Three Essays on Housing, Credit and Uncertainty

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university.

Benjamin Finch
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Abstract

This thesis comprises three essays in macroeconomics. The key aim of our work is to quantify the link between housing, credit and uncertainty. In the first chapter we investigate the propagation mechanism of a temporary uncertainty shock for the UK. We adopt a factor augmented VAR model which facilitates an examination of variables which have not been included in previous studies. Our empirical analysis establishes that while the 'traditional' channels generally hold; across different sectors there are asymmetric responses. For example, precautionary behaviour implies that agents cut back on consumption and increase saving in order to mitigate the risks associated with uncertainty. However, decomposing consumption, we provide evidence that for food and fuel markets the impact of an increase in uncertainty is close to zero. This follows because we do not capture the expected fall in demand given the consumption decision is a necessity. In terms of housing and credit we propose a new housing uncertainty channel which is closely linked to growth option theory. The idea is that a second moment uncertainty shock extends the tails of the distributions and thus increases the potential payoffs. This in turn leads to an increase in investment. For those who are able to access credit, we capture an increase in housing investment and a corresponding expansion in mortgage credit which contributes to a reduction in the negative impacts of uncertainty shocks.

The second paper extends the discussion in Chapter 1, by examining the transmission of uncertainty shocks in the US. Specifically, we quantify the linear and non linear impacts of uncertainty. For the linear analysis, we estimate a proxy SVAR using

narrative identification, net of first moment shocks, and provide supporting evidence of the housing uncertainty channel. The interaction between housing and credit is shown to be crucial, reinforcing the findings we present in Chapter 1. The intuition for our non linear analysis builds upon the idea that once uncertainty has reached a certain level, any additional increases in uncertainty are unlikely to have any impact on macroeconomic aggregates. In order to test this conjecture, we propose an instrument to identify uncertainty shocks, which is constructed by isolating the variation in the price of gold around events associated with uncertainty. We argue that the change in the price of gold accurately represents uncertainty, because it is perceived as a safe haven asset. When faced with the additional risk associated with uncertainty agents invest in gold. This reflects a flight to safety. We adopt a threshold VAR model which isolates responses dependant on regimes synoptic with high and low uncertainty. We show that in a low uncertainty regime, uncertainty propagates similarly to the linear case. In contrast, there is a clear distinction in a high uncertainty regime driven by impatient behaviour.

In our final chapter, we propose a DSGE model which is consistent with the empirical evidence we provide in the previous chapters. We choose to order the chapters in such a way that we first establish the empirical facts of uncertainty shocks and then use these to inform our theoretical model. The key empirical takeaway following a shock to uncertainty is a co-movement between consumption and investment. We demonstrate that a vanilla housing real business cycle model is not consistent with these empirical facts. In order to match the theoretical model to the empirics, we extend the baseline model by including both banks and financial frictions. We document first a credit channel which limits access to external funds for the credit dependant sector of the economy. Second, we find a housing demand channel, which leads to tighter constraints for households and entrepreneurs and lowers the return on capital. Together, both channels amplify precautionary saving for household borrowers. The credit channel creates a real option channel for entrepreneurs, while the housing demand channel impacts households savers by amplifying their reduction in investment. In the absence of credit constraints, the housing uncertainty channel dominates behaviour. However, this channel is reversed when agents face difficulty in accessing credit consistent with Chapter 1.

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Chapter 1

Uncertainty and the UK Housing Market: A Structural Analysis

Abstract This chapter examines the relationship between economic uncertainty, the housing market, and the macroeconomy in the United Kingdom by employing a structural vector autoregression and a factor augmented vector autoregression. Through the use of a novel identification scheme, we are able to identify a temporary uncertainty shock. Our key findings suggest that i) precautionary saving and the real option channel dominate the transmission of an uncertainty shock. However, there are asymmetric impacts across different sectors. ii) Uncertainty reduces the cost of credit which contributes to an expansion of mortgage debt and increased risk in the housing market. Finally, iii) we find a new housing-uncertainty channel. Specifically, higher uncertainty leads to an increase in investment in housing, which counteracts the negative impact of the real option channel. These results are robust to controlling for global uncertainty.

1.1 Introduction

Uncertainty has become an increasingly important factor to consider when examining fluctuations in business cycles. Bloom (2014) attributes one third of the drop in US GDP in the 2008 recession to increases in uncertainty, while Stock and Watson (2012) find the value to be closer to two thirds. For other world economies, such as the UK, events such as Brexit have ensured that uncertainty remains in the political and economic conversation.

The consensus is that increased uncertainty has a negative impact on real activity. Born and Pfeifer (2014) argue that this is driven largely by two channels; firstly, a precautionary saving channel and secondly, the real options effects. When faced with higher uncertainty, precautionary saving suggests that agents reduce consumption and supply more labor, to insure themselves against future risk. In a closed economy, this increase in saving implies a one to one increase in investment. However, as Bloom (2009, 2014) outlines, the real option theory suggests that an important feature of uncertainty is that there is a benefit from delaying investment decisions. When the investor has imperfect information about future returns, the optimal decision is to 'wait and see', thus obtaining more relevant information in the next period which makes it more likely a better investment will be made (Bonciani and van Roye, 2015).

For the types of investments which are irreversible, i.e. there is a high cost associated with changing the decision, or they face high adjustment costs, the impact of uncertainty is amplified. Intuitively, the benefit from waiting is greater in order to avoid large losses. The most notable example of such an investment are those associated with the housing market, due to the large transaction and time costs associated with housing. However, housing is unique in the sense that it is seen as both an investment and a consumption good. Unlike non housing investment, it may be difficult to reduce housing due to the necessity of owning a form of housing for economic agents. Similarly, from an investment perspective, housing is illiquid which means reversing the investment decision becomes increasingly difficult. As Bernanke and Gertler (1995) argue, fluctuations in the housing market are a vital component of the business cycle and thus act as a leading indicator for economic activity. Considering this, quantifying the interlinkages between housing and uncertainty is therefore crucial and comprises the key aim of this chapter.

We make a number of contributions to the literature. First, we examine how housing and uncertainty are linked by including a variable representing the housing market into a structural vector autoregression (SVAR) model. Specifically, we estimate an eight variable model which utilises UK data running from 1991 until 2017. We argue that the UK comprises a good setting to examine uncertainty and housing because of the wide availability of housing market data, and the vital role housing plays in the economy with two thirds of balance sheets in the UK comprising of housing. The SVAR model is also well motivated to address our research question because it allows us to assess the implied structural relationships in a parsimonious manner. Although the main contribution of our first empirical exercise is to examine and establish a baseline relationship between housing and uncertainty, we make an additional contribution by developing the identification scheme of Antolin-Diaz and Rubio Ramírez (2016) to account for housing. This method identifies a temporary uncertainty shock by imposing a set of admissible sign restrictions for a set window. We chose to focus on temporary uncertainty shocks because uncertainty has been shown to have both short and long run components (Barrero et al., 2017). Given that the majority of uncertainty shocks witnessed in the data tend to be short term in nature, we aim to capture only the short run aspect which allows our results to not become conflated with the long run components of uncertainty.

Second, we examine the propagation of uncertainty shocks utilising an extended dataset, featuring data at a more disaggregated level. Although the SVAR model is well suited to examine the key, general, aspects of the transmission mechanism of uncertainty shocks, previous studies are naturally limited in the amount of variables they can include in their empirical analysis. In order to develop the current discussion, we utilise the factor augmented vector autoregression (FAVAR) model of Bernanke et al. (2005). The attraction of the FAVAR model is that it overcomes the curse of dimensionality often associated with small scale SVAR models. We take the data set of Ellis et al. (2014) which includes data on GDP and components, manufacturing and production, inflation, monetary aggregates, financial variables and exchange rates. We also extend the dataset with a number of housing market variables. Our work comprises the first study to examine uncertainty and housing utilising disaggregagted data which allows us to offer a more complete picture in regards to the propagation of uncertainty shocks. This facilitates our analysis on a wider range of variables and allows us to deep dive into the mechanisms which underpin the channels of uncertainty.

The final contribution we make is to examine how uncertainty impacts on housing risk. Since 2015, the Financial Stability Reports produced by the Bank of England have paid particular attention to developments in the housing market by including housing risk variables as core indicators. Our FAVAR model approach allows us to include these housing risk variables as additional endogenous variables which thus allows us to examine how uncertainty shocks impact on housing risk.

From our empirical analysis we have three main findings. First, results are consistent with the theoretical channels of uncertainty. In particular, we show that the response of macroeconomic aggregates to an uncertainty shock are characterised by precautionary saving and the real option channel. This allows us to offer clarity on how uncertainty impacts GDP empirically. We are also able to extend the discussion of how uncertainty propagates into the economy because our results also indicate that the channels of uncertainty do not hold across all types of consumption and investment. Thus, the greater informational content of the FAVAR is important in fully understanding how uncertainty impacts the real economy. Second, the impact on mortgage credit conditions is crucial in the transmission of uncertainty shocks. The inclusion of housing highlights a new channel for uncertainty. Specifically, we find an interaction between housing and credit which facilitates an increase in housing investment which counteracts the negative impact of the real option channel. Finally, results from the FAVAR indicate that increased uncertainty contributes significantly to a build up of total mortgage debt and debt to income ratios, which is also accompanied with an expansion of household credit. These results echo work by Brunnermeier et al. (2017) in that the observed uncertainty in the UK has undoubtedly led to increased housing risk.

The remainder of the chapter proceeds as follows. Section 2 provides an overview of the literature regarding the transmission of uncertainty shocks. Section 3 introduces the SVAR and FAVAR models, discusses estimation methodology and outlines the identification strategy. The corresponding results are presented in Section 4. Finally, Section 5 concludes.

1.2 The Transmission of an Uncertainty Shock

Generally, fluctuations in uncertainty are seen to have a negative impact on macroeconomic aggregates. The real option channel, precautionary saving behaviour and increasing risk premia are consistent with both theoretical and empirical models. However, the impact on output is often difficult to determine a priori because conflicting mechanisms, such as the Oi-Hartmann-Abel effects suggest that greater uncertainty is able to lead to a positive payoff. This section discusses these channels and highlights the areas in which our model is aiming to offer clarity.

1.2.1 The Real Option Channel

The real option channel is a mechanism which occurs when economic agents account for the option value associated with delaying an investment decision (Bernanke, 1983;

Bloom, 2014). When a firm makes an investment expenditure, it gives up the possibility of waiting for new information to arrive that might affect the desirability of the expenditure (Born and Pfeifer, 2014). Central to this channel is an adjustment cost which makes it difficult to reverse such investment decisions. The more difficult it is to alter the investment decision, the more significant impact the real option channel plays because those decisions which are easily reversed do not lead to a loss of an option. As a result, irreversible investments, i.e. those with a large adjustment cost, are particularly sensitive to risk concerning future cash flows and therefore, are equally sensitive to uncertainty. Consequently, uncertainty makes economic agents cautious about their actions by having a negative effect on the payoff of the agent owning the investment and a positive impact on the payoff of the agents who have waited (Bonciani and van Roye, 2015).

Although the idea is often linked closely to investment decisions, the channel is also relevant for other economic actions. From a firm perspective the real option channel suggests that firms are likely to delay undertaking long term projects because they are faced with both financial and physical adjustment costs. This follows because capital is likely to get damaged the longer a project lasts (Ramey and Shapiro, 1998). The channel is also significant for labour demand decisions. The market is characterised by the time spent in the recruitment process, training new employees to learn a new role and search frictions. Firms are therefore likely to wait and reevaluate hiring decisions when faced with greater uncertainty. This is consistent with the model of Valletta et al. (2013) who suggest that when faced with uncertainty firms may choose to more 'reversible' options such as part time labour.

Theoretically, the real option channel is consistent with general equilibrium models. Baker et al. (2016a) build a model characterised by heterogenous firms with capital and labour adjustment costs and countercyclical macro and micro uncertainty. For the average increase in uncertainty which occurs during recessions, there is a corresponding reduction in investment. The model is also able to capture a reduction in aggregate capital and labour. However, on the firm side, pent up demand for hiring and demand leads to a rapid rebound. This suggests that shocks to uncertainty, through the real option channel is able to exaggerate business cycle fluctuations.

