except I include a GDP component/industry (e.g. household consumption or the construction industry) separately in the model and aggregate output is real GDP less the GDP component. That is, the endogenous variables are $\boldsymbol{X_t} = (y_t - y_t^i, y_t^i, \pi_t, cgap_t, ocr_t, fci_t)'$ where y_t^i is the real output of component/industry i. I analyse both GDP expenditure and production components, and estimate a separate FASTVAR for each component. The approach broadly follows Manalo et al. (2015) and Lawson and Rees (2008) who analyse sectoral responses to exchange rate and macroeconomic shocks in Australia.

Figure 2.8 shows how the output of different industries responds to an unanticipated 1 standard deviation tightening in financial conditions.[24] When the shock occurs in a high credit regime, the construction, financial services and manufacturing sectors all display much larger declines in output than the economy as a whole. However, when the shock occurs in a low credit regime, construction and manufacturing output rises while financial services output initially doesn't respond significantly but increases further out the impulse horizon. Output in most other industries tends to decline when the shock occurs in a high credit regime, and eventually rise when the shock occurs in a low credit regime, consistent with

[24]The average share of each industry/sector in aggregate output over 1984 to 2018 (in per cent) are: construction = 7; financial services = 8; goods distribution = 13; manufacturing = 8; other business services = 14; social services = 11; personal services = 5; mining = 6. The industry classifications follow those used in Manalo et al. (2015).

Figure 2.8: Impulse Response to a Financial Shock - Production Sectors

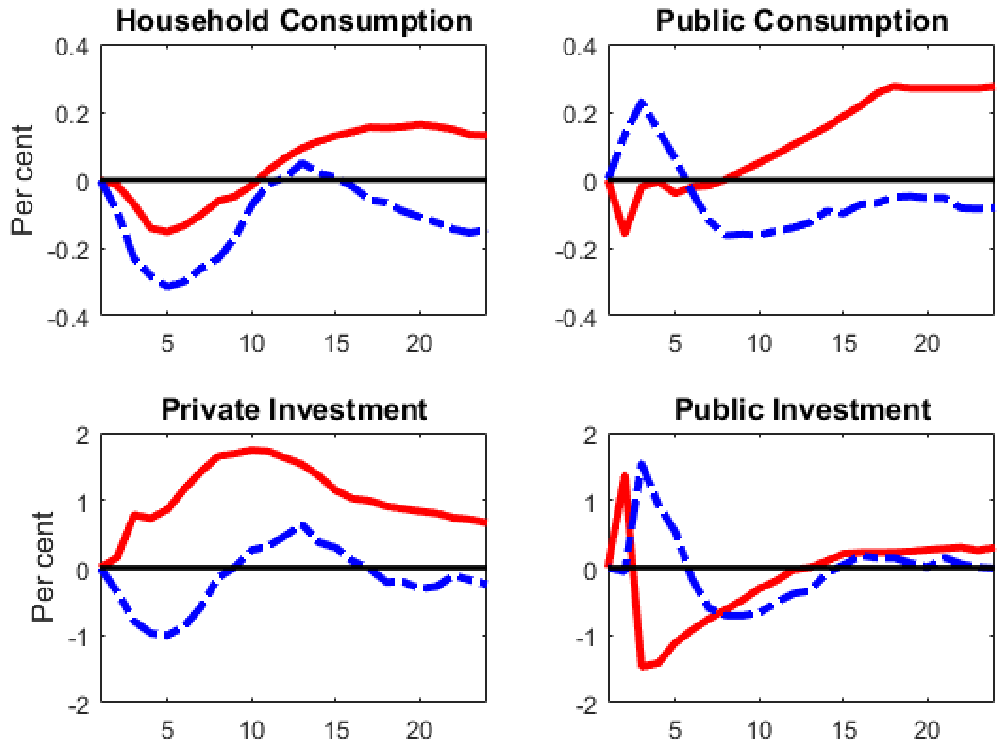


Notes: Response of different industries gross value added to an unanticipated 1 standard deviation tightening in the FCI. The red like shows the response when the shock occurs in a low credit regime and the dash-dot blue line shows the response in a high credit regime.

the asymmetric aggregate output response. The responses in the construction, financial services and manufacturing sectors appear to drive a significant portion of the asymmetric aggregate output response.

Figure 2.9 shows how the output of different expenditure components responds to an

Figure 2.9: Impulse Response to a Financial Shock - Expenditure Components



Notes: Response of different GDP expenditure components to an unanticipated 1 standard deviation tightening in the FCI. The red like shows the response when the shock occurs in a low credit regime and the dash-dot blue line shows the response in a high credit regime.

unanticipated 1 standard deviation tightening in financial conditions.[25] When the shock occurs in a high credit regime, household consumption declines by 0.35 per cent, while private investment declines by up to 1 per cent after 5 quarters. Both public consumption and investment initially rise following the shock, consistent with automatic stabilisers responding to the decline in aggregate output. In contrast, when the shock occurs in a low credit regime, household consumption decreases by 0.15 per cent while private investment increases to be nearly 2 per cent higher after 10 quarters. The response of private investment appears particularly important for driving the asymmetric aggregate output response, although the household consumption response is also notable given its large share

[25]The average share of each component in aggregate output over 1984 to 2018 (in per cent) are: household consumption = 55; private investment = 19; public consumption = 19; public investment = 5.

of aggregate output (55 per cent over the sample).[26]

In general, the results illustrate how the aggregate effect of the financial shock in each regime masks substantial heterogeneity in responses across GDP components. The results of the sectoral models are consistent with those from the baseline aggregate model, while the production and expenditure sectoral responses are also coherent. The state-dependent private investment response is consistent with the construction sector response (dwelling investment is around 30 per cent of private investment), while the household consumption response aligns with the response of goods distribution (which comprises retail trade). The industry models indicate that the asymmetric output response is largely driven by the state-dependent responses in the construction and manufacturing industries to the financial shock, while the expenditure models suggest that the asymmetric response of private investment is particularly important. In previous Australian linear VAR studies, Lawson and Rees (2008) find that the construction sector is more sensitive to monetary shocks than other sectors, while Manalo et al. (2015) find that the manufacturing sector is particularly sensitive to exchange rate shocks. Overall, the results are informative for academics and policymakers both in understanding the effects of financial shocks on the macroeconomy and designing policy to respond to financial shocks.

2.5.3 Which shocks are most important?

GIRFs show how the response of the endogenous variables to financial and monetary shocks differs in high and low credit regimes. However, GIRFs do not tell us anything about the relative importance of the shocks for Australian macroeconomic volatility, or how the importance of the shocks differs in high and low credit regimes. To assess the importance of financial and monetary shocks for the Australian business cycle, I compute a state-dependent

[26]A potential problem with this approach is that the financial shocks estimated in each sectoral model may not be identical. To investigate if this is a major issue, I analyse the responses of the FCI and inflation in each regime to the financial shock in each of the industry models. Reassuringly, the FCI response is almost identical across all models, and while the inflation responses differ slightly, they are broadly similar. In addition, visually inspecting the financial shocks implied by each model shows that they are virtually identical in all cases. Therefore, I conclude that the financial shocks I identify are similar across the industry models.

generalised forecast error variance decomposition (GFEVD) following the method proposed by Lanne and Nyberg (2016).[27] This reports the proportions of the errors of forecasts in each regime, generated by the FASTVAR, that are attributable to financial and monetary shocks to each of the endogenous variables in the model.[28]

Figure 2.10 shows the amount of variation in the endogenous variables which is explained by the financial and monetary shocks in low (red line) and high (blue line) credit regimes. Financial shocks account for 13 and 20 per cent of the variation in output at business cycle frequencies in low and high credit regimes, respectively. This is broadly in line with the amount of variation explained by monetary policy shocks. Financial shocks also account for a significant portion of the variation in the credit gap and cash rate, especially during high credit regimes.[29] The identified financial shocks account for the vast majority of variation in the FCI at business cycle frequencies, and monetary shocks explain around 10 per cent of the variation in the FCI. Overall, the figure suggests that financial shocks are a significant source of macroeconomic fluctuations in both regimes, but typically a more important source of fluctuations in the high credit regime. Financial shocks also account for a similar amount of variation in output and inflation as monetary shocks.

2.5.4 Discussion

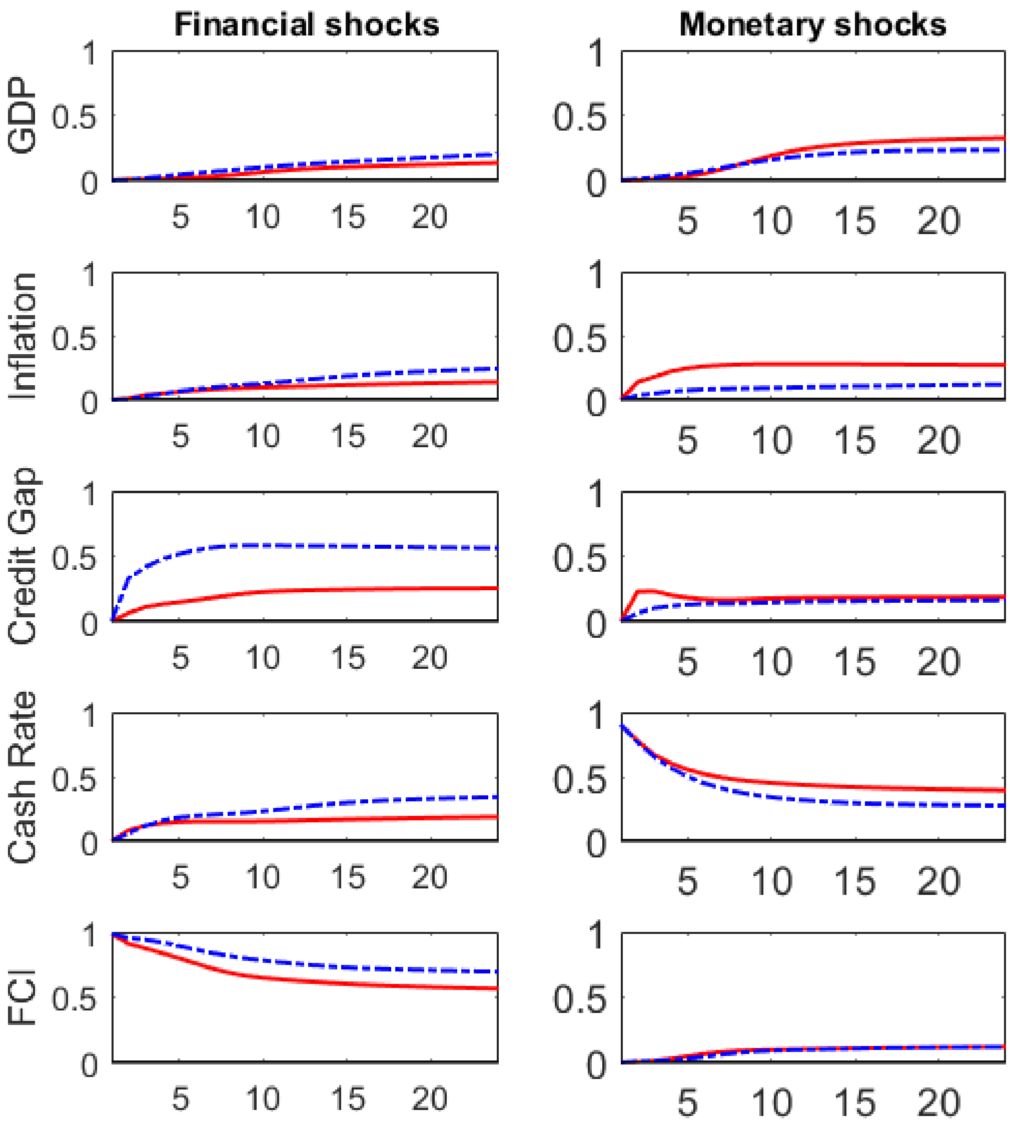
The macroeconomic dynamics reported above suggest that the effects of financial and monetary shocks vary significantly depending on whether the household credit gap is positive or negative (i.e. whether credit is above or below estimates of its equilibrium). The results are consistent with a framework whereby credit above its equilibrium level is an indicator of heightened macroeconomic vulnerability which leaves the economy more susceptible to

[27] The Lanne and Nyberg (2016) method is based on the GIRF and builds on previous GFEVD approaches for linear multivariate models by extending the analysis to nonlinear models and also forcing the relative contributions to the h-period impact of the shocks to sum to unity, which facilitates convenient interpretation. See Appendix B.1 for more information on the computation of the GFEVD.

[28] As commodity prices enter the model as exogenous I do not separately identify the proportion of variation explained by commodity shocks.

[29] In particular, financial shocks account for around 20-25 per cent of the variation in the cash rate. This is consistent with recent work by Beckers (2020) which shows that the cash rate systematically responds to credit market shocks.

Figure 2.10: Generalised Forecast Error Variance Decomposition



Notes: Generalised forecast error variance decomposition shows the amount of variation in the endogenous variables which is explained by the financial and monetary shocks in low credit (red line) and high credit (dash-dot blue line) regimes. The method used to compute the variance decomposition is explained in Appendix B.1.

a financial shock. In response to a financial shock, output declines significantly, driven by a fall in household consumption and a sharp decline in private investment. The cash rate is systematically lowered in response, however the monetary transmission mechanism is attenuated in a high credit regime. In contrast, if financial conditions exogenously tighten in a low credit regime, household consumption declines by less and private investment rises substantially, which leads to an eventual increase in aggregate output. This may be, at least in part, due to the more aggressive and persistent lowering of the cash rate in response to the financial shock in a low credit regime where monetary policy is found to be more powerful.

The asymmetric private investment response appears to drive a considerable proportion of the aggregate output response to a financial shock. The increase in private investment following the financial shock in a low credit regime may seem surprising given that the transition variable is a measure of household credit not corporate credit. However, two points are worth noting. First, private non-financial corporate credit in Australia is largely driven by household credit (see Figure B.2), so the household credit gap explains a significant proportion of the economy-wide credit gap. In addition, the results are robust to the use of the BIS gap as the transition variable, which measures the deviation of private non-financial corporate sector credit from its trend (discussed in Section 2.6). Second, the asymmetric private investment response may be somewhat explained by small business investment which is largely financed by households. Small businesses account for around one-third of production in Australia and they are often financed through housing collateral (Connolly et al. (2015) provide evidence of the housing collateral channel of entrepreneurship in Australia). It may be that in a low credit regime, households are less leveraged and able to use housing collateral along with lower interest rates to invest in small businesses, whereas in a high credit regime, households' ability to access finance through either housing or lower interest rates is impaired. This is also consistent with the regime-dependent credit gap responses.

The findings provide strong evidence that the credit gap is an important conditioning variable for the relationship between financial conditions and the macroeconomy. The results are broadly consistent with Aikman et al. (2020), who focus on an expansionary impulse to financial conditions in the US, and find that it leads to a larger increase in economic activity and the credit gap in a high credit regime. Furthermore, existing empirical estimates of the effects of financial shocks that do not condition on the credit gap are masking important nonlinearities in the transmission mechanism. More broadly, the findings are related to the recent empirical work of IMF (2017), Adrian et al. (2019) and Reichlin et al. (2020) who study the relationship between financial conditions and the distribution of future economic outcomes (commonly referred to as 'growth-at-risk'). However, to my knowledge, studies that use financial conditions to measure growth-at-risk do not condition on the credit gap. Extending the growth-at-risk framework to allow for an interaction with the credit gap is an interesting avenue for further research.

With respect to monetary policy, the results suggest that monetary policy shocks lead to significantly larger and more persistent output and inflation responses in a low credit regime. This is consistent with credit constraints binding in a low credit regime, and credit constrained borrowers adjusting spending substantially in response to monetary policy shocks. However, in a high credit regime when borrowers are unconstrained, agents may base consumption decisions on their permanent income and be less sensitive to shifts in income. These findings are consistent with the results presented in Jääskelä (2007) for Australia, Aikman et al. (2020) and Alpanda and Zubairy (2019) for the US and Cumming and Hubert (2019) for the UK. In addition, the effects of monetary shocks in a linear version of the baseline model are in line with previous estimates for Australia (shown in Figure B.10) .

This work has important implications for theoretical macroeconomic modelling. At a high level, the GFEVD suggests that financial shocks are a significant source of macroeconomic fluctuations, especially in a high credit regime, and models that do not account for financial intermediation are omitting a key source of business cycle fluctuations. Models that consider the role of financial conditions in the supply of credit, such Brunnermeier and Sannikov (2014), show how constraints on financial intermediaries and shifts in the vulnerability of the financial sector can lead to changes in the supply of credit. However, these models do not allow for a nonlinear interaction with the level of macroeconomic vulnerability in the non-financial sector. The empirical results also suggest that the strength of the financial accelerator varies over the credit cycle: It is stronger in periods where credit constraints are binding and the credit gap is negative.

These results have important policy implications. First, accurately identifying periods of excessive or restrained household credit growth appears crucial in accounting for state-dependence in the effects of financial and monetary shocks. The results point to the benefit of research that evaluates how macroprudential policies can reduce excessive credit growth and contain macroeconomic vulnerability. Second, the results suggest that financial shocks are a significant source of macroeconomic fluctuations. However, existing models of the Australian economy – such as the DSGE model (Rees et al., 2016) and macroeconometric model MARTIN (Ballantyne et al., 2019) used by the Reserve Bank of Australia – do not account for the financial intermediation process. Third, I find strong evidence that the central bank eases the policy rate significantly in response to an unanticipated tightening of financial conditions. The combination of a policy rate constrained by the effective lower bound and a positive credit gap appears to be a particularly vulnerable economic position. Central banks may need to consider alternative sources of policy accommodation to respond to financial shocks at the lower bound.

2.6 Extensions and Robustness

This section presents a number of exercises which show the robustness of the results. All tables and figures associated with the extensions and robustness exercises are reported in Appendix B.3.

2.6.1 Identification

The structural shocks in the FASTVAR are identified by employing a recursive ordering. Ramey (2016) shows that it is crucial to check the sensitivity of the results to the specific ordering of endogenous variables. In the baseline recursive identification, the FCI was ordered last which assumes that the FCI responds to macroeconomic shocks contemporaneously and impacts the endogenous variables with a lag. Figure B.6 shows that the results are robust to an alternative identification scheme where the cash rate is ordered after the FCI $\boldsymbol{X_t} = (y_t, \pi_t, cgap_t, fci_t, ocr_t)$, which assumes that the FCI responds to cash rate shocks with a lag (blue line). The results are also robust to an identification scheme where the credit gap is ordered last in the model $\boldsymbol{X_t} = (y_t, \pi_t, ocr_t, fci_t, cgap_t)$, which assumes that the FCI responds to credit shocks with a lag (red line). In general, the results are robust to alternative orderings of the endogenous variables.

2.6.2 Controlling for Foreign Financial Shocks

The FCI includes both domestic and foreign financial variables reflecting Australia's status as a small open economy that is closely integrated with global capital markets. In Section 2.3, I showed that US financial conditions explain a significant amount of variation in Australian financial conditions. As a consequence, the identified financial shocks in the baseline may have either domestic or foreign origins. It is possible that foreign financial shocks affect the real economy differently than domestic shocks. I test this hypothesis by using either the US NFCI or the excess bond premium from Gilchrist and Zakrajšek (2012) to isolate domestic financial shocks. I do so by including the measure of foreign financial conditions as an exogenous variable in the FASTVAR, which implies that the identified financial shock will reflect only domestically-sourced financial shocks.

Figure B.7 shows that domestic financial shocks have broadly similar effects to the baseline. Although the domestic financial shocks lead to a slightly smaller effect in high credit regimes, these responses are not precisely estimated and the differences are not statistically significant. In general, it appears that it is the financial shock and the credit regime when the shock occurs that matters, not the source (foreign or domestic) of the shock.

2.6.3 Alternative Specifications

The real exchange rate has an important influence on the Australian economy through altering the relative prices of domestic- and foreign-produced goods and services, which leads to changes in the macroeconomy. Manalo et al. (2015) provide evidence that suggests real exchange rate movements act as an important stabilising influence on the Australian economy. To assess the exchange rate response to a financial shock, I include the real trade-weighted exchange rate index (log level) as an endogenous variable in the FASTVAR (ordered last). Figure B.8 shows that in response to a 1 standard deviation financial shock, the real exchange rate contemporaneously depreciates by around 2 per cent in both regimes and returns to its initial level after around 4 quarters. The endogenous response of the real exchange rate acts to support the economy in response to an unanticipated tightening of financial conditions.

Figure B.9 shows that the results are robust to a number of alternative FASTVAR specifications. The green line shows the baseline results are very similar to those from a model where the terms of trade (log level) replaces the real commodity price index. The results are also similar when I control for economic uncertainty shocks using the Moore (2016) economic uncertainty index (cyan line). Caldara et al. (2016) note that increases in economic uncertainty are often associated with a tightening of financial conditions, so controlling for economic uncertainty in the FASTVAR ensures that the identified financial shock is orthogonal to economic uncertainty shocks.[30] The results are robust to setting $\gamma = 10$ in the transition function, which implies a very abrupt shift between regimes similar to a TVAR (red line).[31] Lastly, the results are robust to increasing the lag length to three (blue line).

[30]The sample begins in 1987Q1 as this is when the Moore (2016) series begins.

[31]I also estimated γ using the grid search method discussed in Hubrich and Teräsvirta (2013). I set a 200-by-200 grid of $\{\gamma, c\}$ combinations and constrain the grid so that no less than 10 per cent of the sample is in a given regime. The grid search estimates $\hat{\gamma} = 4.55$ for the baseline; however, this is not robust to minor changes in the specification which is why I favoured calibrating the transition function in the baseline. Auerbach and Gorodnichenko (2013) discuss how it is difficult to identify the location and curvature of the transition function in the data, which is why STVAR studies typically calibrate rather than estimate the transition function.

Figure B.10 shows the dynamic responses to both financial and monetary shocks obtained with a linear VAR (black line), as well as those conditional on low and high credit regimes estimated by the baseline FASTVAR model. In the linear model, an unanticipated tightening in financial conditions leads to a decline in output, inflation, the credit gap and the cash rate, consistent with evidence for other countries (e.g. Gilchrist and Zakrajšek 2012). The effects of monetary shocks in the linear model are broadly in line with previous estimates for Australia (e.g. Lawson and Rees 2008; Dungey and Pagan 2009; Bishop and Tulip 2017). However, the linear model clearly provides a distorted picture of the dynamic responses to both financial and monetary shocks when we condition on the credit regime.

2.6.4 Transition Function

The baseline FASTVAR uses the credit gap estimated in Section 2.2 as the transition variable z. An alternative credit gap often considered by academics and policymakers is the BIS credit-to-GDP gap. The BIS gap is calculated as the difference between private non-financial sector credit-to-GDP and its HP-filtered trend. Private non-financial sector credit comprises credit to both households and non-financial firms, and is therefore a more broad measure of macroeconomic vulnerability (see Figure B.3 and Appendix B.2 for more information). I also consider a household credit-to-GDP gap where the equilibrium is calculated with the HP filter (shown in Figure B.4).[32] Figure B.11 shows that the results are qualitatively similar to the baseline when these alternative credit gaps are used as the transition variable z. Output declines significantly when the shock occurs in a high credit regime, while output eventually rises following a shock in a low credit regime.

I also consider the 4-quarter moving average of growth in the household credit-to-GDP ratio as the transition variable z. This does not require an estimate of the (unobservable) equilibrium level of credit-to-GDP. However, Figure B.11 (green line) shows that there are no obvious asymmetries in the responses when credit-to-GDP growth is the transition

[32] The household credit-to-GDP gap is calculated using the HP filter with a smoothing parameter $\lambda = 10,000$ following Alpanda and Zubairy (2019).

variable. This suggests that an increase in the growth rate of the credit-to-GDP ratio is not necessarily a sign of increasing macroeconomic vulnerability, and the deviation of credit from its equilibrium level is the relevant metric for assessing macroeconomic vulnerability.

2.6.5 Statistical Properties of the Shocks

Figure B.12 shows estimates of the probability distribution function of financial shocks (Panel A) and monetary shocks (Panel B) in different credit regimes. The credit regime-dependent distributions are broadly similar in shape, suggesting that neither the size nor the frequency of positive and negative monetary or financial shocks depend on the credit regime.[33] Alternatively, Panels C and D show the financial and monetary shocks alongside the transition function $F(z_{t-1})$, which reinforces that the size or sign of the shocks do not depend on the credit regime. Therefore, asymmetries related to the size or sign of the shock cannot explain any state-dependent effects of monetary or financial shocks.

In Table B.3, I report tests of autocorrelation for both the financial and monetary shock series. Specifically, I estimate the following autoregressive (AR) model:

$$\varepsilon_t^i = c + \sum_{j=1}^{2} \rho_j \varepsilon_{t-j}^i + \sum_{j=1}^{2} \gamma_j F(z_{t-j}) \cdot \varepsilon_{t-j}^i + u_t, \tag{2.8}$$

where c is a constant, ε_t^i are the shocks with $i \in \{\text{financial, monetary}\}$, and $F(z_{t-1})$ is the probability of being in a high credit regime. Columns 1 and 3 show that there is no evidence that either of the shock series are autocorrelated when the credit regime is not accounted for (i.e. assuming $\gamma_1 = \gamma_2 = 0$). Columns 2 and 4 include interaction terms with the transition function to test for the presence of regime-dependent autocorrelation. None of the lag terms are significant at conventional levels and partial F-tests indicate that there is no evidence of regime-dependent autocorrelation.[34] The results are robust to alternative AR lag orders. Overall, the shock series are zero mean and I find no statistical evidence

[33]Further, in both cases the Kolmogorov-Smirnov test provides no evidence against the hypothesis that the two samples are drawn from populations with the same distribution. Results available on request.

[34]The partial F-test compares the model with interaction terms with the nested model (i.e. assuming $\gamma_1 = \gamma_2 = 0$).

that they are serially correlated. Therefore, I conclude that the identified shocks capture unanticipated movements in the FCI and the cash rate.

2.6.6 The Business Cycle and the Credit Cycle

The majority of the literature investigating the state dependence of monetary policy effects focuses on the business cycle (e.g. Tenreyro and Thwaites 2016). In contrast, these results suggest that there is evidence of nonlinearities in the responses of financial and monetary shocks over the credit cycle. Figure B.14 shows the credit gap alongside a measure of the output gap.[35] Note that positive credit gap periods in my sample do not necessarily coincide with a positive output gap. In fact, the correlation coefficient is negative (-0.28) and positive and negative output gap periods are distributed approximately equally between positive and negative credit gap periods. Therefore, I am capturing a nonlinearity relating to the credit cycle, which differs from the business cycle.

2.7 Conclusion

I investigate if the effects of financial and monetary policy shocks differ between high and low credit regimes in Australia. The empirical approach models the Australian economy using a factor-augmented smooth-transition vector autoregression model, where the factor is a broad indicator of aggregate financial conditions and the credit regime is determined by the credit gap (defined as the deviation of household credit-to-GDP from its estimated long-run equilibrium). The results provide novel evidence that the effects of both financial and monetary policy shocks depend nonlinearly on the credit gap.

The main result is that the adverse effects of an unanticipated tightening in financial conditions are far more pronounced when the shock occurs in a high credit regime than in a low credit regime. In particular, output, inflation, the credit gap, and the policy rate all decline significantly following the shock in a high credit regime. However, when the

[35] The output gap is calculated using the HP filter with a smoothing parameter $\lambda = 1600$ as is common with quarterly data.

shock occurs during a low credit regime, output doesn't initially respond before eventually increasing, and the credit gap declines by significantly less. Sectoral models indicate that the asymmetric output response is largely driven by the state-dependent responses in the construction and manufacturing industries. In addition, financial shocks are found to be a significant source of business cycle fluctuations, especially in a high credit regime. Overall, the results are consistent with high credit regimes coinciding with periods of increased macroeconomic vulnerability where the economy is more prone to adverse financial shocks.

With respect to monetary policy, contractionary shocks to monetary policy during low credit regimes lead to significantly larger and more persistent output and inflation responses than during high credit regimes. This suggests that monetary policy is most potent when households are credit constrained. In addition, the central bank systematically lowers the cash rate in response to a financial shock, and this is both larger and more persistent in the low credit regime. The more aggressive monetary policy response during low credit periods where monetary policy is more powerful partly explains the asymmetric output response to a financial shock.

Overall, the results suggest that macroeconomic theory and policy should account for the role of the credit gap in the transmission of financial conditions and monetary policy. Empirical estimates of the effects of financial and monetary shocks that do not condition on the credit gap are masking important nonlinearities in the transmission mechanism. Theoretical models of financial intermediation should seek to account for a nonlinear interaction between financial conditions and the level of macroeconomic vulnerability in the household sector. Lastly, additional research on identifying periods of excessive credit growth and policies to address the associated build-up in macroeconomic vulnerabilities is warranted.

Chapter 3

Determinants of the Natural Rate of Interest: An Empirical Investigation

Abstract

In this chapter, I investigate the determinants of the decline in the natural rate of interest (NRI) – the short-term real interest rate consistent with a zero output gap and stable inflation – over 1984 to 2016. To empirically analyse the determinants, I estimate the NRI for the US and the UK using three different approaches: a semi-structural model, a time-varying parameter vector autoregression, and a novel financial market-based approach. These estimates are used to analyse long-run equilibrium determinants of the NRI by estimating country-level dynamic regressions using a general-to-specific model selection algorithm. Most notably, I find evidence of a negative relationship between the NRI and economic uncertainty in both the US and the UK, while both productivity growth and the relative price of capital are positively related to the NRI. The decline in the NRI over 1984 to 2016 has predominantly been associated with a persistent decline in the relative price of capital in the US and an increase in population growth in the UK. Since the 2007–2008 financial crisis, the 1.5–2 percentage point fall in the NRI in both economies was largely associated with a decline in productivity growth and heightened economic uncertainty.

3.1 Introduction

Real interest rates have declined over the past few decades and remain at an unprecedented low level in many advanced economies. Numerous explanations have been offered regarding the low level of interest rates and why this may or may not persist into the future. These explanations typically focus on reasons why the natural rate of interest (NRI) – the short-term real interest rate consistent with a zero output gap and stable inflation – has fallen. However, while there is consensus that the NRI has fallen in many economies, whether this is permanent or transitory remains an open question. Researchers have debated the extent to which the decline depends on longer-run real-side factors, such as lower productivity growth, or on temporary factors relating to the 2007–2008 financial crisis, such as increased economic uncertainty. The primary aim of this chapter is to empirically analyse the determinants of the decline in the NRI over 1984 to 2016.

The empirical approach consists of two key steps. First, I estimate the NRI for the United States (US) and the United Kingdom (UK) over 1984Q1 to 2016Q4. As NRI estimates are model-dependent and subject to large uncertainty, I estimate the NRI in each economy using a semi-structural model, a time-varying parameter vector autoregression (TVP-VAR), and a novel financial market-based approach. I account for the effect of unconventional monetary policy by using estimates of shadow rates instead of observed nominal short-term interest rates.[1] Second, the NRI estimates are used to analyse their determinants by estimating country-level error correction models (ECMs) using a general-to-specific model selection algorithm. Specifically, the analysis quantifies the role that productivity growth, the relative price of capital, population growth, economic uncertainty, public debt, and the demand for safe assets play in determining the NRI.

Most notably, I find evidence of a negative relationship between the NRI and economic uncertainty in both the US and the UK. The results suggest that increased economic un-

[1] The shadow rate is obtained from an estimated yield curve and corresponds to the policy rate in periods where the effective lower bound (ELB) is not binding, but can freely evolve to negative values during periods of unconventional policy where the ELB is binding. For further information, see Appendix C.1.

certainty during the financial crisis was associated with a permanent decline in the NRI of around 0.5–1.2 and 0.0–0.5 percentage points in the US and the UK, respectively. In addition, both productivity growth and the relative price of capital are positively related to the NRI in both economies, consistent with economic theory. The decline in the NRI over 1984 to 2016 has predominantly been associated with a persistent decline in the relative price of capital in the US and an increase in population growth in the UK. Since the 2007–2008 financial crisis, the approximately 1.5–2 percentage point fall in the NRI in both economies was largely associated with a decline in productivity growth and heightened economic uncertainty.

Analysing the determinants of the decline in the NRI is relevant to a number of policy debates. The secular stagnation hypothesis introduced by Hansen (1939) and revived by Summers (2014) is based on a lower NRI. In addition, a decline in the NRI implies less scope for central banks to cut interest rates in response to deflationary shocks, and suggests that the effective lower bound (ELB) on nominal interest rates is likely to remain an important threat to future monetary policy. Faced with such a prospect, economists have suggested increasing inflation targets (Ball, 2014), introducing temporary price-level targeting (Bernanke, 2017), or phasing out paper currency to allow significantly negative interest rates (Rogoff, 2014). These proposals are all based on the premise of a new lower level of the NRI. Thus, understanding the determinants of the decline in the NRI is vital to inform policy debates.

Determinants of the NRI are typically analysed using structural models that are able to quantify the effect of specific determinants within a general equilibrium setting. Researchers have studied how the NRI is impacted by demographic shifts (Carvalho et al. 2016; Aksoy et al. 2019), fiscal policy (Rachel and Summers, 2019), the decline in the relative price of investment goods (Sajedi and Thwaites, 2016), and the flight to quality as savings are shifted from risky investments to US Treasury debt (Del Negro et al., 2017). Rachel and Smith (2017) use a saving–investment framework to investigate a range of factors that have contributed to the decline in the global NRI. Their results suggest that demographic forces and precautionary savings in emerging markets have increased global savings, while a lower relative price of capital and an increase in the spread between risk-free and actual interest rates have led to lower investment. However, a limitation of using structural models is that the underlying theory is not tested; therefore, the conclusions reached are conditional on the theory.

This chapter falls within the related literature that has adopted an empirical approach to analysing interest rate determinants. Lunsford and West (2019) estimate long-run correlations between US safe real interest rates and a large number of variables over 1890 to 2016. Their results suggest that safe real interest rates are correlated with demographic measures, but do not find a strong positive correlation between productivity growth and interest rates. Borio et al. (2017) use a sample from 1870 and find weak support for most traditional real interest rate determinants but show that monetary regimes are significantly associated with shifts in the level of real interest rates. However, their analysis primarily concerns the long-term real interest rate, while the NRI should be independent of monetary regimes.[2] Hamilton et al. (2015) analyse the correlation between real interest rates and GDP growth across countries and conclude that there is some evidence of a modestly positive relationship between the two (though this is sensitive to the specific sample). Kiley (2019) finds statistically significant relationships between the real interest rate, the dependency ratio, and life expectancy. However, he finds that GDP growth is not a statistically significant determinant of the real interest rate and the relationship with the dependency ratio is inconsistent with standard economic theory.

The empirical method used in this chapter has benefits relative to much of the literature that analyses real interest rate determinants. In particular, I use a general-to-specific approach that allows the data to determine the nature and stability of the relationship be-

[2] The NRI in this chapter (defined more precisely in Section 3.2) filters out the transitory impact of monetary influences from the real interest rate. Therefore, I make the common assumption that monetary policy is neutral in the long run. However, Borio et al. (2017, pg. 6) argue that this assumption is "exceedingly strong" which is why they choose to focus on real interest rates.

tween the NRI and its determinants. This involves constructing a general model with many potentially relevant variables and then using an algorithm to remove irrelevant variables and choose a parsimonious final model. The general model includes data on a larger set of potential NRI determinants than many studies (e.g. Kiley 2019; Hamilton et al. 2015), and incorporates economic uncertainty and demand for safe assets which have typically been overlooked in previous empirical studies.[3] I focus on the NRI, rather than real interest rates, which disentangles fluctuations associated with the business cycle or the influence of monetary policy from fundamental shifts in interest rates. In addition, I focus on the decline in interest rates since 1984, which largely avoids concerns around measurement issues and structural breaks in studies that use very long samples (e.g. Borio et al. 2017; Lunsford and West 2019; Hamilton et al. 2015). Relative to the theoretical literature, this data-driven approach does not impose any theoretical restrictions on the relationship between the NRI and any of its determinants.

This chapter also contributes to the literature aimed at estimating the NRI. The most common method follows the approach developed by Laubach and Williams (2003). The Laubach and Williams (2003) method uses a small-scale New Keynesian model and the Kalman filter to jointly estimate the time-varying natural rates of interest, output, and trend growth. Alternatively, researchers may take a more structural approach and use DSGE models to estimate the NRI. Semi-structural methods are popular as they exploit relationships based on economic theory, yet retain a degree of flexibility compared to DSGE methods. However, these macro-based approaches have serious potential shortcomings. For example, Kiley (2020) and Clark and Kozicki (2005) find weak empirical support for the economic relationships these methods rely on, and as a result NRI estimates from such models may be distorted. In this chapter, I estimate the NRI in the US and the UK using the semi-structural method proposed by Holston et al. (2017) and also follow Lubik and Matthes (2015a) and estimate the NRI using a TVP-VAR. I explicitly account for the effects

[3]Rachel and Smith (2017) consider the emerging market savings glut and find it led to a decline in the global NRI of around 25 basis points.

of unconventional monetary policy by incorporating shadow policy rates during periods where the ELB is binding.[4] These two macro-based approaches use the same observable data but differ in the assumptions used to identify the NRI and the degree of economic structure imposed.

Financial models and data may also be used to estimate the NRI. I contribute to this literature by proposing a new financial market-based approach to estimate the NRI. The method subtracts inflation expectations and a nominal term premium from forward interest rates to derive a market-implied NRI. Specifically, the NRI is defined as the average expected real short-term interest rate over the five-year period starting five years ahead. In contrast to existing financial market-based approaches such as Christensen and Rudebusch (2019) and Bauer and Rudebusch (2020), this method uses only nominal yields to estimate the NRI, rather than a joint model of nominal and real yields or only real yields.[5] This results in a longer sample and does not require the estimation of a liquidity premium. However, a potential disadvantage of using only nominal yields is that I have to account for time-varying inflation expectations. Unlike macro-based methods, financial models do not rely on a correct and stable identification of the dynamics of inflation and output. Consequently, the approach I propose is a useful complement to existing macro-based methods and contributes to the nascent literature that estimates the NRI using financial market-based approaches.

The remainder of the chapter proceeds as follows. Section 3.2 discusses the theoretical determinants of the NRI. Section 3.3 outlines the methods used to estimate the NRI and the general-to-specific modelling approach. Section 3.4 discusses the data. Section 3.5 presents the results and Section 3.6 provides extensions and robustness checks. Section 3.7 concludes.

[4]Pescatori and Turunen (2016) and Johannsen and Mertens (2016) also use shadow rates in their estimation of the NRI in the US. However, this is the first study to incorporate shadow rates for the UK.

[5]Christensen and Rudebusch (2019) estimate a term structure model on the prices of Treasury inflation-protected securities (TIPS) and adjust for real term and liquidity premiums to estimate the NRI in the US. They define the NRI to be the average expected real short-term interest rate over the five-year period starting five years ahead. Bauer and Rudebusch (2020) use nominal yields in their model, but they do not account for inflation expectations and instead provide estimates of the *nominal* NRI.

3.2 Theoretical Motivation

In this section, I outline the key theoretical relationships that motivate the variables that are examined in this chapter. There are a vast number of potential NRI determinants and I primarily contain the discussion in this section to the relationships that are examined in the general-to-specific analysis.

In a closed economy, investment must be funded by domestic saving. The NRI is the price that equates desired savings and desired investment at a level consistent with zero output gap and stable inflation.[6] Therefore, the determinants of the NRI are those factors that influence the amount of desired savings or investment in the economy. Factors that increase desired savings or reduce investment demand will lower the NRI, holding all else constant.

- **Productivity growth:** In the Ramsey model for a representative household with an infinite horizon and constant relative risk aversion utility, the steady-state real interest rate is given by:

$$r = \frac{1}{1-\beta} + \sigma p, \tag{3.1}$$

where r is the real interest rate, $1/(1-\beta)$ is the household's subjective rate of time preference, σ is the inverse intertemporal elasticity of substitution in consumption, and p is the steady-state growth rate of consumption per capita (or equivalently productivity growth). Higher productivity growth leads to greater future income per capita. Utility maximising households will reduce savings and bring consumption forward in order to smooth consumption over time. In addition, an increase in productivity growth increases the marginal return on capital, and if this is greater than the real interest rate, households will increase their demand for investment, which

[6] This is a "long-run" concept of the NRI (also referred to as r^*, the "neutral" or "equilibrium" rate of interest), as it refers to the level of real interest rates that is expected to prevail in five to ten years' time after transitory shocks to aggregate demand and supply have abated (Laubach and Williams, 2016). In contrast, a "short-run" perspective, which is formalised in Woodford (2003) and commonly used in DSGE models, defines the NRI as the short-term real interest rate that would occur in each period if prices were fully flexible.

raises real interest rates (Bernhardsen and Gerdrup, 2007). Thus, a positive relationship between productivity growth and the real interest rate is at the core of many macroeconomic models.

- **Relative price of capital:** A decline in the relative price of physical capital reduces the level of investment needed to maintain a given level of output. However, a lower cost of capital also incentivizes firms to invest in capital. The net impact of these two effects will be determined by the curvature of the production function (Sajedi and Thwaites, 2016). Assuming that the former effect dominates, as is common in the literature, a lower relative price of capital will lead to a decrease in the NRI.

- **Demographics:** A decline in population growth increases capital per worker, which initially exerts downward pressure on real interest rates through a reduction in the marginal product of capital. However, it will eventually lead to a higher dependency ratio, which will place upward pressure on real interest rates. Therefore, the overall effect of population growth on the NRI is ambiguous (Carvalho et al., 2016).

  Other demographic factors may also shift desired savings. Carvalho et al. (2016) use a life-cycle model to show how an increase in the dependency ratio (the ratio of retirees to workers) places upward pressure on real interest rates because retirees save less than workers, while an increase in life expectancy leads to lower real interest rates as the anticipation of a longer retirement period increases agents' propensity to save. Note that these are partial effects, as an increase in life expectancy will eventually increase the dependency ratio, which lowers savings and increases interest rates. However, in contrast, Aksoy et al. (2019) argue that a higher dependency ratio actually lowers real interest rates through depressing innovation and growth. Overall, demographic shifts imply complex dynamics that impact interest rates over long periods.

- **Economic uncertainty:** A rise in economic uncertainty leads to lower real interest rates through an increased desire for precautionary savings. Economic uncertainty may also be positively associated with the expected variance of the return on the market portfolio. The intertemporal IS relationship derived under recursive utility preferences, such as Epstein and Zin (1991), suggests a negative relationship between the real interest rate and the expected variance of the return on the market portfolio.[7] In addition, an increase in economic uncertainty can lead to lower interest rates through reduced investment demand, as firms and households refrain from investing in an uncertain environment (Lunsford and West, 2019).

- **Public debt:** Economic theory is ambiguous about the relationship between public debt and interest rates. If Ricardian equivalence holds, forward-looking consumers alter private savings in response to a change in public debt, so that national savings and real interest rates do not change with public debt. However, in a wide class of models where Ricardian equivalence breaks down, a permanent rise in public debt will increase interest rates by crowding out private capital (Rachel and Summers, 2019).

- **Demand for safe assets:** Global foreign exchange reserve accumulation increased sharply over the 2000s, largely reflecting a precautionary savings motive by emerging markets against a sudden stop of capital inflows. In his "savings glut" speech, Bernanke (2005) argued that a sharp increase in emerging market foreign exchange reserves following the late 1990s financial crises led to lower interest rates through an increase in global desired savings. Caballero et al. (2008) show how increased demand for safe assets by emerging markets can spread to the world at large and lead to a decline in the real interest rate (also see Caballero et al. 2017).

Table 3.1 summarises the key theoretical relationships that are examined in the empirical analysis (data discussed in Section 3.4). This list of posited NRI determinants is far from exhaustive and ideally the analysis would include data on the larger set of variables, however

[7] This assumes that $\theta < 1$ where $\theta = (1-\gamma)/(1-\sigma)$ and γ is the coefficient of relative risk aversion. Lunsford and West (2019) argue evidence based on previous calibration and estimation studies suggests $\theta < 1$.

this is not possible due to data limitations.[8] Nevertheless, the variables considered are broadly consistent with the logic of DSGE models that dominate monetary economics. For example, the relationship between productivity growth and the NRI comes from an intertemporal IS equation, such as (3.1), which is common in monetary DSGE models and is the theoretical justification for the law of motion of the NRI in the Laubach and Williams (2003) model. Some models include a trend in the relative price of investment due to investment-specific technology shocks (e.g. Justiniano et al. 2011). However, these models typically do not link secular movements in the NRI to shifts in economic uncertainty, safe asset demand or include a life-cycle component to capture population dynamics. The general-to-specific approach in Sections 3.3.2 and 3.5 allows the data to determine the nature and stability of the relationship between the NRI and its determinants.

Table 3.1: Theoretical Determinants of the Natural Rate of Interest

Factor	**Expected relationship**	**Channel (S or I)**	**Variable definition**
Productivity growth (p)	Positive	Both	Annual growth in output per hour (5-year moving average)
Relative price of capital (k)	Positive	Investment	Gross fixed capital formation deflator divided by the private final consumption expenditures deflator
Population growth (n)	Ambiguous	Savings	Annual population growth
Economic uncertainty (u)	Negative	Both	News-based economic policy uncertainty index
Public debt (d)	Ambiguous	Investment	Government debt as a % of GDP
Safe assets/ Global reserves (s)	Negative	Savings (global)	Annual change in world official reserves as a % of US nominal GDP

Notes: Data is at a quarterly frequency and sources are listed in Appendix C.2.

[8] For example, the NRI is largely discussed and estimated using a closed-economy framework. However, in a small open economy which cannot influence the global real interest rate, perfect capital mobility equalises interest rates and the NRI would be determined solely by global factors. If we allow for risk and assume there is imperfect capital mobility following Mendes (2014), the domestic NRI in the small open economy will differ from the global NRI by a risk premium. The risk premium will depend on country-specific factors such as default risk, the net foreign asset position, and political risk.

3.3 Methodology

This section is organised into two parts. First, I describe the three methods used to estimate the (unobservable) NRI. Second, I outline the general-to-specific approach used to analyse the determinants of the NRI.

3.3.1 Estimating the Natural Rate of Interest

3.3.1.1 Macroeconomic methods

I estimate the NRI using the semi-structural method used in Holston et al. (2017) and the flexible time series approach proposed by Lubik and Matthes (2015a) (referred to as the HLW and TVP-VAR methods respectively). The methods use the same data but differ in the assumptions used to identify the NRI and the degree of economic structure imposed.

Holston–Laubach–Williams method. The HLW approach builds on the method proposed by Laubach and Williams (2003). The model uses a small-scale New Keynesian model and the Kalman filter to jointly estimate the time-varying natural rates of interest, output, and trend growth. The investment–savings (IS) and Phillips curves are given by

$$\tilde{y}_t = a_{y,1}\tilde{y}_{t-1} + a_{y,2}\tilde{y}_{t-2} + \frac{a_r}{2}\sum_{j=1}^{2}(r_{t-j} - r^*_{t-j}) + \epsilon_{\tilde{y},t} \tag{3.2}$$

$$\pi_t = b_\pi \pi_{t-1} + (1 - b_\pi)\pi_{t-2,4} + b_y \tilde{y}_{t-1} + \epsilon_{\pi,t}, \tag{3.3}$$

where $\tilde{y}_t = 100 \cdot (y_t - y^*_t)$ denotes the output gap, y_t is log real GDP and y^*_t is potential output, r_t is the ex ante real interest rate, r^*_t is the NRI, π_t is consumer price inflation, $\pi_{t-2,4}$ measures inflation expectations as the average of the second to fourth lag of inflation, and $\epsilon_{\tilde{y},t}$ and $\epsilon_{\pi,t}$ are error terms. The law of motion of the unobservable variables is given by:

$$y^*_t = y^*_{t-1} + g_{t-1} + \epsilon_{y^*,t} \tag{3.4}$$

$$r^*_t = g_t + z_t \tag{3.5}$$

$$g_t = g_{t-1} + \epsilon_{g,t} \tag{3.6}$$

$$z_t = z_{t-1} + \epsilon_{z,t}, \tag{3.7}$$

where g_t denotes trend potential output growth, z_t represents all other factors affecting r_t^*, $\epsilon_{y^*,t}$ and $\epsilon_{g,t}$ are one-period and persistent shocks to the potential output growth rate, respectively, and $\epsilon_{z,t}$ denotes a shock to z_t. The model is estimated using the maximum likelihood approach described in Holston et al. (2017).

Intuitively, the size of the real interest rate gap $(r - r^*)$ leads to fluctuations in $\tilde{y}$ through the IS curve (3.2), which in turn lead to changes in the rate of inflation through the Phillips curve (3.3), allowing the Kalman filter to estimate g_t and z_t which determine r^* through (3.5). The NRI is identified as the variable that best fits the IS curve, and therefore a reasonably large and precisely estimated slope coefficient a_r is crucial. The method uses data on real GDP, inflation, and the short-term nominal interest rate; r_t is calculated as the short-term nominal interest rate minus expected inflation over the coming year (calculated as the average of the second to fourth lag of inflation). Accurate estimation of the NRI crucially depends on the above model specification, and any misspecification will result in contaminated NRI estimates.

TVP-VAR method. The TVP-VAR approach to estimate the NRI imposes much less economic structure than the HLW approach, and is therefore less prone to model misspecification. Lubik and Matthes (2015a) estimate a TVP-VAR with stochastic volatility and identify the NRI as the conditional five-year forecast of the real interest rate. Time-varying parameters allow the VAR lag coefficients to change over time, while stochastic volatility allows for time variation in the variances of the VAR error processes. This results in a flexible model that is able to capture a range of nonlinearities apparent in the data, such as the decline in macroeconomic volatility throughout the Great Moderation. The five-year forecast horizon is chosen to allow time for transitory shocks to abate. Therefore, identification of the NRI relies on the assumption that the real interest rate will be at its natural level in five years' time.

The following model is based on the TVP-VAR outlined in Primiceri (2005).[9] Consider the model

$$x_t = c_t + B_{1,t}x_{t-1} + B_{2,t}x_{t-2} + A_t^{-1}\Sigma_t\varepsilon_t \qquad t = 1, ..., T \tag{3.8}$$

where $x_t = (\Delta y_t,\ r_t,\ \pi_t)'$ and the variables are defined as in HLW and Δ denotes the first difference; c_t is a 3 x 1 a vector of time-varying intercepts; $B_{i,t}, i = 1, 2$ are 3 x 3 matrices of time-varying coefficients; A_t is a lower-triangular matrix with ones on the main diagonal and time-varying coefficients below it; Σ_t is a diagonal matrix of time-varying standard deviations; and ε_t is a 3 x 1 vector of unobservable shocks with variance equal to the identity matrix. The time-varying coefficients evolve as random walks, except the diagonal elements of Σ_t are assumed to follow geometric random walks. All the innovations in the model are jointly normally distributed, with the mean equal to zero and the covariance matrix equal to V. The matrix V is block diagonal, with blocks corresponding to the time-varying elements of B_1, B_2, A, Σ and ε. Estimation follows the approach proposed by Primiceri (2005) and is described in Appendix C.1.

Accounting for the effective lower bound

The short-term nominal interest rate, often the policy rate, is a key input in both of these models. However, policy rates reached the ELB during the financial crisis in the US and the UK, and central banks employed a range of unconventional policy measures to provide further policy accommodation. Empirical evidence (e.g., Yu 2016) suggests that these measures have been effective in lowering interest rates. Consequently, the policy rate ceases to provide an accurate measure of the policy stance during periods of unconventional monetary policy.

To account for this I use shadow rate estimates from the Krippner (2015b, 2016) framework in place of the policy rate. Krippner estimates shadow rates using an affine term structure model that relaxes the ELB constraint, thereby obtaining short-term rates that

[9] For a detailed description of the model and estimation algorithm see Primiceri (2005) and Del Negro and Primiceri (2015). See Lubik and Matthes (2015b) and Nakajima (2011) for further discussion of TVP-VARs and the role of stochastic volatility.

are equal to the policy rate when interest rates are above the ELB, but can become negative at the ELB to account for unconventional policy (see Appendix C.1 for further details on the Krippner methodology). The shadow rate is the shortest maturity interest rate from the estimated shadow yield curve, and reflects the effects that unconventional policy measures have on longer-maturity interest rates. As a robustness exercise, I also estimate the NRI using Wu and Xia (2016, 2017) shadow rates.

3.3.1.2 Financial market-based method

Financial market-based approaches to estimate the NRI have received far less attention in the literature than methods based on macroeconomic models. However, these approaches provide a promising alternative to macroeconomic approaches as they draw on information from market participants who summarise a vast range of information in observable prices and do not rely on a correct and stable specification of output and inflation dynamics. In this subsection, I propose a financial market-based approach to estimate the NRI.

The NRI is the short-term real interest rate that is expected to prevail in five to ten years. Long-term nominal interest rates can be thought of as the sum of the expected future short-term real interest rate, long-term inflation expectations, and an (unobservable) term premium specific to that maturity. Therefore, I calculate the NRI as

$$r_t^* = i_{5-10,t} - \pi_{5-10,t}^e - \lambda_{5-10,t} \tag{3.9}$$

where r_t^* is the NRI, $i_{5-10,t}$ is the 5-to-10-year forward nominal interest rate, $\pi_{5-10,t}^e$ is expected inflation over the period five to ten years in the future, and $\lambda_{5-10,t}$ is the time-varying term premium specific to that maturity. In this model, r_t^* can be thought of as the market-implied risk-neutral short-term real interest rate over the period five to ten years in the future. The approach assumes that market participants expect real interest rates to be at their natural level, on average, over this period.

- The 5-to-10-year forward nominal interest rate is the five-year interest rate that is expected to prevail in five years' time, implied by the zero-coupon yield curve.

- Long-term inflation expectations are commonly measured using surveys of consumers, firms, or professional forecasters. For the US, I use the University of Michigan Survey of Consumers which measures expected inflation over the period five to ten years in the future. For the UK, I use 5-to-10-year break-even inflation (calculated as the yield differential between nominal and real 5-to-10-year forward interest rates) as survey-based measures are not available over a sufficiently long sample period.[10]

- The 5-to-10-year forward term premium reflects the compensation that investors receive for holding a five-year bond over this period instead of rolling over short-term risk-free bonds. I use the discrete-time affine term structure model proposed by Wright (2011) to estimate $\lambda_{5-10,t}$. For more details on the model, see Appendix C.1.

In comparison to NRI estimates based on macroeconomic models, this approach has three main differences. First, it avoids potential misspecification of output and inflation dynamics. A number of empirical studies (Clark and Kozicki 2005; Hamilton et al. 2015; Kiley 2020; Lunsford and West 2019) suggest that the link between trend potential output growth and real interest rates may not be as strong as is often assumed, implying that standard macroeconomic estimation methods may be misspecified. Instead of relying on the macroeconomists' model, this method relies on market participants who summarise a vast range of information in observable prices. Second, the measure is market-implied and uses long-term interest rates, thereby avoiding problems associated with the ELB constraint on short-term nominal interest rates. However, the ELB may still pose a problem to the extent that the ELB impacts long-term interest rates through effectively truncating the distribution of future short-term interest rates. Third, macroeconomic estimation methods use revised data that would not have been available historically, and filtered (one-sided) and smoothed (two-sided) estimates often differ substantially, indicating real-time estimation issues (Clark

[10] According to the Fisher hypothesis, this is the market-implied average inflation rate that is expected to prevail over the five-year period starting in five years' time.

and Kozicki, 2005). In contrast, this measure uses forward-looking information priced into active markets and can be updated at a daily frequency.

This approach also differs to existing financial-market based methods. The most notable method proposed by Christensen and Rudebusch (2019) estimates a term structure model on the prices of Treasury inflation-protected securities (TIPS) and adjusts for real term and liquidity premiums to estimate the NRI in the US. However, TIPS were first issued in 1997, which poses a problem for researchers requiring a NRI estimate over a longer sample. Alternative methods jointly model both real and nominal yield curves (e.g, Abrahams et al. 2016) to estimate over a larger sample. In addition to estimating a liquidity premium to account for the liquidity risk associated with inflation-indexed bonds, this requires additional modelling structure which increases the risk of model misspecification. The method I propose differs from the existing literature by using only nominal bond yields, rather than inflation-indexed yields. This results in a longer sample and does not require the estimation of a real term premium and liquidity premium, but rather requires the estimation of a nominal term premium. In summary, the financial market-based approach I propose is a useful complement to the macroeconomic methods previously discussed and contributes to the nascent literature that estimates the NRI using finance-based approaches.

3.3.2 General-to-specific modelling

I use a general-to-specific approach to identify long-run equilibrium determinants of the NRI.[11] General-to-specific modelling involves constructing a general unrestricted model (GUM) with many potentially relevant NRI determinants and using a multi-path search algorithm known as *Autometrics* to choose a parsimonious final model by selecting between relevant and irrelevant variables. This approach allows the data to determine the nature and stability of the relationship between the NRI and its equilibrium determinants and contrasts with the approach of focusing exclusively on individual NRI determinants.

[11] See Hendry and Doornik (2014) for a detailed description of the general-to-specific modelling framework.

I specify general unrestricted models (GUMs) of the form

$$r_t^* = \delta + \sum_{s=1}^{8} \gamma_s r_{t-s}^* + \sum_{j=0}^{8} \boldsymbol{\beta}_j \mathbf{X_{t-j}} + \epsilon_t, \tag{3.10}$$

where r_t^* is the NRI, δ is a constant, γ_s is the coefficient for lag s of the NRI, $\mathbf{X_t} = (p_t, n_t, k_t, u_t, d_t, s_t)'$ is a vector of posited NRI determinants (discussed in Sections 3.2 and 3.4) and $\boldsymbol{\beta_j}$ is the corresponding vector of coefficients for lag j. It is assumed that the GUM nests the local data generating process (LDGP), and under these conditions *Autometrics* consistently recovers the same model as if selection began from the LDGP. Although it is possible in the framework, I impose no theoretical restrictions on the relationship between the NRI and the posited determinants during model selection. Model selection consists of the following key steps (see Hendry and Doornik (2014) for more information).

- **GUM congruence:** The GUM (3.10) is the starting point for model selection. To check congruence of the GUM, *Autometrics* tests for residual normality, autocorrelation, autoregressive conditional heteroskedasticity, and parameter constancy. Provided that these tests do not indicate any notable misspecification, I proceed with model selection.

- ***Autometrics* settings:** I use a significance level of $\alpha = 0.01$, which defines the level at which variables must be significant to be retained during model selection. I also use a pre-search lag reduction, no sign restrictions, heteroskedasticity and autocorrelation-consistent (HAC) standard errors, and otherwise default *Autometrics* settings.[12]

- **Model selection:** Model reduction begins with the ranking of the explanatory variables in the GUM by their t^2-statistics. Every insignificant variable in the GUM defines a reduction path. For the first path, the variable with the smallest t^2-statistic is eliminated to form a new GUM. This procedure is repeated to progressively eliminate

[12] There is always the possibility of variables being incorrectly retained under automatic model selection. For a GUM with K explanatory variables, αK will be incorrectly retained. Thus, $\alpha = 0.01$ ensures that on average less than one variable is incorrectly retained in each country-level dynamic regression.

insignificant variables and reduce the GUM to a terminal model with only significant variables, which is then diagnostically checked (if the terminal model fails any diagnostic test the algorithm back-tracks to find an earlier valid model).

- **Tree search:** As the order of elimination can influence the final model selection, *Autometrics* uses a tree search algorithm to conduct multiple path-reduction searches. Equation (3.10) has 63 regressors, which implies a search space of 2^{63} ($> 9 \times 10^{18}$) possible model combinations when allowing for every variable to be selected over. The tree search algorithm tests all possible reduction paths by varying the order in which insignificant variables are deleted. This allows entire branches of possible models to be deleted which significantly narrows the search space, while also potentially leading to multiple terminal models being selected.

- **Encompassing principle:** The terminal models are checked for "parsimonious encompassing", which takes the form of an F-test of the reductions against the GUM. This ensures that the terminal model provides a parsimonious explanation of the GUM within which it is nested, conditional on the acceptable amount of information loss (determined by α). If model selection results in more than one terminal model, the final model is selected from the terminal models using the minimum Schwarz Criterion.

I use the final model to calculate the static long-run equilibrium relationship between r^* and its long-run determinants. Using a cointegration framework assumes that the NRI and its determinants are non-stationary processes (shown formally in the next section).[13] The deviation of r_t^* from its long-run equilibrium at time t is given by the disequilibrium term, ecm_t. If the ADF test indicates that the disequilibrium term is stationary based on

[13]This analysis also assumes that there is a single unique cointegrating vector and that the variables in $\mathbf{X}$ are weakly exogenous. Weak exogeneity implies the variables in $\mathbf{X}$ do not error-correct when there is disequilibrium in the long-run relationship. If this assumption is not met, estimation remains consistent but is less efficient than a model encompassing the entire system (Harris, 1995).

MacKinnon (2010) critical values, I conclude that model selection has identified the long-run equilibrium (cointegrating) relationship between the NRI and its determinants.[14]

I analyse the short-run dynamics through an ECM of the form

$$\Delta r_t^* = \boldsymbol{\phi} \Delta \mathbf{X_t} + \vartheta ecm_{t-1} + u_t, \tag{3.11}$$

where $\boldsymbol{\phi}$ is a vector of coefficients, $\Delta \mathbf{X_t}$ denotes the first differences of the variables and ecm_{t-1} is the disequilibrium term from the final model selected. The coefficient ϑ captures the speed with which the NRI error corrects back to its long-run equilibrium level.

3.4 Data

3.4.1 Natural rate of interest estimates

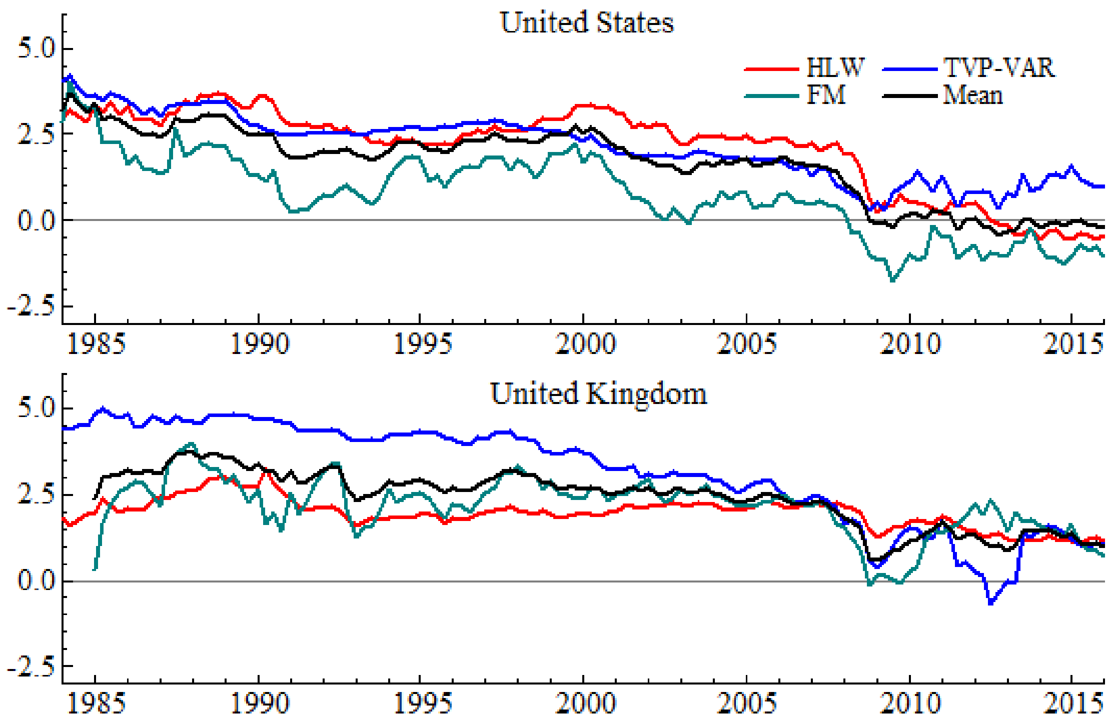
Figure 3.1 presents estimates of the NRI in the US and the UK over 1984 to 2016. Consistent with previous literature, the NRI in both economies averaged around 2–4 per cent over the Great Moderation, and declined sharply during the financial crisis and has remained around 2–4 percentage points lower since. The estimates provide robust evidence that the NRI has declined over time, and this is apparent across all estimation methods considered. As expected, the estimates differ across different methods, though appear to show a reasonable degree of co-movement.

Figure C.3 (in Appendix C.3) shows the financial market-based NRI decomposed into the 5-to-10-year nominal forward interest rate, expected inflation and the term premium. The 5-to-10-year forward rate has exhibited a secular decline over the sample period, while long-run inflation expectations appear to be well-anchored since the early 1990s. The term premium estimates have declined over the sample period in each economy and are broadly

[14] MacKinnon (2010) extends the critical values presented in Engle and Granger (1987) to a larger simulation and reports critical values for any finite sample size. The critical values account for the fact that, by construction, OLS effectively "chooses" the residuals to have the smallest variance, so they will appear as stationary as possible and lead to over-rejection of the null under a standard Dickey–Fuller distribution. Additionally, the distribution of the test statistic under the null depends on the number of $I(1)$ variables, so different critical values are needed as the number of $I(1)$ variables changes.

consistent with the previous literature.[15] However, in both economies the term premium rose sharply during the financial crisis as investors demanded additional compensation for interest rate risk, and this led to a sharp fall in the finance-based NRI estimate during 2007 and 2008 (as inflation expectations and forward interest rates remained relatively stable). Additional figures related to estimation of the NRI are shown in Appendix C.3.[16]

Figure 3.1: Natural Rate of Interest Estimates



Notes: FM denotes the financial market-based NRI estimate. The "mean" estimate corresponds to the arithmetic average of the HLW, TVP-VAR and FM estimates at each point in time.

[15]See Adrian et al. (2013) for alternative estimates for the US and Kaminska et al. (2015) for the UK. Joyce et al. (2012) attribute the decline in term premiums in the UK to a global "search for yield" associated with excess liquidity. Abrahams et al. (2016) find that quantitative easing by the Federal Reserve lowered US yields primarily by reducing real term premiums.

[16]In Appendix C.3, Figure C.1 displays the NRI estimation inputs (excluding GDP growth) for the HLW and TVP-VAR models over the full estimation sample 1960Q1–2016Q4. Figure C.4 displays the HLW and FM estimates alongside the TVP-VAR estimates with the associated 90% confidence region. Figure C.5 compares the HLW and TVP-VAR estimates computed with and without Krippner shadow rates (the observed policy rate is used instead of the shadow rate).

3.4.2 Posited determinants

Table 3.1 summarises the NRI determinants I analyse and how they're measured, together with their expected relationship based on economic theory (see Section 3.2). The data are quarterly and cover both economies over 1984Q1–2016Q4. Detailed data definitions and sources are provided in Appendix C.2.

Figure 3.2 plots the posited determinants over the period 1984–2016. As expected, there are some common themes across both economies. Productivity growth averaged around 2 per cent over the Great Moderation but has declined and remained at a lower level since the financial crisis, while public debt increased in both economies during the crisis. Economic policy uncertainty increased during the financial crisis and has also risen markedly in the UK at the end of the sample alongside concerns around the UK leaving the European Union. Foreign exchange reserve accumulation increased sharply over the 2000s, led primarily by demand for safe assets by emerging markets.[17] There are two noteworthy differences between the two economies: the relative price of capital has declined by around 25% in the US over the sample, while it has fluctuated around its average in the UK; population growth has declined from the early 1990s in the US alongside an increase in the UK over the same period.[18]

3.4.3 Non-stationarity and cointegration

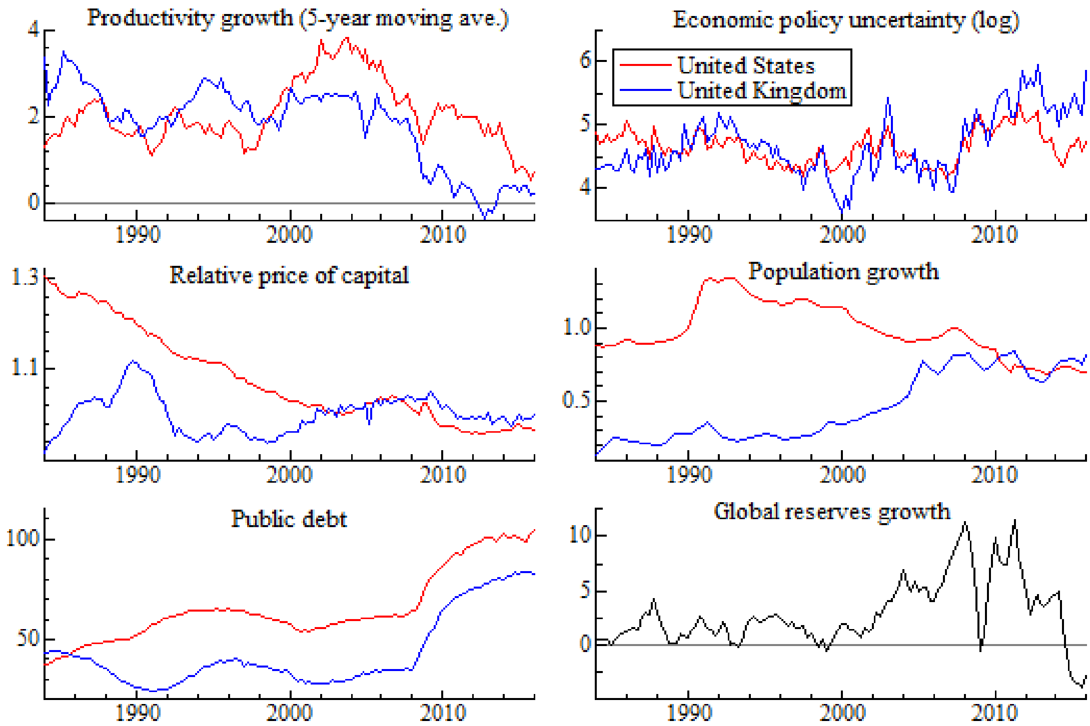
In order to formally test for any economic relationships, it is necessary to identify any non-stationary $I(1)$ processes. I conduct augmented Dickey–Fuller (ADF) unit root tests on all four NRI series and the posited determinants for each economy.

ADF unit root tests provide no evidence against the null hypothesis that the NRI in levels is non-stationary, and this holds across all NRI estimates for both economies.

[17]Figure C.2 in Appendix C.3 shows the relative contribution of advanced and emerging economies to global foreign exchange reserves growth.

[18]The different trends in the relative price of capital in the US and the UK is surprising given the decline is likely, at least in part, due to common global forces (e.g. shift towards information technology). Figure 8 in Thwaites (2015) indicates a notable decline in the relative price of capital in the UK since the mid 1980s. Nevertheless, my results are qualitatively similar when I measure the relative price of capital as the gross fixed capital formation deflator divided by either the GDP deflator or consumer price index.

Figure 3.2: Posited Determinants



Notes: Data are quarterly. Productivity growth is the 20-quarter moving average of the quarterly growth rate (annualised). Relative price of capital is indexed to 1984Q1–2016Q4 average = 1. Population growth is annual. Economic policy uncertainty index from Baker et al. (2016) is in log terms.

Furthermore, I find no evidence against non-stationarity for the NRI determinants. ADF tests on the first differences for all variables provide evidence against the null hypothesis of non-stationarity in first differences (for full results, see Table C.1 in Appendix C.3). Thus, I conclude that the NRI and its determinants are $I(1)$ processes. This is reassuring and supports my approach of modelling the equilibrium determinants of the NRI within a cointegrating framework.

In a literal sense, a non-stationary specification for interests rates is unlikely given nominal interest rates have been bounded for centuries. However, in finite samples, imposing a unit root is a common way to account for a secular trend in a dynamic model, and a persistent stationary process can be approximately arbitrarily well by a unit root process (Bauer and Rudebusch, 2020). Consequently, it is common in macroeconomic models to assume that the NRI is non-stationary (e.g. Laubach and Williams 2003).

Are the NRI estimates cointegrated?

The NRI estimates differ across estimation method for each economy, however they appear to exhibit a degree of co-movement over time (see Figure 3.1). More formally, the ADF tests indicated the NRI estimates are $I(1)$ processes, therefore if the NRI estimates contain the *same* unit root, the series are said to be cointegrated. Cointegrated series may deviate in the short-run but will move together over time around a common stochastic trend (Harris, 1995). I test for cointegration between the HLW, TVP-VAR, and FM estimates for each economy over 1984Q1–2016Q4 using the Johansen (1988) procedure.

The Johansen procedure sequentially tests to identify the rank of the coefficient matrix corresponding to the first lag in the vector error correction model of the three NRI series. The rank, r, is the number of cointegrating vectors, and $r > 0$ implies a cointegrating relationship between the NRI series. The first hypothesis tested in the Johansen procedure, $r = 0$, is a test of the null hypothesis of no cointegration against the alternative hypothesis of cointegration. In both economies, I find evidence against the null hypothesis (for full results, see Table C.2 in Appendix C.3). However, I fail to reject that $r \leq 1$ at the 10% level, for both the trace and maximum eigenvalue tests, and therefore conclude that in each economy there is one cointegrating vector. The presence of cointegration implies that while the NRI estimates for each economy differ, the differences between them are stationary deviations around a common stochastic trend.

3.5 Results

This section outlines the results for the long-run equilibrium and short-run NRI determinants. Statistically significant results should be interpreted as evidence of a correlation which does not necessarily imply causation. Most notably, I find evidence of a negative relationship between the NRI and economic uncertainty, and a positive relationship between the NRI and both productivity growth and the relative price of capital, which are all consistent with economic theory.