Empirically, the seminal work of Bloom (2009) offers a structural framework in which the impact of uncertainty shocks can be addressed.[1] Based on this framework, results from empirical studies are also consistent with the real option channel. Most notably, Stock and Watson (2012) show that uncertainty has a causal impact on unemployment and industrial production for the US and the UK, respectively. In line with this reasoning, Bloom (2009, 2014) finds that uncertainty shocks have real impacts as they reduce both investment and output. Similarly, in an SVAR setting (Bloom, 2009) show uncertainty shocks hinder employment, have the potential to reduce trade and also share the same characteristics as a demand shock in the inflationary response (Belke and Göcke, 2005; Handley and Limao, 2015). Leduc and Liu (2016) and Caggiano et al. (2017) also find that these impacts extend to firm-side decisions who are more cautious with hiring and investment decisions.

However, while the current empirical literature is able to capture the key movements suggested by the real option channel, the link to housing remains mostly unexplored. The housing market is likely to be highly sensitive to the real option channel given the irreversible nature caused by high adjustment and time costs associated with the market. Although there is a small number of studies that assess the causality between housing and uncertainty, there are no empirical studies which examine the impact uncertainty has on the housing market in a structural framework (for example see André et al. (2015); Christidou and Fountas (2017)).[2] Hence, by aiming to examine the

[1] Bloom builds a general measure of uncertainty using large changes in realised stock market volatility as exogenous changes in uncertainty.

[2] Both studies use a news based measure of uncertainty and focus on in sample predictability of economic uncertainty for house prices and house price volatility. André et al. (2015) uses non-linear

link between housing and uncertainty shocks in our SVAR model, we hope to bridge this gap in the literature.

1.2.2 Precautionary Saving

Under the assumption of additivity of the utility function, an increase in uncertainty with respect to future income streams leads to an increase in saving (Leland, 1972). Specifically, when faced with higher uncertainty, precautionary saving suggests that agents reduce consumption and supply more labor, to insure themselves against future risk. Ilut and Schneider (2014) show that confidence is central to the precautionary saving channel. The main idea is that agents are so uncertain that they are unable to form a probability distribution. Instead, they have a range of possible outcomes and act as if the worst outcomes are likely to occur. In a phenomenon analogous to ambiguity aversion, agents cut back on consumption (Bonciani and van Roye, 2015). As outlined in Bloom (2009, 2014), there is a large crossover to the real option channel. In a closed economy, the increase in saving implies a one to one increase in investment. However, the real option theory suggests that an important feature of uncertainty is that there is a benefit from delaying investment decisions in order to 'wait and see'. If both channels hold, uncertainty is characterised by both a reduction in consumption and a reduction in investment. This co-movement is the key empirical fact associated with uncertainty. In terms of the policy response, precautionary saving not only reduces the level of consumption but also makes economic agents less sensitive to changes in business conditions. This makes monetary and fiscal policy less effective as consumers react more cautiously to interest rate and tax policy changes. As a result, policy aiming to stimulate the economy in order counter higher uncertainty may need to be more aggressive (Bloom, 2014).

In his seminal paper, Bloom (2009) proposes that second moment uncertainty shocks are also able to generate a precautionary saving motive which triggers a sharp decline

causality testing to reveal that economic uncertainty can predict both housing returns and their volatility, while Christidou and Fountas (2017) examines whether this is consistent across US states.

in real activity of 3% in the first year with medium term volatility overshoot. Caggiano et al. (2017) provide evidence for a stronger effect of uncertainty shocks in recessions than in expansions, suggesting that the effects of uncertainty shocks vary according to the state of the business cycle. Similarly, Baker et al. (2016a), Jurado et al. (2015) and Scotti (2016) find that precautionary saving contributes to reductions in output. For the effectiveness of policy, Aastveit et al. (2017) investigate the effects of uncertainty on the monetary policy transmission mechanism and conclude that U.S. monetary policy is less effective during periods of high uncertainty. In particular, the response of investment to monetary policy shocks is much weaker when uncertainty is high.

Results in partial equilibrium analysis are conclusive in finding evidence of both the real options channel and a precautionary saving motive. However, general equilibrium models often fail to capture this co-movement. In a standard Real Business Cycle model the endogeneity of the real interest and flexible prices are crucial in preventing sizeable impacts following uncertainty shocks. The intuition stems from the fact that because prices are fully flexible, consumption falls and labor increases because of precautionary behaviour. Given that capital is predetermined, the increase in labour corresponds to an increase in output and hence savings. This implies a rise in investment (Basu and Bundick, 2017). Consistent with this, Bachmann and Bayer (2013) show that the endogenous feedback of nominal interest rates and nominal wages mitigate the negative effects on output. In contrast, New Keynesian models are characterised by sticky prices and the potential for a monetary policy response. When prices are sticky, prices and the interest rate are constrained and so are unable to fall enough to clear markets. This means there is no offsetting rise in investment and thus a reduction in output (Bonciani and van Roye, 2015; Fernandez-Villaverde et al., 2011; Leduc and Liu, 2012).

Our work is motivated by the conflicting nature of the empirical and theoretical literature. Our disaggregated data approach allows us to assess first, if the comprehensive nature of the results presented in the empirical work is driven by model specification. When examining the modelling approach of the empirical literature, the focus is on small scale models which look at key macroeconomic variables. Our approach allows us to deep dive into these conclusions and assess to what extent the channels hold across different markets. For example, we are able to show that uncertainty shocks and the precautionary saving motive holds for durable consumption, whereas for non durables, the effect is much weaker because these are seen as necessity purchases.

1.2.3 Additional Channels of Uncertainty

In addition to the real option channel and precautionary saving behaviour, a number of complimentary channels have been explored. First, investors want to be compensated for higher risk because greater uncertainty leads to increasing risk premia. This should raise the cost of finance (Bloom, 2014). Uncertainty also increases the probability of default which raises borrowing costs and reduces growth. Extending this narrative, Arellano and Ramanarayanan (2012), Christiano et al. (2014) and Gilchrist et al. (2014) argue that financial mechanisms are important. Specifically, increasing uncertainty leads to a rise in the cost of external finance which amplifies the real option channel. Consistent with this is more recent work which further expands these models by including risk aversion. Bordo et al. (2016) develop a model in which uncertainty shocks are amplified via a reduction in the supply of credit. In line with this prediction, Brunnermeier and Sannikov (2014) argue that a deterioration in borrowers balance sheet conditions can induce greater financial market volatility.

Empirically, Caldara et al. (2016) aim to disentangle the roles of financial and uncertainty shocks using the penalty function proposed by Uhlig (2005).[3] They conjecture that both shocks have real effects, yet the impact of uncertainty is much stronger

[3]This approach identifies SVAR models by using a criterion by which each shock should maximise the impulse response of its respective target variable over a pre-specified horizon. These assumptions allow for financial conditions to react immediately to a macroeconomic uncertainty shock, while financial shocks can also have a contemporaneous effect on the level of uncertainty.

when it coincides with worsening financial conditions. To summarise, both of these mechanisms are important and complementary, simultaneously working to further increase uncertainty, tighten financial conditions and reduce economic activity. Both Popescu and Smets (2010), using a proxy VAR approach with German data, and Redl (2017) find results consistent with the Caldara argument. We develop the discussion by demonstrating that the link between financial conditions and credit availability are crucial to the dichotomy between housing and non housing investment.

Our results also draw on niche transmission mechanisms associated with uncertainty. Our housing uncertainty channel links closely to growth option theory through which investment is encouraged because a mean preserving second moment shock raises expected profit by increasing the potential prize.[4] Similarly, our results link closely to the Oi-Hartmann-Abel channel which implies that increases in uncertainty can lead to accelerating investment. This relates to models with risk neutral competitive firms, with convex adjustment costs. If the marginal revenue product of capital is a strictly convex function of the price of output, then investment is an increasing function of the variance of total factor productivity (Bonciani and van Roye, 2015). Hence, any uncertainty shock, measured as an increase in the variance of productivity, directly impacts investment. As discussed in Ferrara and Guérin (2018), the channel is typically weak in the short run but carries more strength in the long run. While previous studies have suggested that these channels are important in positive GDP responses, our estimation procedure allows us to focus purely on short run uncertainty shocks, which in turn allow us to provide clarity on how GDP is impacted by uncertainty.

[4]This channel is similar to the good news principle discussed in Bernanke (1983), whereas the real option channel reflects bad news. Belke and Osowski (2017) suggest this may allow for a positive response of investment following higher uncertainty, as there is a payoff from being able to react to different future states of the world. An example of this channel is the dot com bubble. Uncertainty about the internet increased investment as the worst outcome was the loss of development costs, whereas the upside was more significant as firms began to look more profitable (Bloom, 2014).

1.3 Methodology

1.3.1 Measuring Uncertainty

A second strand of the uncertainty literature addresses the empirical challenge of measuring uncertainty. The main challenge is to disentangle and offer an interpretation of an uncertainty shock, because the largest shocks to uncertainty historically coincide with first moment shocks. This, in turn, can lead to biased estimation (Belke and Osowski, 2017). As a result, it is essential that uncertainty is measured with sufficient accuracy in order to avoid false inference. Following Bloom (2009), a wide range of literature has examined this issue. Haddow et al. (2013) utilise the first principal component of a number of uncertainty proxies, while Leduc and Liu (2012) and Dovern et al. (2012) examine forecaster disagreement. Other studies utilise econometric techniques in order to capture the time varying volatility of time series. Fernández-Villaverde et al. (2011) estimate time varying volatility in the real interest rate of four small emerging economies. Similarly, Mumtaz and Surico (2013) and Carriero et al. (2015b) augment standard SVAR models to allow for time variation in the volatility of identified monetary policy shocks.

Alternatively, the news based approach of Baker et al. (2016a) is a popular index often used when examining uncertainty. The authors develop an economic policy uncertainty index for a range of countries comprising of a frequency count of news stories. This is based on uncertainty surrounding the economy and fiscal or monetary policy, the number and revenue impact of scheduled federal taxes set to expire and the extent of disagreement among forecasters over future government purchases and future inflation. However, given the nature of our study we argue that news based index is not suitable for our analysis. First as argued by Jurado et al. (2015) the methodology adopted by Baker et al. (2016a) fails to control for a deterioration in expectations of the mean economic outcome when volatility increases. This makes it more likely that first moment news shocks and second moment uncertainty shocks become conflated.

Furthermore, the Baker et al. (2016a) index utilises a small number of proxies for uncertainty which can lead to a misleading relationship between uncertainty and the real economy when one of those proxies is particularly volatile. An obvious example of this is media citations which are highly volatile, yet may have a weak correlation to real variables. Hence, estimation by measures which utilise these methods, such as the one proposed by Baker et al. (2016a), can lead to misleading signals about the real effects of increasing uncertainty. Instead, we prefer a model which captures a number of sources of uncertainty which can cause fluctuations across a wide range of variables.