3.5.1 Long-run determinants

Tables 3.2 and 3.3 display the long-run equilibrium relationship in the US and the UK, respectively. Model selection has resulted in well-specified final models that satisfy diagnostic tests for autocorrelation, normality and heteroskedasticity at the 1 per cent level. The Wald test provides very strong evidence against the hypothesis that all the long-run coefficients equal zero. The ADF tests on the disequilibrium term provide strong statistical evidence against the null hypothesis of no cointegration in all cases.

Table 3.2: Long-run Equilibrium Relationship - United States

Dependent variable:	HLW	TVP-VAR	FM	Mean
Productivity	0.76***	0.38*	0.20*	0.34***
growth (p)	(0.20)	(0.20)	(0.12)	(0.09)
Relative price	7.41***	0.87	5.02***	5.98***
of capital (k)	(1.69)	(1.81)	(1.21)	(0.67)
Population		1.33**	-0.25	0.38*
growth (n)		(0.55)	(0.26)	(0.19)
Economic policy	-1.56**	-0.71	-1.12***	-1.11***
uncertainty (u)	(0.66)	(0.63)	(0.23)	(0.25)
Public	-0.008	-0.04***	-0.02***	-0.01*
debt (d)	(0.014)	(0.013)	(0.008)	(0.005)
Global		-0.11***	-0.05***	-0.05***
reserves (s)		(0.04)	(0.02)	(0.02)
Autocorrelation (p-value)	0.65	0.88	0.63	0.28
Normality (p-value)	0.98	0.09	0.61	0.45
Heteroskedasticity (p-value)	0.05	0.03	0.93	0.88
Static long-run $\hat{\sigma}$	0.96	0.66	0.46	0.35
Wald test: $\chi^2(K)$	361***	379***	507***	2224***
Sample	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4
Observations	132	132	132	132
Cointegration testing				
ADF test statistic	-8.19***	-8.29***	-7.00***	-6.86***

Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium. For the ADF test, lag length was selected using the AIC and finite-sample critical values taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

I find a significant negative long-run equilibrium relationship between the NRI and economic policy uncertainty in both economies. Economic uncertainty increased by 75%

Table 3.3: Long-run Equilibrium Relationship - United Kingdom

Dependent variable:	HLW	TVP-VAR	FM	Mean
Productivity	-0.04	0.55***	0.41***	0.18***
growth (p)	(0.05)	(0.21)	(0.09)	(0.06)
Relative price	5.35***	13.06***	1.54**	4.13***
of capital (k)	(0.60)	(2.46)	(0.69)	(0.45)
Population	-0.89***	-4.88***	-1.02**	-2.04***
growth (n)	(0.16)	(0.62)	(0.39)	(0.24)
Economic policy	-0.16**	-0.40	-0.13	-0.18**
uncertainty (u)	(0.08)	(0.32)	(0.14)	(0.09)
Public	-0.009**	0.01	0.002	-0.007**
debt (d)	(0.003)	(0.010)	(0.005)	(0.003)
Global	0.03	-0.10***	-0.11***	0.007
reserves (s)	(0.01)	(0.03)	(0.03)	(0.02)
Autocorrelation (p-value)	0.48	0.68	0.73	0.68
Normality (p-value)	0.07	0.07	0.02	0.15
Heteroskedasticity (p-value)	0.17	0.05	0.02	0.13
Static long-run $\hat{\sigma}$	0.16	0.68	0.40	0.29
Wald test: $\chi^2(K)$	352***	339***	3312***	7475***
Sample	1984:1-2016:4	1984:1-2016:4	1987:1-2016:4	1984:1-2016:4
Observations	132	132	120	132
Cointegration testing				
ADF test statistic	-8.91***	-8.30***	-7.60***	-8.11***

Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium, including indicator variables. For the ADF test, lag length was selected using the AIC and finite-sample critical values taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

and 120% in the US and the UK, respectively, between 2007 and 2011. The range of long-run coefficient estimates indicates that this is associated with a permanent decline in the long-run equilibrium NRI of around 0.5–1.2 and 0.0–0.5 percentage points in the US and the UK respectively, holding all else constant. This is consistent with the narrative (e.g., see the speech by Carney 2017) that increased economic uncertainty throughout the financial crisis and Great Recession has led to a decline in the NRI. However, these results indicate correlations and do not imply causation. The decline in the NRI during the financial crisis may, to some extent, have led to an increase in economic policy uncertainty (for example, as central banks shifted to unconventional policy). More recently, the results suggest that the sharp increase in economic policy uncertainty alongside COVID-19 would be associated with a further decline in the NRI. To my knowledge, this is the first paper to document evidence of a negative relationship between economic uncertainty and the NRI. I investigate this further in Section 3.6.1 and find that in the US there is also strong evidence of a negative correlation between the NRI and macroeconomic uncertainty, while there is no consistent evidence of a relationship between the NRI and financial uncertainty.

The results indicate a positive and statistically significant relationship between productivity growth and the NRI, consistent with economic theory. However, the coefficient magnitude is smaller than the one-for-one relationship often used in theoretical models.[19] For example, a 1 percentage point decrease in domestic productivity growth would be associated with a 0.2–0.8 percentage point decline in the US NRI, holding all else constant. As productivity growth is a key determinant of potential output growth, this finding is consistent with that of Lunsford and West (2019), Hamilton et al. (2015) and Kiley (2020), who all find that the relationship between the NRI and potential output is weaker than suggested by economic theory. In general, there are not economically significant differences in the correlation across different NRI estimation methods, which is interesting given that the HLW method assumes that potential growth is a primary determinant of the NRI (see equation (3.5)), whereas the FM measure is based on information from the yield curve.

The results indicate a statistically and economically significant long-run equilibrium relationship between the relative price of capital and the NRI. The coefficient magnitudes are broadly similar in both economies, despite the fact that the relative price of capital has declined by 25% over the sample in the US, but has only declined by 10% in the UK since its peak in the late 1980s (see Figure 3.2). The results indicate that the decline in the relative price of capital in the US has been associated with around a 1.8 percentage point fall in the NRI over the sample. This is consistent with the model predictions in Sajedi and Thwaites

[19] In equation (3.1), assuming the inverse intertemporal elasticity of substitution $\sigma = 1$, the equation implies a one-for-one relationship between productivity growth and the equilibrium real interest rate. Intuitively, (3.1) implies a given decline in the productivity growth rate is associated with a commensurate decline in the equilibrium real interest rate (assuming $\sigma = 1$).

(2016) and Rachel and Smith (2017) and the narrative advocated by Summers (2014) that a decline in the relative price of capital has led to reduced investment demand, causing the NRI to fall. However, Lunsford and West (2019) do not find evidence of a statistically significant correlation between the relative price of capital and real interest rates.

Population growth has a statistically significant negative relationship with the NRI in the UK, while there is weak evidence of a positive relationship in the US. Economic theory makes no clear predictions on the relationship between population growth and the NRI. As discussed in Section 3.2, an increase in population growth decreases capital per worker, which exerts upward pressure on real interest rates through a rise in the marginal product of capital. However, a higher population growth rate will eventually lead to a lower dependency ratio, which will decrease real interest rates (Carvalho et al., 2016). One could argue that it is more likely that the latter effect dominates in the UK, as population growth over the sample has been determined to a greater extent by immigration of working-age individuals, rather than natural increase, and therefore the effect via the dependency ratio channel may be more important.[20] Further examination of the relative importance of the channels through which population growth affects the NRI would be an interesting avenue for further research.

The results suggest there is some evidence of a negative long-run relationship between global reserves accumulation and the NRI which is consistent with the "savings glut" hypothesis and an increased demand for safe assets. The range of estimates suggest that the increase in global reserves growth over the 2000s was associated with a fall in the NRI of up to 0.7 percentage points in both economies. This is broadly in line with estimates from Rachel and Smith (2017) who find the emerging market savings glut led to a decline in the global NRI of around 0.25 percentage points.

There is also some evidence of a negative long-run relationship between the NRI and public debt. This is inconsistent with economic theory (in a non-Ricardian economy) which

[20] Cangiano (2018) estimates that more than half of the UK's population growth between 1991 and 2016 was the result of net migration.

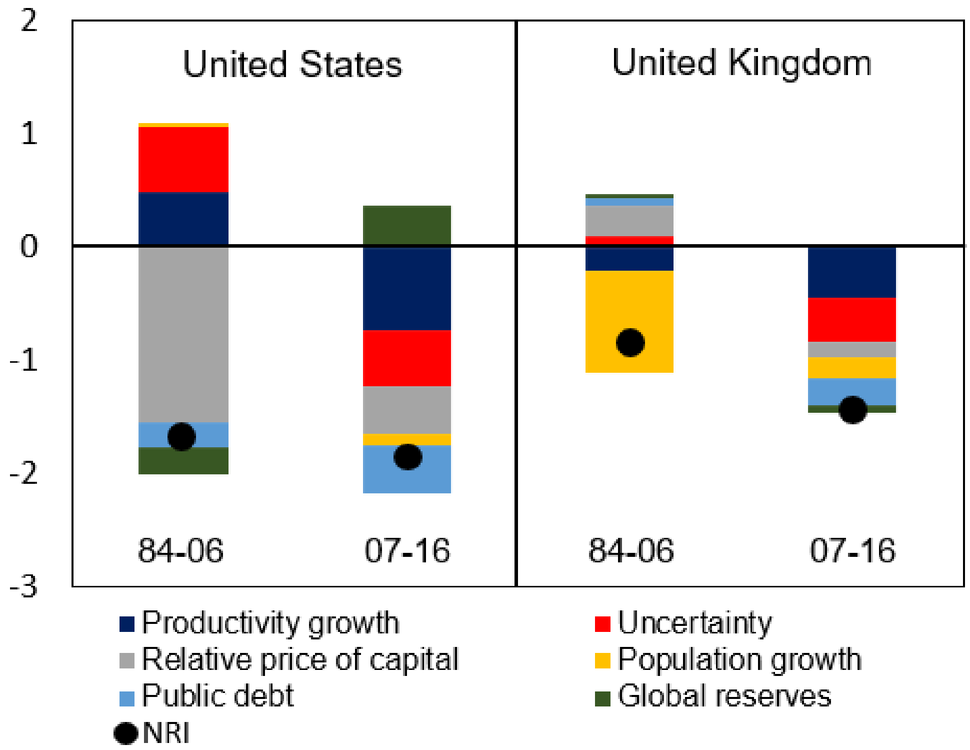
suggests a positive relationship. However, in Section 3.6 I show that this result is sensitive to the sample period. In general, there is not consistent statistical evidence of a relationship between public debt and the NRI.

Which determinants are most important? Figure 3.3 displays the long-run partial equilibrium contribution of each NRI determinant to the decline in the NRI over 1984 to 2006 and 2007 to 2016.[21] The sample periods are chosen to capture two major shifts in the NRI which broadly coincide with 1) the Great Moderation and 2) the financial crisis and following economic recovery. This figure shows how the movements of each NRI determinant, scaled by the estimated long-run coefficient, is associated with the decline in the NRI. In the US, the 1.7 percentage point decline in the NRI over 1984 to 2006 was largely associated with a notable decline in the relative price of capital, while the increase in productivity growth and decline in economic uncertainty over this period each indicate an increase in the NRI of around 0.5 percentage points. Over 2007 to 2016, the 1.8 percentage point fall in the NRI coincided with lower productivity growth and heightened economic policy uncertainty that were associated with a decline in the NRI of 0.7 and 0.5 percentage points, respectively. In addition, a continued fall in the relative price of capital and higher public debt over 2007 to 2016 were associated with falls in the NRI of around 0.4 percentage points.

In the UK, the NRI fell approximately 0.8 and 1.5 percentage points over 1984 to 2006 and 2007 to 2016, respectively. The right panel of Figure 3.3 shows that the increase in population growth over 1984 to 2006 was associated with a 1 percentage point decline in the NRI, while a rise in the relative price of capital suggested an increase in the NRI. Over 2007 to 2016, as in the US, lower productivity growth and an increase in economic policy uncertainty were associated with a decline in the NRI of 0.3 and 0.4 percentage points, respectively, while movements in each of the other NRI determinants were also correlated with smaller declines in the NRI.

[21] Note that the long-run partial equilibrium contributions do not sum to the total change in the NRI due to the unexplained long-run variation and the short-run variation around the long-run equilibrium.

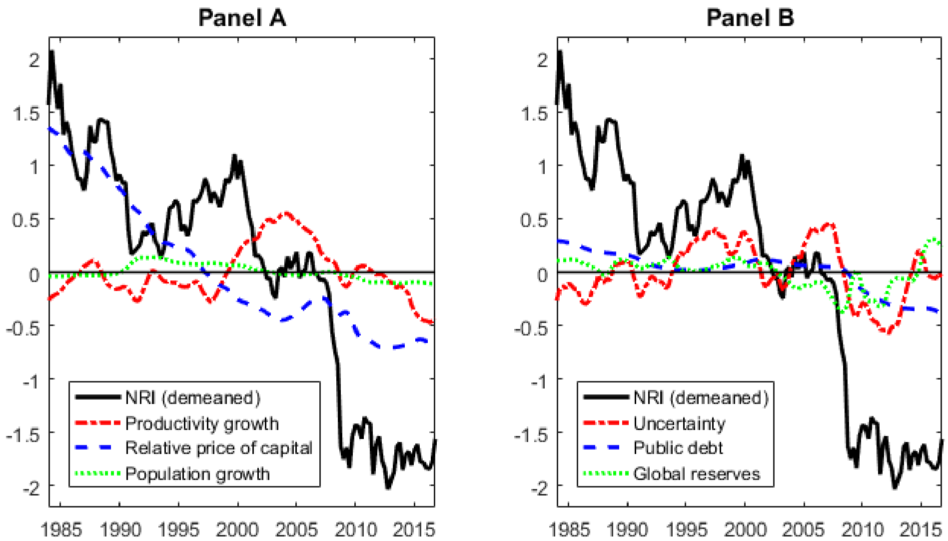
Figure 3.3: Relative Contribution of Determinants



Notes: Figure shows the relative contributions to the decline in the NRI implied by the long-run equilibrium coefficients for the mean NRI estimate. Note that the long-run partial equilibrium contributions do not sum to the total change in the NRI due to the unexplained variation and short-run dynamics.

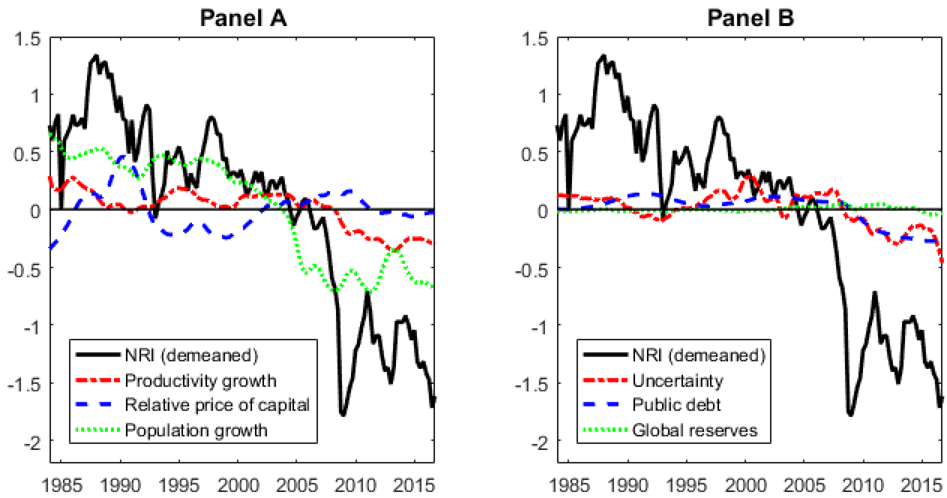
An alternative approach to decompose movements in the NRI is to plot the partial equilibrium long-run influences on the NRI over the sample. Figure 3.4 shows that in the US, the relative price of capital, productivity growth and economic uncertainty appear to be particularly important long-run influences on the NRI. In particular, the decline in the relative price of capital over the sample correlates with a 1.8 percentage point fall in the NRI, while the fall in productivity growth since the mid 2000s and increase in policy uncertainty over 2007 to 2011 are both associated with a decline in the NRI of around 1 percentage point. Figure 3.5 shows that in the UK, the increase in population growth over the sample has been associated with a 1 percentage point fall in the NRI, while lower productivity growth and the increase in economic policy uncertainty following the financial crisis were associated with a decline in the NRI of 0.3 and 0.4 percentage points.

Figure 3.4: Natural Rate of Interest Decomposition - United States



Notes: Figure shows the demeaned contributions from the NRI determinants. The contribution is calculated as the four-quarter moving average of: $\beta_i(x_{it} - mean(x_i))$ where β_i is the long-run coefficient on variable x_i. NRI corresponds to the mean estimate of the HLW, TVP-VAR and FM measures.

Figure 3.5: Natural Rate of Interest Decomposition - United Kingdom



Notes: Figure shows the demeaned contributions from the NRI determinants. The contribution is calculated as the four-quarter moving average of: $\beta_i(x_{it} - mean(x_i))$ where β_i is the long-run coefficient on variable x_i. NRI corresponds to the mean estimate of the HLW, TVP-VAR and FM measures.

3.5.2 Short-run determinants

Tables 3.4 and 3.5 display the results from the ECM equation (3.11) for the US and the UK. Firstly, the speed of adjustment to disequilibrium $\hat{\vartheta}$ (see the ecm_{t-1} row) is negative and statistically significant at the 1 per cent level in all cases. The speed of adjustment varies across country and with different NRI estimates but is typically around a 30–50% adjustment to disequilibrium in each quarter. This implies a half-life to eliminate any deviation from equilibrium of around 1–2 quarters, which suggests that the NRI adjusts reasonably quickly to any deviation from its long-run equilibrium.[22]

Table 3.4: Short-run Error-correction Model - United States

	HLW	TVP-VAR	FM	Mean
Δp_t	0.12*	0.07	0.17	0.12**
	(0.07)	(0.09)	(0.15)	(0.06)
Δk_t	-12.30***	-0.99	-0.44	-4.71**
	(2.56)	(2.51)	(4.42)	(2.05)
Δn_t	-0.06	-0.83	-1.62	-0.60
	(0.81)	(0.89)	(1.06)	(0.63)
Δu_t	-0.12	-0.21**	-0.54***	-0.35***
	(0.09)	(0.09)	(0.21)	(0.09)
Δd_t	-0.06***	-0.02	-0.04**	-0.05***
	(0.01)	(0.02)	(0.02)	(0.01)
Δs_t	-0.005	-0.000	0.01	0.000
	(0.01)	(0.01)	(0.02)	(0.01)
ecm_{t-1}	-0.36***	-0.60***	-0.55***	-0.33***
	(0.11)	(0.18)	(0.11)	(0.10)
Half-life (quarters)	1.6	0.8	0.9	1.7
$\hat{\sigma}$	0.15	0.17	0.32	0.15
R^2	0.42	0.20	0.22	0.32
Sample	1984:2-2016:4	1984:2-2016:4	1984:2-2016:4	1984:2-2016:4
Observations	131	131	131	131

Notes: HAC standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively.

The results indicate a negative relationship between changes in economic uncertainty and the NRI in all cases. This suggests that a rise in economic uncertainty not only reduces the NRI through its effect on the long-run equilibrium, but also has a significant short-run impact in the US and the UK. Changes in productivity growth have a positive, albeit relatively small, impact in both economies, consistent with economic theory. There is some evidence that changes in the rate of global reserve accumulation have a positive impact on

[22]The half-life is calculated as $ln(0.5)/ln(1+\hat{\vartheta})$ following Rossi (2005) and is an intuitive measure to explain what the speed of adjustment implies for any deviation from the long-run equilibrium.

the NRI in the UK, which is inconsistent with economic theory, though I find no evidence of a short-run relationship in the US. I find no compelling evidence that changes in the population growth rate affect the NRI in the short-run.

Table 3.5: Short-run Error-correction Model - United Kingdom

	HLW	TVP-VAR	FM	Mean
Δp_t	0.08	0.34***	0.07	0.08
	(0.07)	(0.08)	(0.21)	(0.07)
Δk_t	0.58	-0.24	-4.51*	-0.90
	(0.88)	(1.34)	(2.30)	(1.12)
Δn_t	0.19	2.46	-1.66	-0.04
	(0.53)	(1.37)	(1.38)	(0.68)
Δu_t	-0.06**	-0.20***	-0.15*	-0.15***
	(0.03)	(0.07)	(0.08)	(0.05)
Δd_t	-0.01	0.01	-0.05	-0.02
	(0.007)	(0.01)	(0.03)	(0.01)
Δs_t	0.04***	0.05**	0.02	0.04***
	(0.01)	(0.02)	(0.02)	(0.01)
ecm_{t-1}	-0.24**	-0.56***	-0.39***	-0.43***
	(0.04)	(0.10)	(0.13)	(0.04)
Half-life (quarters)	2.5	0.8	1.4	1.2
$\hat{\sigma}$	0.12	0.21	0.35	0.14
R^2	0.19	0.35	0.14	0.20
Sample	1984:2-2016:4	1984:2-2016:4	1987:2-2016:4	1984:2-2016:4
Observations	131	131	119	131

Notes: HAC standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively.

3.5.3 Discussion

There is significant evidence for both the US and the UK of a negative long-run relationship between the NRI and economic policy uncertainty, while both productivity growth and the relative price of capital are positively related to the NRI. The decline in the NRI over the sample has predominantly been associated with a persistent decline in the relative price of capital in the US and an increase in population growth in the UK. Since the 2007–2008 financial crisis, the fall in the NRI in both economies was largely associated with a decline in productivity growth and heightened economic uncertainty.

The empirical results are informative for macroeconomic theory. In particular, there is strong evidence of a negative relationship between economic uncertainty and the NRI. The sign is consistent with models of aggregate saving and investment, but policy uncertainty does not typically play a role in mainstream macroeconomic models. Utility preferences that separate risk aversion from intertemporal substitution, such as Epstein and Zin (1991), typically suggest a negative relationship between the real interest rate and the expected variance of the market portfolio which suggests one possible explanation of the effects of economic uncertainty on the NRI. In addition, the relationship between productivity growth and the NRI is weaker than often assumed in theoretical models. Consistent with the findings and recommendations of both Lunsford and West (2019) and Hamilton et al. (2015), this suggests that other factors in addition to trend productivity growth are important in explaining movements in the NRI. For example, there is strong evidence that a secular decline in the relative price of capital is associated with a fall in the NRI. Incorporating these findings into structural models may shed further light on the effects highlighted here and help clarify how the various effects interact, in addition to allowing interesting policy experiments.

The decline in the NRI since the 1980s implies less scope for central banks to lower interest rates and suggests that the ELB may remain an important threat to future monetary policy. However, the future level of the NRI depends, to a large degree, on the evolution of the NRI determinants that have led to the decline. To the extent that these correlations hold going forward, policies that increase productivity growth and reduce policy uncertainty (for example, transparent economic policy communication) will, holding all else constant, be associated with an increase in the NRI. There is no consensus over the future path for the relative price of investment goods. Rachel and Smith (2017) weigh the evidence and conclude that it is likely that the relative price of investment will continue to decline, albeit at a lower rate, which suggests this will continue to contribute to a lower NRI. In addition, increases in the net supply of safe assets would also be associated with a higher NRI.

3.6 Extensions and Robustness

This section begins by examining how the NRI is related to different sources of uncertainty before analysing the robustness of the findings along a number of dimensions. I consider the long-run equilibrium robustness to (1) recursive estimation over smaller samples, (2) different measures of productivity growth, the emerging market savings glut and the relative price of capital, (3) different automatic model selection settings, and (4) the use of Wu and Xia (2016, 2017) shadow rates. In each instance, the overriding conclusions from Section 3.5 remain largely intact. All tables and figures relating to this section are in Appendix C.3.

3.6.1 Does the type of uncertainty matter?

The previous section documented a statistically significant negative relationship between the NRI and economic uncertainty. The proxy for economic uncertainty used in the baseline reflects "economic policy uncertainty-related" key words in news publications (Baker et al., 2016). Consequently, the index reflects uncertainty related to economic policy, although it is commonly used in empirical work as a proxy for a broad measure of economic uncertainty. A key challenge in empirically examining the macroeconomic implications of uncertainty is that no objective measure of uncertainty exists. Jurado et al. (2015) and Ludvigson et al. (2018) construct proxies of macroeconomic and financial uncertainty for the US by measuring variation in the predictability of a large series of macroeconomic and financial variables.[23] In this subsection I investigate the relationship between the NRI and economic policy, macroeconomic and financial uncertainty in the US.

Figure C.6 plots the economic policy, macroeconomic and financial uncertainty series over 1984–2016. The three series positively covary but also exhibit notable independent variation as the correlation between the macroeconomic and financial series with the policy

[23]The macroeconomic uncertainty index measures a common component in the time-varying volatility of forecast errors from a large dataset of 132 macroeconomic series. The financial uncertainty index is estimated using the same approach on a dataset of 147 financial variables. Unit root tests indicate that the series are $I(1)$ processes over the sample (see Table C.1).

series is only 0.31 and 0.40, respectively. It is possible that the NRI is only related to specific types of uncertainty. I investigate this for the US by adding the macroeconomic and financial uncertainty indices to the GUM (3.10) and proceed with model selection as in the baseline.[24]

The long-run equilibrium estimated coefficient on economic policy uncertainty is significant at the 1 per cent level in all cases and similar in magnitude to the baseline (see Table C.3). There is also strong evidence of a negative relationship between macroeconomic uncertainty and the NRI, and the coefficient is typically similar in magnitude to the coefficient on economic policy uncertainty. There is no strong statistical evidence of a consistent relationship between financial uncertainty and the NRI. The estimated long-run coefficients on the other NRI determinants are qualitatively similar to the baseline. Taken together, the results provide strong statistical evidence of a negative correlation between the NRI and both economic policy and macroeconomic uncertainty, while there is no consistent evidence of a relationship between the NRI and financial uncertainty.

3.6.2 Sub-sample stability

The baseline sample period covers 1984Q1–2016Q4. To investigate the stability of the long-run equilibrium over the full sample, I estimate the equilibrium recursively over 2007Q1–2016Q4.[25] Figures C.7 and C.8 show recursive estimates of the long-run equilibrium coefficients with 68 and 95 per cent confidence bands in the US and the UK, respectively. In general, the coefficients appear reasonably stable and there is not much variation in the size of the standard errors. In the US, the coefficient on productivity growth becomes larger as the sample expands, while the population growth coefficient fluctuates in sign and is not statistically significant which further confirms the baseline finding that there is not

[24]Specifically, I include in the GUM the component of macroeconomic and financial uncertainty that is orthogonal to the other uncertainty indices. By the Frisch-Waugh-Lovell theorem this leads to the same long-run coefficient estimates in theory, but given the size of the GUM this will allay any concerns around multicollinearity impacting the model selection procedure.

[25]The first sample is 1984Q1-2007Q1, I then perform successive regressions moving forward one quarter at a time. To ensure the specification remains constant for each regression, in each case the long-run equilibrium is estimated from a dynamic regression model with 2 lags.

consistent statistical evidence of a relationship between population growth and the NRI in the US. Overall, the main conclusions do not substantively change when the equilibrium is estimated recursively, indicating that the long-run equilibrium relationship is stable.

3.6.3 Alternative measures of determinants

To analyse the sensitivity of the results to the specific measures of posited determinants, I estimated the long-run equilibrium as in the baseline, however I measure productivity growth by GDP per worker (20-quarter moving average), the savings glut as the emerging market current account surplus as a share of US GDP (Rachel and Smith, 2017), and in the US the relative price of capital is measured as the producer price index for capital equipment divided by the GDP deflator (Summers, 2014). The main results for productivity growth, economic policy uncertainty and the relative price of capital are qualitatively similar to the baseline for both economies (see Tables C.4 and C.5 for full results). However, there is only evidence of a relationship between the emerging market current account surplus and the NRI in one instance (for the US TVP-VAR estimate). In addition, for the UK FM estimate, model selection fails to find evidence of a long-run cointegrating relationship. Overall, the overriding conclusions remain largely unchanged when these alternative measures are used.[26]

3.6.4 Automatic model selection settings

To investigate the sensitivity of the results to the specific automatic model selection choices made, I re-estimated the long-run equilibrium relationship with 4 lags in the GUM instead of 8, no pre-search lag reduction and a significance level of $\alpha = 0.025$ instead of $\alpha = 0.01$. Overall, the long-run equilibrium results in both the US and the UK are qualitatively similar

[26] I also considered a model with real consumption per capita growth (20-quarter moving average) instead of productivity growth. In each economy, I only found evidence of a statistically significant positive relationship for the HLW measure (coefficients of 0.32 and 0.44 for the US and the UK, respectively). Full results available on request.

under these alternative model selection settings (see Tables C.6 and C.7).[27]

3.6.5 Wu and Xia (2016) shadow rates

There is no consensus on the most accurate measure of the (unobservable) shadow rate. Indeed, Krippner (2020) shows that both the level and profile of shadow rate estimates are very sensitive to model specification and suggests that researchers should consider multiple different shadow rates in their empirical analyses. Consequently, in addition to estimating the NRI using Krippner shadow rates in the baseline, I estimated the NRI using both the HLW and TVP-VAR methods with Wu-Xia shadow rates (see Figure C.9 for a graphical comparison and Appendix C.1 for further details on the methodological differences between the two approaches). The HLW estimates in both economies are very similar under the two shadow rate estimates considered. The TVP-VAR estimates in the US are also similar, however in the UK the NRI estimate using Wu-Xia shadow rates is significantly below the estimate using Krippner shadow rates over 2009–2016. Figure C.9 shows that the Wu-Xia shadow rates are 2–3 percentage points below the Krippner shadow rates at the end of the sample in the UK, which has led the TVP-VAR to estimate a significantly lower NRI.

Table C.8 displays the long-run equilibrium relationship in the US and the UK when Wu-Xia shadow rates are used. In the US, the results are very similar to those calculated with Krippner shadow rates. In the UK, the HLW estimates are similar to the baseline, however I no longer find evidence of a long-run relationship between population growth and the NRI. For the TVP-VAR estimate in the UK, model selection fails to find evidence of a long-run cointegrating relationship and the long-run coefficients are estimated imprecisely and not significantly different from zero. Overall, the NRI estimates and long-run determinants are robust to the use of Wu-Xia shadow rates in the US and for the HLW estimate in the UK,

[27] Testing the sensitivity of the results to model selection settings is prudent, however note that this may also adversely impact the model selection procedure. For instance, as the unit of time for agents' interactions has not been theoretically derived, shortening the GUM lag length may not provide enough time to accurately capture dynamic interactions. However, the resulting lower number of regressors means that, on average, 34 x 0.025 = 0.85 variables will be incorrectly retained during model selection, which is similar to the baseline.

but the TVP-VAR estimates for the UK are materially different when using Wu-Xia shadow rates.

3.7 Conclusion

I empirically analyse the determinants of the NRI between 1984 and 2016 in the US and the UK. In order to analyse the determinants, I estimate the NRI for each economy using a semi-structural model, a TVP-VAR, and a novel financial market-based measure. The NRI estimates are used to analyse their determinants via country-level dynamic regressions using a general-to-specific methodology.

I document robust evidence of a negative relationship between the NRI and economic uncertainty in both the US and the UK. The results suggest that increased economic uncertainty during the financial crisis was associated with a permanent decline in the NRI of around 0.5–1.2 and 0.0–0.5 percentage points in the US and the UK, respectively. In addition, both productivity growth and the relative price of capital are positively related to the NRI, consistent with economic theory. The decline in the NRI over 1984 to 2016 has predominantly been associated with a persistent decline in the relative price of capital in the US and an increase in population growth in the UK. Since the 2007–2008 financial crisis, the approximately 1.5–2 percentage point fall in the NRI in both economies was largely associated with lower productivity growth and heightened economic policy uncertainty.

The results in this chapter are informative for both macroeconomic theory and policy. Formally incorporating these findings into structural models may shed further light on the effects highlighted here and allow interesting policy experiments. To the extent that these correlations hold going forward, policies that increase productivity growth and reduce policy uncertainty through improving economic policy communication will, holding all else constant, be associated with an increase in the NRI.

Appendix A

Chapter 1 Appendix

A.1 Theoretical Motivation

This section of the appendix discusses different theoretical mechanisms that explain why an economy may respond asymmetrically to monetary policy shocks.

Convex short-run aggregate supply curve

If an economy exhibits a convex short-run aggregate supply (AS) curve, the effects of monetary policy depend on which portion of the supply curve the economy is facing. Convexity implies that the slope of the AS curve is steeper at higher levels of output and prices than at lower levels. Thus, shifts in aggregate demand (AD) that are driven by changes in monetary policy will have a stronger (weaker) effect on output and a weaker (stronger) effect on prices in recessions (expansions).

Numerous classes of models give rise to a convex short-run AS curve.[1] For example, in a capacity constraint model, as the economy expands, firms find it increasingly difficult to produce in the short run, and inflation becomes more sensitive to AD shifts at higher rates of capacity utilisation (Peersman and Smets, 2001). Alternatively, Daly and Hobijn (2014) show that both the slope and curvature of the Phillips curve depend on the extent

[1] Alternatively, Vavra (2014) suggests that the slope of the Phillips curve depends on the state of the economy. He argues that recessions are characterised by high volatility, which leads to increased aggregate price flexibility and a steepening of the Phillips curve. In such an environment, expansionary monetary policy will mostly generate inflation rather than output growth (the opposite of the case with a convex AS curve).

of downward nominal wage rigidities in the economy.[2] Their model simulations point to two mechanisms through which downward nominal wage rigidities bend the Phillips curve. Firstly, in recessions the rigidities become more binding and labour market adjustment primarily occurs through increasing unemployment instead of wage adjustment. Secondly, the presence of downward nominal wage rigidities during recessions leads to notable pent-up wage deflation, which results in lower wage inflation and a faster decline in the unemployment rate during the following economic recovery.

Durable goods consumption

Empirical evidence suggest that the response of activity to monetary policy is largely driven by the durable goods sector (Sterk and Tenreyro, 2018). McKay and Wieland (2019) and Berger and Vavra (2015) develop heterogeneous agent models where households' willingness to hold durable goods declines during recessions, and this implies that households are less sensitive to monetary stimulus during recessions. For example, in the McKay and Wieland (2019) model of durable consumption demand, monetary policy actions induce an intertemporal trade-off in aggregate demand as encouraging households to adjust today leaves fewer households demanding durable goods in the future. In a recession, a shock to durable demand means there are fewer households near the adjustment threshold, so monetary policy loses power.

Credit market imperfections

Models that include credit market imperfections generally suggest that a given interest rate change has more impact on the economy during a recession. These models assume that asymmetric information between lenders and borrowers leads to an external finance premium that is negatively correlated with the borrowers' net worth. The dependence of the external finance premium on the borrowers' net worth gives rise to a 'financial accelerator' propagation mechanism (developed by Bernanke and Gertler 1989). During an

[2]Downward nominal wage rigidities are well documented. See, for example, Dickens et al. (2007) for cross-country empirical evidence using micro-level data.

expansion, firms have strong balance sheets and can largely finance themselves via retained earnings, which leads to a low external finance premium and mitigates the financial accelerator mechanism. In contrast, in a recession, firm net worth falls, and therefore they are more dependent on external finance. Consequently, the associated premium will be more sensitive to changes in interest rates, and monetary policy shocks should have larger effects during recessions (Peersman and Smets, 2001).

Changes in the economic outlook

The effects of monetary policy may depend on the time-varying level of business and consumer confidence in an economy. If agents are more or less pessimistic during recessions than they are optimistic during economic booms, this will lead to state dependence in the monetary policy response. For example, some economists have argued that the Great Depression was so severe because pessimism discouraged borrowing and lending and counteracted the supposedly expansionary policy settings (Morgan, 1993).[3] However, pessimism alone cannot explain an asymmetric response, as by the same reasoning, optimism during booms would reduce the impact of contractionary policy. Thus, if changes in the economic outlook are to explain asymmetries, pessimism must dampen the effects of expansionary policy by more or less than optimism dampens the effects of contractionary policy. While this mechanism may seem plausible, it has not received any attention in the literature beyond the narrative discussed in Morgan (1993).

State-dependent nominal rigidities

Keynesian economics argues that nominal shocks lead to fluctuations in nominal aggregate demand, and this leads to fluctuations in output and employment as price and wage rigidities prevent adjustments to offset the shocks. In state-dependent sticky price models, firms choose when to change prices, and this choice depends on the associated "menu cost" (e.g., Ball and Mankiw 1994). This is the cost incurred by the firm when changing nominal

[3] Friedman and Schwartz (1963) argue instead that the severity of the Great Depression was because the Federal Reserve's policy stance during the early 1930s was actually contractionary rather than expansionary.

prices between periods. In a state-dependent pricing framework, we may expect the effect of monetary policy shocks to depend on the size of the shock. For example, in the Ball and Mankiw (1994) menu cost model, small shocks may not move firms far enough from their optimal price that they are willing to pay the menu cost to change prices, and therefore these shocks lead to no change in prices and a change in output. In contrast, large shocks may shift firms far enough from their optimal price that they are willing to pay the menu cost to change prices, and this tempers the impact on output. In summary, state-dependent pricing implies that large shocks will lead to a greater change in prices and a smaller change in output in response to a monetary policy shock.

A.2 Technical Details

Time-varying parameter estimation details

Estimation of equation (1.2) and the following explanation is based on Boivin (2006); for more information please see Boivin's original paper. First, an estimate of the variance of the parameters is obtained using the median-unbiased estimator approach proposed by Stock and Watson (1998). Second, conditional on the estimated variance, the time-varying parameters are estimated using the Kalman smoother and allowing for a shift in the variance of the policy shock in 1993Q1 (to coincide with the introduction of inflation targeting in the UK).

The TVP first-stage regression is given by

$$\Delta i_m = \boldsymbol{\Theta_m Z_m} + \varepsilon_m,$$

where the vector $\boldsymbol{\Theta_m}$ denotes the parameters to be estimated for each meeting m and $\boldsymbol{Z_m}$ denotes the corresponding regressors. I assume that the policy parameters follow driftless random walks:

$$\boldsymbol{\Theta_m} = \boldsymbol{\Theta_{m-1}} + \omega_m,$$

where $E(\omega_m) = 0$.

Once we have an estimate of $Var(\omega_m)$, we can estimate $\boldsymbol{\Theta_m}$ using the Kalman smoother. In principle, all the parameters of the model can be estimated jointly by maximum likelihood estimation (MLE), using the Kalman filter to construct the likelihood. However, as Stock and Watson (1998) showed, when $Var(\omega_m)$ is small, its maximum likelihood estimate is biased towards zero. This is a problem in this context, as even with statistically and economically significant time variation in the parameters over the sample, there is small period-to-period variation in the parameters. Therefore, estimation of $Var(\omega_m)$ uses the median-unbiased estimator approach proposed by Stock and Watson (1998) that explicitly accounts for the deficiency of MLE when the parameters' variance is small.

The estimation method exploits the fact that the distribution of the QLR test under the alternative hypothesis of a TVP model depends on $Var(\omega_m)$. Therefore, we use a realisation of the QLR test statistic to infer an estimate of $Var(\omega_m)$. Specifically, the time-varying parameters can be rewritten as

$$\Delta\boldsymbol{\Theta_m} = \omega_m = \tau v_m,$$

where v_m and the policy shock ε_m are assumed to be mutually uncorrelated mean zero random disturbances. The asymptotic distribution of the QLR test under the alternative hypothesis is a functional of Brownian motions, indexed by λ. τ is a scalar that determines the size of the variance of the parameters, and Boivin sets $\tau = \lambda/T$.

Estimation of $Var(\omega_m)$ proceeds via the following steps:

- An estimate of λ is obtained from the heteroskedasticity-robust version of the QLR test. In order to ensure that heteroskedasticity in the policy shocks does not contaminate the time variation in the reaction function, a heteroskedasticity-robust version of the QLR test is used. In the baseline application, $\lambda = 7$ (from Table 1.1).

- $\Sigma_{zz} = E(Z_m Z_m')$ is estimated with $T^{-1}\Sigma_{m=1}^{M} Z_m Z_m'$ and Ω is estimated by $T^{-1}\Sigma_{m=1}^{M}\hat{\varepsilon}_m^2 Z_m Z_m'$ based on the OLS residuals $\hat{\varepsilon}_m$ from a constant-coefficient version of (1.2). The number of Bank Rate meetings $M = 235$.

- $\hat{\Sigma}_{vv}$ is given by $\hat{\Sigma}_{zz}^{-1}\hat{\Omega}\hat{\Sigma}_{zz}^{-1}$ and $\widehat{Var(\omega_m)} = (\hat{\lambda}/T)^2\hat{\Sigma}_{vv}$.

Conditional on $\widehat{Var(\omega_m)}$, the time series $\{\hat{\Theta}_m\}$ is estimated using the Kalman smoother as in the standard MLE approach. Intuitively, in the estimation of $\hat{\Theta}_m$, the observations away from m, on both sides, are down-weighted, where the rate at which the weights decline increases with the estimated variance of the parameters. To ensure that heteroskedasticity in the policy shocks does not contaminate $\{\hat{\Theta}_m\}$, the variance of the policy shocks is estimated separately over the periods 1975Q1–1992Q4 and 1993Q1–2007Q4 from the OLS residuals, and the implementation of the Kalman smoother allows for the shift in the variance of the policy shock at 1993Q1.

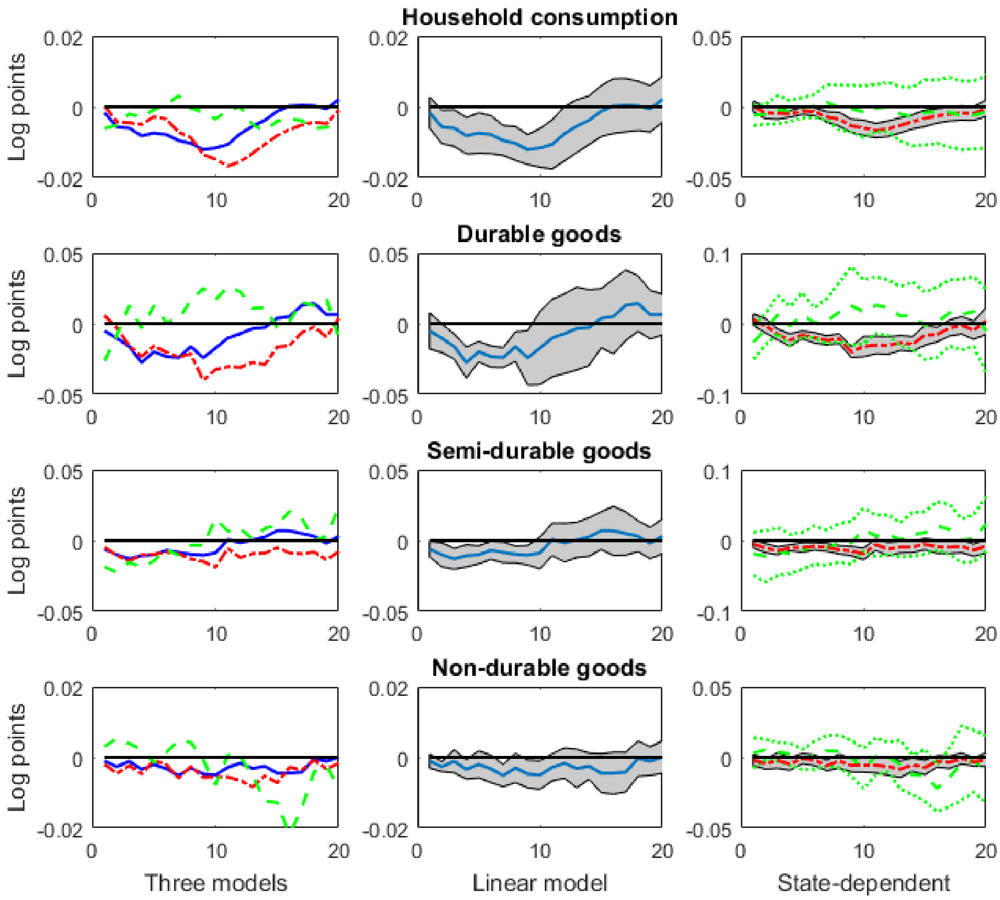
A.3 Additional Tables and Figures

Table A.1: Data Definitions and Sources

Variable	Definition	Source
GDP	Log, Chained volume	ONS
Price level	Log, CPI	ONS
Bank Rate	Level	FRED (BOERUKM)
Unemployment rate	Level	FRED (AURUKM)
GFCF	Log, Chained volume, SA	FRED (GBRGFCFQDSNAQ)
Government consumption	Log, Chained volume, SA	FRED (RGCGASUKQ)
Private consumption	Log, Chained volume, SA	FRED (NAEXKP02GBQ661S)
Commodity prices	Log, IMF index	Cloyne and Hürtgen (2016)
US GDP	Log, Chained volume	FRED (GDPC1)
GDP deflator	Implicit price deflator	FRED (GBRGDPDEFQISMEI)
Real exchange rate	Effective exchange rate	BIS
RPI inflation	All items index	ONS
M4 money stock	Break Adjusted	Bank of England

Notes: The real-time dataset used to estimate the monetary policy shocks is published by Cloyne and Hürtgen (2016). FRED refers to the Federal Reserve Economic Data published by the St. Louis Fed.

Figure A.1: State-dependent Impulse Responses to a Monetary Policy Shock – Household Consumption Components



Notes: Response of the log-level of household consumption, durable, semi-durable, and non-durable goods to a monetary policy shock that increases the Bank Rate by 1 percentage point. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-independent response. The third column shows the same interval around the state-dependent responses. Sample uses shocks occurring during the period 1985Q1–2007Q4.

Table A.2: Statistical Analysis of the Shock Series

D_t	0	$F(z_t)$	$\mathbf{1}\{\varepsilon_t > 0\}$	ε_t^3
Constant	0.046	0.043	-0.020	0.037
	(0.058)	(0.056)	(0.060)	(0.057)
ε_{t-1}	-0.158*	-0.211	0.122	-0.466
	(0.088)	(0.171)	(0.256)	(0.643)
ε_{t-2}	-0.051	-0.162***	0.221	0.433
	(0.077)	(0.060)	(0.247)	(0.805)
ε_{t-3}	-0.036	-0.084	-0.523***	1.088
	(0.114)	(0.140)	(0.198)	(0.659)
ε_{t-4}	0.272*	0.511**	-0.025	-2.165**
	(0.152)	(0.237)	(0.060)	(1.083)
D_{t-1}		0.098	-0.422**	0.323
		(0.276)	(0.324)	(0.634)
D_{t-2}		0.258	-0.315	-0.480
		(0.185)	(0.264)	(0.826)
D_{t-3}		0.036	0.712***	-1.142*
		(0.177)	(0.263)	(0.667)
D_{t-4}		-0.510	0.325	2.458**
		(0.327)	(0.313)	(1.074)
σ	0.67	0.66	0.64	0.66
R^2	0.14	0.20	0.23	0.19
Adj. R^2	0.11	0.15	0.18	0.14
RSS	55.29	51.17	49.24	51.74
F-statistic		2.38*	3.62***	2.02*
F (p-value)		0.056	0.008	0.096
Observations	128	128	128	128

Kolmogorov-Smirnov two-sided test

	Expansion vs Recession	Positive vs Negative
KS statistic	0.35	0.31
p-value	0.0000	0.0001

Notes: Heteroskedasticity and autocorrelation-robust (HAC) standard errors are shown in parentheses. ***, **, and * denote statistical significance at the 1, 5 and 10 per cent level, respectively. The F-test compares the full model given by equation (1.8) with the reduced model given by equation (1.8) with $D_t = 0 \quad \forall\, t$. The null hypothesis is the case where $\gamma_1 = ... = \gamma_p = 0$ and the persistence does not differ for the type of shock identified by the interaction term.

Table A.3: Determinants of the Change in Bank Rate

Sample	1975Q1-1992Q4		1993Q1-2007Q4		1993Q1-2007Q4	
	Coeff.	HACSE	Coeff.	HACSE	Coeff.	HACSE
Constant	-0.18	(1.21)	0.12	(0.19)	0.32**	(0.16)
Initial Bank Rate	0.01	(0.06)	-0.08***	(0.02)	-0.04*	(0.02)
Forecasted output growth						
-1	-0.02	(0.09)	0.06***	(0.02)		
0	0.09	(0.08)	0.01	(0.03)		
1	0.09	(0.10)	-0.10***	(0.03)		
2	0.03	(0.12)	0.11***	(0.03)		
Forecasted inflation						
-1	0.14*	(0.08)	-0.00	(0.08)	-0.02	(0.10)
0	-0.23	(0.15)	0.25	(0.15)	0.23	(0.23)
1	0.03	(0.19)	-0.27	(0.19)	-0.18	(0.27)
2	0.08	(0.15)	-0.11	(0.15)	-0.27*	(0.16)
Change in forecasted output						
-1	0.10	(0.06)	-0.00	(0.02)		
0	0.07	(0.05)	0.08**	(0.04)		
1	0.04	(0.07)	-0.00	(0.03)		
2	0.10	(0.09)	-0.09***	(0.03)		
Change in forecasted inflation						
-1	0.03	(0.19)	0.09	(0.13)	0.03	(0.17)
0	0.45	(0.33)	-0.09	(0.23)	-0.21	(0.24)
1	-0.30	(0.29)	0.16	(0.28)	0.42*	(0.24)
2	0.13	(0.16)	-0.05	(0.17)	-0.01	(0.14)
Unemployment rate						
-1	-1.97	(1.35)	-0.02	(0.19)	-0.08	(0.17)
-2	1.37	(2.29)	-0.26	(0.30)	-0.23	(0.29)
-3	0.53	(1.32)	0.35	(0.25)	0.38	(0.27)
Adj. R^2	0.17		0.35		0.22	
No. of observations	96		139		139	
F-Statistic	1.95		4.76		4.24	

Notes: The estimated equation is the same as the first-stage regression used in Cloyne and Hürtgen (2016) and shown in equation (1.1). Heteroskedasticity and autocorrelation-robust standard errors (HACSE) are shown in parentheses. ***, **, and * denote statistical significance at the 1, 5 and 10 per cent level, respectively.

Table A.4: Cumulative Impulse Responses – CH Shocks

Cumulative impact on	Horizon	Regime/Shock type Expansion	Recession	$H_0 : \hat{\beta}^b - \hat{\beta}^r = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	-0.006	0.007	0.087	0.562
	8	-0.052	0.009	0.015	0.276
	12	-0.105	0.023	0.006	0.253
	16	-0.138	0.046	0.000	0.120
	20	-0.146	0.031	0.001	0.114
Prices	4	0.032	-0.004	0.083	0.521
	8	0.097	-0.026	0.015	0.784
	12	0.140	-0.067	0.003	0.877
	16	0.148	-0.073	0.002	0.894
	20	0.128	-0.073	0.002	0.900
		Positive shock	Negative shock	$H_0 : \hat{\beta}^{pos} - \hat{\beta}^{neg} = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	0.031	-0.041	0.000	0.962
	8	0.045	-0.115	0.001	0.976
	12	0.075	-0.198	0.001	0.977
	16	0.087	-0.213	0.001	0.970
	20	0.079	-0.198	0.006	0.951
Prices	4	-0.010	0.056	0.070	0.192
	8	-0.028	0.155	0.027	0.144
	12	-0.052	0.198	0.021	0.189
	16	-0.055	0.181	0.032	0.253
	20	-0.049	0.131	0.097	0.337
		Cubed shock		$H_0 : \hat{\beta}^{large} = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	0.000		0.482	0.699
	8	-0.002		0.284	0.459
	12	-0.004		0.271	0.432
	16	0.004		0.334	0.472
	20	0.012		0.137	0.540
Prices	4	0.002		0.161	0.512
	8	0.011		0.007	0.590
	12	0.013		0.013	0.652
	16	0.006		0.165	0.673
	20	0.002		0.400	0.686

Table A.5: Cumulative Impulse Responses – Cochrane (2004) Shocks

Cumulative impact on	Horizon	Regime/Shock type		$H_0: \hat{\beta}^b - \hat{\beta}^r = 0$	
		Expansion	Recession	Driscoll-Kraay	Bootstrapped
GDP	4	-0.009	0.003	0.077	0.348
	8	-0.055	0.001	0.004	0.123
	12	-0.112	0.012	0.001	0.127
	16	-0.144	0.022	0.000	0.078
	20	-0.154	0.005	0.000	0.095
Prices	4	0.033	0.002	0.082	0.465
	8	0.109	-0.016	0.007	0.764
	12	0.166	-0.047	0.001	0.836
	16	0.192	-0.042	0.002	0.838
	20	0.191	-0.033	0.004	0.838
		Positive shock	Negative shock	$H_0: \hat{\beta}^{pos} - \hat{\beta}^{neg} = 0$	
				Driscoll-Kraay	Bootstrapped
GDP	4	0.014	-0.030	0.004	0.958
	8	0.013	-0.090	0.005	0.978
	12	0.028	-0.165	0.002	0.976
	16	0.034	-0.181	0.001	0.950
	20	0.021	-0.171	0.009	0.923
Prices	4	-0.005	0.055	0.038	0.137
	8	-0.005	0.146	0.012	0.092
	12	0.002	0.180	0.019	0.168
	16	0.038	0.160	0.083	0.253
	20	0.066	0.129	0.252	0.345
		Cubed shock		$H_0: \hat{\beta}^{large} = 0$	
				Driscoll-Kraay	Bootstrapped
GDP	4	-0.003		0.000	0.171
	8	-0.008		0.000	0.155
	12	-0.012		0.000	0.196
	16	-0.010		0.021	0.230
	20	-0.006		0.198	0.247
Prices	4	0.001		0.034	0.638
	8	0.006		0.000	0.711
	12	0.006		0.002	0.671
	16	0.002		0.229	0.592
	20	-0.001		0.350	0.485

Table A.6: Cumulative Impulse Responses – Recursive Identification

Cumulative impact on	Horizon	Regime/Shock type Expansion	Recession	$H_0 : \hat{\beta}^b - \hat{\beta}^r = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	0.001	-0.002	0.363	0.822
	8	-0.023	-0.009	0.271	0.589
	12	-0.051	0.002	0.120	0.415
	16	-0.065	0.007	0.070	0.335
	20	-0.072	-0.018	0.087	0.343
Prices	4	0.020	-0.006	0.097	0.662
	8	0.059	-0.021	0.050	0.836
	12	0.087	-0.057	0.023	0.901
	16	0.098	-0.054	0.015	0.891
	20	0.096	-0.044	0.008	0.885
		Positive shock	Negative shock	$H_0 : \hat{\beta}^{pos} - \hat{\beta}^{neg} = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	0.009	-0.022	0.012	0.953
	8	0.009	-0.067	0.001	0.903
	12	0.018	-0.110	0.001	0.828
	16	0.026	-0.115	0.021	0.787
	20	0.020	-0.122	0.067	0.768
Prices	4	0.006	0.028	0.079	0.293
	8	-0.009	0.106	0.003	0.206
	12	-0.029	0.133	0.004	0.221
	16	-0.027	0.127	0.006	0.235
	20	-0.019	0.111	0.025	0.229
		Cubed shock		$H_0 : \hat{\beta}^{large} = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	0.000		0.250	0.800
	8	0.001		0.321	0.672
	12	0.002		0.288	0.658
	16	0.005		0.056	0.728
	20	0.008		0.004	0.786
Prices	4	0.001		0.179	0.686
	8	0.002		0.270	0.548
	12	0.002		0.375	0.442
	16	-0.001		0.414	0.350
	20	-0.002		0.299	0.315

Table A.7: Cumulative Impulse Responses for Alternative State Variables

Cumulative impact on	Horizon	Regime/Shock type Expansion	Recession	$H_0 : \hat{\beta}^b - \hat{\beta}^r = 0$ Driscoll-Kraay	Bootstrapped
		Output Gap			
GDP	4	-0.006	0.007	0.093	0.505
	8	-0.040	0.002	0.008	0.237
	12	-0.067	-0.004	0.027	0.199
	16	-0.082	0.012	0.031	0.104
	20	-0.080	0.015	0.044	0.144
Prices	4	0.023	0.015	0.336	0.234
	8	0.058	0.040	0.258	0.543
	12	0.072	0.048	0.239	0.670
	16	0.076	0.042	0.206	0.663
	20	0.059	0.044	0.359	0.611
		Unemployment Gap			
GDP	4	-0.006	0.000	0.388	0.504
	8	-0.043	0.020	0.084	0.255
	12	-0.068	0.033	0.060	0.187
	16	-0.050	0.011	0.221	0.265
	20	-0.016	-0.029	0.451	0.477
Prices	4	0.022	0.019	0.462	0.285
	8	0.081	-0.001	0.141	0.669
	12	0.090	0.006	0.136	0.682
	16	0.064	0.034	0.332	0.524
	20	0.040	0.052	0.427	0.386

Table A.8: Cumulative Impulse Responses for Recession at 50%

Cumulative impact on	Horizon	Regime/Shock type Expansion	Recession	$H_0 : \hat{\beta}^b - \hat{\beta}^r = 0$ Driscoll-Kraay	Bootstrapped
GDP	4	-0.007	0.009	0.043	0.380
	8	-0.048	0.011	0.001	0.135
	12	-0.090	0.014	0.001	0.107
	16	-0.113	0.025	0.001	0.092
	20	-0.114	0.025	0.004	0.151
Prices	4	0.026	0.013	0.242	0.384
	8	0.076	0.023	0.048	0.840
	12	0.104	0.019	0.024	0.906
	16	0.111	0.017	0.038	0.891
	20	0.091	0.018	0.101	0.830

Table A.9: Cumulative Impulse Responses – Alternative Intensity of Regime Switching

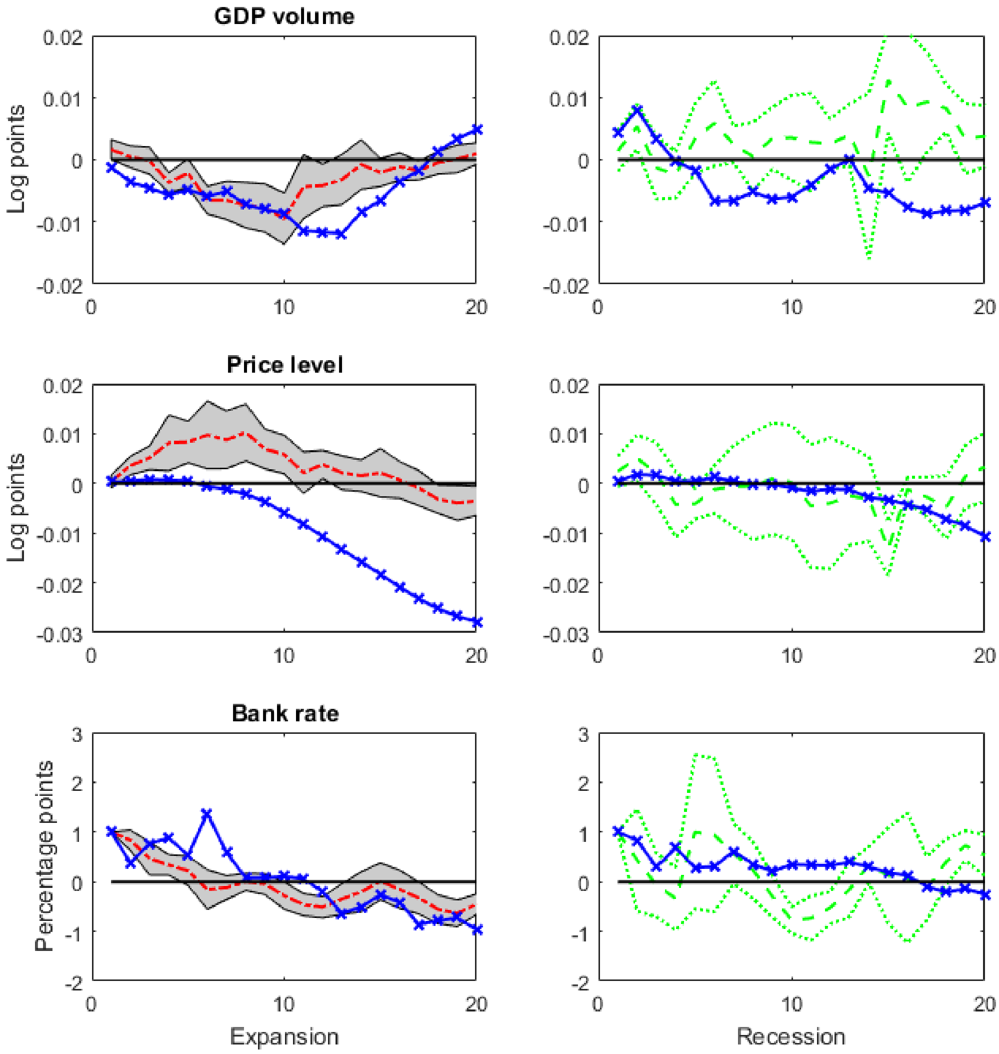
Cumulative impact on	Horizon	Regime/Shock type		$H_0 : \hat{\beta}^b - \hat{\beta}^r = 0$	
		Expansion	Recession	Driscoll-Kraay	Bootstrapped
Theta = 1 (slow transition between states)					
GDP	4	-0.004	0.019	0.167	0.412
	8	-0.039	0.051	0.004	0.161
	12	-0.070	0.086	0.012	0.127
	16	-0.088	0.131	0.020	0.102
	20	-0.089	0.138	0.019	0.145
Prices	4	0.024	-0.004	0.186	0.440
	8	0.064	-0.021	0.023	0.833
	12	0.083	-0.049	0.049	0.887
	16	0.092	-0.073	0.038	0.872
	20	0.076	-0.058	0.098	0.839
Theta = 10 (fast transition between states)					
GDP	4	-0.003	0.007	0.116	0.343
	8	-0.036	0.014	0.001	0.068
	12	-0.065	0.018	0.001	0.071
	16	-0.080	0.025	0.001	0.043
	20	-0.079	0.022	0.001	0.075
Prices	4	0.024	0.002	0.054	0.641
	8	0.063	-0.001	0.005	0.846
	12	0.083	-0.008	0.009	0.892
	16	0.088	-0.013	0.010	0.862
	20	0.071	-0.008	0.038	0.816

Table A.10: Nonlinearities in the slope of the Phillips curve

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Output gap, κ_1	0.794***	1.084***	1.576***	2.391***
	(0.209)	(0.37)	(0.579)	(0.85)
Interaction term, κ_2			-1.053*	-1.182
			(0.641)	(0.98)
Constant, c	-1.13***	-1.13***	-0.185	0.68
	(0.19)	(0.42)	(0.71)	(0.84)
Constant interaction, θ			-0.72	-2.39**
			(0.69)	(1.05)
Observations	132	132	132	132
R^2	0.22	0.20	0.26	0.18
$\kappa_1 + \kappa_2$			0.523**	1.208**
			(0.210)	(0.50)

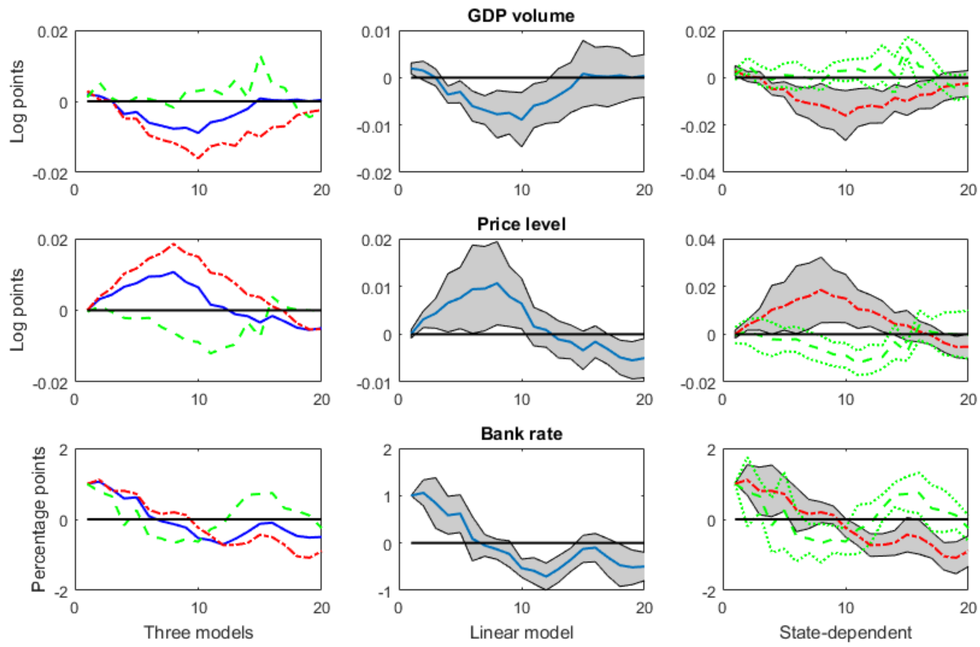
Notes: The estimated specification is given by equation (1.9). The IV regressions use the first lag of the output gap and the interaction term as instruments. Heteroskedasticity and autocorrelation-robust (HAC) standard errors are shown in parentheses. ***, **, and * denote statistical significance at the 1, 5 and 10 per cent level, respectively.

Figure A.2: Baseline Results compared to Tenreyro and Thwaites (2016)



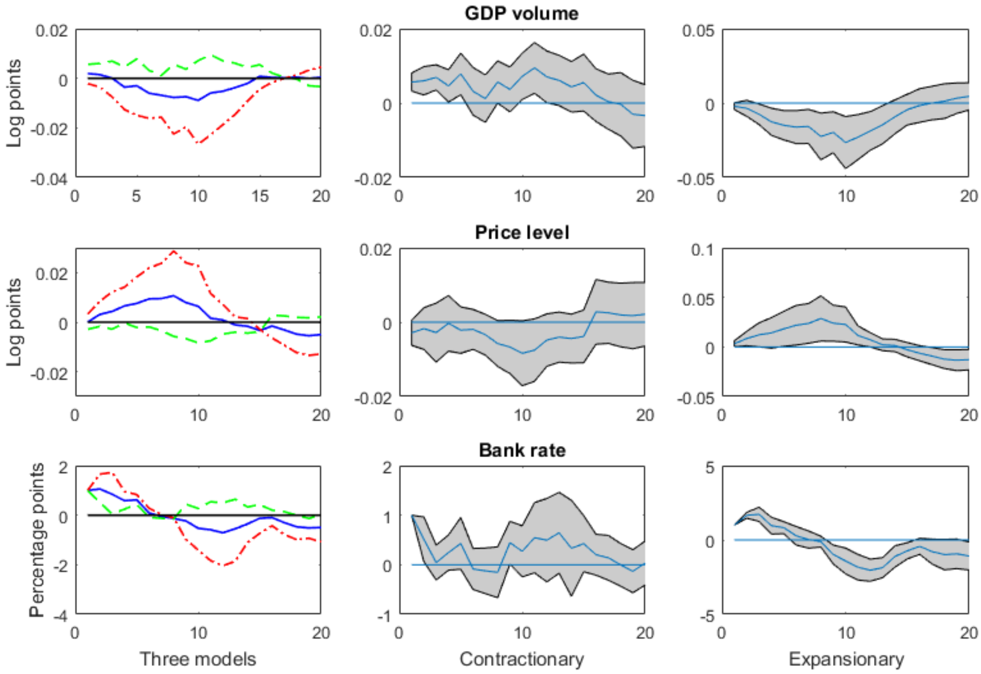
Notes: Response of the log-level of real GDP, the price level (CPI for the UK, PCE deflator for the US) and the level of the policy rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. The graphs on the left show the IRFs when the shock occurs during an expansion, while the graphs on the right show the IRFs when the shock occurs during a recession. The blue line shows the response in the US while the red and green lines show the response in the UK. In each case, the IRF is scaled to increase the policy rate by 1 percentage point on impact.

Figure A.3: State-dependent Impulse Responses to a CH Monetary Policy Shock



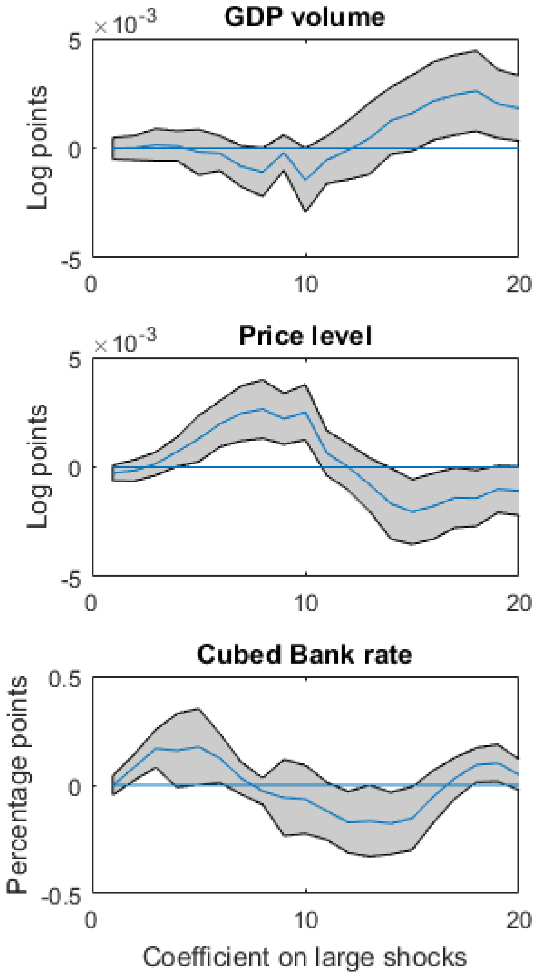
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-independent response. The third column shows the same interval around the state-dependent responses.

Figure A.4: Impulse Responses for Positive and Negative CH Shocks



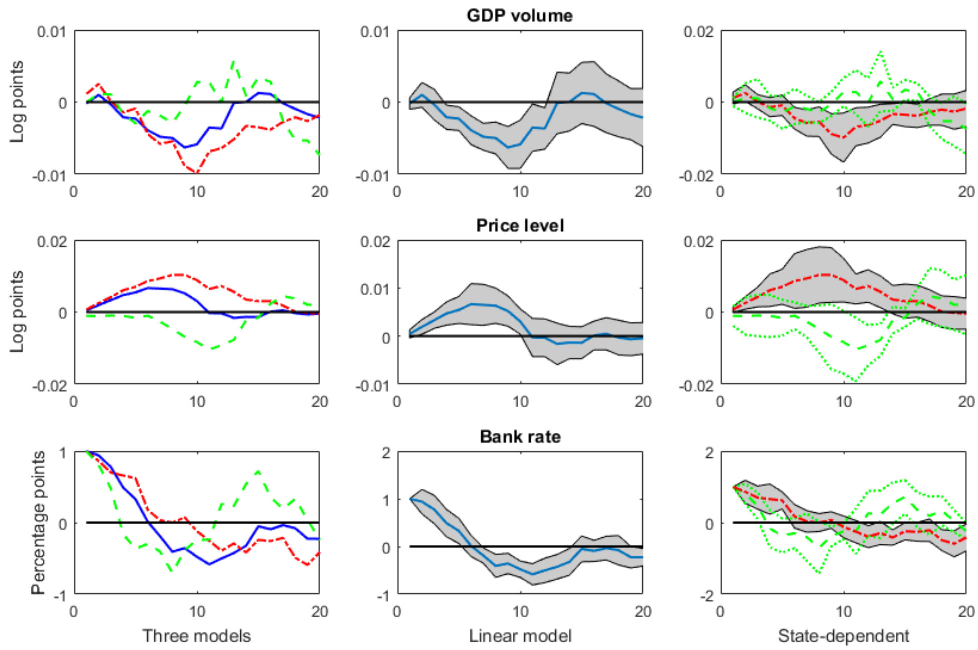
Notes: All columns show the impulse response to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the linear model, the dashed green line shows the response for positive/contractionary shocks, and the dashed red line shows the response for negative/expansionary shocks. The second and third columns show the 90 per cent confidence interval around the positive and negative shock IRFs, respectively.

Figure A.5: Impulse Responses to Cubed CH Shocks



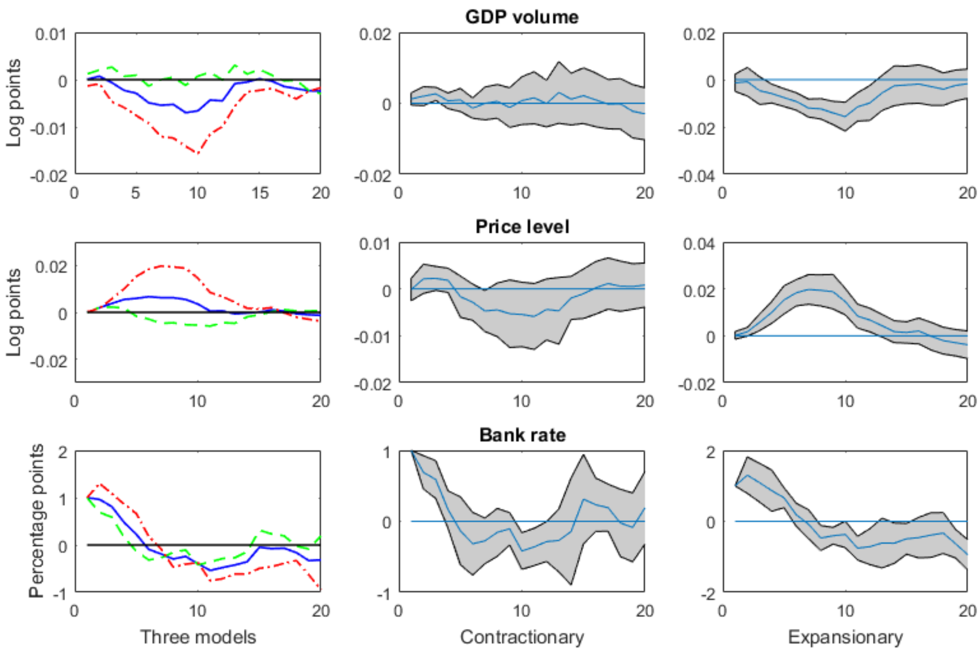
Notes: Impulse response of the coefficient on the cubed monetary policy shocks β_h^{large} and the 90 per cent confidence interval.