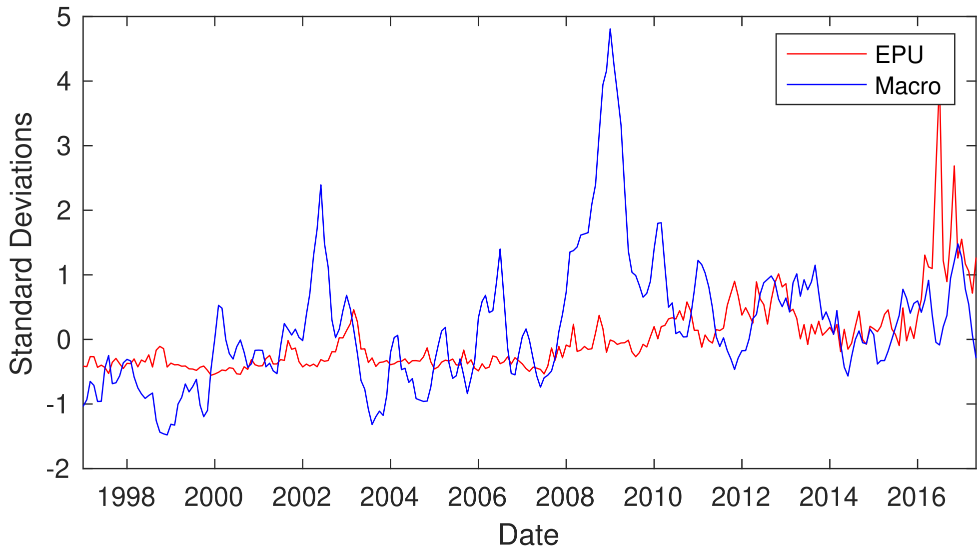
In support of this, Jurado et al. (2015) develop an innovative methodology which makes use of a dynamic factor model.[5] This model measures uncertainty as the conditional variance of the unforecastable component common to a large number of macroeconomic and financial variables. By doing so, it captures the deterioration in the actual predictability of variables rather than changes in volatility. Thus, the benefit of the approach is that it avoids any disproportionate influence of any one series, thereby directly addressing the majority of issues raised within the literature. Another advantage of this methodology is that it allows one to construct separate estimates of macroeconomic, financial and global uncertainty from a number of sources. This is central to our decision to adopt the index due to the difficulty of disentangling the impact of global shocks as well as utilising a more general measure of uncertainty as opposed to a more micro based measures. A number of studies have found co-movement between uncertainty domestically and uncertainty across countries. This is particularly evident when using financial variables. Once global uncertainty shocks are accounted

[5]Alternative approaches are Scotti (2013), who develops a macroeconomic uncertainty index reflecting the agents uncertainty about the current state of the economy, defined as a weighted average of squared news surprises. The weights are estimated from a dynamic factor model applied to a set of macroeconomic variables. Similarly, Rossi and Sekhposyan (2015) and Jo and Sekkel (2019) offer a model based approach which measures uncertainty from the distance between the realised value of a variable and its unconditional forecast error distribution based on survey data.

for domestic uncertainty has relatively modest real effects (Cesa-Bianchi et al., 2014; Mumtaz and Theodoridis, 2017). Therefore, accounting for global shock is vital before any robust conclusions can be made.

1.3.2 Examining the Uncertainty Index

Fig. 1.1 Estimated Measures of Uncertainty



Notes: Macro uncertainty (blue line) and economic policy uncertainty (red line) plotted between 1997 and 2017. Variables are in standard deviations. Macro uncertainty captures uncertainty in the economy net of financial and global factors and is calculated using a big data approach. Specifically it is computed as the principle component of the macro block of data. We acquire the data from Chris Redl's personal website who computes the macro uncertainty index for the UK based on the methodology outlined above. Policy uncertainty is instead calculated as a count of key words being flagged in news stories. Source: policyuncertainty.com (epu)

Figure 1.1 plots the measure of macroeconomic uncertainty for the UK, alongside the news based index of Baker et al. (2016a).[6] Over the sample analysed there have been four major cases of uncertainty: first in 2002 with the dot-com bubble, the financial crisis in 2008, the Euro crisis in 2012 and finally the Brexit referendum in 2016. Although the two measures capture different sources of uncertainty, the macro

[6] The measure of uncertainty used in this chapter is varied between the UK macro and financial uncertainty indexes estimated by Redl (2017), using the Jurado et al. (2015) methodology. In order to compare the results of macro uncertainty to policy uncertainty, the same SVAR models are estimated using the news index of Baker et al. (2016a). Results from this exercise are presented in the Appendix. This approach takes two data sets, one capturing 33 macroeconomic time series and one capturing 29 financial time series, in order to estimate separate uncertainty measures.

index is more relevant for the housing market because it is captures uncertainty from different sources. Given the range of factors considered when making a housing the decision, uncertainty across a wider range of variables is desirable as it allows us to more accuratley interpret the impact on such decisions. We choose our data set to conclude before the no deal Brexit decision and the COVID-19 pandemic. The main reason for this decision is because we are interested in the long term relationship between housing and uncertainty and therefore want to avoid the disproportionate levels of uncertainty associated with the two events being able to drive the results.

1.3.3 SVAR Model

A baseline SVAR model is given by:

$$Y_t' A_0 = \sum_{i=1}^{p} Y_{t-i}' A_i + c + u_t;\ t = 1, ..., T, \tag{1.1}$$

where Y_t is an $n \times 1$ vector of endogenous variables and u_t is an $n \times 1$ vector of unobservable, zero mean white noise processes which are independent. A_i, $i = 1,\ldots,p$, is an $n \times n$ matrix of coefficients, where A_0 is invertible, c is a $1 \times n$ vector of parameters, p is the lag length and T is the size of the sample. Variables included in the vector Y_t are the Bank of England bank rate, CPI, hours worked, investment, consumption, GDP, mortgage credit spreads and the measure of uncertainty. All variables included in the SVAR are the cyclical component from an HP filter except for credit spreads, the monetary policy instrument and the measure of uncertainty which are taken in levels. The sample runs from 1991 Q1 until 2017 Q2.

The reduced form of the SVAR model is given by:

$$y_t = B(L) y_{t-i} + \varepsilon_t, \tag{1.2}$$

y_t is assumed to have zero mean and *B(L)* is a matrix of lag polynomials with dimension $n\ x\ n$, where $B(L) = KA_0^{-1}$ and $K = [A_1'...A_p'\ c']$. $\varepsilon_t = u_t Ao^{-1}$ are structural shocks, with $E[\varepsilon_t \varepsilon_t'] = (A_0 A_0')^{-1} = \Omega$. Both *B(L)* and Ω are reduced form parameters.

In general, given some arbitrary structural parameters $[A_0, K]$, the impulse response function, $R_h(A_0, K)_{ij}$, of the i-th variable to the j-th shock at a finite horizon, h, corresponds to the element in row i and column j of the matrix $[A_0^{-1} J' F^h J]'$, where

$$F = \begin{bmatrix} A_1 A_0^{-1} & I_n & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_{p-1} A_0^{-1} & 0 & \dots & I_n \\ A_p A_0^{-1} & 0 & \dots & 0 \end{bmatrix} \text{ and } J = \begin{bmatrix} I_n \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

Following Uhlig (2005), all possible impulse response functions are characterised by an $n\ x\ n$ orthonormal matrix $q \in \theta(n)$, where $\theta(n)$ denotes the set of all orthonormal $n\ x\ n$ matrices. As previously discussed, identification of the SVAR model is achieved by imposing admissible restrictions on the matrix q.

1.3.4 Identification and Estimation of the SVAR Model

We choose to adopt the flexible sign restriction identification strategy of Antolin-Diaz and Rubio Ramírez (2016) and develop the methodology in order to account for housing. The key benefit from this approach is that offers greater flexibility in terms of the assumptions regarding the timing of the responses of the variables included in the SVAR model.[7] In our context, identification is achieved by specifying a set of admissible q

[7] In contrast, a Cholesky approach imposes a recursive ordering of the SVAR which we view as too restrictive as potential contemporaneous impacts could potentially be lost. Similarly, Caldara et al. (2016) warns against this approach in the context of identifying uncertainty shocks in SVAR models, especially when including a measure of financial conditions. This critique is one of the key reasons we steer away from a traditional recursive identification strategy. Alternatively, the use of identification by an instrument, closely following Ludvigson et al. (2015), has emerged. This approach produces separate measures for financial and macroeconomic uncertainty and then identifies the impact of

matrices that ensure the response of the variables included in the vector Y_t correspond to the well developed results in the current theoretical literature. Examining Barrero et al. (2017), uncertainty has both long term and short term components with the long term impacts often conflating short term results. Our methodology is well suited because by specifying the timing of the shock we are able to identify a temporary uncertainty shock which allows for a focus on the short term impact of uncertainty. Under the baseline model, uncertainty shocks are identified by assuming that the bank

Table 1.1 Sign Restrictions

	Bank Rate	CPI	Hours	Investment
Baseline	-	+/-	-	+/-
SR1	-	+/-	-	-
SR2	-	+/-	-	-
	Consumption	GDP	Mortgage	MU
Baseline	-	+/-	+	+
SR1	-	+/-	+	+
SR2	-	+/-	-	+

rate and hours respond with a negative sign, while the measures of credit spreads and uncertainty respond with a positive sign. The majority of the theoretical literature proposes precautionary behaviour and so we restrict consumption to be negative. We leave investment unrestricted, because precautionary saving and the real option channel imply opposite responses. In line with this, a priori, we are unable to conclude on the direction of the response of GDP. Hence, we choose to leave GDP unrestricted. With regard to inflation, in theory, uncertainty shocks are transmitted as demand shocks and so one would expect a negative relationship. However, Popescu and Smets (2010)

uncertainty shocks on GDP by constructing an external instrument. A valid instrument is correlated with both measures but contemporaneously uncorrelated with real activity shocks. However, we argue that the sign restriction approach is more tractable for the means of our research question. A key aim of the chapter is to establish a baseline response of housing markets to uncertainty shocks from which further analysis can be developed. We argue that the sign restriction approach is more parsimonious in the sense that it directly includes uncertainty endogenously as opposed to external instruments representing uncertainty. Secondly, and more influentially, the identification approach allows us to draw on on the strong theoretical prior work in an empirical setting. We explore uncertainty shocks identified by instruments in Chapter 2.

and Carriero et al. (2015b) find an inflationary response. Thus, our choice of leaving these variables unrestricted allows us to remain agnostic about their impact.

Alongside the baseline restrictions, two other identification strategies are utilised. The first, SR1, adds an additional restriction by imposing that investment responds with a negative sign. This follows from Leduc and Liu (2012) and Aastveit et al. (2017) who emphasise the impact uncertainty has on delaying investment decisions. We choose to take a stance on the impact uncertainty has on investment because the theoretical literature emphasises that it is an important mechanism in which uncertainty is transmitted into the economy (see Born and Pfeifer (2014) and Bonciani and van Roye (2015)). The final set of restrictions, SR2, extends the restrictions of SR1 by allowing credit spreads to respond negatively. By doing so, this set of restrictions captures a situation where rising credit spreads do not reinforce the real effects of the uncertainty shock (Redl, 2017). Novel temporary uncertainty shocks are defined when these restrictions are imposed for two periods on all variables. Following the Bayesian information criteria, the model includes two lags. The full list of restrictions are found in Table 1.1.

1.3.5 FAVAR Model

A documented drawback of standard VARs is that they are naturally limited in the amount of variables that can be included, the so called curse of dimensionality. This leads to potential identification problems in SVARs due to the fact that the methodology may omit several important variables. Hence, the second structural exercise undertaken in this chapter is to estimate a FAVAR model to explore the fact that the sources of variation of a large number of macroeconomic time series are common and, thus, can be approximated by common factors. In fact, the FAVAR methodology is particularly suited to capture the effects of uncertainty because it augments the information content in a VAR, which allows one to identify the model recursively (Colombo, 2013) and so responses capture the relationships between the variables implied by the data rather than the identification strategy.[8]

The FAVAR model draws on the potential for macroeconomic variables to be driven by a few common latent factors. This allows us to take a large panel of macroeconomic data and reduce the number of endogenous variables by generating principle components (Chudik and Pesaran, 2011). The principal components represent latent factors, F_t, which explain a large degree of the variance of the dataset. The model also includes observable variables, Y_t. Formally, Stock and Watson (2016) outline that the dynamic factor model expresses the data in terms of latent (unobserved) common variables, which follow a law of motion that is Markov. To be exact, these unobserved variables follow lagged dynamics, which have finite dependence. Thus, the model incorporates N observed time series, X_t , in terms of a number of unobserved common factors which are allowed to evolve over time, the number of observed variables plus a shock term.

The variables included in this model are those from the dataset of Ellis et al. (2014), extended by the core house risk indicators from the financial stability report, alongside general housing variables. This data set contains 55 time series covering seven categories. These include GDP and components, manufacturing and production, inflation, monetary aggregates, housing variables, financial variables and exchange rates. The collection of financial stability variables is a recent phenomenon, therefore the inclusion of these variables has led to a more limited time period when compared to the SVAR estimation, running from 1997 Q1 until 2017 Q2. It is standard within the literature for the entire dataset to be transformed to reach stationarity with all variables being standardised to unit variance and zero mean.[9] The Appendix provides a complete list

[8]We argue that the FAVAR model is essential for the means of our research question. Although more parsimonious SVAR models exist (see Barrero et al.(2017) for a discussion of small scale models which capture uncertainty), they crucially only establish the responses at an aggregate level. The key benefit of the FAVAR model is that it is able to efficiently deal with the panel of data we are interested in. It is this analysis which allows us to draw interesting distinctions within the aggregate responses dictated by the mechanisms of an uncertainty shock, which in turn adds an additional layer to the discussion around the responses of macroeconomic aggregates to uncertainty shocks.

[9]We take the transformations of Ellis et al. (2014) in order to be comparable to previous results and add context to the introduction of our housing sector variables. For the data involved in extending

of variables and transformations.

A general factor model is given by:

$$X_t = \lambda^f F_t + \lambda^y Y_t + e_t, \tag{1.3}$$

where λ^f is an $N\ x\ K$ matrix of factor loadings. λ^y is an $N\ x\ M$ matrix and the $N\ x\ 1$ vector of idiosyncratic error terms, e_t, are mean zero and are assumed to be weakly correlated. These shocks represent measurement error or idiosyncratic movements of a time series, which likely stem from sectoral or regional dynamics (Luciani, 2015). K is the number of unobserved factors, whereas M is the number of variables in Y_t. The number of unobservable factors is assumed to be small, $K << N$. Factors are also assumed to be orthogonal to both other factors and idiosyncratic components. This model can then be interpreted as a dynamic factor model because in (1.3), F_t can include both contemporaneous and lagged observations of the factors. This leads to the FAVAR model:

$$\begin{bmatrix} F_t \\ \\ Y_t \end{bmatrix} = \phi(L) \begin{bmatrix} F_{t-1} \\ \\ Y_{t-1} \end{bmatrix} + \xi_t, \tag{1.4}$$

where, $\phi(L)$, is a polynomial lag operator. The error term, ξ_t, is mean zero with covariance matrix Q.

1.3.6 Identification and Estimation of the FAVAR Model

Regarding the statistical identification of uncertainty shocks, this chapter utilises the often used split between slow and fast moving variables, first introduced in Bernanke et al. (2005). Slow moving variables contain economic activity and price variables, whereas the set of fast moving variables includes primarily financial data, which is assumed to react immediately to shocks. Splitting the dataset as such allows for

the dataset, we strictly follow the stationarity tests. We follow the stationarity tests as they align with our priors expected for the transformations.

identification by a Cholesky decomposition. In terms of the ordering, this chapter follows Colombo (2013) and Belke and Osowski (2017) by ordering the estimated factors first, followed by uncertainty. The implication is that all variables respond to uncertainty shocks with a lag, while uncertainty is able to respond contemporaneously to changes in the factors.

Table 1.2 Onatski (2009) Test for Number of Dynamic Factors

	1	2	3	4	5	6
0	0.998	0.421	0.465	0.996	0.998	0.999
1	0	0.999	0.421	0.999	0.996	0.998
2	0	0	0.996	0.999	0.999	0.996
3	0	0	0	0.999	0.999	0.999
4	0	0	0	0	0.998	0.998
5	0	0	0	0	0	0.999

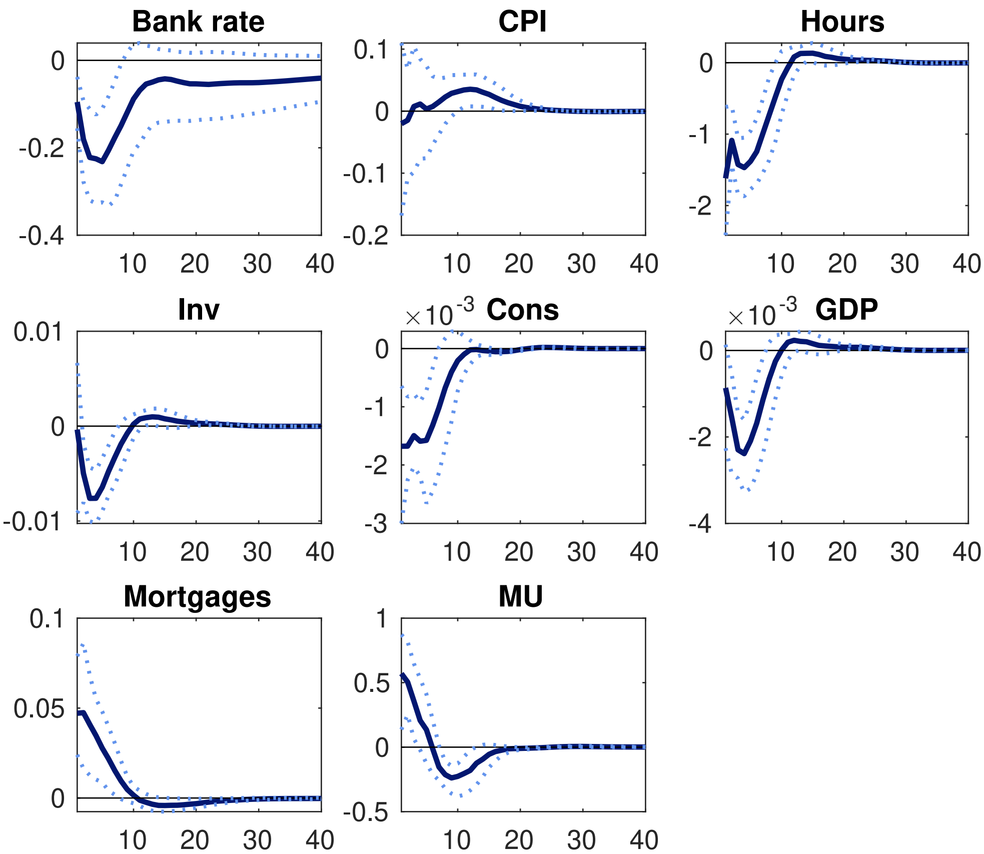
Notes: This table documents results from the Onatski (2009) test for the number of dynamic factors The first column is K0, the first row is K1 and H0 = K0, H1 = K1.

The FAVAR is estimated using a Gibbs sampler as introduced by Carter and Kohn (1994). We use 10,000 replications and discard the first 8,000. For the parameters of the model, we include four lags and two factors following the results of the Bayesian information criteria and the Onatski (2009) test, respectively. The results from the Onatski (2009) test are presented Table 1.2. Onatski (2009) establishes a test of K0 factors against the alternative that the number of factors is between K0 and K1. Results indicate between two and three dynamic factors. This is corroborated by the Bai and Ng (2007) test which indicates two factors.

1.4 Results

Our results largely confirm the prevalent channels of an uncertainty shock previously examined within the literature in that we find evidence of both precautionary behaviour and the real option channel. Results from our SVAR estimation, as documented in

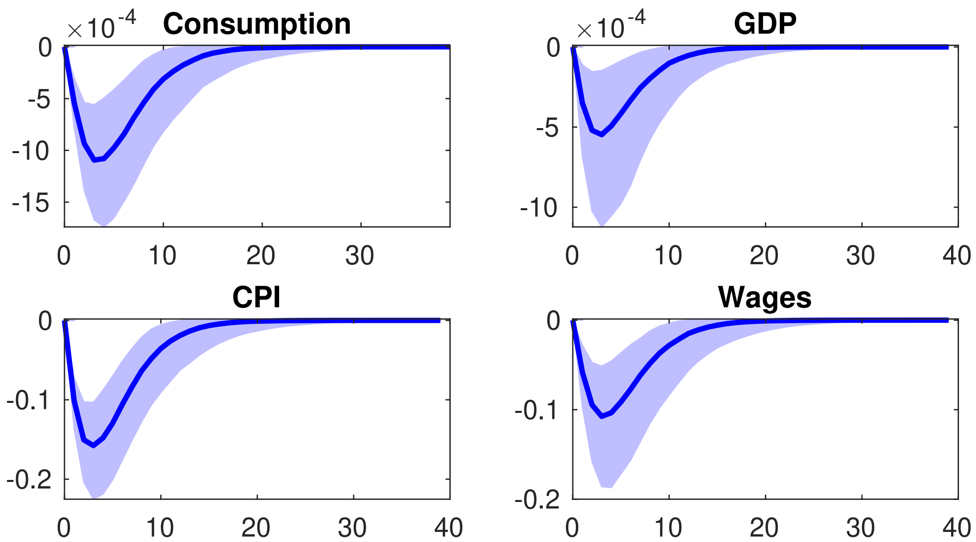
Fig. 1.2 SVAR Model Identified with Baseline Restrictions



Notes: Median impulse responses from a one standard deviation shock to uncertainty from the SVAR model. Identification is achieved by imposing the Baseline restrictions as outlined in Table 1.1. Our sign restriction method accepts draws which conform to our restriction matrix and creates a distribution based on these accepted draws. We compute 68% confidence intervals from this distribution. The y axis is percentage deviation from trend. The data included is bank rate, CPI, hours worked, investment, consumption, GDP, mortgage credit spreads and macro uncertainty.

Figure 1.2, are consistent with Basu and Bundick (2017) because we find a co-movement in the consumption and investment response. Specifically, we document a statistically significant negative response for investment and consumption, with our estimated median IRF's indicating that this lasts for up to 10 periods. Although the response of investment is zero on impact, we still argue that the delayed response is an uncertainty effect as opposed to endogenous feedback within the model. It is likely that investment decisions are more likely to be characterised by frictions which can explain the delayed response. Given that we capture a growing response over time synonymous with the real option channel, we are confident that the real option channel holds. Similarly, Figure 1.3 presents selected impulse response functions from our FAVAR estimation. We are able to affirm the presence of a wait and see narrative which is synoptic with an increase in uncertainty as consumption falls by a similar magnitude and duration.

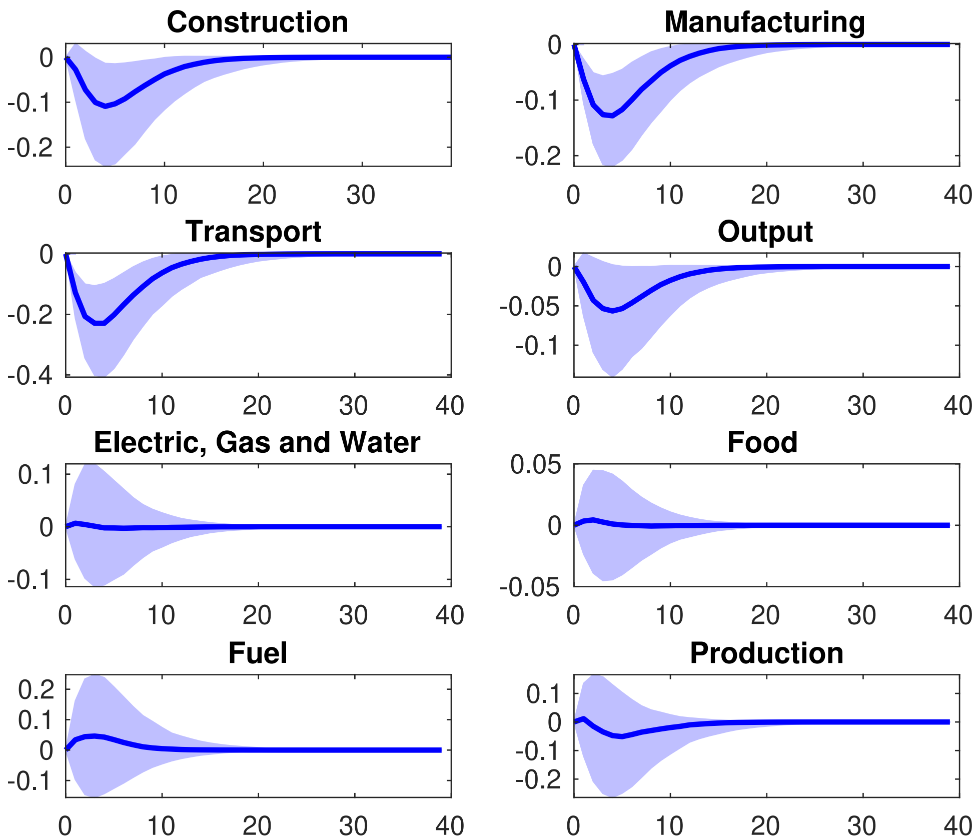
Fig. 1.3 Precautionary Saving: FAVAR model



Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes.