Figure A.6: State-dependent Impulse Responses to a Monetary Policy Shock Identified Recursively



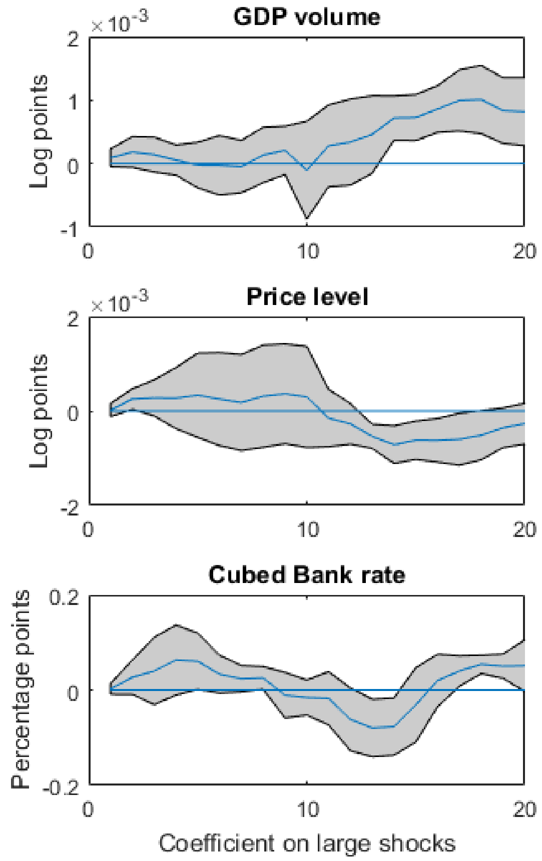
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-independent response. The third column shows the same interval around the state-dependent responses.

Figure A.7: Impulse Responses for Positive and Negative Shocks Identified Recursively



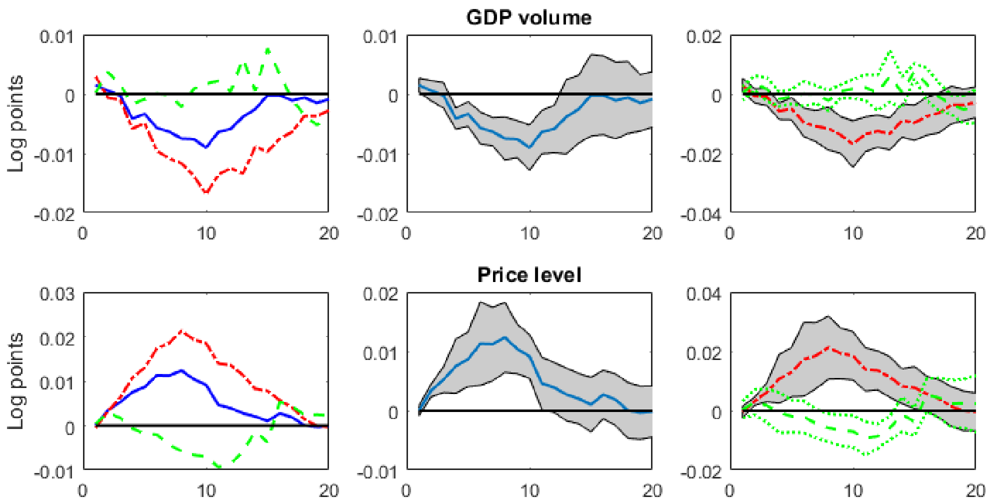
Notes: All columns show the impulse response to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the linear model, the dashed green line shows the response for positive/contractionary shocks, and the dashed red line shows the response for negative/expansionary shocks. The second and third columns show the 90 per cent confidence interval around the positive and negative shock IRFs, respectively.

Figure A.8: Impulse Response to Cubed Shocks Identified Recursively



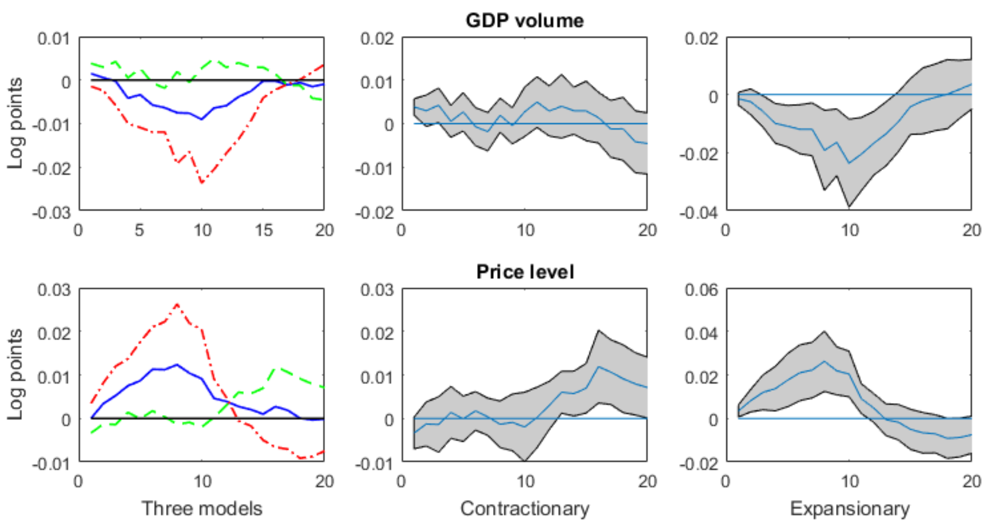
Notes: Impulse response of the coefficient on the cubed monetary policy shocks β_h^{large} and the 90 per cent confidence interval.

Figure A.9: State-dependent Impulse Responses to a Cochrane (2004) Monetary Policy Shock



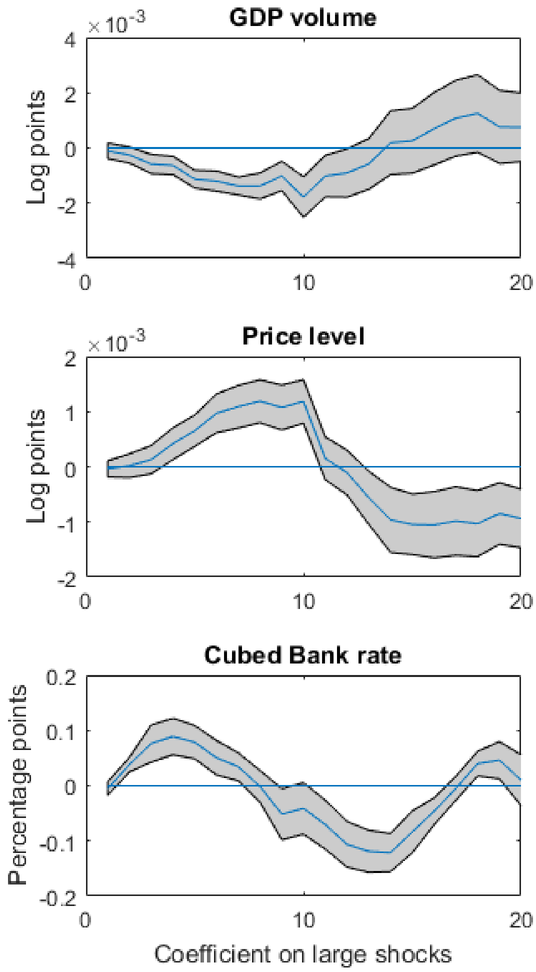
Notes: Response of the log-level of real GDP and the consumer price index to a shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-independent response. The third column shows the same interval around the state-dependent responses.

Figure A.10: Impulse Responses for Positive and Negative Cochrane (2004) Shocks



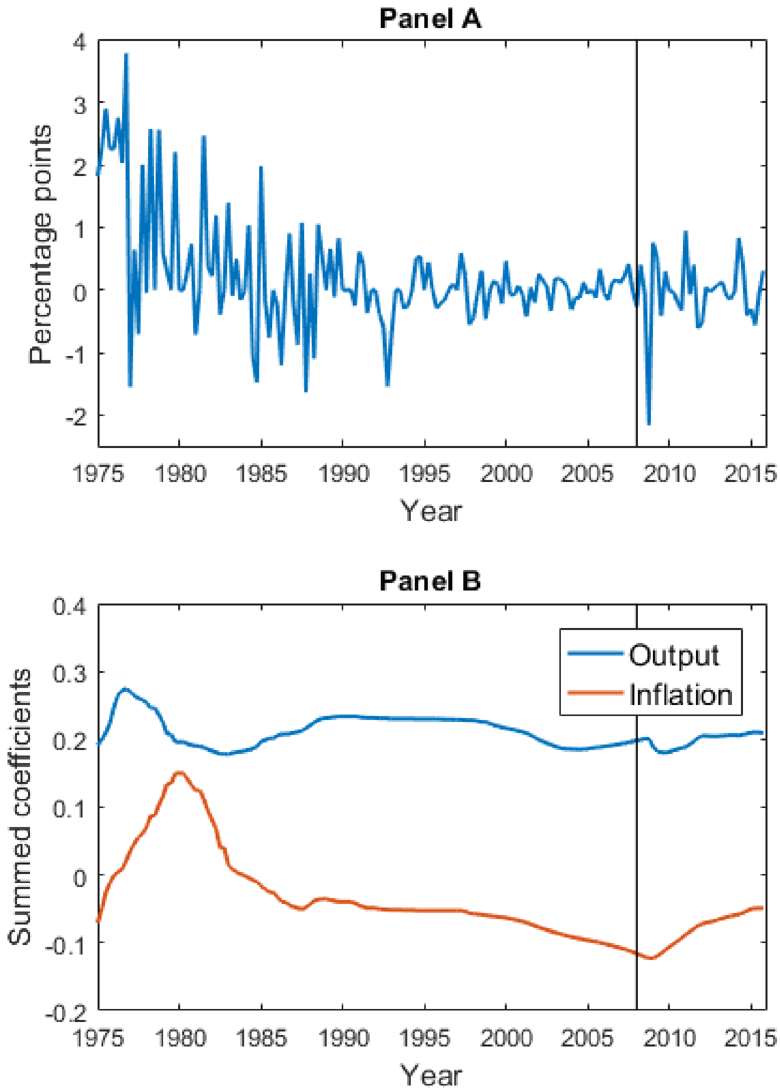
Notes: All columns show the impulse response to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the linear model, the dashed green line shows the response for positive/contractionary shocks, and the dashed red line shows the response for negative/expansionary shocks. The second and third columns show the 90 per cent confidence interval around the positive and negative shock IRFs, respectively.

Figure A.11: Impulse Responses for Cubed Cochrane (2004) Shocks



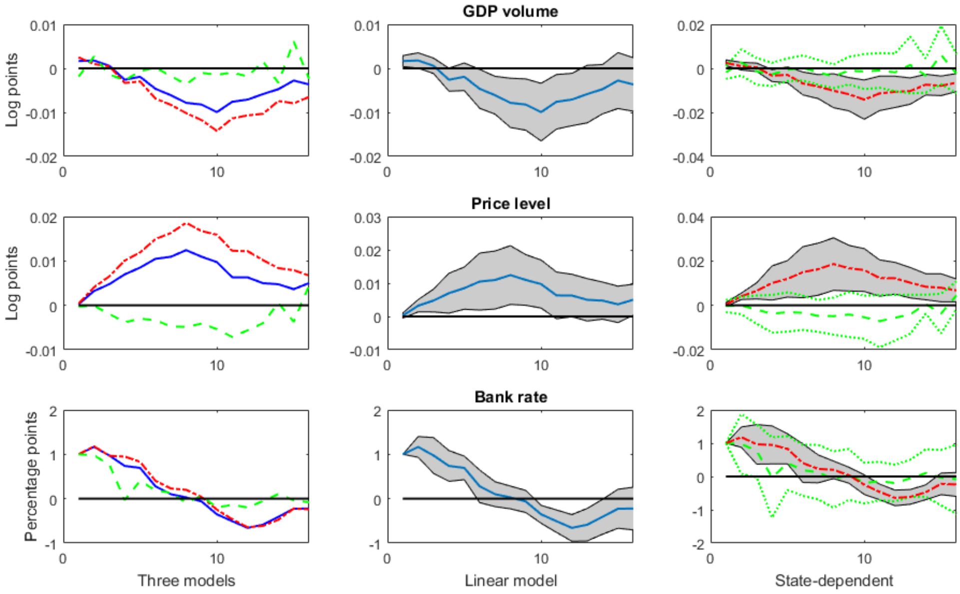
Notes: Impulse response of the coefficient on the cubed monetary policy shocks β_h^{large} and the 90 per cent confidence interval.

Figure A.12: Monetary Policy Shocks and Time-varying Coefficients – 1975 to 2015



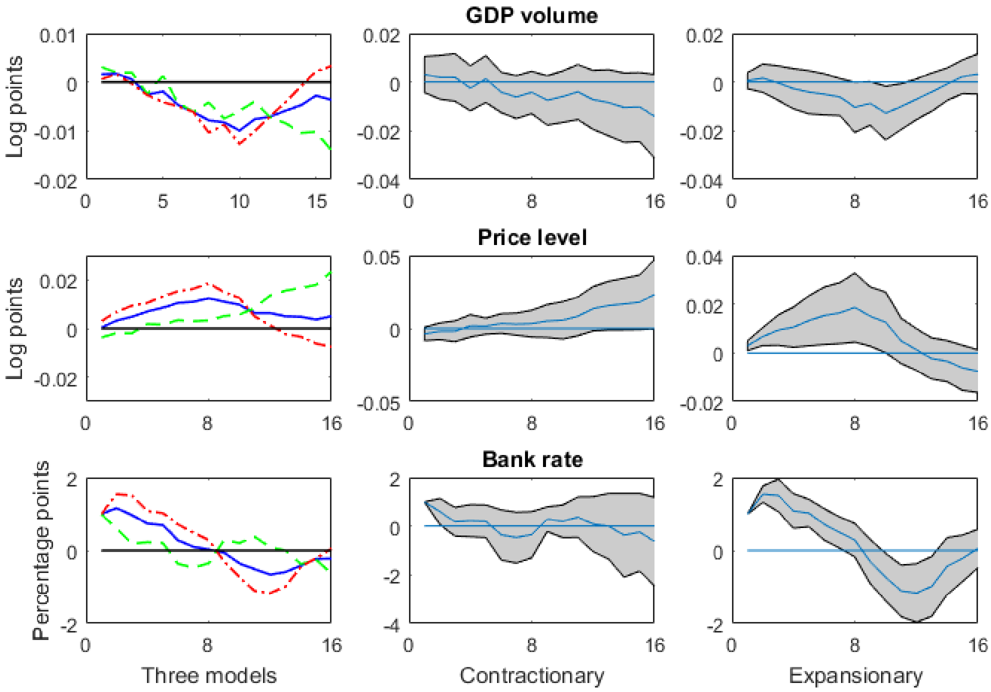
Notes: The black vertical line is at 2008Q1. Panel A shows the extended shock series calculated by estimating equation (1.2) with Wu and Xia (2016, 2017) shadow rates. In Panel B, the blue line shows the response to a 1 percentage point increase in expected GDP, calculated by summing the TVP coefficients on GDP growth forecasts and forecast revisions at each meeting. The orange line shows the response to a 1 percentage point increase in expected inflation, calculated using the same approach.

Figure A.13: State-dependent Impulse Responses – 1975 to 2015



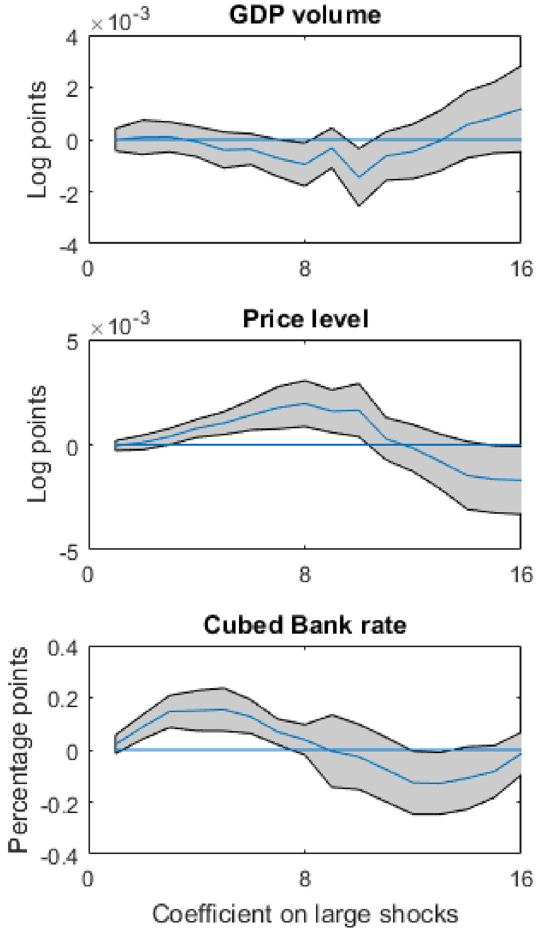
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-dependent responses.

Figure A.14: Impulse Responses for Positive and Negative Shocks – 1975 to 2015



Notes: All columns show the impulse response to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the linear model, the dashed green line shows the response for positive/contractionary shocks, and the dashed red line shows the response for negative/expansionary shocks. The second and third columns show the 90 per cent confidence interval around the positive and negative shock IRFs, respectively.

Figure A.15: Impulse Responses to Cubed Shocks – 1975 to 2015



Notes: Impulse response of the coefficient on the cubed monetary policy shocks β_h^{large} and the 90 per cent confidence interval.

Figure A.16: Alternative Transition Functions

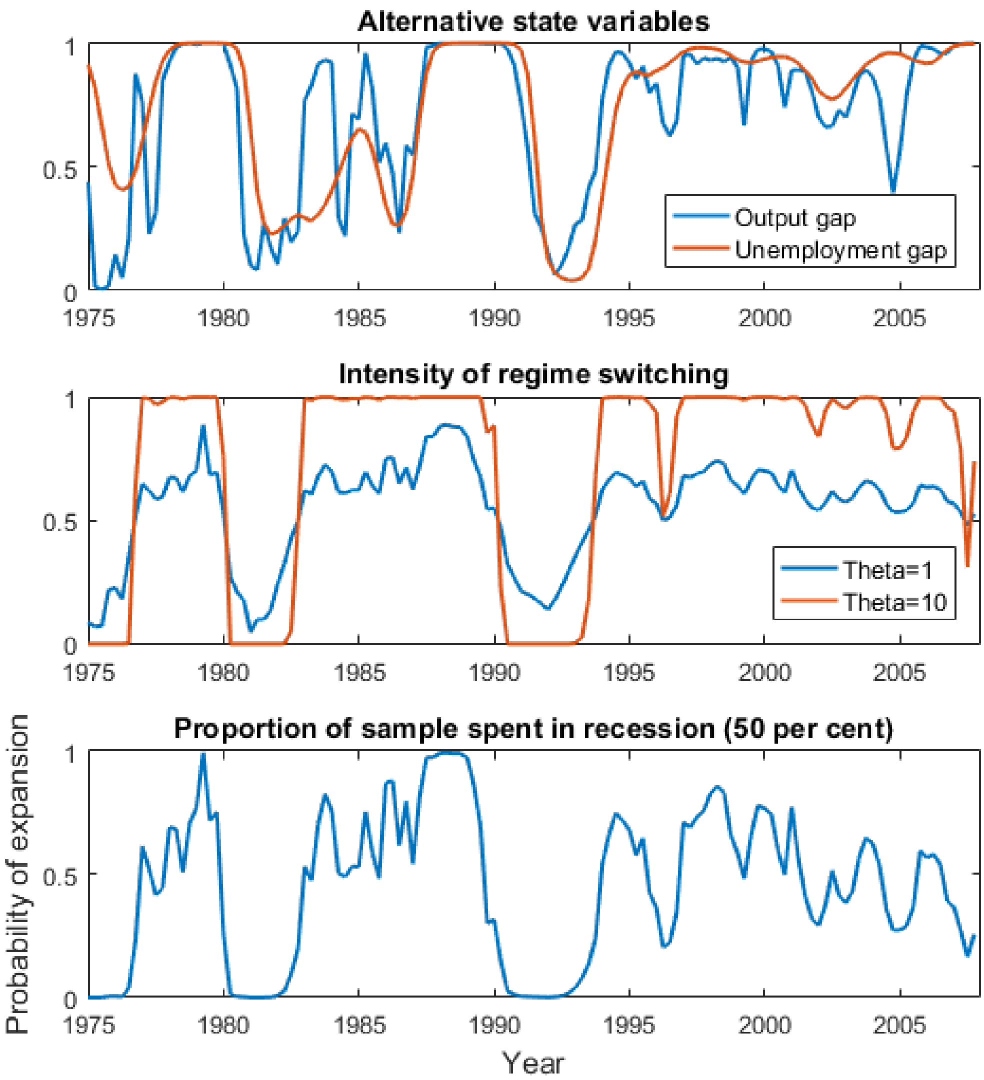
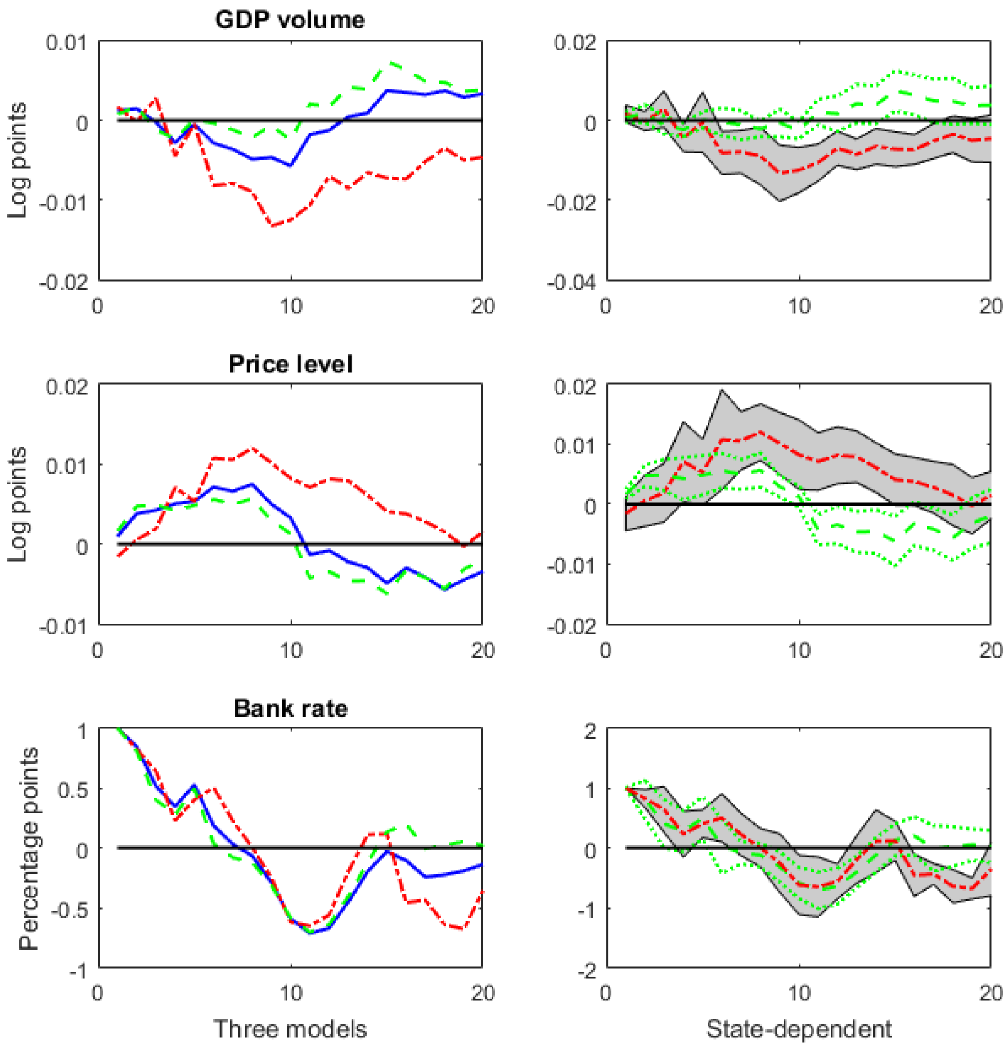
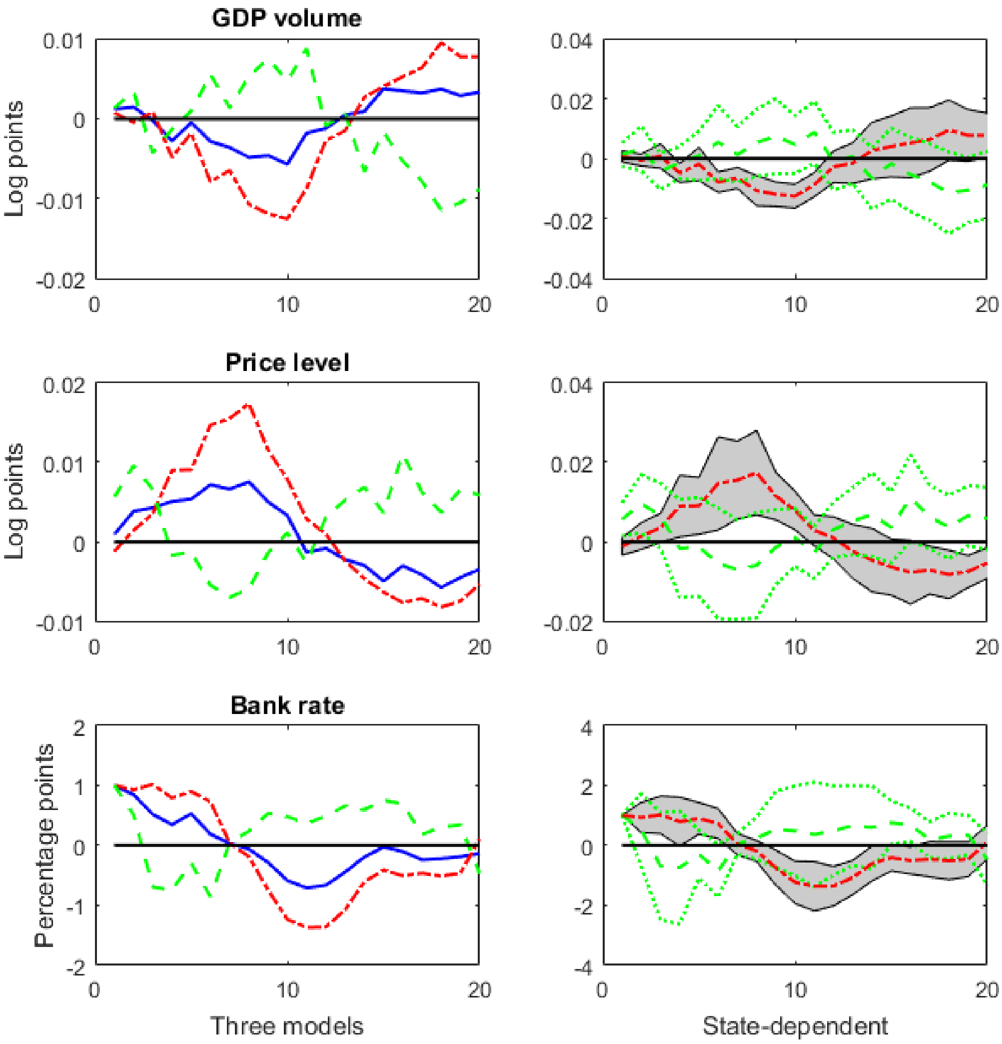


Figure A.17: State-dependent Impulse Responses with the Output Gap as the State Variable



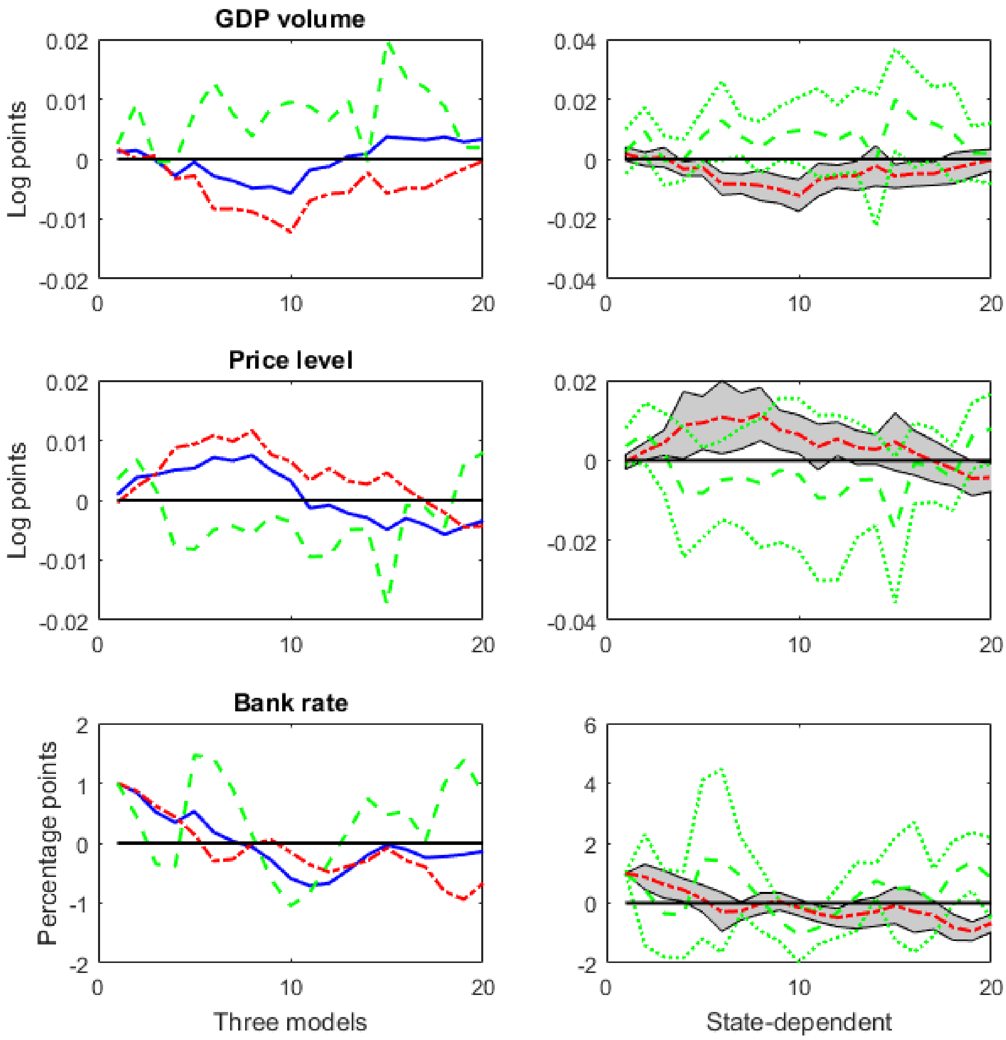
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-dependent responses.

Figure A.18: State-dependent Impulse Responses with the Unemployment Gap as the State Variable



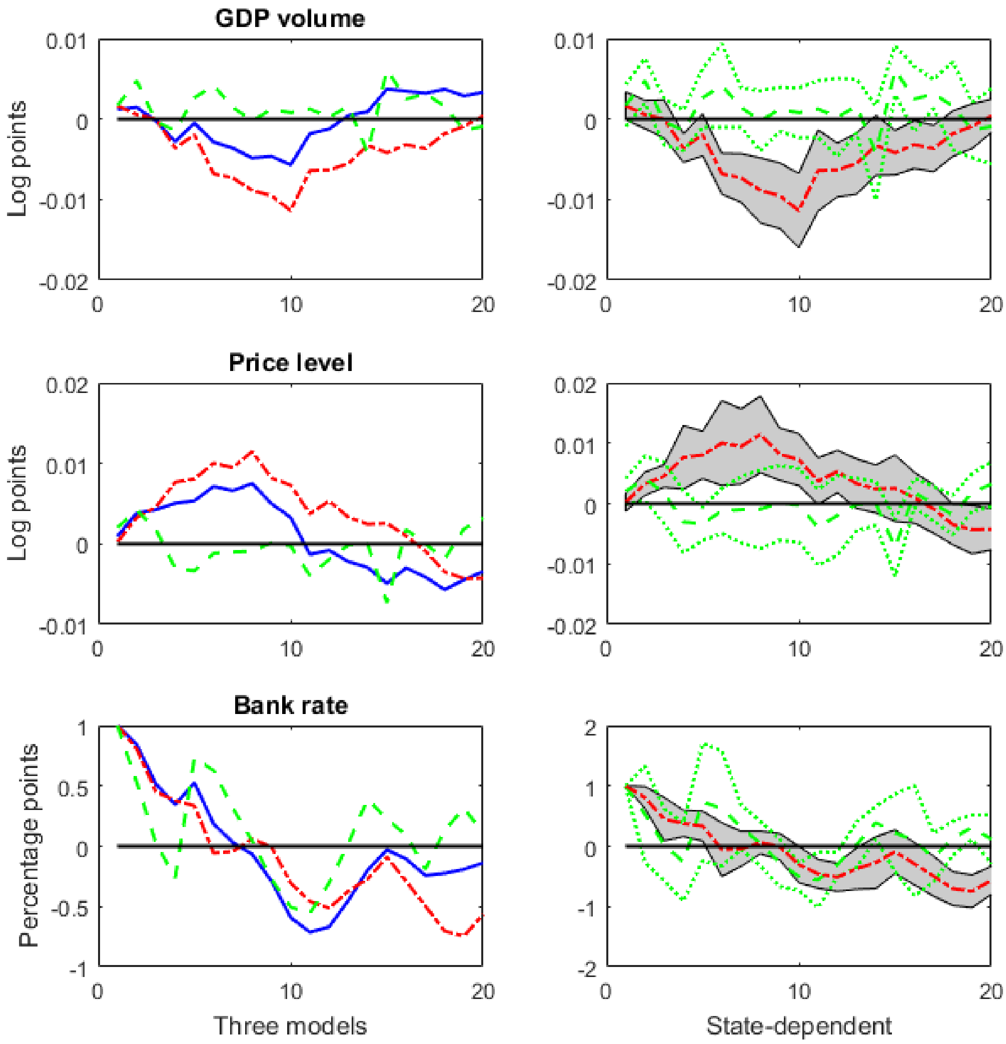
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-dependent responses.

Figure A.19: State-dependent Impulse Responses to a Monetary Policy Shock: Theta = 1



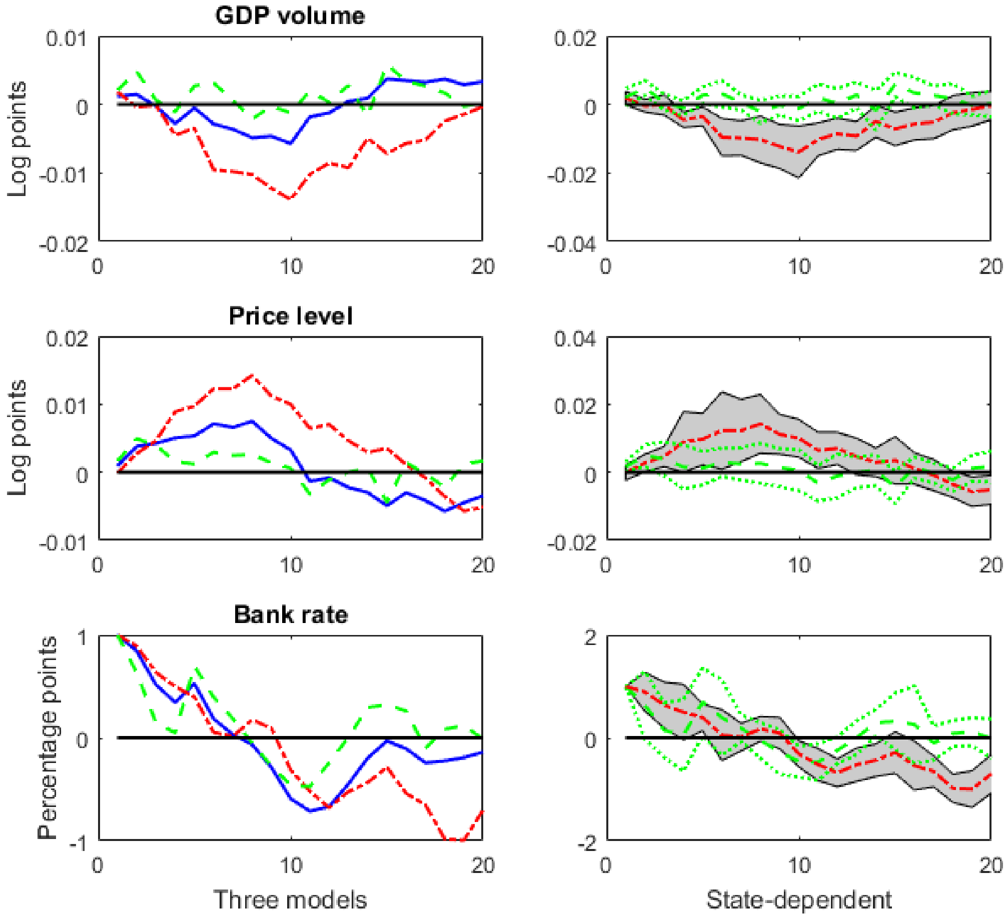
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-dependent responses.