Likewise, in line with Valetta et al. (2013), we provide evidence of precautionary motives in the labour decision, with hours falling. A priori, both demand and supply side factors exist, however, we document overall negative responses as hours worked fall by 1.2% from trend which is likely driven by the real option channel on the firm demand side. In support of this, results from our FAVAR show a reduction across a number of sectors. As highlighted in Figure 1.4, the reduction in overall manufacturing, coupled with the the increased risk aversion associated with uncertainty lead to a reluctance to engage in employment decisions. Although the previous literature has found contrasting results in terms of the empirical response of GDP, we provide clarity by suggesting that both precautionary saving and the real option channel hold, such that there is a prolonged and significant recession following increases in uncertainty.

Fig. 1.4 Decomposing Precautionary Saving: FAVAR Model

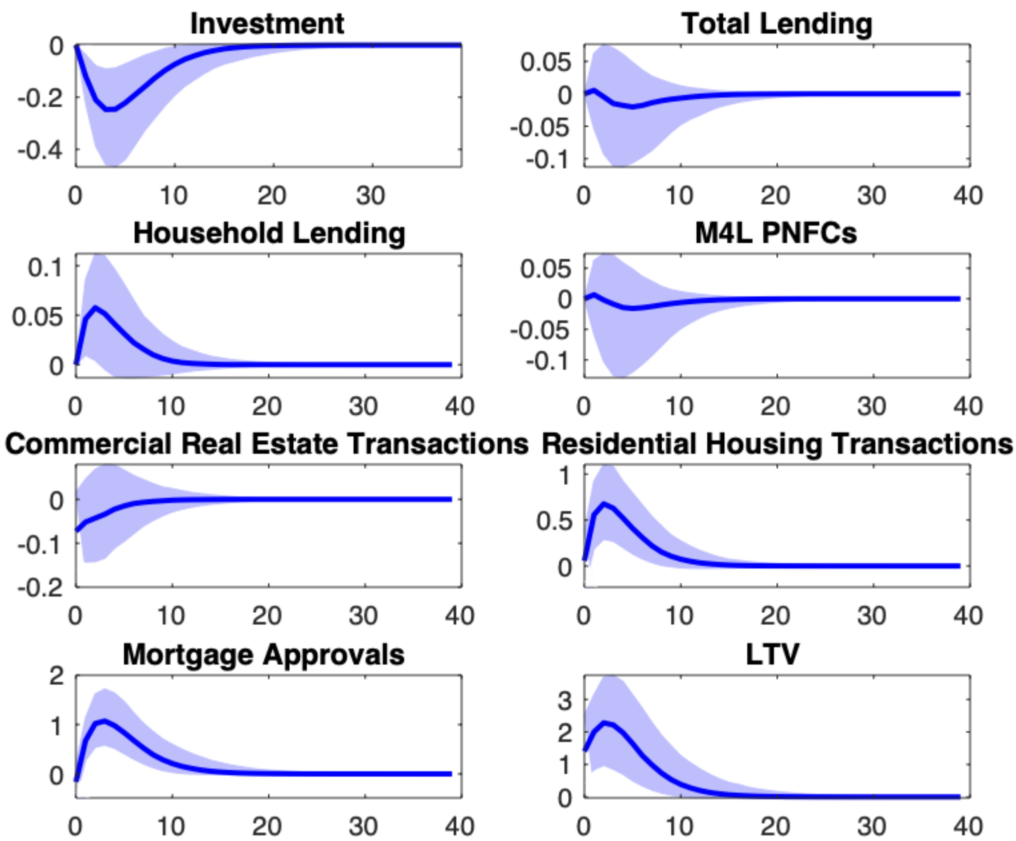


Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes.

It is also worth noting the overall sizes of the responses. While precautionary saving and the real option channel hold, the responses corresponding to precautionary saving are strictly smaller in the SVAR and only equal for real option channel based responses.

We instead draw particular attention to the negative responses on the firm side which appear to be playing a large role in the observed negative impact of GDP.

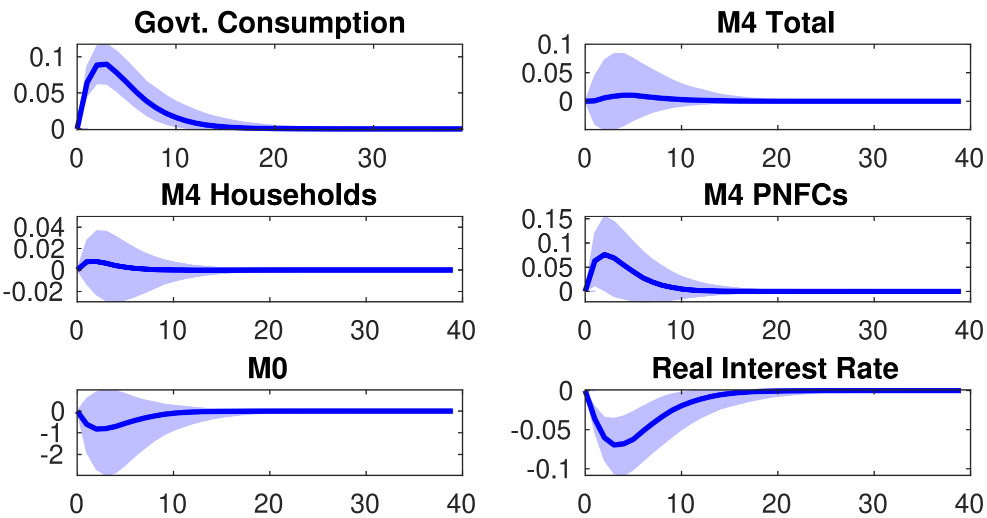
Fig. 1.5 The Real Option Channel: FAVAR Model



Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes. Investment takes transformation 2. Housing variables have been multiplied by 100.

Although our SVAR results suggest a story whereby increases in uncertainty reduce economic aggregates, it is worth noting that this holds in a general sense. The novel aspect of our FAVAR estimation procedure allows us to include a wide variety of time series and allows us to decompose the results across sectors and at a more disaggregated level. This is particularly evident in Figure 1.4, because there is a distinction in the degree to which precautionary behaviour drives behaviour across durable and non durable industries. Overall, those industries associated with non durable consumption are unlikely to experience a reduction in demand due to the necessity nature of the consumption decision. This behaviour is indicative of electricity, food and fuel industries which all have near zero, non statistically significant, impacts following the shock to uncertainty. In contrast, we show that manufacturing falls by close to 15%, transport by 20% while construction by 10%. This implies that industries driven by ad-hoc purchases are particularly sensitive to uncertainty, and precautionary saving, as it becomes much easier to delay purchasing decisions. While our results are consistent with Bloom (2014), we extend the narrative by providing specific information about the extent precautionary saving holds for particular industries.

Fig. 1.6 The Policy Response: FAVAR Model



Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes.

We are also able to show that the real option channel equally impacts investment decisions asymmetrically. Although the FAVAR indicates that the responses of non housing investment exhibit behaviour analogous with the real option channel, we show that the real option channel is not prominent in the response of residential housing transactions.[10] Instead, following the increase in uncertainty, residential transactions respond positively, expanding by 0.5%. We propose this housing uncertainty channel as a new propagation mechanism following a shock to uncertainty which is in line with growth option theory. We argue that the perceived historic strength of the housing market is enough to incentivise investment in housing. Intuitively, this follows because the downside risk is limited given the historic strength of the housing market. Conversely, the range of outcomes associated with uncertainty could lead to greater payoffs in terms of increased wealth which are significant for consumption smoothing. Quantifying these dynamics suggested by our empirical analysis comprises the key finding from this chapter.

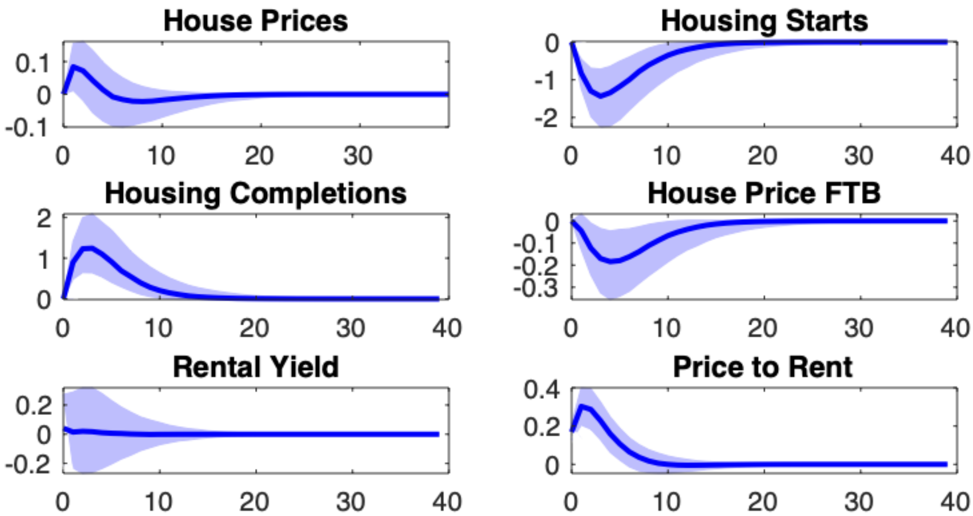
The driving force behind the housing uncertainty channel is captured endogenously within our model. Demonstrated in Figure 1.5 is that the increase in uncertainty leads to an expansion of household credit. This follows from the aggressive expansionary monetary policy response which we document in Figure 1.6.[11] We also provide evidence of a strong fiscal policy response as government expenditures increase by 10%. The monetary response leads all other interest rates, which in turn leads to the potential to access cheap credit. This is particularly relevant for mortgages, given that 85% of UK mortgages are variable and so a large proportion of mortgages will follow changes in the base rate (Aron and Muellbauer, 2016). Access to this cheap credit is the main driving force behind the observed increase in housing transactions, household lending and mortgage approvals which in turn drive the housing uncertainty channel.[12]

[10] Interestingly, there is zero statistical significant response for commercial real estate following an uncertainty shock.

[11] Our empirical results are consistent with the theoretical models of Bloom (2014), who capture the aggressive nature of the policy following the increase in uncertainty.

[12] This links closely to the increased mortgage spreads we document in our SVAR analysis. Increased demand, driven by the housing uncertainty channel, despite increased risk often associated with uncertainty pushes the spreads up.

Fig. 1.7 Housing Markets: FAVAR Model



Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes.