Figure A.20: State-dependent Impulse Responses to a Monetary Policy Shock: Theta = 10



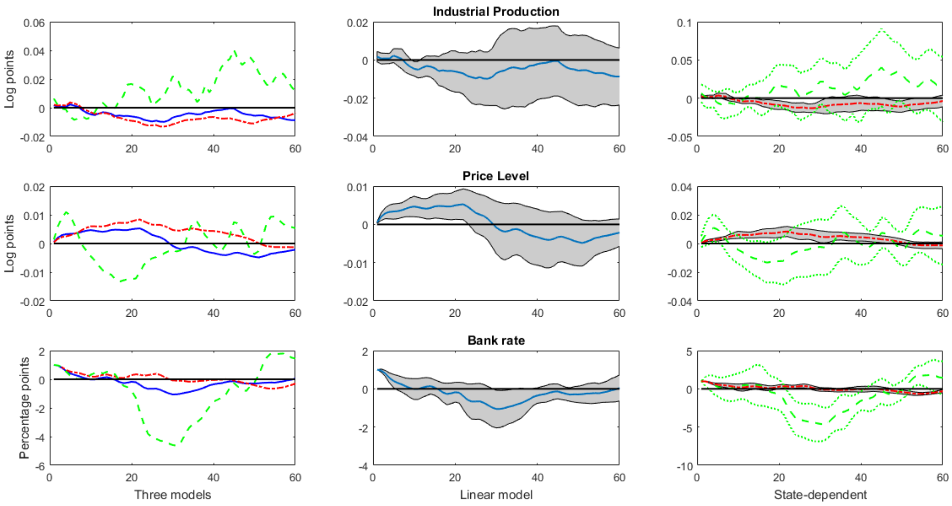
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-dependent responses.

Figure A.21: State-dependent Impulse Responses to a Monetary Policy Shock: Recession at 50 per cent



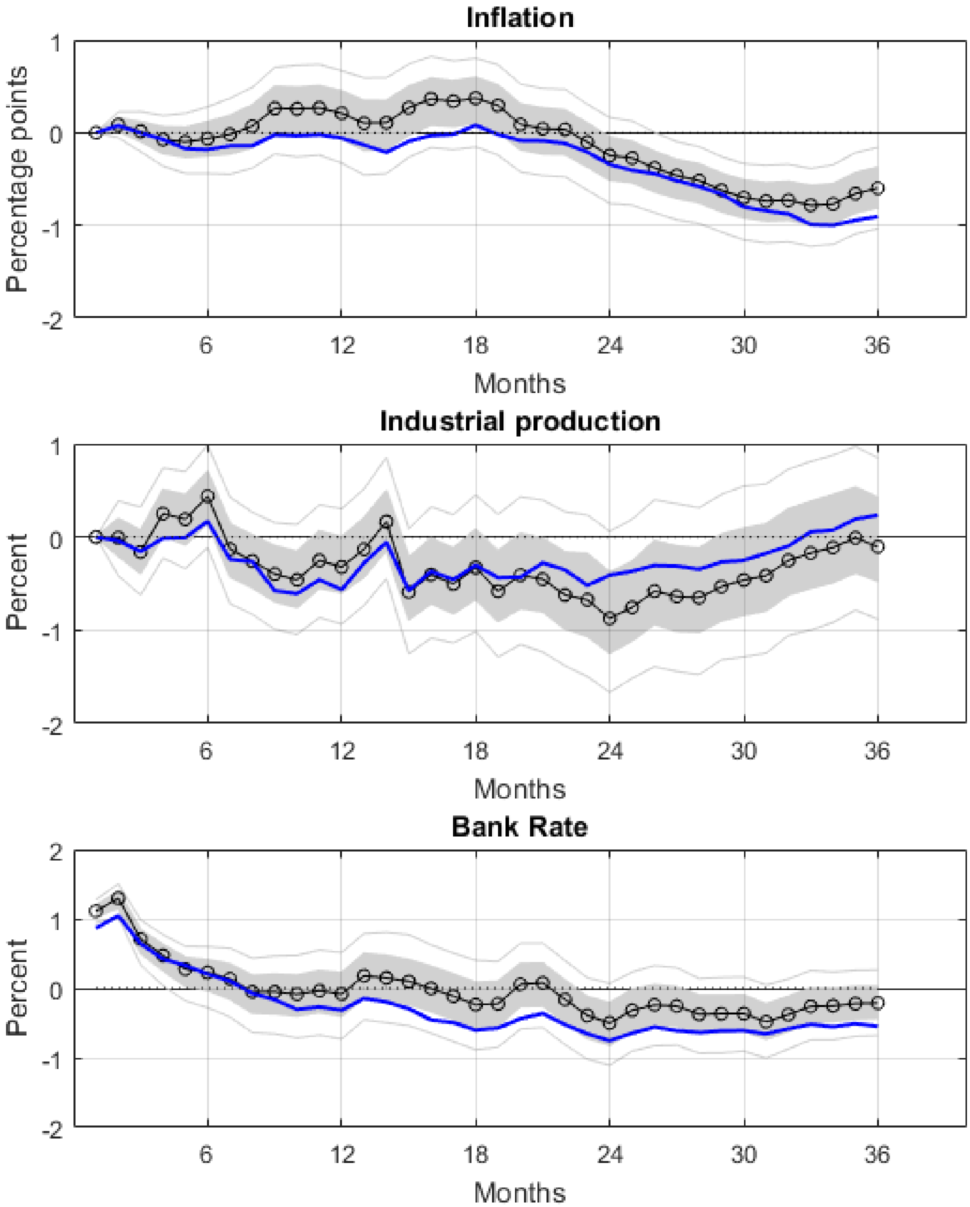
Notes: Response of the log-level of real GDP, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-dependent responses.

Figure A.22: State-dependent Impulse Responses at a Monthly Frequency



Notes: Response of the log-level of industrial production, the consumer price index and the level of the Bank of England Bank Rate to a monetary policy shock that increases the Bank Rate by 1 percentage point on impact. In the first column, the solid blue line shows the response in a linear, state-independent model, the red dotted line shows the response in an expansion and the green dashed line shows the response in a recession. The second column shows the 90 per cent confidence interval around the state-dependent responses. The state variable used is the 24-month average of industrial production and 25% of the sample is judged to be in recession. Equation 1.4 is estimated with 6 lags of the dependent variable and Bank Rate as controls. The IRFs shown are smoothed (i.e., three-period centred moving averages).

Figure A.23: Comparison to Cloyne and Hürtgen (2016)



Notes: Impulse responses to a 1 percentage point contractionary monetary policy shock estimated using the code and baseline VAR from Cloyne and Hürtgen (2016). The black line with circles is the central estimate obtained with the new TVP monetary policy shock measure, and the confidence bands indicate 68 and 95 per cent intervals. The blue line shows the original CH central estimates from Figure 2 in their paper.

Appendix B

Chapter 2 Appendix

B.1 Technical Details

Test of Linearity

I apply the test proposed by Teräsvirta and Yang (2014) to test the null hypothesis of linearity versus the alternative hypothesis of a STVAR specification. For full details of the testing procedure, see Teräsvirta and Yang (2014). Consider the following 2-regime logistic STVAR model:

$$\boldsymbol{X_t} = \boldsymbol{\Gamma_0 Y_t} + \sum_{i=1}^{n} \boldsymbol{\Gamma_i' Y_t z_t}^i + \boldsymbol{\varepsilon_t}$$

where $\boldsymbol{X_t}$ is the $(p \times 1)$ vector of endogenous variables, $\boldsymbol{Y_t}$ is the $((k \times p + q) \times 1)$ vector of exogenous variables (including endogenous variables lagged k times), $\boldsymbol{z_t}$ is the transition variable, and $\boldsymbol{\Gamma_0}$ and $\boldsymbol{\Gamma_i}$ are matrices of parameters.

Under the null hypothesis of linearity, $\boldsymbol{\Gamma_i} = 0 \quad \forall i$.

The test for linearity versus the STVAR proceeds as follows:

1. Estimate the restricted model ($\boldsymbol{\Gamma_i} = 0 \quad \forall i$) by OLS. Collect the residuals $\boldsymbol{E}$ and compute the matrix of residual sum of squares $\boldsymbol{RSS_0} = \boldsymbol{E'E}$.

2. Run an auxiliary regression of $\boldsymbol{E}$ on $(\boldsymbol{Y_t}, Z_n)$ where $Z_n = [Z_1|Z_2|...|Z_n] = [\boldsymbol{Y'}_t z_t|\boldsymbol{Y'}_t z_t^2|...|\boldsymbol{Y'}_t z_t^n]$. Collect the residuals $\boldsymbol{\Theta}$ and compute the residual sum of squares matrix $\boldsymbol{RSS_1} = \boldsymbol{\Theta'\Theta}$.

3. Compute the test statistic $LM = T\{p - tr[\boldsymbol{RSS_0}^{-1}\boldsymbol{RSS_1}]\}$ where $LM \sim \chi^2(p(kp+q))$ under the null hypothesis of linearity.

The LM statistic is computed by fixing the order of the Taylor expansion at $n = 3$.

Computation of GIRFs

I compute GIRFs following the approach proposed by Koop et al. (1996) and report the median response in high and low credit regimes. For generality, consider a K-dimensional nonlinear multivariate model,

$$\boldsymbol{X_t} = G(\boldsymbol{X_{t-1}}, ..., \boldsymbol{X_{t-p}}; \boldsymbol{\theta}) + \boldsymbol{\varepsilon_t}$$

where G is a nonlinear function that depends on the parameter vector $\boldsymbol{\theta}$ and $\boldsymbol{\varepsilon_t}$ is an i.i.d error term. Following Koop et al. (1996) I compute GIRFs as follows:

$$\begin{aligned} GIRF(h, \delta, \omega_{t-1}) = E\{&\mathbf{X_{t+h}} | \hat{\varepsilon}_t = \delta, \varepsilon_{t+h} = \hat{\varepsilon}_{t+h}, h > 0, \omega_{t-1}) \\ &- E\{\mathbf{X_{t+h}} | \varepsilon_{t+h} = \hat{\varepsilon}_{t+h}, h > 0, \omega_{t-1}) \end{aligned}$$

where h is the horizon of the impulse responses, δ is the size of the shock, ω_{t-1} is the history identifying a particular regime in the sample, and $\hat{\varepsilon}_{t+h}$ is a set of draws of residuals from the empirical distribution $\boldsymbol{\Omega}$. The GIRFs are computed as the difference between a stochastic simulation in which the orthogonal shock of interest (i.e., financial or monetary) takes the value δ and a stochastic simulation in which the orthogonal shock of interest takes the value zero. The shock is calibrated to induce a one standard deviation impulse to the variable of interest in the vector. A given history ω_{t-1} is associated with a given realisation of the transition indicator z_{t-1}. Thus, conditional on the threshold parameter c in the transition function, it is possible to classify each history to a particular regime.

For each identified regime, I draw 500 histories with replacement from the set of all possible histories belonging to a particular regime. For each history, I draw 500 different realisations of the residuals which leads to 500 different point estimates of the GIRFs. Next, I compute the median across the 500 histories, and the figures show the regime-specific median for each horizon.

To compute confidence bands, I repeat the previous steps for 500 bootstrap replications of the FASTVAR model, which provides me with 500 median realisations of the GIRFs per regime. The 16th and 84th percentiles are computed over the distribution of medians.

Computation of GFEVD

I compute a GFEVD following the approach proposed by Lanne and Nyberg (2016) which is based on the GIRFs explained above. The GFEVD is given by:

$$\lambda_{ij,\omega_{t-1}}(l) = \frac{\sum_{h=0}^{l} GIRF(h, \delta, \omega_{t-1})^2}{\sum_{j=1}^{K} \sum_{h=0}^{l} GIRF(h, \delta, \omega_{t-1})^2}$$

where j and i refer to the shock and variable, respectively, l is the horizon and ω_{t-1} denotes the history. The numerator is the cumulative effect of the jth shock whereas the denominator measures the aggregate cumulative effect of all the shocks.

As is the case with GIRFs, since the effects of the shock δ depend on its size, sign and history, simulation methods are needed to compute the GFEVD. The GFEVD is computed by drawing 500 histories with replacement from the set of all possible histories belonging to a particular regime. For each history, I draw 500 different realisations of the residuals which leads to 500 different point estimates of the GIRFs, which can be used to calculate $\lambda_{ij,\omega_{t-1}}(l)$ for $l = 0, 1, 2, ...$ for each history and shock. Finally, the GFEVD is computed as the average of $\lambda_{ij,\omega_{t-1}}(l)$ for $l = 0, 1, 2, ...$ over each history and type of shock.

B.2 Supplementary Information

B.2.1 The BIS Gap

The Bank for International Settlements (BIS) publish a credit-to-GDP gap which has been used in many studies (e.g. Aikman et al. 2020). The gap is calculated as the difference between the ratio of non-financial private sector credit to nominal GDP and an estimate of its equilibrium. The equilibrium is estimated with a HP filter with a smoothing parameter $\lambda = 400,000$ to capture the longer duration of credit cycles (shown in Figure B.3). The large smoothing parameter follows Borio and Lowe (2002) and is motivated by the observation that credit cycles are typically about four times longer than business cycles.[1] A number of studies suggest that the BIS credit gap is one of the best early indicators of systemic banking crises (e.g. Borio and Lowe 2002). As a consequence, the BIS view this measure as a robust single indicator for the build-up of financial vulnerabilities and recommend using it as a guide for setting countercyclical capital buffers under Basel III (see BIS 2010).

However, a univariate filter may have some undesirable properties. For example, if an economy enters a prolonged period of excess credit growth, the univariate filter will begin to underestimate the positive credit gap as part of the credit excesses will be incorporated into the (highly persistent) trend. This results in a trend that is higher than what is justified by economic fundamentals. In addition, the negative credit gap that follows the period of excess credit growth will be overestimated due to the higher-than-justified univariate trend estimate. To address these concerns, I incorporate additional variables and draw on economic theory to estimate a time-varying equilibrium credit-to-GDP ratio that evolves in line with economic fundamentals.

B.2.2 A Brief History of Financial Conditions Indexes

Early research on broad measures of financial conditions was pioneered by the Bank of Canada with their monetary conditions index (MCI) (Freedman, 1994). MCIs combine information on interest rates and the exchange rate to summarise the impact that the stance of monetary policy was having on the economy. As a policy tool, the MCI could be used to help evaluate how much the policy rate would need to change to offset the macroeconomic effects of exchange rate movements in order to maintain the desired stance of monetary conditions. During the 1990s, central banks of small open economies, such as Sweden and Norway, often used MCIs to explain changes in policy. The Reserve Bank of New Zealand announced a future path for the MCI, conditional on information available, which they deemed most likely consistent with their inflation target. MCIs are subject to a number of criticisms though: For example, MCI estimates are model dependent and the

[1] See Drehmann and Tsatsaronis (2014) for further details on the estimation of the credit-to-GDP gap.

model underlying the MCI typically failed to incorporate dynamics (Stevens, 1998). MCIs largely fell out of favour in subsequent years, potentially due to some of these criticisms.

The 2007-08 financial crisis was a stark reminder of the importance of financial conditions for macroeconomic outcomes. In response, a literature has developed attempting to measure the state of financial conditions often following the influential work of Hatzius et al. (2010). This literature largely builds on the techniques used to estimate MCIs but broadens the scope of variables used to construct the index. For example, FCIs often include interest rate spreads which measure the relative price at which finance is available to certain market participants as well as house and equity prices which determine the amount of capital households can borrow against.

FCIs are typically estimated using either a weighted-average or a factor model approach. The weighted-average approach estimates weights for each financial variable based on estimates of the relative impact of changes in the financial variables on some outcome variable (typically real GDP). By assuming an economic model or specification, these methods impose more economic structure during the estimation process than the factor model approach, which produces relevant information on macro-financial linkages. However, if the economic model underlying the estimation process is misspecified, this will contaminate the resulting FCI.

The factor model approach consists of extracting a common factor from a number of financial variables. The weight each financial series receives is determined by its importance in explaining the common variation in the set of financial variables over the sample. The precise estimation method ranges from principal components analysis (Hatzius et al., 2010), to dynamic factor models (Brave and Butters, 2011), and time-varying parameter factor-augmented VARs (Koop and Korobilis, 2014). Prior to factor estimation, researchers sometimes purge the variables entering the FCI of information related to current and lagged GDP growth and inflation following Hatzius et al. (2010). The resulting index will therefore identify exogenous shifts in financial conditions, as opposed to those shifts in response to broader economic conditions.[2] Rather than imposing an economic model, this approach typically assumes that the underlying data series are largely driven by a single factor regardless of how much of the common variation in the financial variables the factor explains.

Lastly, it is worth noting that the precise definition and method used to estimate a FCI often depends on the purpose for which it was constructed. Many researchers focus on the use of FCIs as a forecasting tool. Alternatively, the primary aim may be to distil information from a large number of financial variables in a single latent index. Consequently, some FCIs can be interpreted as summarising the impact of financial conditions on economic growth, while others can be interpreted as whether financial conditions are tight or loose relative to some sample average. Other researchers are primarily interested in monitoring instability in the financial sector and construct financial stress indexes which are closely related to FCIs (see Kliesen et al. 2012 for a survey of financial stress indexes).

[2] Kapetanios et al. (2017) argue against purging the financial time series prior to estimation. They explain their reasoning through a thought experiment: if all financial and macroeconomic variables in the economy were driven by one common financial shock, then purging the financial series prior to estimation would remove the information we aim to summarise.

B.3 Additional Tables and Figures

Table B.1: Data Sources and Definitions

Series	Sources	Definition
Error Correction		
Mortgage rate	RBA: F5	Owner-occupier variable rate
Real interest rate	RBA: F2 & G1	10-year government bond deflated by year-ended trimmed mean inflation
Demographics	ABS: 3101	30-65 year old share in population
House price-to--income	OECD	Log-level of the IDX2015 measure
GDP volatility	RBA: H1	5-year moving average of the standard deviation of GDP growth
Foreign		
US real GDP	FRED: GDPC1	Chain volume, sa
US NFCI	FRED: NFCI	Chicago Fed NFCI
US EBP	Gilchrist and Zakrajsek (2012)	Excess bond premium
Federal funds rate	FRED: FEDFUNDS	Quarterly average
Terms of trade	RBA: H1	Ratio of export to import prices
Domestic		
Real GDP	RBA: H1	Chain volume, sa
Nonfarm GDP	RBA: H1	Chain volume, sa
Trimmed mean inflation	RBA: G1	CPI quarterly inflation
Cash rate	RBA: F1	Cash rate, quarterly average
Real exchange rate	RBA: F15	Real trade-weighted index, adjusted for relative CPI levels
Credit-to-GDP gap	BIS	Difference between the credit-to-GDP ratio and its HP-filtered trend, credit to the private non-financial sector
Real credit	RBA: D2 & H1	Total credit deflated by GDP deflator
Commodity prices	RBA: I2 FRED: GDPDEF	RBA commodity price index (USD), deflated by US GDP deflator
Unemployment rate	RBA: H5	Number of unemployed divided by the labour force

Table B.2: Unit Root Testing

Variable	Lags	ADF t-statistic	Order
Levels			
Real interest rate	0	-2.34	I(1)
Unemployment rate	1	-1.60	I(1)
Nominal mortgage rate	0	-2.11	I(1)
Demographics	2	-1.14	I(1)
Macro volatility	0	-2.06	I(1)
House prices	1	-1.14	I(1)
Real GDP	1	-1.35	I(1)
Real commodity prices	1	-1.70	I(1)
Inflation	2	-1.62	I(1)
Credit gap	4	-3.74***	I(0)
Cash rate	3	-1.56	I(1)
FCI	2	-4.90***	I(0)
First differences			
Real interest rate	1	-8.23***	I(0)
Unemployment rate	0	-6.45***	I(0)
Nominal mortgage rate	1	-6.82***	I(0)
Demographics	1	-3.62**	I(0)
Macro volatility	0	-11.05***	I(0)
House prices	0	-9.51***	I(0)
Real GDP	1	-7.00***	I(0)
Real commodity prices	1	-6.04***	I(0)
Inflation	2	-8.24***	I(0)
Cash rate	3	-5.06***	I(0)

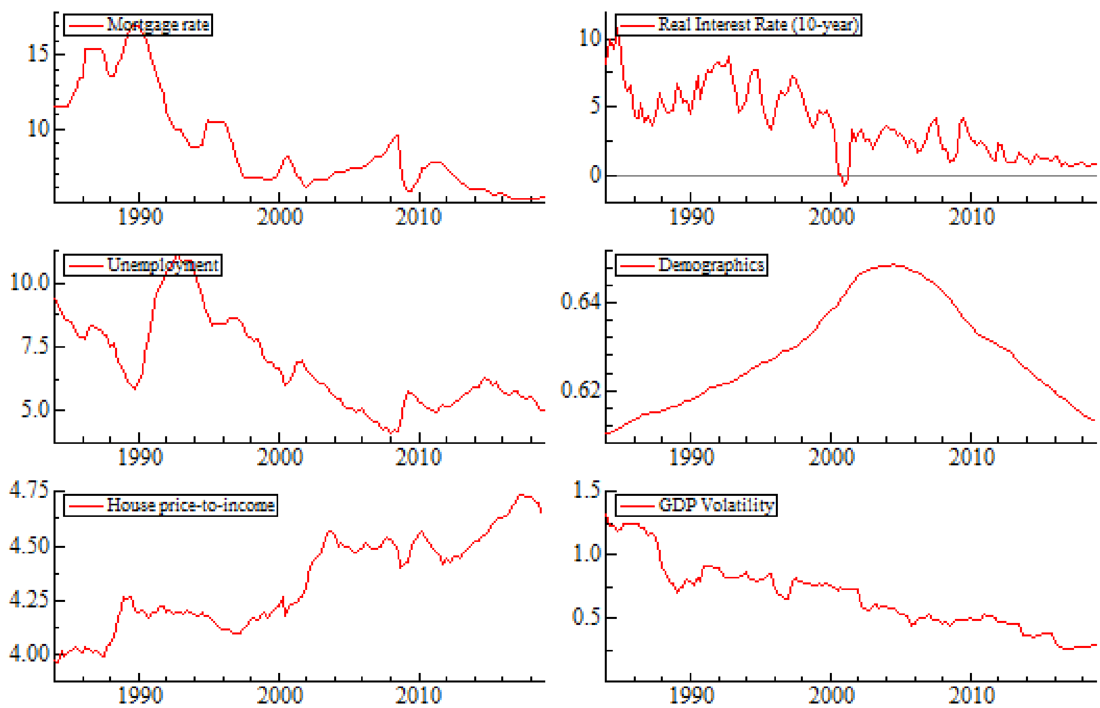
Notes: The model includes an intercept; model for real GDP also includes a linear trend. Unit root tests and critical values implemented in ur.df in R. Lag order selected by AIC up to a maximum lag length of 4.

Table B.3: Shock Series Autocorrelation Tests

	Financial		Monetary	
Constant	0.004	0.007	0.010	0.008
	(0.09)	(0.09)	(0.08)	(0.09)
ε^i_{t-1}	0.01	-0.14	-0.08	-0.01
	(0.11)	(0.10)	(0.14)	(0.12)
ε^i_{t-2}	-0.03	0.06	0.04	0.04
	(0.09)	(0.09)	(0.07)	(0.17)
$F(z_{t-1}) \cdot \varepsilon^i_{t-1}$		0.41		-0.12
		(0.26)		(0.35)
$F(z_{t-2}) \cdot \varepsilon^i_{t-2}$		-0.26		-0.02
		(0.29)		(0.22)
R^2	0.001	0.027	0.008	0.010
F-statistic		1.23		0.86
Observations	136	136	136	136

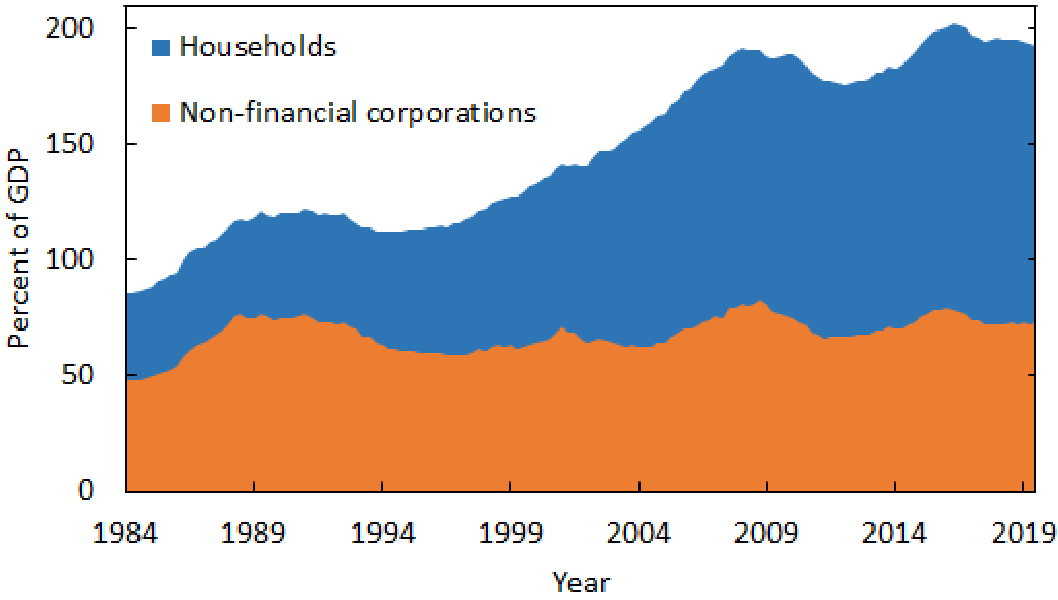
Notes: Heteroskedasticity and autocorrelation-robust (HAC) standard errors are shown in parentheses. ***, **, and * denote statistical significance at the 1, 5 and 10 per cent level, respectively. The partial F-test compares the model with interaction terms (columns 2 and 4) with the nested model (columns 1 and 3).

Figure B.1: Error Correction Model Input Variables



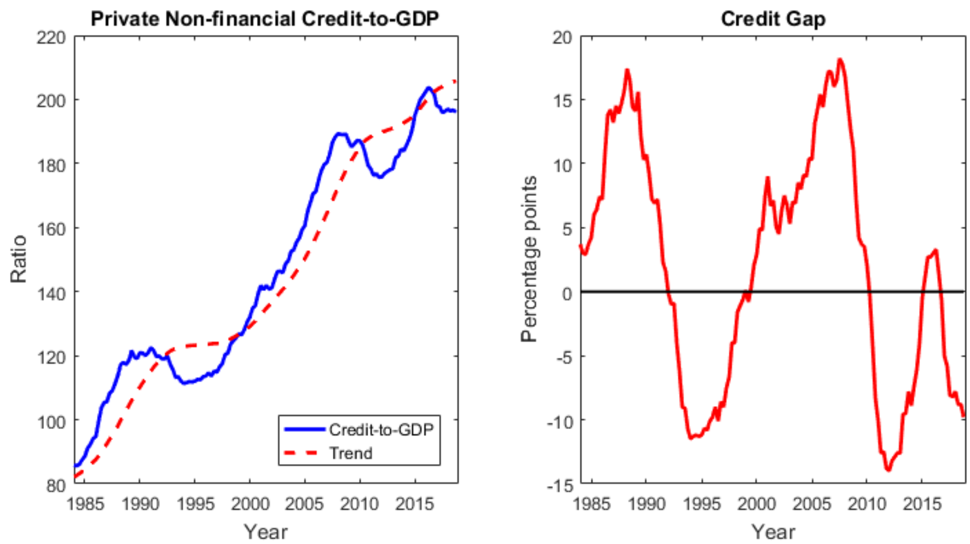
Notes: Input variables used in the error correction model described in Section 2.2. See Table B.1 for detailed definitions and sources.

Figure B.2: Private Non-financial Credit-to-GDP



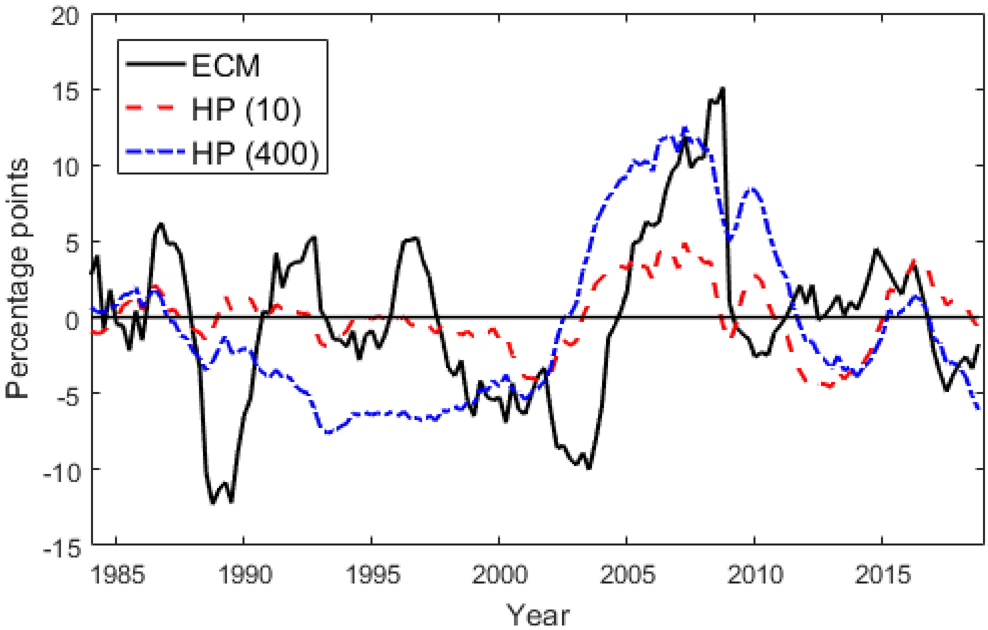
Notes: Private Non-financial Credit-to-GDP is comprised of credit to households (blue) and the non-financial corporate sector (orange) and is published by the Bank for International Settlements.

Figure B.3: BIS Credit-to-GDP Ratio and Credit Gap



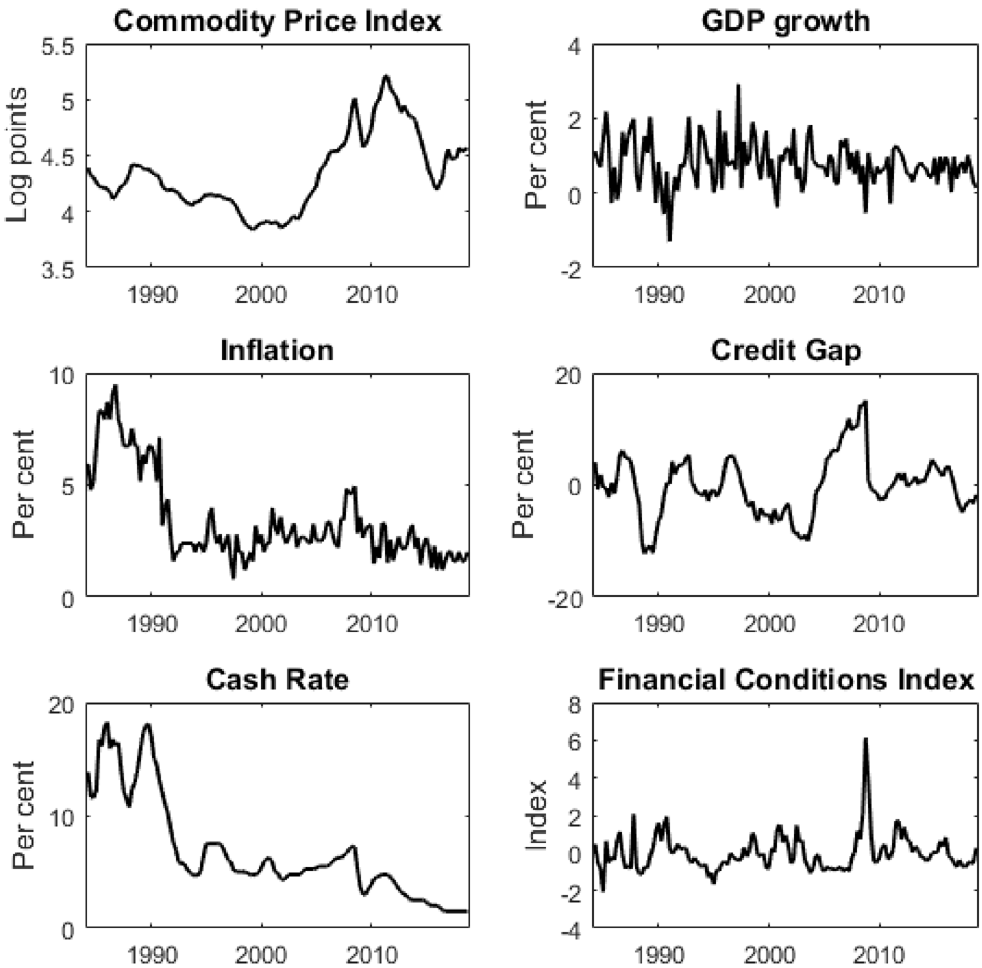
Notes: The left panel shows private non-financial credit-to-GDP ratio (blue line) alongside its HP-filtered trend (dashed red line). The right panel shows the resulting credit gap. Series published by the Bank for International Settlements and explained in Appendix Section B.2.

Figure B.4: Household Credit Gap Comparisons



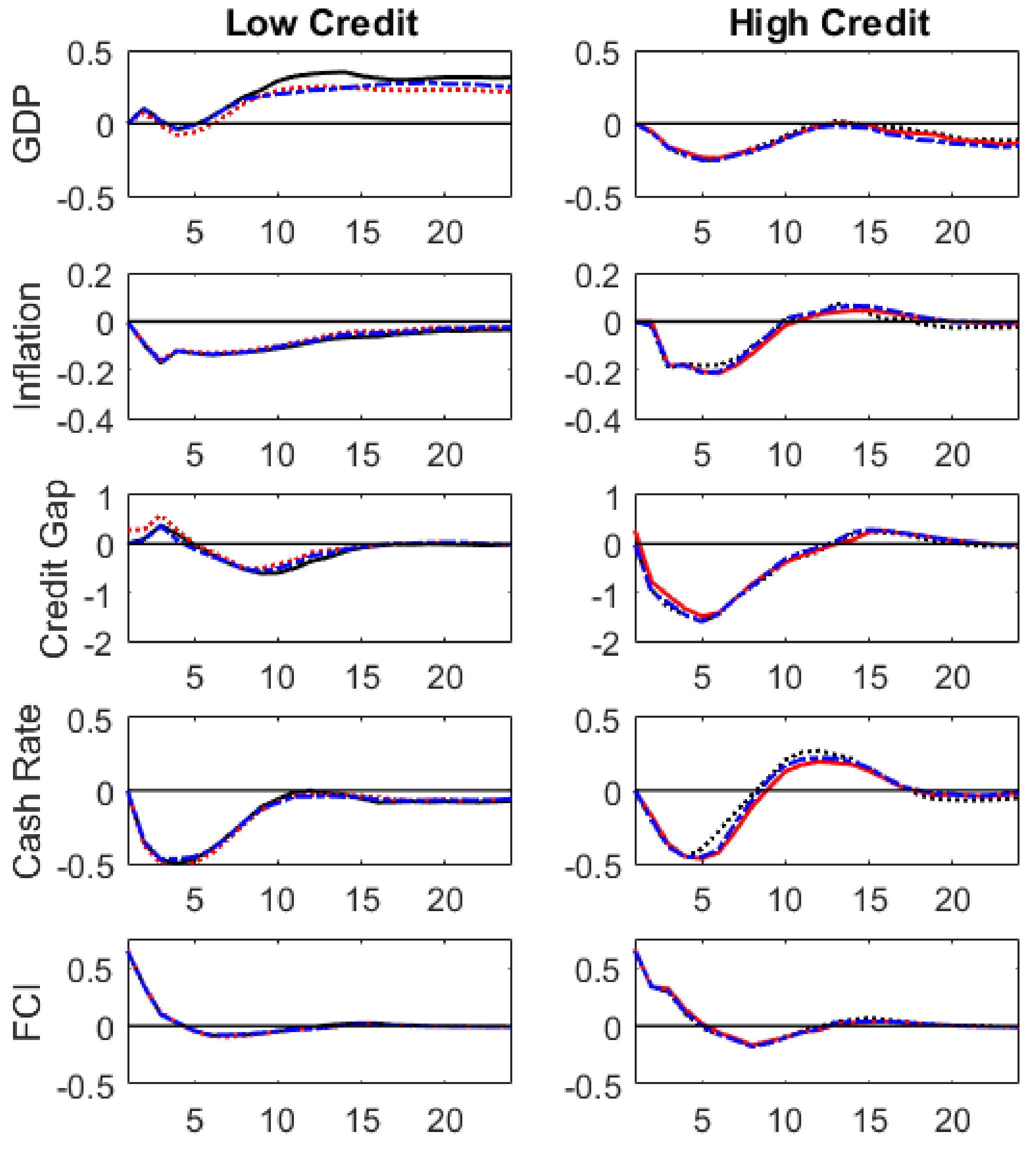
Notes: The black line shows the baseline credit gap where the trend is calculated with the ECM. The red dashed line calculates the trend with the HP filter and $\lambda = 10,000$, while the blue dash-dot line calculates the trend with the HP filter and $\lambda = 400,000$.