However, access to this cheap credit and therefore the housing-uncertainty channel is limited by the observed increase in loan to value ratios, indicative of increased risk, which corresponds to those attempting to borrow at a 90% level. First time buyers are likely to be the buyers constrained by the increased restrictions on mortgage loans, due to the fact that they are unlikely to have enough equity to afford mortgages at less than a 90% loan to value rate. This leads to a curtailing of demand and a shifting of preferences towards houses they can afford. Conversely, agents with enough equity are able to access this cheap credit, such that the expansion in housing transactions is largely driven by them. Overall, there is an inequality issue with the response of monetary policy, as the reduction in rates is only transmitted to wealthy agents.[13]

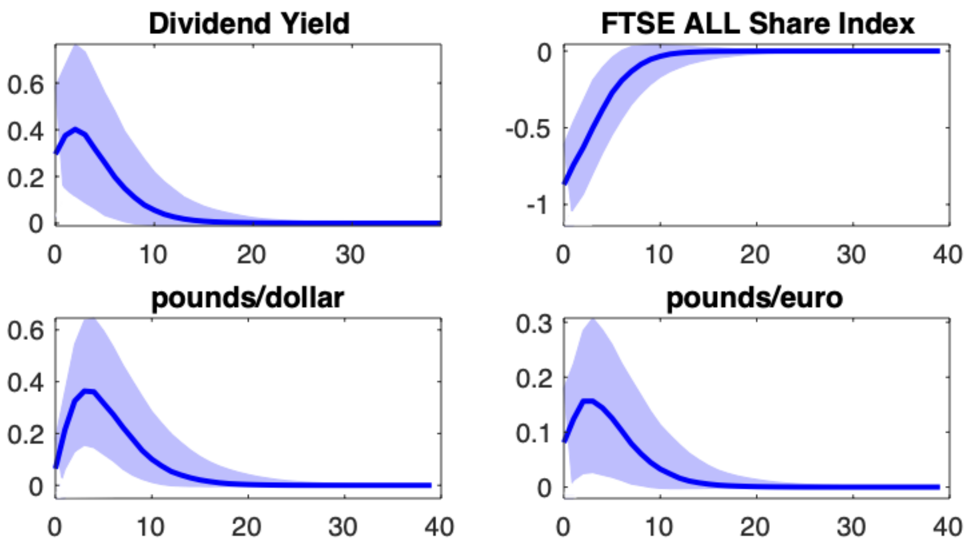
[13] This point raises a number of interesting questions which are beyond the scope of the chapter. First, decomposing the size and impact of this inequality would be useful from a policy viewpoint. Second which variables are significant in affecting this conclusion would also be interesting to explore, specifically in terms of the link to responses of borrowers and savers.

Decomposing the housing uncertainty channel further in Figure 1.7, we observe a statistically significant reduction in prices for first time buyers, which follows given that these agents struggle to get finance for mortgage credit. This is important when put into context. On the one hand, although some agents may be constrained in their access to wider financial markets, housing accounts for nearly 1/2 of total assets for UK households, while 2/3 of purchases are funded by mortgage debt. This suggests that those able to access the housing uncertainty channel are better able to absorb the impact of increased uncertainty due to increasing wealth. In contrast, highly indebted households or those unable to access credit are more vulnerable to unexpected increases in uncertainty. That is, mortgages repayments are subject to default and so households ensure payment of the higher mortgage repayments due to the important nature of housing as a consumer good. In the context of general financial investment, this mechanism does not exist as agents instead have the option to lose the value of their investment and so there is no further impact on consumption. The implication is that housing plays a vital role in amplifying the impact of uncertainty shocks for these agents.

It is also important to acknowledge the unique composition of the residential housing transaction which is viewed as both an investment opportunity and a consumption good. We capture a similar distinction across housing markets as the standard consumption decision. That is, markets more closely linked to the consumption element of housing are not impacted by the traditional mechanisms of uncertainty. We report a small increase on impact of the uncertainty shock in rental markets, but this is insignificant. The necessity of rental housing means that there is a strong preference factor to account for in rental markets which acts to downplay any impacts uncertainty may have. In contrast, the housing uncertainty channel is significant in raising both house prices and widening price to rent ratios. While the increased demand for housing transactions contributes to this, nominal house prices are likely to exhibit a high degree of price stickiness and so the reduced inflation also plays an important role in this result.

Overall, the response of real variables is subject to three main channels: a precautionary saving effect, the real option effects and the housing-uncertainty effects. However, which of these channels are most relevant? Both the precautionary saving channel and the real option effect dominate, such that we find a negative response for GDP in both the SVAR and FAVAR respectively. In fact, the precautionary saving channel is particularly relevant for the UK as the data suggests that there has been a limited number of delinquencies for UK mortgages. This results in a higher proportion of money being spent on mortgage repayments, further reducing consumption and amplifying this channel. However, the housing-uncertainty channel plays an important role in counteracting the negative effects of uncertainty.

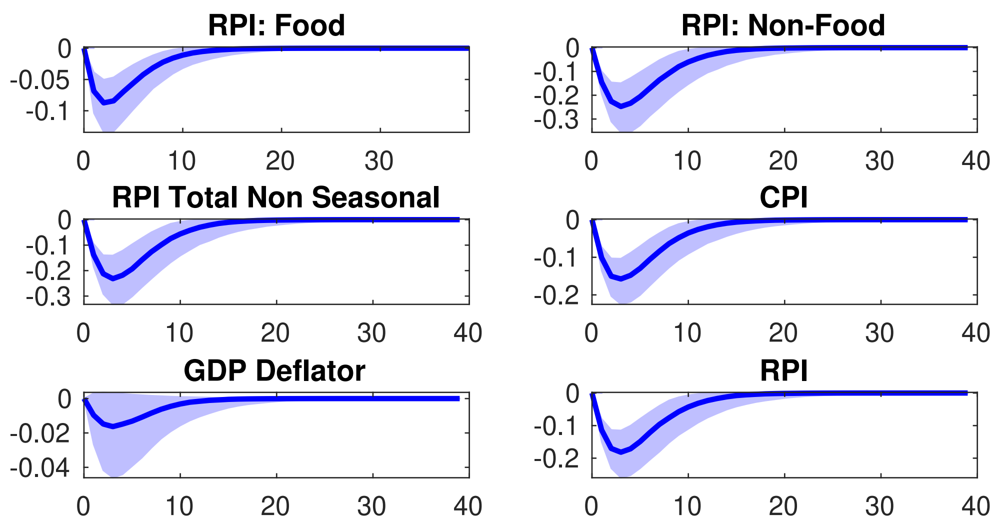
Fig. 1.8 Financial Markets: FAVAR Model



Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes.

Figure 1.8 documents that under our baseline FAVAR estimation we capture a decrease in the FTSE, which indicates a worsening of financial markets. While this is consistent with the Caldara conclusion, our results generally contrast their conclusion of increased uncertainty only having real effects if it is accompanied by a worsening of credit conditions for the US. Instead, we suggest that the interlinkage between housing and credit is central in downplaying the impact of uncertainty. For comparison purposes, the existing literature finds an impact on GDP of around 0.6% (Redl, 2017). These existing studies do not account for housing in the transmission of the uncertainty shock. Housing is seen as a central market within the economy, so any positive change within this market is multiplied. Hence, the muted impact for GDP found in this chapter is driven by the housing uncertainty channel.

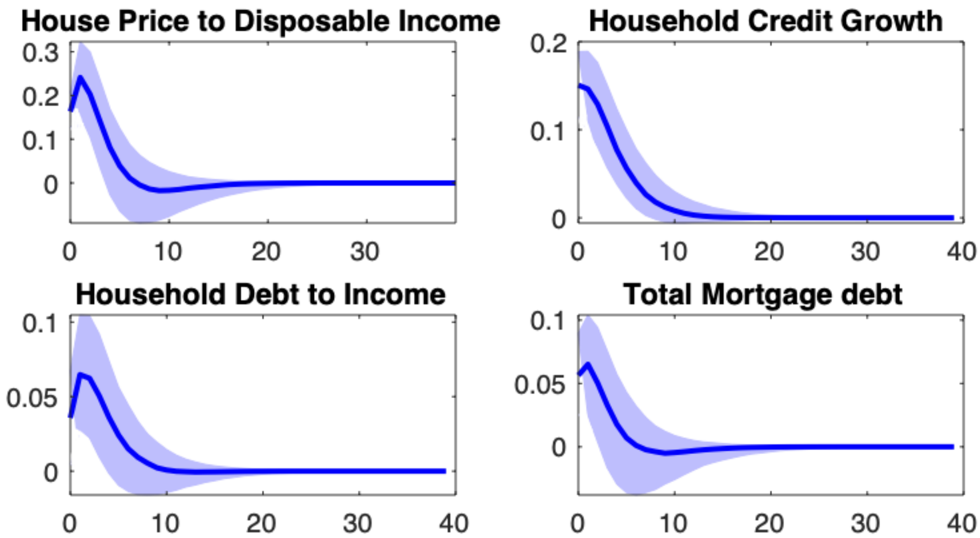
Fig. 1.9 Inflation Response: FAVAR Model



Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes.

The dynamics of inflation demonstrate that the greater informational content in the FAVAR methodology is vital. Although both the SVAR and the FAVAR show the sign as would be expected under a demand shock, as documented in Figure 1.9, the result is only significant under the FAVAR estimation. When placed in the context of the current literature, this is unsurprising due to there currently being no consensus about the response of inflation to an uncertainty shock. For example, in a model with search frictions and nominal rigidities, Leduc and Liu (2012) find an inflationary response in line with a demand shock. Conversely, Popescu and Smets (2010) show inflation responds in the opposite way to what would be expected by demand theory, while Mumtaz and Theodoridis (2017) argue uncertainty has little impact on inflation. Our results suggest that small scale models struggle to capture the significance of the inflation response, whereas the FAVAR captures a greater degree of information which inform the inflation response.

Fig. 1.10 Housing Risk: FAVAR Model



Notes: Impulse responses from a one standard deviation shock to uncertainty from the 2 factor FAVAR model. Identification is achieved by a recursive ordering which relies on splitting our factor model dataset into fast and slow moving variables. The solid dark blue line corresponds to the estimated responses, while the shaded blue represent the 68% confidence intervals drawn from the distribution. Estimation utilises a Gibbs sampler using a flat prior for the factor loadings, variances and the VAR. All IRF's utilise transformation 1, indicating that the y axis can be interpreted as percentage changes.

With regard to the impact on house risk, we find higher uncertainty leads to increased risk in the housing market. We see an expansion of total mortgage debt, debt to income and an expansion of household credit. We show that household credit growth increases by 15%. Household debt to income by 7% while total mortgage debt increases by 5% respectively in Figure 1.10. The result of which is a situation where loan to value ratios increase. As argued by Brunnermeier et al. (2017), the expansion of these metrics where one of the root causes of the financial crisis. Our results draw important parallels to these dynamics. Although those engaging in housing purchases are likely to be able to afford to, the recession and higher leveraged households is an issue of concern. Specifically, there is substantial risk of mortgage defaults leading to a housing crisis.

1.5 Conclusion

This chapter aims to bridge a gap in the literature by assessing the relationship between economic uncertainty, the housing market, and the macroeconomy in the United Kingdom by employing a structural vector autoregression and a factor augmented vector autoregression. We provide clarity on the propagation of uncertainty shocks which are consistent with general equilibrium models. Specifically, we show that the real option channel and precautionary saving dominate the response of macroeconomic aggregates, such that the response of GDP is negative. However the key contribution of this chapter to the literature is is that we find evidence of a new housing uncertainty channel. This is driven by an expansion in household credit and low mortgage rates which act to make housing investment an attractive option. Although the 'traditional' channels dominate, the housing-uncertainty effect reduces the negative impacts associated with uncertainty. Hence, the significance of this result is to highlight the importance of housing when modelling uncertainty.

Our FAVAR methodology allows us to make a novel contribution in terms of understanding the specifics of how an uncertainty shock operates. We establish empirically that precautionary saving is more relevant for durable consumption industries, while for necessity goods the channel breaks down. Without the reduction in demand, uncertainty has limited passthrough to both consumers and in terms of firm side decisions. In a similar vein, the real option channel is particularly important for non housing investment, whereas residential housing investment is characterised by the housing uncertainty channel. We also make the distinction between first time buyers who are subject to worsening financial conditions and so are unable to access the housing uncertainty channel.

In order to address our second research question, we include house risk variables from the Bank of England Stability Report into a FAVAR model. This allows us to assess the impact uncertainty has on financial stability. We find that uncertainty negatively impacts on financial stability. Namely, there is an expansion in housing transactions, which is explained by the access to cheap credit for those with enough equity. This expansion of housing transactions contributes to increased mortgage debt, debt to income ratios and an expansion of household credit which leads to increased risk in the housing market, particularly with the increased risk often associated with increased uncertainty.

Chapter 2

The Non Linear Effects of Uncertainty, the Housing Uncertainty Channel and Monetary Policy

Abstract We establish both the linear and non linear effects of uncertainty shocks on macroeconomic variables by identifying a proxy structural vector autoregression (SVAR) and a threshold vector autoregression (TVAR) respectively. In order to identify our empirical models we update the uncertainty instrument of Piffer and Podstawski (2018) until 2020. The instrument equals the variation in the price of gold around events we choose to represent exogenous shocks to uncertainty. Our results indicate that credit plays a crucial role in the responses of macroeconomic variables by facilitating a housing uncertainty channel. For our non linear model, we present a clear distinction across regimes. We show that shocks to uncertainty incorporate an impatience narrative in a high uncertainty regime, while low uncertainty regimes are characterised by wait and see behaviour. In terms of monetary policy, we argue that changes to policy should only be conducted when uncertainty about the future developments of the economy is low.