Figure B.5: FASTVAR Input Variables



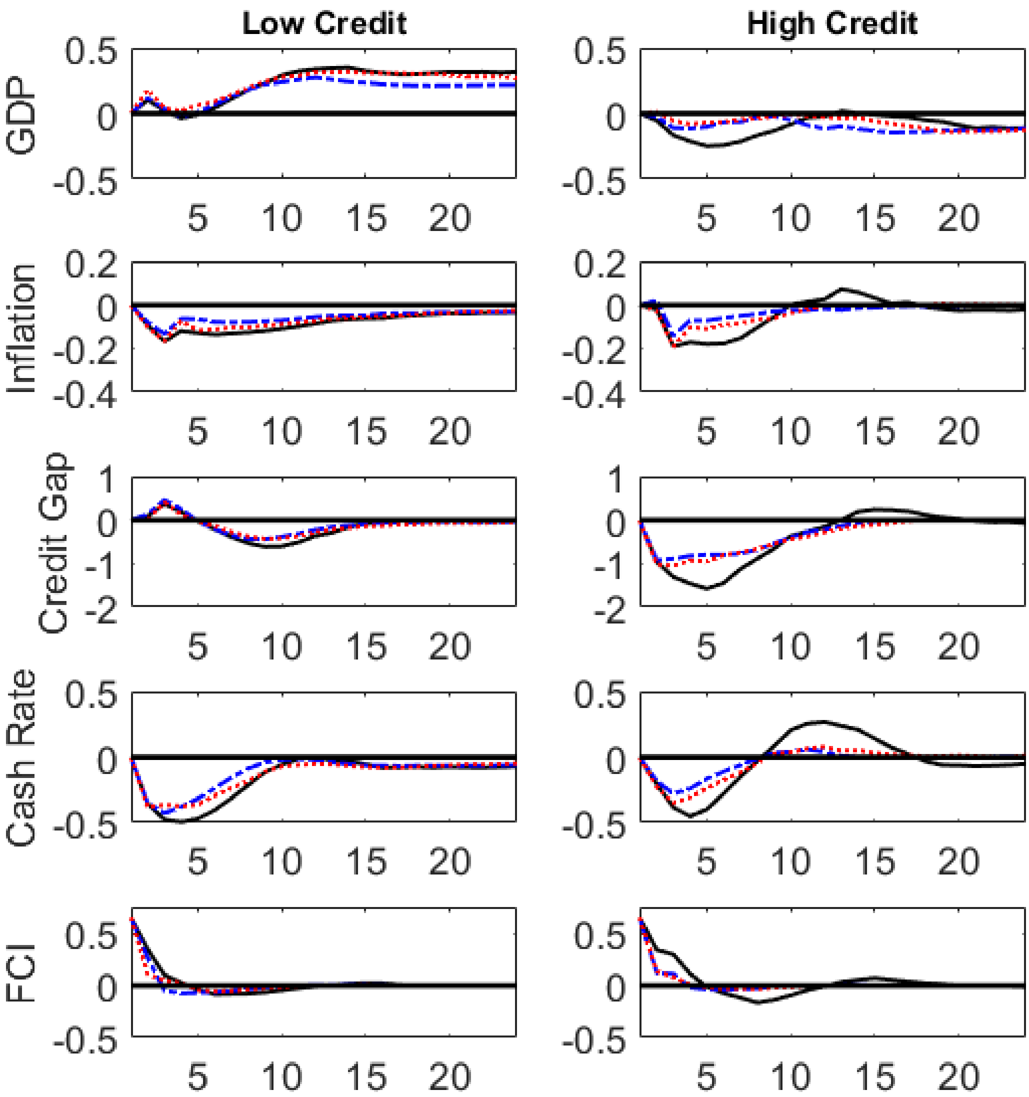
Notes: See Table B.1 for detailed definitions and sources. Note that real GDP enters the FASTVAR in log-levels.

Figure B.6: Impulse Response to a Financial Shock – Alternative Identification



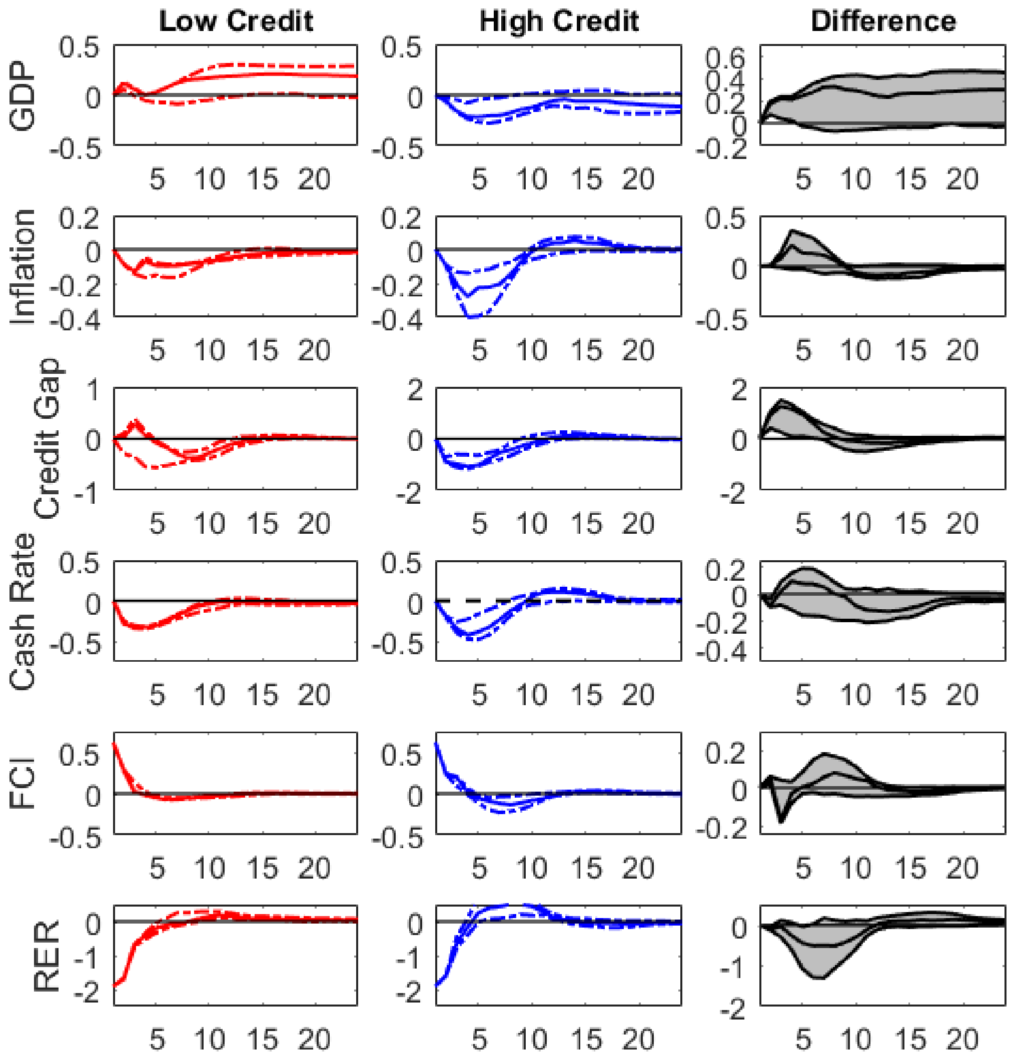
Notes: Response of the log-level of real GDP, quarterly trimmed mean inflation (annualised), the credit gap, the cash rate and the FCI to an unanticipated 1 standard deviation tightening in the FCI. The black line is the baseline, the dash-dot blue line is an identification scheme where the cash rate is ordered after the FCI $\boldsymbol{X_t} = (y_t, \pi_t, cgap_t, fci_t, ocr_t)$, the dotted red line is an identification scheme where the credit gap is ordered last in the model $\boldsymbol{X_t} = (y_t, \pi_t, ocr_t, fci_t, cgap_t)$.

Figure B.7: Impulse Response to a Financial Shock – Controlling for Foreign Financial Shocks



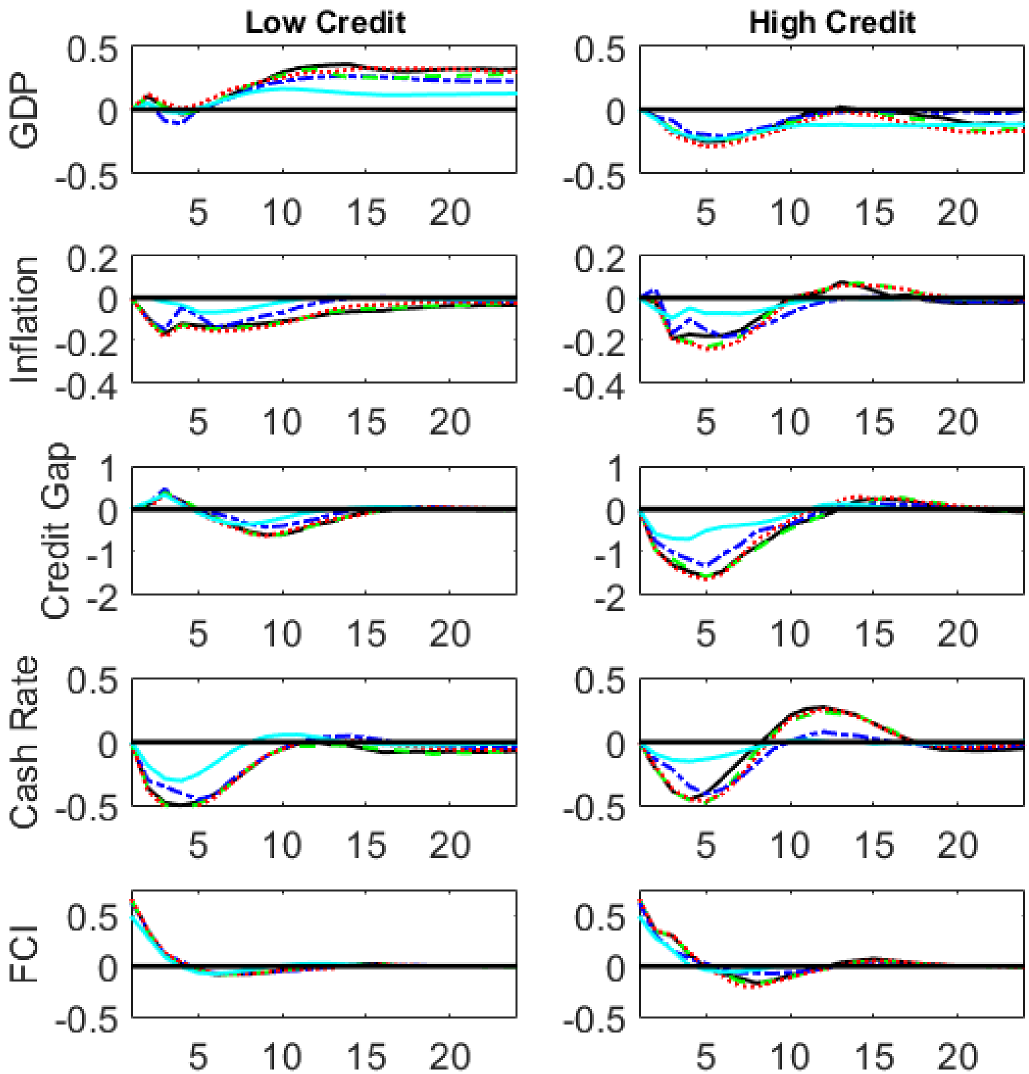
Notes: Response of the log-level of real GDP, quarterly trimmed mean inflation (annualised), the credit gap, the cash rate and the FCI to an unanticipated 1 standard deviation tightening in the FCI. The black line is the baseline, the dash-dot blue line shows the responses with the US NFCI included as an exogenous variable, the dotted red line shows the responses with the excess bond premium from Gilchrist and Zakrajšek (2012) included as an exogenous variable.

Figure B.8: Impulse Response to a Financial Shock – Model with Real Exchange Rate



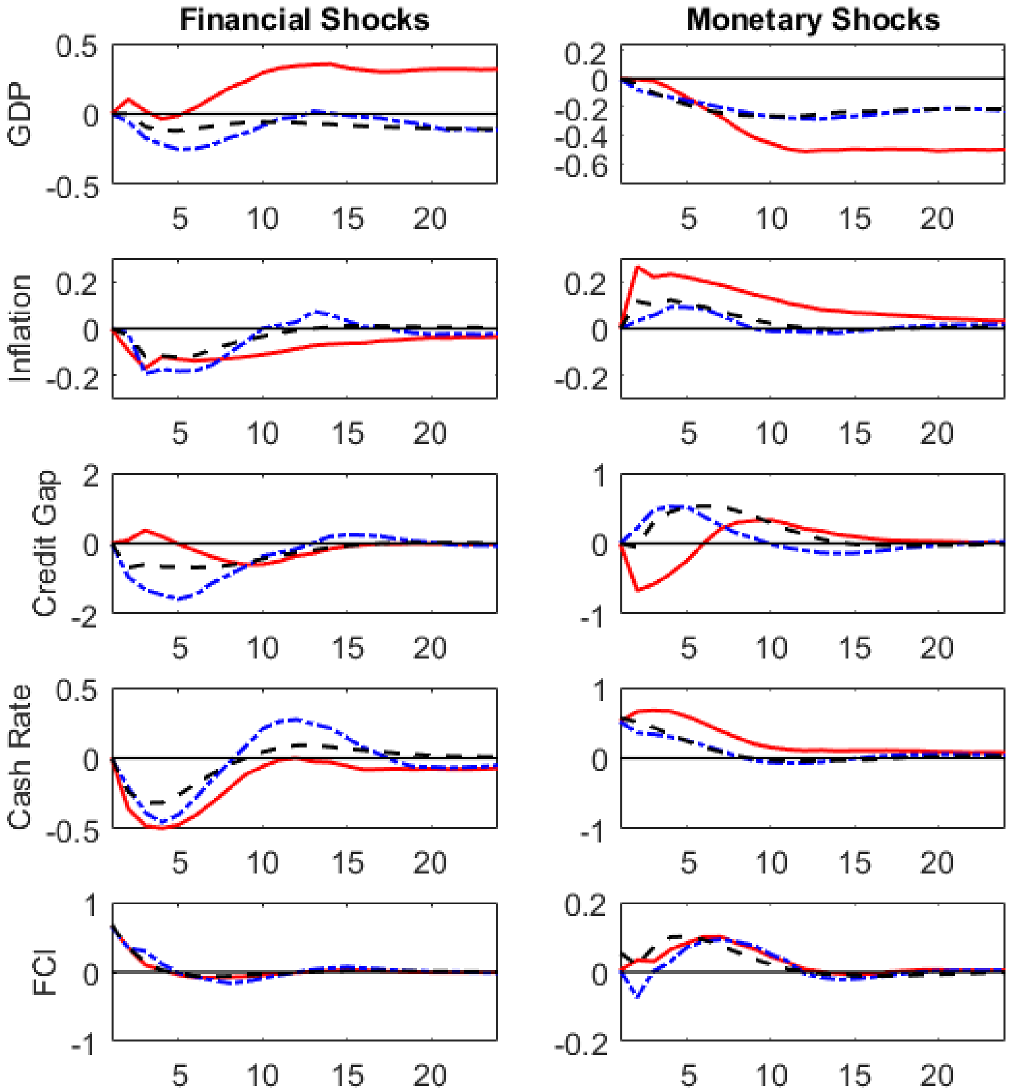
Notes: Response of the log-level of real GDP, quarterly trimmed mean inflation (annualised), the credit gap, the cash rate, the FCI and the real exchange rate index to an unanticipated 1 standard deviation tightening in the FCI. The first column shows the central estimate and the associated 68 per cent confidence interval in a low credit regime, the second column shows the equivalent in a high credit regime and the third column shows the difference between the low and high credit regimes.

Figure B.9: Impulse Response to a Financial Shock – Alternative Specifications



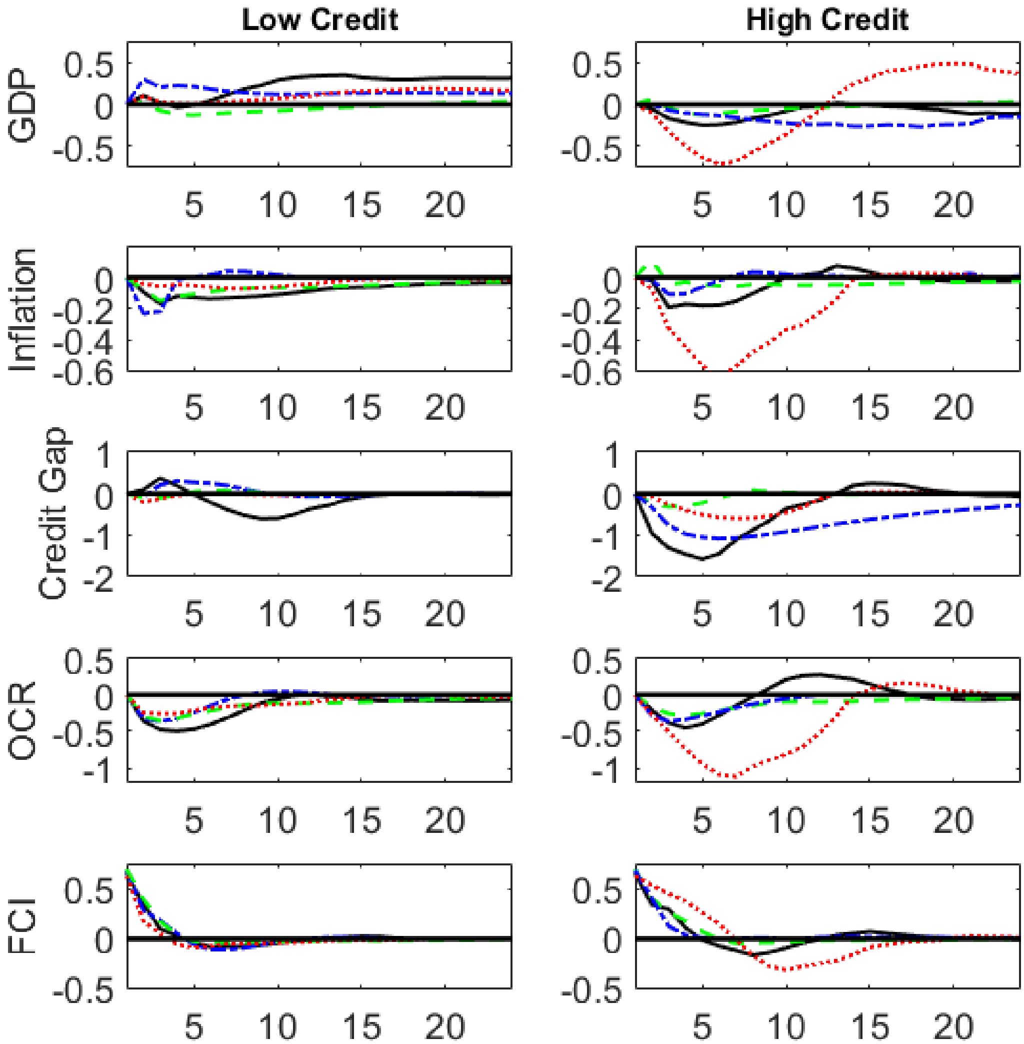
Notes: Response of the log-level of real GDP, quarterly trimmed mean inflation (annualised), the credit gap, the cash rate and the FCI to an unanticipated 1 standard deviation tightening in the FCI. The black line is the baseline, the dash-dot blue line shows the responses when the lag order is 3, the dotted red line shows the results when setting $\gamma = 10$ in the transition function, the dashed green line shows the responses from a model where the terms of trade (log level) replaces the real commodity price index, the cyan line shows the responses when I control for economic uncertainty shocks using the Moore (2016) economic uncertainty index.

Figure B.10: Linear versus Nonlinear Models



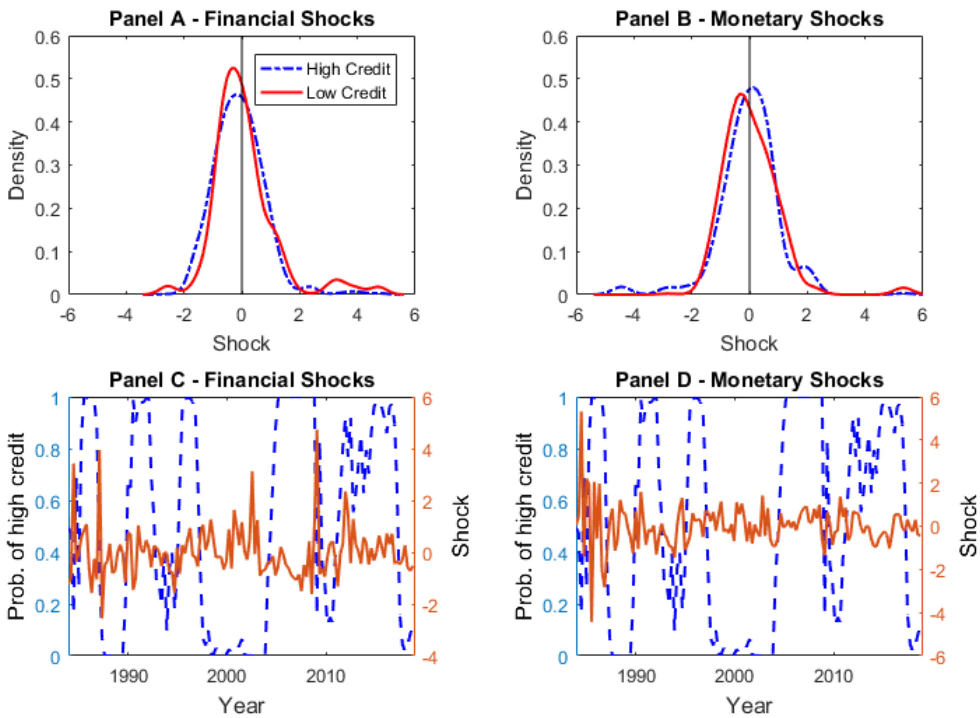
Notes: Dynamic responses to both financial and monetary shocks obtained with a linear VAR (black line), as well as those conditional on low (red line) and high (blue line) credit regimes estimated by the baseline FASTVAR model.

Figure B.11: Impulse Response to a Financial Shock – Alternative Transition Variables



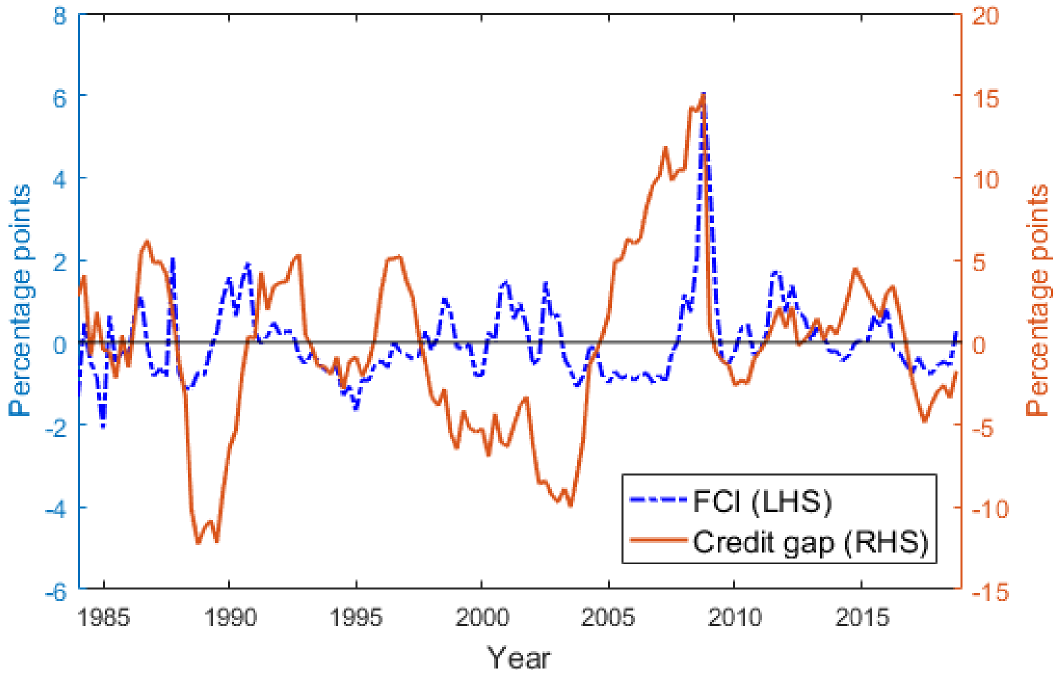
Notes: Response of the log-level of real GDP, quarterly trimmed mean inflation (annualised), the credit gap, the cash rate and the FCI to an unanticipated 1 standard deviation tightening in the FCI. The black line is the baseline, the dash-dot blue line shows the responses with the BIS private non-financial sector credit gap as the transition variable, the dotted red line shows the responses with the credit gap as the transition variable where the household credit-to-GDP equilibrium is calculated with the HP filter, the dashed green line shows the responses with growth in the household credit-to-GDP ratio as the transition variable.

Figure B.12: Shock Distributions



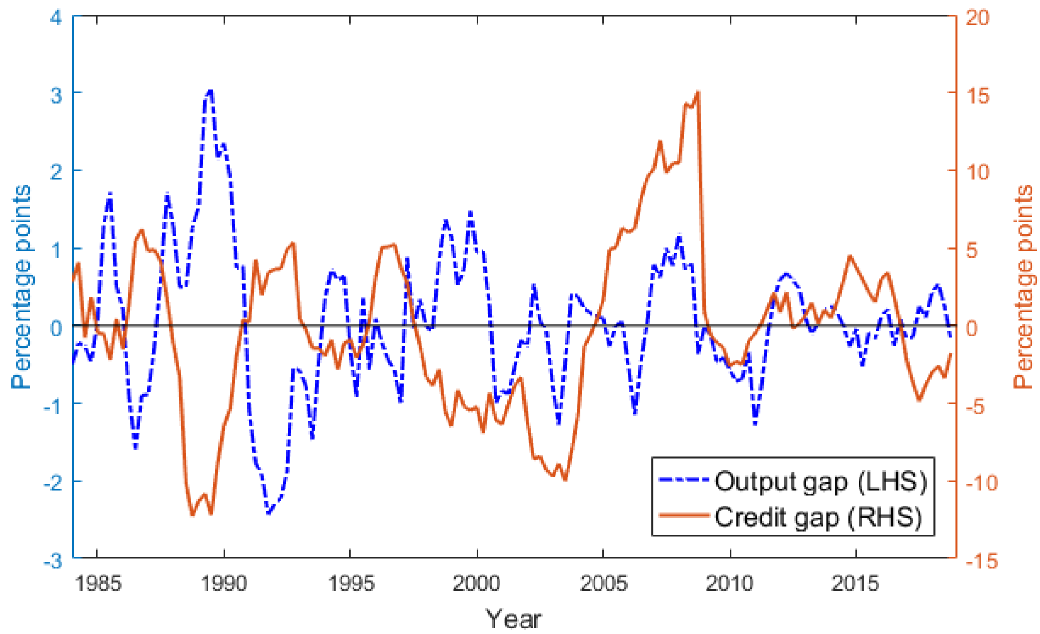
Notes: Panels A and B show estimates of the probability distribution function of the financial shocks and monetary shocks, respectively, in different credit regimes. The shocks are smoothed with a normally distributed kernel and the high and low credit regimes are generated by weighting the kernel function with $F(z_{t-1})$ and $1 - F(z_{t-1})$, respectively. Panels C and D show the financial and monetary shocks (orange line) alongside the transition function (dashed blue line).

Figure B.13: Financial Conditions Index and the Credit Gap



Notes: The baseline credit gap (orange line) is explained in Section 2.2. The FCI (dash-dot blue line) is explained in Section 2.3. Correlation coefficient = 0.14.

Figure B.14: Output and Credit Gaps



Notes: The baseline credit gap (orange line) is explained in Section 2.2. The output gap (dash-dot blue line) is computed as the difference between the log-level of Australian real GDP and an estimate of its trend calculated with the HP filter (smoothing parameter $\lambda = 1600$). Correlation coefficient = -0.28.

Appendix C

Chapter 3 Appendix

C.1 Technical Details

Time-varying parameter vector autoregression (TVP-VAR) approach

The following model is based on the TVP-VAR outlined in Primiceri (2005). Consider the model

$$x_t = c_t + B_{1,t}x_{t-1} + B_{2,t}x_{t-2} + A_t^{-1}\Sigma_t\varepsilon_t \qquad t = 1, ..., T \tag{C.1}$$

where $x_t = (\Delta y_t,\ r_t,\ \pi_t)'$, Δy_t denotes real GDP growth, r_t is the ex ante real interest rate used in the HLW model, and π_t is consumer price inflation; c_t is a 3 x 1 a vector of time-varying intercepts; $B_{i,t}, i = 1, 2$ are 3 x 3 matrices of time-varying coefficients; A_t is a lower-triangular matrix with ones on the main diagonal and time-varying coefficients below it; Σ_t is a diagonal matrix of time-varying standard deviations; and ε_t is a 3 x 1 vector of unobservable shocks with variance equal to the identity matrix.

The dynamics of the time-varying parameters are specified as

$$B_t = B_{t-1} + \nu_t\ , \tag{C.2}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t\ , \tag{C.3}$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t\ , \tag{C.4}$$

where α_t is a vector of the lower-triangular elements of the matrix A_t and σ_t is the vector of the diagonal elements of the matrix Σ_t. All the innovations to the model are assumed to follow a joint normal distribution with the following assumptions on the variance-covariance matrix:

$$V = Var \left\{ \begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \right\} = \begin{bmatrix} I_3 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}, \tag{C.5}$$

where Q, S, and W are positive definite matrices and I_3 is the 3 x 3 identity matrix. Therefore, the elements of B_t and the free elements of the matrix A_t are assumed to follow a random walk. In order to identify either a structural change or a permanent shift in the coefficients, it is necessary to assume that the coefficients follow a random walk, rather than a stationary process. Furthermore, the TVP-VAR is already heavily parameterised, and thus assuming a random walk process for the innovation of parameters reduces the number of parameters to estimate (Nakajima, 2011). The coefficients σ_t are assumed to follow a geometric random walk, as is common in the literature incorporating stochastic volatility (Lubik and Matthes, 2015b).

The estimation approach follows Primiceri (2005). In short, the process begins by specifying a prior distribution for the parameters of the model, and I estimate a fixed-coefficient VAR to initialise the prior. Following prior selection, a likelihood function is used to extract information in the data in order to update the prior. The Gibbs sampler proposed by Primiceri (2005) is used for the posterior numerical evaluation of the parameters of interest.[1]

Once the TVP-VAR has been estimated, the NRI is the five-year conditional forecast of the real interest rate. The point forecast is the median posterior estimate, and the associated 90% confidence region is calculated following Lubik and Matthes (2015a).

[1]The Gibbs sampling method in Primiceri (2005) delivers smoothed, rather than filtered, estimates. The suitability of this cannot be determined *a priori*, but depends on the specific problem at hand. In general, smoothed estimates are preferable when the objective is an investigation of the true evolution of the unobservable states over time (Primiceri, 2005). Therefore, smoothed estimates are desirable as the objective is to obtain the most accurate estimate of the NRI.

Wright (2011) Affine Term Structure Model

I use the macro-finance dynamic term structure model described in Wright (2011) to estimate the term premium specific to a 5-to-10-year security. I briefly describe the model here, but for more information, see Wright (2011).

The one-period (three months in this context) interest rate, r_t, and the market price of risk, λ_t, are both assumed to be affine functions of a 5 x 1 vector of state variables, X_t (discussed in more detail below):

$$r_t = \delta_0 + \delta_1' X_t, \tag{C.6}$$

$$\lambda_t = \lambda_0 + \lambda_1 X_t. \tag{C.7}$$

Next, assume that there exists a physical probability measure P under which X_t follows a VAR,

$$X_{t+1} = \mu + \Phi X_t + \Sigma \varepsilon_{t+1}, \tag{C.8}$$

where ε_{t+1} is an i.i.d. standard normal random vector. Imposing a no-arbitrage condition implies that there exists a risk-neutral probability measure Q that prices all financial assets, and under Q the vector of state variables follows a VAR,

$$X_{t+1} = \mu^* + \Phi^* X_t + \Sigma \varepsilon_{t+1}^*, \tag{C.9}$$

where $\mu^* = \mu - \Sigma\lambda_0$, $\Phi^* = \Phi - \Sigma\lambda_1$, Σ is a lower-triangular matrix, and ε_{t+1}^* is an i.i.d. standard normal random vector. Wright assumes a conditionally lognormal pricing kernel and shows that the price of an n-period zero-coupon bond is given by $P_t^n = \exp(A_n + B_n' X_t)$ where A_n and B_n are functions of the model parameters (see Wright (2011) for more details).

Choosing the state variables (also commonly referred to as "risk factors") is a key modelling choice. "Macro-finance" models differ from "yield-only" models in that X_t includes information from macroeconomic variables, as well as the yield curve (Bauer and Rudebusch, 2016). Following Wright (2011), the state vector X_t is partitioned into $(X_{1t}', X_{2t}')'$, where X_{1t} is a 3 x 1 vector consisting of the first three principal components of zero-coupon yields from three months to ten years, X_{2t} is 2 x 1 vector of the exponentially weighted moving average of quarterly inflation and GDP growth, and the variables in X_{2t} are treated as unspanned factors. That is, the macroeconomic factors are important for forecasting future interest rates, but changes in these factors have no contemporaneous effect on bond yields.

Maximum likelihood estimates of the model parameters are obtained following the approach in Wright (2011). Following estimation, the term premium equals the difference between the 5-to-10-year forward rate under the Q measure and the average expected one-period interest rate from five to ten years in the future under the P measure.

Shadow short rate estimation methods

The level and profile of shadow rate estimates vary according to the model specification and there is currently no consensus over the best way to estimate shadow rates (Krippner, 2020). The Krippner (2015b, 2016) and Wu and Xia (2016) approach both estimate the shadow rate as the shortest maturity rate from an estimated shadow yield curve. However, the Krippner method uses a *continuous* time Gaussian affine term structure model with *two* factors (level and slope), whereas Wu and Xia use a *discrete* time Gaussian affine term structure model with *three* factors (level, slope, and curvature). In the baseline, I used updated estimates from the Krippner two-factor framework (referred to as K-ANSM(2) in Krippner 2015b), as these are relatively robust in profile and magnitude, and correspond well with unconventional monetary policy events compared to estimates from models with three factors (Krippner, 2015a). I briefly describe the Krippner approach and how it differs from the Wu-Xia approach. For more details, see the original papers and Krippner's (2015a) comment comparing two- and three-factor models.

Shadow rate models are based on the lower bound mechanism:

$$r(t) = \max[s(t), r_{LB}] \tag{C.10}$$

where $s(t)$ is the shadow rate that can adopt negative values and $r(t)$ is the lower bound or the actual short rate which is constrained to a minimum value r_{LB}. The Krippner method imposes $r_{LB} = 0.125$ whereas Wu-Xia use $r_{LB} = 0.25$, though r_{LB} can also be estimated with the model.

After introducing the lower bound mechanism (C.10), the Wu-Xia method proceeds largely as detailed for Wright (2011) above except for two main differences. Equation (C.6) is the same in Wu-Xia except that now $s(t)$ is an affine function of the state variables. Equation (C.10) introduces a nonlinearity into an otherwise linear system, so Wu-Xia propose an analytical approximation for the forward rate which is detailed in Wu and Xia (2016). The shadow rate model is written as a nonlinear state space model, and the extended Kalman filter is used for estimation (see Wu and Xia (2016) for details).

Krippner's method is essentially the continuous time equivalent of Wu-Xia. Krippner proposes a closed-form analytic solution for lower-bounded forward rates in continuous time which is the measurement equation in the nonlinear state space model. The state equation is obtained from a vector Ornstein-Uhlenbeck process that the state variables follow under the P measure. The nonlinear state space model is estimated using the iterated extended Kalman filter. Further details and discussion are provided in Krippner (2015b).

C.2 Data Sources

HLW and TVP-VAR Input Data Sources

US: Real GDP and PCE inflation (excluding food and energy) data are published by the Bureau of Economic Analysis (BEA). The short-term interest rate is the annualised Federal Funds Rate available from the Board of Governors and prior to 1965 the Federal Reserve Bank of New York's discount rate.

UK: Real GDP data are taken from the Office of National Statistics (ONS). Inflation is CPI excluding food and energy, and all-items CPI prior to 1970, both from the OECD Main Economic Indicators database. The short-term interest rate is the annualised Bank

Rate available on the Bank of England website.

Replication code for the HLW method, Krippner and Wu-Xia shadow rates are all available from the authors' websites. In addition, thanks to Christian Matthes for providing TVP-VAR code.

FM Input Data Sources

For the FM NRI method, I require zero-coupon nominal government bond yield curve data out to a ten-year maturity, a measure of long-run inflation expectations, real GDP, and inflation data.

Zero-coupon nominal government bond yield curves were initially obtained from the Wright (2011) Data Appendix and then updated using publicly available sources. The US yield curve is described in Gürkaynak et al. (2007) and is available on the Federal Reserve website. The UK yield curve is described in Anderson and Sleath (2001) and is available on the Bank of England website.

Long-run inflation expectations were collected from a range of data sources. For the US, the primary measure used was the University of Michigan Survey of Consumers which asks survey respondents "By about what percent per year do you expect prices to go (up/down) on average, during the next 5 to 10 years?" and is available on their website. Semi-annual data (linearly interpolated to quarterly frequency) is available from 1980-1985 and quarterly data is available from 1986. For robustness, I also obtained long-run inflation expectations from the Federal Reserve Bank of Philadelphia Survey of Professional Forecasters and 5-to-10-year break-even inflation obtained from the Federal Reserve Bank of St. Louis. For the UK, I use 5-to-10-year break-even inflation (calculated as the yield differential between nominal and real 5-to-10-year forward interest rates) as survey-based measures are not available over a sufficiently long sample period. Break-even inflation was calculated using 5- and 10-year nominal and inflation-indexed yields from the Bank of England website.

For the macroeconomic factors in the Wright (2011) term structure model, I follow Wright and use real GDP and consumer price inflation (all items) from the OECD's Main

Economic Indicators database. The variables are smoothed by applying an exponentially weighted moving average filter with a smoothing parameter of $\lambda = 0.75$.

NRI Determinants

For the US, real output per hour for the nonfarm business sector and population growth are available from the US Bureau of Labor Statistics. The relative price of capital (calculated using household consumption and gross fixed capital formation deflators) is available from the BEA. For the UK, output per hour worked, population growth and the relative price of capital data are all available from the ONS. For both economies, the economic policy uncertainty index was accessed at `http://www.policyuncertainty.com/` and the approach to measuring uncertainty is detailed in Baker et al. (2016); global reserves data is from the IMF International Financial Statistics, and US nominal GDP is published by the BEA.

For robustness testing: GDP per person employed is available from the OECD Main Economic Indicators database; the Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity is available from the Federal Reserve Bank of St. Louis; the Producer Price Index for Private Capital Equipment is available from the US BLS and the GDP deflator is from the US BEA.

C.3 Additional Tables and Figures

Table C.1: Unit Root Test Results

ADF test	United States		United Kingdom	
Natural rate of interest	Levels	First difference	Levels	First difference
HLW	-1.45	-4.68***	-2.02	-4.21***
TVP-VAR	-2.64	-4.52***	-2.94	-5.93***
FM	-2.82	-5.18***	-3.05	-5.09***
Mean	-2.28	-4.51***	-2.95	-5.22***
Determinants				
Productivity growth	-1.50	-8.85***	-1.47	-8.21***
Relative price of capital	-0.96	-4.01**	-3.03	-3.60**
Population growth	-2.52	-4.03**	-2.13	-4.53***
Economic policy uncertainty	-2.43	-4.77***	-1.18	-4.92***
Macroeconomic uncertainty	-2.85	-5.40***		
Financial uncertainty	-3.29*	-4.43***		
Public debt	-1.81	3.17*	-2.01	-3.31*
Global reserves	-2.13	-5.23***	-2.13	-5.23***

Notes: Sample is 1984:1 to 2016:4 except FM in the UK begins in 1985:1. Number of lags is determined by the default truncation lag length in *adf.test* within the *'tseries'* package in R. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively.

Table C.2: Johansen's Cointegration Test Statistics

	United States		United Kingdom	
	Eigenvalue	Trace	Eigenvalue	Trace
$r = 0$	28.81***	43.33***	16.59*	29.74*
$r \leq 1$	10.80	14.42	9.05	13.15
$r \leq 2$	3.62	3.62	4.09	4.09

Notes: Model with a constant and no linear trend in the cointegration. VAR lag length selected using the AIC with a maximum lag length of 10. ***, **, and * indicates statistical significance at the 1, 5, and 10% levels, respectively.

Table C.3: Uncertainty and the Long-run Equilibrium - United States

Dependent variable:	HLW	TVP-VAR	FM	Mean
Productivity	0.74***	0.30***	0.10	0.53***
growth (p)	(0.09)	(0.11)	(0.12)	(0.10)
Relative price	7.30***	1.99*	6.93***	8.21***
of capital (k)	(0.96)	(1.14)	(0.80)	(0.67)
Population	1.29***	-0.32	-0.18	0.04
growth (n)	(0.13)	(0.21)	(0.25)	(0.16)
Economic policy	-0.85***	-1.10***	-1.32***	-1.88***
uncertainty (u)	(0.17)	(0.22)	(0.34)	(0.29)
Macroeconomic	-1.59***	-5.05***	-1.30*	-1.91***
uncertainty (u^M)	(0.29)	(0.62)	(0.70)	(0.57)
Financial	1.29***	-0.80***	-0.52	-0.33
uncertainty (u^F)	(0.15)	(0.30)	(0.48)	(0.33)
Public	-0.007	-0.04***	-0.01*	0.002
debt (d)	(0.006)	(0.008)	(0.007)	(0.006)
Global	0.03	-0.05***	-0.07***	0.01
reserves (s)	(0.01)	(0.01)	(0.02)	(0.01)
Autocorrelation (p-value)	0.09	0.50	0.56	0.90
Normality (p-value)	0.29	0.05	0.02	0.78
Heteroskedasticity (p-value)	0.20	0.68	0.24	0.99
Static long-run $\hat{\sigma}$	0.15	0.21	0.34	0.20
Wald test: $\chi^2(K)$	3763***	1067***	452***	2519***
Sample	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4
Observations	132	132	132	132
Cointegration testing				
ADF test statistic	-8.31***	-9.08***	-9.04***	-8.05***

Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium. For the ADF test, the lag length was selected using the AIC and finite-sample critical values were taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.4: Long-run Equilibrium in the US - Alternative measures of determinants

Dependent variable:	HLW	TVP-VAR	FM	Mean
Productivity	0.82***	0.07**	0.41***	-0.12
growth (p)	(0.13)	(0.03)	(0.11)	(0.09)
Relative price	5.74***	8.67***	9.93***	8.68***
of capital (k)	(0.98)	(0.26)	(1.04)	(0.79)
Population	-0.22	-1.21***	-1.27***	-0.60***
growth (n)	(0.34)	(0.06)	(0.26)	(0.18)
Economic policy	-0.58***	-0.98***	-1.19***	-0.98***
uncertainty (u)	(0.21)	(0.06)	(0.23)	(0.17)
Public	-0.03***	-0.01***	-0.02***	-0.03***
debt (d)	(0.003)	(0.001)	(0.003)	(0.003)
EM current	-0.03	-0.10***	0.04	0.03
account surplus (s)	(0.03)	(0.01)	(0.03)	(0.02)
Autocorrelation (p-value)	0.77	0.01	0.78	0.89
Normality (p-value)	0.33	0.82	0.89	0.65
Heteroskedasticity (p-value)	0.52	0.03	0.29	0.29
Static long-run $\hat{\sigma}$	0.34	0.07	0.36	0.22
Wald test: $\chi^2(K)$	2429***	27984***	1233***	3060***
Sample	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4
Observations	132	132	132	132
Cointegration testing				
ADF test statistic	-7.87***	-6.81***	-7.09***	-5.87**

Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium. For the ADF test, the lag length was selected using the AIC and finite-sample critical values were taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.5: Long-run Equilibrium in the UK - Alternative measures of determinants

Dependent variable:	HLW	TVP-VAR	FM	Mean
Productivity	0.01	0.35***		0.10*
growth (p)	(0.05)	(0.14)		(0.06)
Relative price	5.95***	7.02***		4.57***
of capital (k)	(0.50)	(1.30)		(0.51)
Population	-1.00***	-3.90***	-3.72***	-2.27***
growth (n)	(0.22)	(0.77)	(0.80)	(0.26)
Economic policy	-0.22***	-0.61***		-0.23**
uncertainty (u)	(0.08)	(0.26)		(0.10)
Public	-0.002		-0.02***	-0.005*
debt (d)	(0.002)		(0.003)	(0.003)
EM current	0.04	-0.12	0.26	
account surplus (s)	(0.02)	(0.09)	(0.07)	
Autocorrelation (p-value)	0.07	0.83	0.34	0.78
Normality (p-value)	0.01	0.11	0.04	0.01
Heteroskedasticity (p-value)	0.14	0.01	0.05	0.05
Static long-run $\hat{\sigma}$	0.17	0.64	0.49	0.35
Wald test: $\chi^2(K)$	374***	2411***	72**	6562***
Sample	1984:1-2016:4	1984:1-2016:4	1987:1-2016:4	1984:1-2016:4
Observations	132	132	120	132
Cointegration testing				
ADF test statistic	-6.87***	-6.72***	-4.41	-6.01**

Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium. For the ADF test, the lag length was selected using the AIC and finite-sample critical values were taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.6: Long-run Equilibrium in the US - Model selection settings robustness

Dependent variable:	HLW	TVP-VAR	FM	Mean
Productivity	0.82***		0.03	0.25***
growth (p)	(0.19)		(0.10)	(0.07)
Relative price	7.74***	4.20***	6.35***	5.71***
of capital (k)	(1.58)	(0.70)	(0.83)	(0.58)
Population			-0.22	0.27
growth (n)			(0.28)	(0.18)
Economic policy	-1.72***	-0.31	-1.07***	-0.95***
uncertainty (u)	(0.61)	(0.22)	(0.28)	(0.21)
Public	-0.01	-0.01***	-0.02***	-0.01***
debt (d)	(0.01)	(0.004)	(0.005)	(0.004)
Global		-0.05***	0.03	-0.01
reserves (s)		(0.02)	(0.02)	(0.01)
Autocorrelation (p-value)	0.67	0.82	0.83	0.39
Normality (p-value)	0.93	0.26	0.20	0.64
Heteroskedasticity (p-value)	0.68	0.02	0.79	0.29
Static long-run $\hat{\sigma}$	0.95	0.52	0.52	0.31
Wald test: $\chi^2(K)$	399***	902***	565***	2557***
Sample	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4
Observations	132	132	132	132
Cointegration testing				
ADF test statistic	-8.03***	-6.93***	-6.90***	-5.91**

Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium. For the ADF test, the lag length was selected using the AIC and finite-sample critical values were taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.7: Long-run Equilibrium in the UK - Model selection settings robustness

Dependent variable:	HLW	TVP-VAR	FM	Mean
Productivity		0.04	0.43***	0.11*
growth (p)		(0.18)	(0.12)	(0.07)
Relative price	4.43***	9.27***		4.62***
of capital (k)	(0.40)	(1.60)		(0.57)
Population	-1.00***	-6.71***	-1.60***	-2.67***
growth (n)	(0.22)	(0.99)	(0.60)	(0.31)
Economic policy	-0.45***	-0.89***	-0.36***	-0.32***
uncertainty (u)	(0.09)	(0.31)	(0.11)	(0.12)
Public		0.02*	0.005	0.004
debt (d)		(0.01)	(0.008)	(0.004)
Global	0.02	-0.02	-0.07	-0.04***
reserves (s)	(0.02)	(0.04)	(0.05)	(0.015)
Autocorrelation (p-value)	0.60	0.68	0.29	0.86
Normality (p-value)	0.00	0.00	0.07	0.17
Heteroskedasticity (p-value)	0.01	0.01	0.06	0.01
Static long-run $\hat{\sigma}$	0.48	0.93	0.80	0.39
Wald test: $\chi^2(K)$	2251***	1671***	967***	4714***
Sample	1984:1-2016:4	1984:1-2016:4	1987:1-2016:4	1984:1-2016:4
Observations	132	132	120	132
Cointegration testing				
ADF test statistic	-7.69***	-6.91***	-5.46**	-6.85***

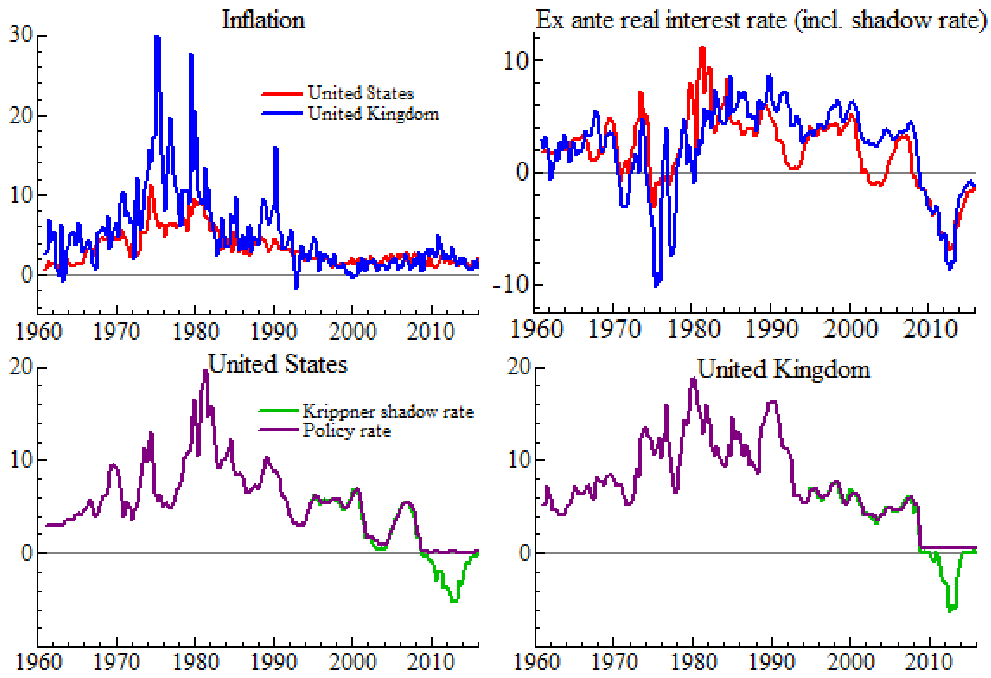
Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium. For the ADF test, the lag length was selected using the AIC and finite-sample critical values were taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.8: Long-run Equilibrium - Wu-Xia Shadow Rates

Country:	US	US	UK
Dependent variable:	HLW	TVP-VAR	HLW
Productivity	0.71***	-0.004	0.16**
growth (p)	(0.19)	(0.34)	(0.08)
Relative price	6.56***	3.69	3.90***
of capital (k)	(1.98)	(2.62)	(0.97)
Population	0.19	2.40**	
growth (n)	(0.55)	(1.07)	
Economic policy	-1.41**	-0.59	-0.49***
uncertainty (u)	(0.66)	(0.94)	(0.16)
(1.78)			
Public	-0.002	-0.02	
debt (d)	(0.014)	(0.019)	
Global		-0.24**	-0.01
reserves (s)		(0.11)	(0.02)
Autocorrelation (p-value)	0.44	0.42	0.81
Normality (p-value)	0.77	0.19	0.00
Heteroskedasticity (p-value)	0.81	0.87	0.01
Long-run sigma	0.71	1.04	0.16
Wald test: $\chi^2(K)$	720***	181***	926***
Sample	1984:1-2016:4	1984:1-2016:4	1984:1-2016:4
Observations	132	132	132
Cointegration testing			
ADF test statistic	-8.11***	-8.51***	-8.20***

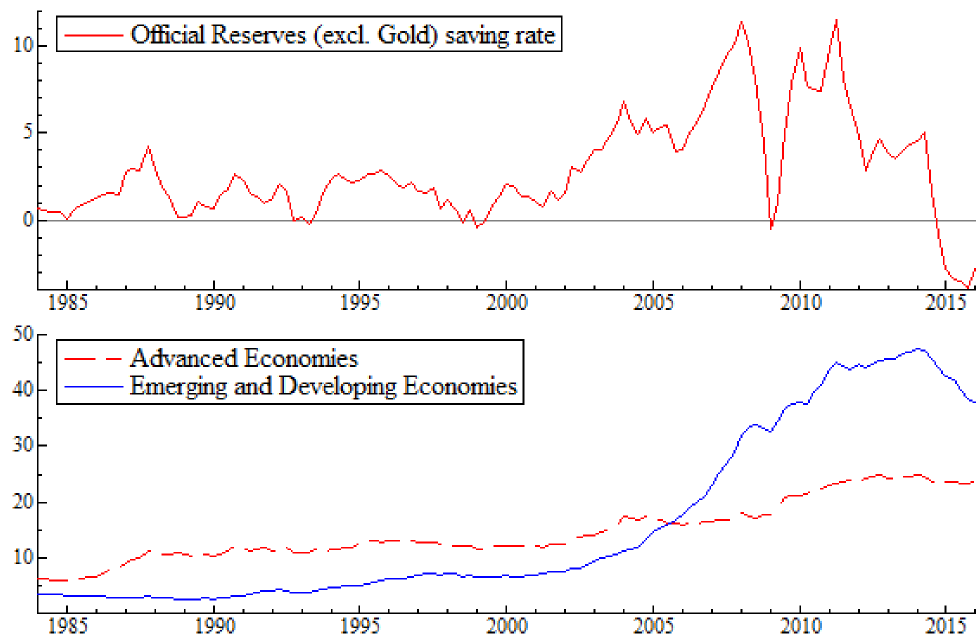
Notes: Standard errors in parentheses. Degrees of freedom for Wald Chi-Squared test K equals the number of variables in the long-run equilibrium, including indicator variables. For the ADF test, the lag length was selected using the AIC and finite-sample critical values were taken from MacKinnon (2010). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure C.1: Macroeconomic Model Estimation Inputs



Notes: Ex ante real interest rate calculated as the shadow rate minus four-quarter moving average of inflation.

Figure C.2: Global Foreign Exchange Reserves



Notes: Top panel shows growth in global reserves from the baseline. The bottom panel shows the level of reserves held by advanced economies and emerging and developing economies (as designated by the IMF) as a share of US GDP.

Figure C.3: Finance-based Natural Rate Decomposition

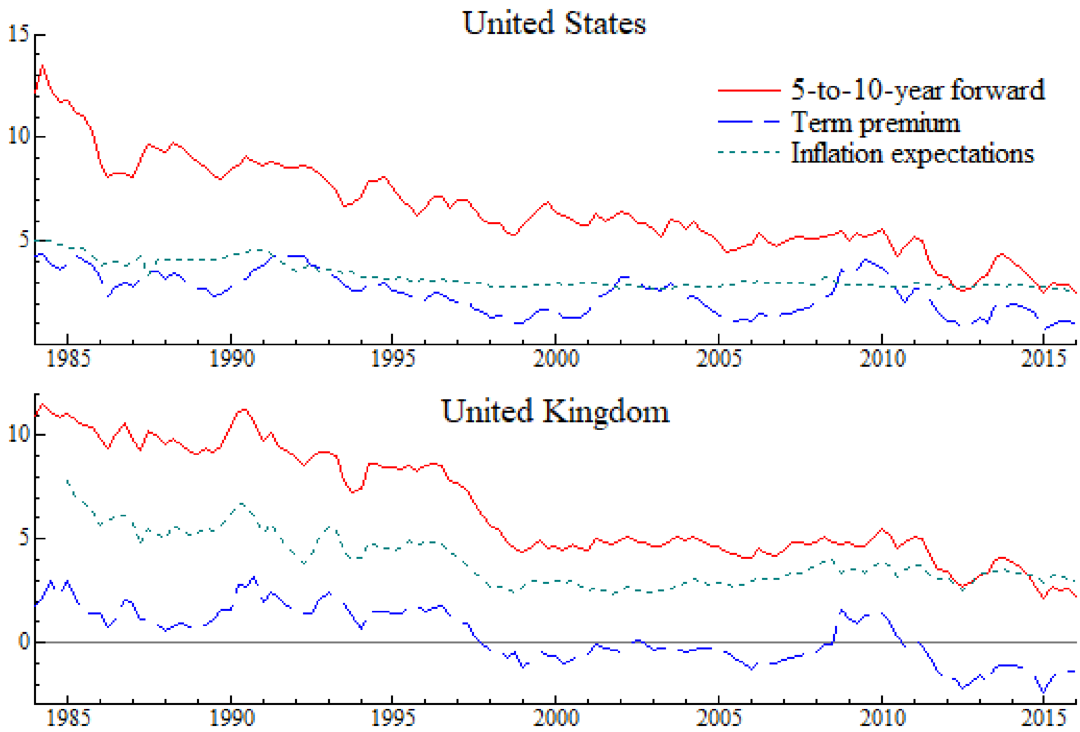


Figure C.4: Natural Rate of Interest Estimation Uncertainty

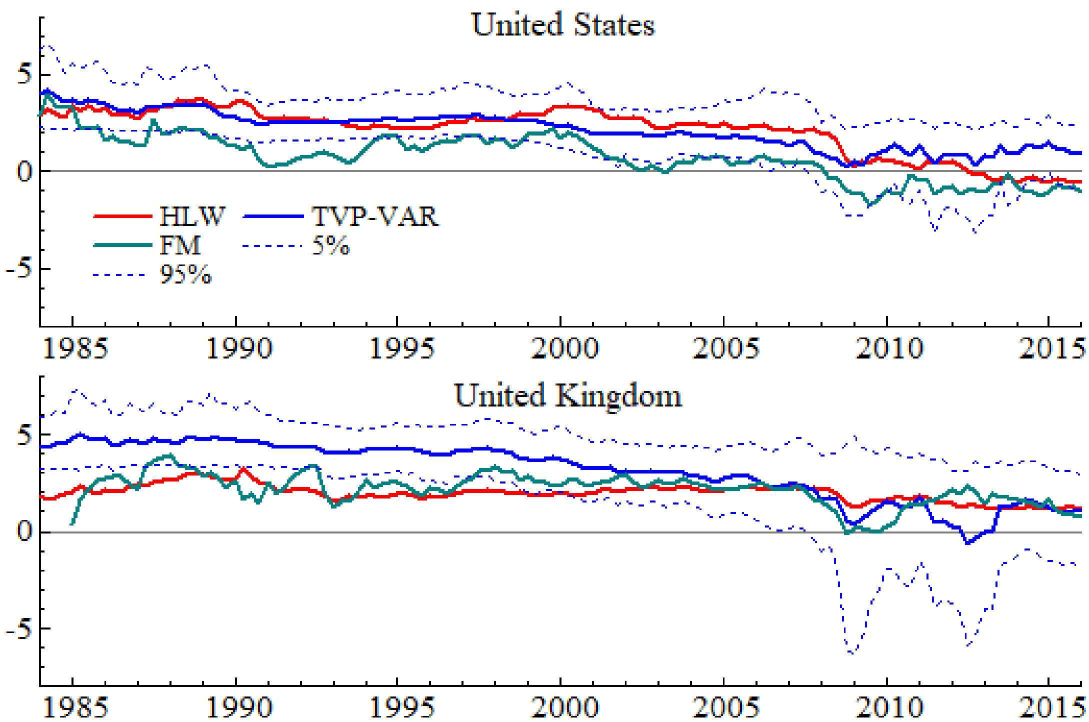


Figure C.5: Shadow Rates and Natural Rate Estimates

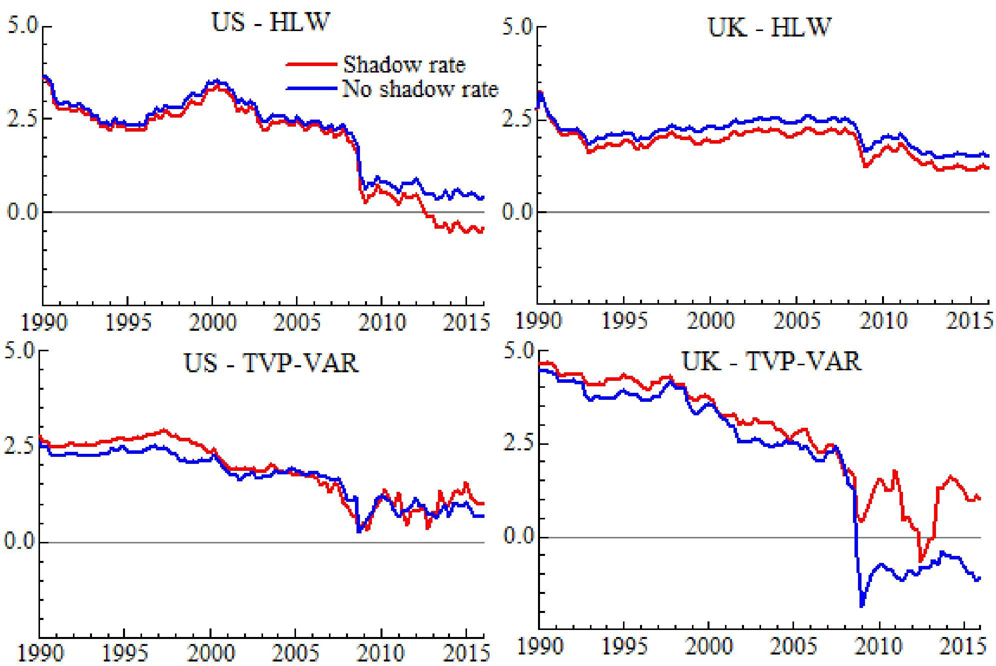
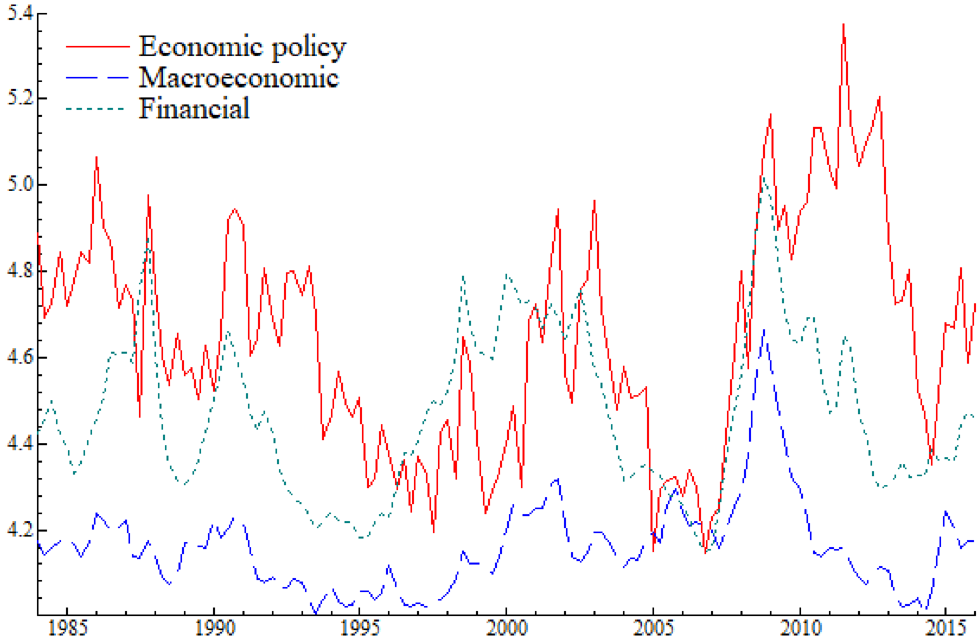
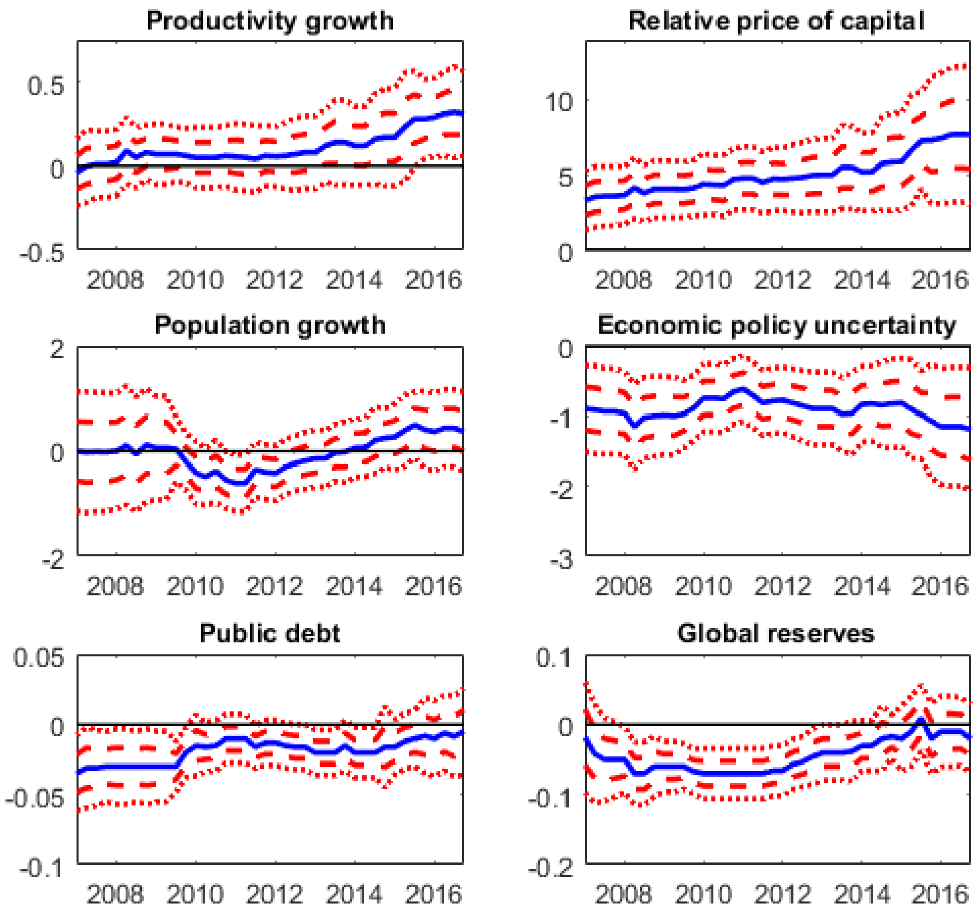


Figure C.6: Economic Uncertainty Proxies



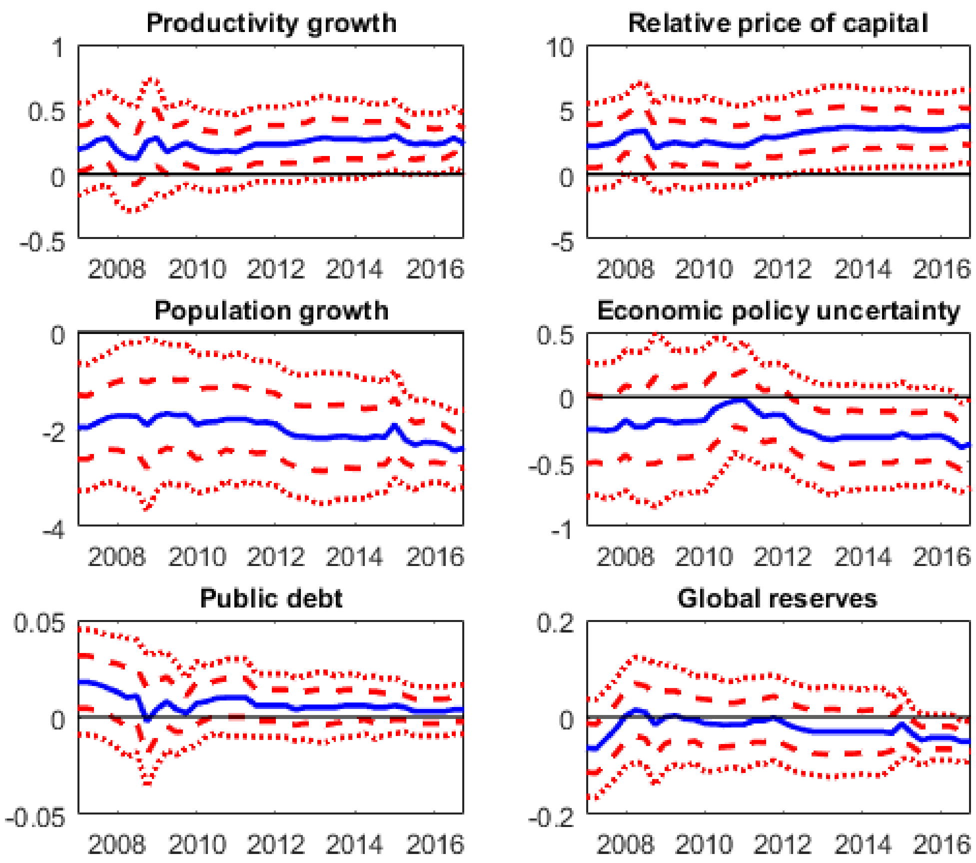
Notes: All variables shown in log-levels. Macroeconomic and financial uncertainty indices (one month horizon) are taken from Jurado et al. (2015) and Ludvigson et al. (2018). Economic policy uncertainty index is detailed in Baker et al. (2016)

Figure C.7: Long-run Equilibrium Stability - United States



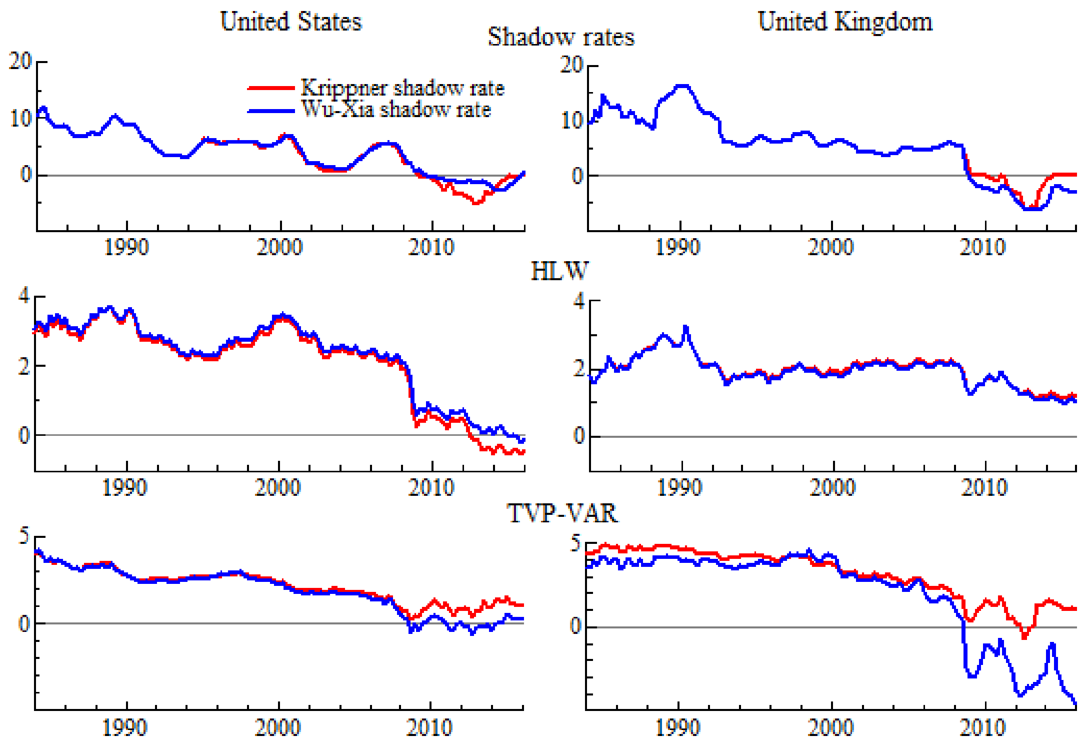
Notes: Figure shows the recursively estimated long-run equilibrium coefficients over 2007Q1–2016Q4 (see Section 3.6.2). Blue line denotes the central estimate and the red dotted lines denote 68 and 95 per cent confidence intervals.

Figure C.8: Long-run Equilibrium Stability - United Kingdom



Notes: Figure shows the recursively estimated long-run equilibrium coefficients over 2007Q1–2016Q4 (see Section 3.6.2). Blue line denotes the central estimate and the red dotted lines denote 68 and 95 per cent confidence intervals.

Figure C.9: Wu-Xia Shadow Rates and NRI Robustness



Notes: US estimates in the left column; UK estimates in the right column.

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