2.1 Introduction

The 2008 financial crisis sparked an interest and a need to understand the propagation and impact of increased uncertainty. This question is addressed by the empirical literature through assessing the causal impact, finding that uncertainty is a key driver behind business cycles (Bloom, 2009; Jurado et al., 2015). These studies primarily utilise linear models using recursive orderings to identify shocks. However, the linear framework is subject to criticism because it is unable to capture all the dynamics following increases in uncertainty (Barrero et al., 2017). For example, an examination of various uncertainty data indicators suggest that some ‘uncertainty shocks’, such as Brexit, occur when the prevailing economic outlook is already highly uncertain. This is in sharp contrast to those in relatively tranquil periods. For a macroeconomic shock realised in a high uncertainty period, or ‘regime’, the response is likely to be asymmetric and in sharp contrast to one realised in a relatively tranquil period (Auerbach and Gorodnichenko, 2012; Benzarti and Carloni, 2019; Bonciani and Oh, 2019; Ramey and Zubairy, 2018). Our work attempts to bridge the gap within the literature by developing the work of Coibion et al. (2020). Specifically, we offer an answer to the question - When uncertainty is already at a high level, how do macroeconomic shocks propagate into the economy?

The contribution of this chapter is as follows; first, we propose an instrument to identify uncertainty shocks which builds upon the work of Piffer and Podstawski (2018). We update the instrument for the period 2015 until the end of 2020, by identifying events which are associated with fluctuations in uncertainty such as Brexit and the 2016 European terror attacks. Second, previous studies show that uncertainty propagates into the economy primarily through a precautionary saving channel, whereby risk averse agents reduce consumption and a real options channel which arises due to the fact that agents prefer to ‘wait and see’ (Alessandri and Mumtaz, 2019; Baker et al., 2012; Ludvigson et al., 2020). That is, agents reduce investment by delaying their decision until a time where they have more information about the outlook of the economy and a better investment decision is likely to be made (Basu and Bundick, 2017; Bernanke, 1983; Gilchrist et al., 2014). However, one challenge in the empirical literature is defining the sign of the investment response, because conflicting mechanisms are present.[1] We introduce both credit and housing in order to offer clarity on this issue. Developing the discussion around the empirical link between uncertainty shocks and the endogenous response of credit constitutes the second contribution of the chapter. We first utilise the proxy SVAR model of Stock and Watson (2012) and impose a set identification strategy developed by Carriero et al. (2015a) and Piffer and Podstawski (2018). For the means of robustness, we also adopt a more agnostic narrative identification strategy developed by Bertolotti and Marcellino (2019). This approach is similar to the set identification, but imposes that the instrument must be contemporaneously correlated with the structural shock, yet uncorrelated with other shocks, without specific restrictions on the level of correlations.

Our final contribution is to examine the non linear impacts of uncertainty. The potential for varying responses, dependant on the prior level of uncertainty in the economy, provides the rationale for the development of our nonlinear econometric framework. In particular, we estimate a TVAR model in which we use the Jurado et al. (2015) measure of macroeconomic uncertainty as the transition variable following Bertolotti and Marcellino (2019) and Alessandri and Mumtaz (2019). In line with Bertolotti and Marcellino (2019), we show via Olivei and Tenreyro (2010) tests that our TVAR methodology is able to generate statistically significant responses across uncertainty regimes.

[1] For example, the Oi-Hartmann-Abel channel implies that increases in uncertainty can lead to accelerating investment. If the marginal revenue product of capital is a strictly convex function of the price of output, then investment is an increasing function of second moment shocks (Bonciani and van Roye, 2015)

We identify two different shocks through the narrative based identification scheme within the TVAR model. First we examine a monetary policy shock, reflecting unexplained fluctuations in the policy rate, using the monetary policy shock series developed by Bu et al. (2020).[2] We are aware of several papers which incorporate monetary policy surprises into TVAR models. Aastveit et al. (2017) find that uncertainty amplifies the transmission of contractionary monetary policy shocks. Similarly, Caggiano et al. (2017) and Pellegrino (2018) estimate Markov-Switching VAR models and find expansionary monetary policy has a lower impact during uncertain times. This is because the real option channel limits the pass through to financial markets. On the fiscal side, Ricco et al. (2016) find the largest effects of government spending shocks on aggregate variables is strongest during less uncertain times, while Bertolotti and Marcellino (2019) estimate a non linear VAR model and find that the effectiveness of tax policy is best when uncertainty is low. In contrast to these papers, we account for housing which has been shown to be crucial in the transmission of monetary policy shocks (Elbourne, 2008; Iacoviello and Neri, 2010). In addition, we utilise a different identification scheme based on a narrative restrictions. We also take the endogenous uncertainty method included in the fiscal models and apply it to the monetary policy case within our TVAR model.

The second shock we identify is an exogenous change in uncertainty. As opposed to including uncertainty within the VAR specification, we augment the TVAR model to impose an exogenous shock, which eliminates endogeneity issues between the shock and the threshold variable. Although it is recognised that uncertainty lends itself to non

[2]This instrument is estimated in two steps and captures monetary policy surprises as measured as the change in interest rate futures prices in narrow windows around FOMC announcements. Such an approach builds upon the work of Gertler and Karadi (2015) and Nakamura and Steinsson (2018) and offers a departure from traditional approaches such as the orthogonalised innovations to the Federal Funds rate in recursive VARs as in Christiano et al. (1994) or the narrative approach championed by Romer and Romer (2004). The key advantage of the Bu et al. (2020) approach is that the instrument captures both conventional policy making through shocks to the target interest rate, as well as unconventional policy making such as forward guidance and large scale asset purchases. We choose this instrument because it provides the most up to date shock series while also being recognised as a unifying measure of US monetary policy shocks by the Governors of the Federal Reserve system.

linear study, no non linear frameworks have been proposed, therefore this chapter offers the first examination of non linear uncertainty shocks. Alternatively, several papers have looked into the long term impact of uncertainty. Bloom (2009) examines the impact of policy uncertainty measured at different horizons and finds mean reverting behaviour for long term uncertainty. Likewise, Barrero et al. (2017), find there is a significant amplification on research and development growth in a similar empirical setting to Bloom.

Our empirical results reveal that within a linear framework, an uncertainty shock has a recessionary effect on the real economy within the month when the shock occurs and is followed by a prolonged monetary expansion. We show that there is an expansion in saving and a corresponding fall in consumption activity, relating to wait and see behaviour implied by precautionary saving. Crucially, we provide evidence that uncertainty shocks lead to an expansion in credit which facilitates the housing uncertainty channel. This housing uncertainty channel suggests that while demand for undertaking more risky investments may fall, due to the real option channel, investment in safer opportunities increases. In the model which includes housing purchases and mortgage loans we show that the expansion of credit, coupled with increased demand for safe haven investments increases house purchases, leads to an increase in house prices. In comparison to the literature, the magnitude of the reduction in GDP we report indicates that housing plays an essential part in mitigating the impact of uncertainty shocks.

For the non linear model, we highlight that the uncertainty regime plays a significant role in the propagation of shocks. We show that in a low uncertainty regime, an uncertainty shock follows the rationale of precautionary saving, and wait and see behaviour, because we are able to demonstrate a reduction in consumption, investment and an increase in saving. In contrast, we show that additional increases to uncertainty, once uncertainty is already high, has very limited impact on real variables. This is driven by impatient behaviour which suggests that agents cannot continue to wait and see forever. Instead, the additional increase in uncertainty acts as a signal to undertake consumption caused by a reduction in saving. We present evidence to suggest that this is primarily driven by an accumulation of saving and access to credit which is in line with the mean reverting channel of Bloom (2009).

In terms of monetary policy, results from our exercise are consistent with Castelnuovo and Pellegrino (2018). That is, monetary policy is less effective during highly uncertain times, yet extremely effective in low uncertainty regimes, leading to an expansion in production, employment and credit. We argue that the unexpected policy acts as a signal in a high uncertainty regime, which adversely affects financial markets and increases the level of uncertainty in the economy. This amplifies uncertainty and strengthens wait and see behaviour, causing agents to not partake in activity. The result is a highly persistent policy response in order to combat both the additional uncertainty and the limited activity. Our results call for policy to be consistent when the macroeconomic outlook is uncertain.

The remainder of the chapter is structured as follows. In Section 2, we introduce the econometric framework for the construction of our instrument. Section 3 outlines the linear model and documents linear impulse responses. Section 4 discusses estimation of the non linear model and presents the key results. In Section 5, we summarise and conclude.

2.2 An Instrument for the Uncertainty Shock

In order to construct our instrument we follow the methodology of Piffer and Podstawski (2018). Specifically, we adopt a two step procedure which first collects a variety of events and then secondly assesses the variation in price of a safe haven asset. We collect a vector of events that generated or reduced uncertainty, that were not anticipated, and that are exogenous with respect to other relevant macroeconomic shocks.

Based on the results of Piffer and Podstawski (2018) and anecdotal evidence, we choose gold prices as the asset to use as a safe haven asset.[3] They show that the price of gold Granger-causes several measures of uncertainty, and thus provides a high informational content of uncertainty dynamics. The study also empirically establishes that the proxy built similarly to this chapter, is exogenous with respect to policy, financial, productivity and news shocks, but correlated with the residuals from the VXO. The VXO index is a measure of implied volatility of a weighted range of 30 day S and P options calculated at the money options.[4] For a complete discussion about the exogeneity and suitability of the instrument see Piffer and Podstawski (2018).

2.2.1 Collecting Events

We start by utilising the events identified by Bloom (2009) through the peaks in the VXO. We also make use of the 38 events identified by Piffer and Podstawski (2018) until the end of 2015. Our series extends the list of events by composing a search of the Bloomberg News Service focusing on key words including natural disasters, armed conflicts, terrorist attacks and political elections. In order to conduct our search; once we identify the event, we search the Bloomberg databases to assess whether the event had been mentioned prior. For those events mentioned before the event we choose to exclude it. We exclude all events that may have been anticipated by economic agents and are potentially related to other relevant macroeconomic shocks. We inform the exogeneity of events by theory. For example, we choose to exclude 'Black Monday'

[3] The anecdotal evidence refers to the tendency for news outlets to report the changes in price of gold following an event which raises economic uncertainty.

[4] It is worth noting that the news shock estimated by Beaudry and Portier (2014) is also correlated with the instrument. However, this shock may not fully disentangle uncertainty from news and so has the potential to pick up the link between our proxy and their estimated news shock. Examining the link to other news shocks, there is no statistically significant relationship to the Barsky and Sims (2011) or Kurmann and Otrok (2013) shocks.

in March 2020 due to the fact that this was linked to oil price shocks in the Middle East.

This chapter identifies 26 additional events, 12 of which occur in 2020. These comprise of events such as Brexit, the various European terror attacks in 2016 and worldwide lockdowns at the start of 2020. The full list of events identified and those included in the computation of the proxy are listed in the Appendix. We acknowledge that there is a degree of subjectivity to some of our events we choose as unanticipated events. Taking Brexit as an example, it can be argued that it is not unanticipated in the strictest sense when compared to say, a terror attack. This derives from the fact that the chance of the event happening is based on some probabilistic distribution, while a terror attack intuitively has close to zero prior knowledge. However, we still argue that these type of events should be included as unanticipated events in our proxy. Examining the prior news before the Brexit vote, the accepted view across all news sources was that it was highly likely remain would win, with low probability attributed to leave. Built within our methodology, we reject events which colloquially are 50/50, such as the election of Obama. We essentially are making a value judgement on these types of events. This value judgement is heavily influenced by the response of asset prices and the media fallout from the event. Based on this rationale we choose to include some of these subjective events such as Brexit and the election of Donald Trump. As a robustness check we estimate our results using the events identified by Albrizio et al. (2021). This study creates a similar proxy to this chapter up until 2019, but has a different choice in events. Results from this exercise highlight that the results are not driven by the choice of event. The exact timing of events hitting the market are collected based on the news release on the Bloomberg News Agency. Bloomberg News aggregates information from several news sources from around the world, providing access to a broad set of information and is consistent with Piffer and Podstawski (2018).

2.2.2 Computing the Proxy

We inform our proxy using the percentage change in the price of gold around the events identified in step one of our procedure and equal to zero otherwise. Formally, given an event e_k, with k = 1,....,K representing the total number of events we identify, we define τ_k as the time the event e_k hit the market based on the Bloomberg News release. For each event we compute p_k as the percentage change in the price of gold between the last available auction price before τ_k and the first price available after. The data for gold prices is taken from the 10:00am and 15:00pm auction prices of the London spot market for physical gold.[5] Our rationale for using the London market is to ensure consistency with the original proxy of Piffer and Podstawski (2018). We create a monthly proxy, U_K, by aggregating our K daily realisations following Romer and Romer (2004) and winsorise the proxy at the 1% level in order to avoid results being driven by outliers.

The intuition behind our methodology is that once an uncertainty shock is realised, gold is perceived as a safe haven asset. By reflecting agents underlying response to uncertainty shocks, the variations in the price of gold are highly correlated with uncertainty and thus provides the basis for our instrument.[6] This allows us to identify the exact timing of uncertain events, so we are able to properly capture the contemporaneous effects of uncertainty shocks.

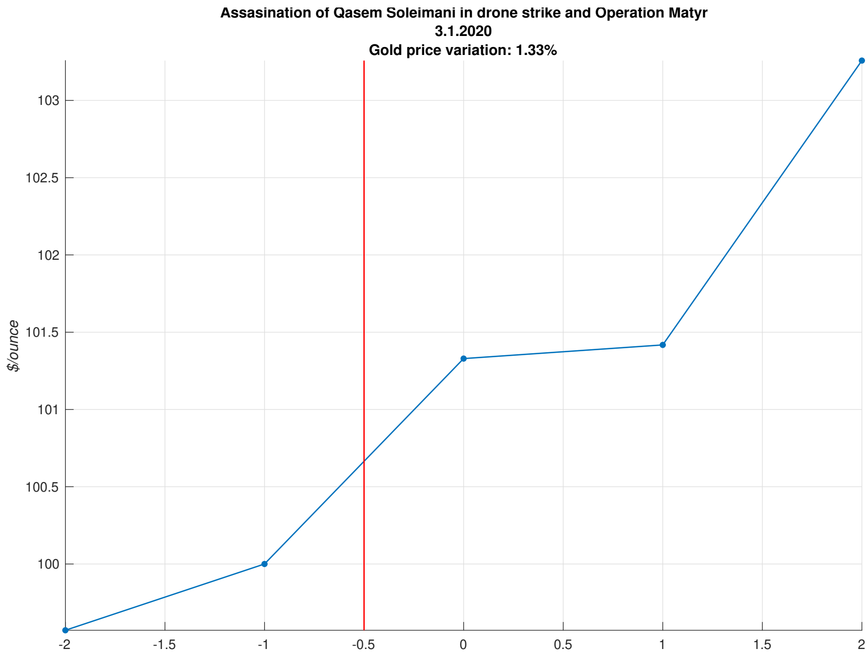
2.2.3 A Discussion of Key Events

In order to illustrate our methodology, Figure 2.1 presents the behaviour of the gold price series around the assassination of Qasem Soleimani, an event included in our

[5]London is the main hub for the trade of physical gold, which occurs through spot transactions over the counter. In comparison, New York is an exchange which trades mainly paper gold, i.e. futures and several derivatives based on gold. The London market is 60% larger in terms of trade volume and also is provides publicly available data dating back to the 1970's as opposed to an 18 month window for the New York market.

[6]Piffer and Podstawski (2018) test the suitability of the correlation between gold and uncertainty. In a test of correlation, the study finds that gold is the most correlated with uncertainty when compared to other precious metals.

Fig. 2.1 Informing the Proxy



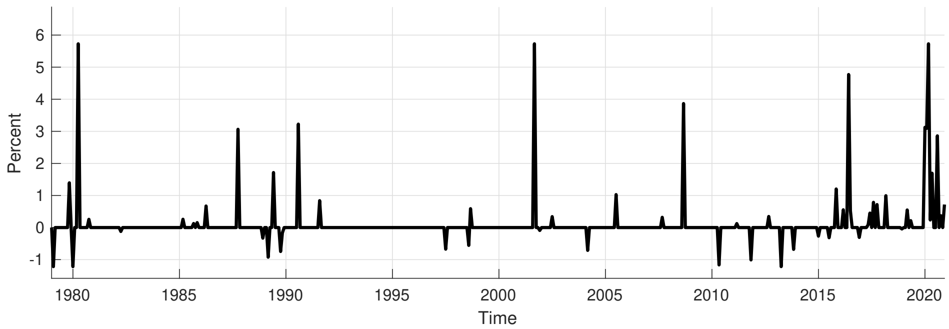
Notes: We document how we inform our proxy. The blue line corresponds to the time series of gold prices. The red horizontal line is the exact timing of the event. We compute the proxy as the difference between the prices in the auctions between this event. The y axis is the pound per ounce of gold, while the x axis represents the timings of auctions.

proxy. Although tensions between the US and Iran had been intensifying throughout 2019, following the bombing at Kata'ib Hezbollah, President Trump held an emergency security briefing at the Mar-a-lago estate. Authorising the mission to kill the Iranian General was presented as the most extreme option. Trump decided to adopt this extreme option, yet did not advise anyone outside the estate of the strike, with news reporting congress claimed no knowledge prior to the event. The event occurred at 1:00am local time and news quickly traveled around the world, such that the price of gold jumped by 1.31% from the closing price from the auction the day before. This reflected the increase in uncertainty for the potential of war between the US and Iran.

2.2.4 The Instrument

Figure 2.2 displays our estimated instrument, U_K. Until 2020, the distribution of

Fig. 2.2 The Estimated Instrument



realisations is uniform and distributed evenly across the sample. Consistent with Bloom (2014) we show that uncertainty shocks are positive, or are larger in magnitude when positive. This informs our decision to focus only on positive uncertainty shocks. Although we capture events that reduce uncertainty, post 2015, the majority of unexpected changes in uncertainty have been positive, reflecting a general increase in the amount of uncertainty in the economy.

2.3 Uncertainty in a Linear Model

Our approach develops a unifying model about the effects of uncertainty shocks on the economy.[7] Methodologically, we estimate our uncertainty shocks independent of news effects. In order to achieve this we incorporate an updated news shock dataset up until the end of 2019. We also incorporate house prices and credit to offer an alternate explanation of how investment propagates into the economy.

[7] In a linear setting, the 'traditional mechanisms' of uncertainty are well established, with both precautionary saving and the real option channel being widely accepted in influencing the transmission of realisations of uncertainty into the economy. The precautionary saving channel suggests that, when faced with higher uncertainty, agents reduce consumption and supply more labor, in order to insure themselves against future risk (Born and Pfeifer, 2014). In a closed economy, this increase in saving implies a one to one increase in investment. However, as Bloom (2009) and Bloom (2014) outline, the real option theory suggests that an important feature of uncertainty is that there is a benefit from delaying investment decisions. When the investor has imperfect information about future returns, the optimal decision is to 'wait and see'. This allows the agent to obtain more relevant information in the next period, which makes it more likely a better investment will be made (Bonciani and van Roye, 2015). In contrast, the Oi-Hartmann-Abel channel discusses the theoretical setting whereby higher uncertainty can lead to accelerating investment. Disentangling the sign on investment is hence crucial in determining the empirical impact of uncertainty.

2.3.1 Accounting for News

As discussed in Bloom (2014) and developed in Piffer and Podstawski (2018), second moment shocks representing increases in uncertainty are often accompanied with a first order shock representing news.For example, a trade war between the US and China may raise uncertainty about the future impact on the economy, but can also be associated with the belief that the economy can be negatively affected by the event.[8] Thus, studies examining the impact of uncertainty often conflate responses with the impact of news and accounting for this becomes essential. The basis of our analysis is to examine the impact of pure uncertainty shocks.

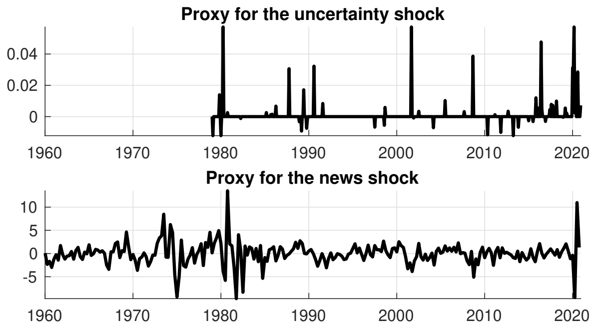
Our approach is to minimise the the risk of contaminating uncertainty shocks with news shocks by estimating both in a unified framework. The identification scheme we adopt makes use of a new proxy for news shocks, N_t, which we create as the first principal component of 16 series of productivity news shocks. Specifically, we update the series of Barksy and Sims (2011), Kurman and Otrok (2013) and Beaudry and Portier (2014) until 2019 which we use in the set of productivity shocks. Our news proxy is displayed alongside our uncertainty instrument in Figure 2.3. For consistency, we apply the same winsorisation used for the proxy for the uncertainty shock to the proxy for the news shock. Our results indicate a number of bad news shocks after 2014, which correspond to uncertain events. In general, we show that uncertainty shocks have a distinct propagation mechanism when compared to news.[9] Bad news shocks

[8] For example Faccini and Palombo (2021) examine Brexit as a case study given that the data following the event did not follow the typical v shaped recession which is often attributed to the impact of an uncertainty shock. In their theoretical model, Brexit is modelled as a news shock with uncertainty instead entering the model in terms of the context of that news. The key takeaway from their model is that the majority of so called policy uncertainty shocks are actually news shocks

[9] We want to make the distinction that news shocks are not strictly first order uncertainty shocks and instead are a subset of potential first order effects. However, given our news based event identification strategy and the implied similarity this has to news shocks, we argue that it is important to condition on news to avoid potential conflated results. We include the same news proxy, albeit with an updated sample, as Piffer and Podstawski (2018) for the means of consistency. In order to achieve this we update each proxy individually with up to date data, and then estimate the principle components as in Piffer and Podstawski (2018).

drive the observed impact on stock markets which is often associated with uncertainty. In comparison, the response of housing and credit following a news shock is not the same and thus news and uncertainty shocks need to be viewed as two distinct entities.

Fig. 2.3 The Uncertainty Instrument and the News Proxy



Notes: The top panel documents our updated uncertainty instrument. To calculate the proxy for news we estimate the first principal component of 16 series of productivity news shocks following Piffer and Podstawski (2018). The y axis for the shocks are displayed in percentage terms.

2.3.2 The Proxy SVAR Model

We estimate a Proxy SVAR following Stock and Watson (2012) and Mertens and Ravn (2013). This builds upon the work of Nevo and Rosen (2012) and Ludvigson et al. (2015) and follows Piffer and Podstawski (2018) in utilising instruments to identify shocks in proxy SVAR settings. The reduced form model is given by

$$y_t = \delta + A(L)y_{t-1} + u_t, \tag{2.1}$$

where y_t is a k x 1 vector of endogenous variables, δ represents the constant terms included in the model and *A(L)* is a lag matrix polynomial. The reduced form shocks u_t are linearly related to the normalised structural shocks, ϵ_t, by

$$u_t = B\epsilon_t. \tag{2.2}$$

We normalise the structural shock by imposing the variance covariance matrix to be the identity matrix.

The approach identifies the uncertainty shock out of the set of k structural shocks in the vector, ϵ_t. We define a scalar ϵ_t^u as an uncertainty shock at time t and let the (k-1) x 1 vector ϵ_t^* represent all other structural shocks. This assumption allows us to rewrite the structural shock relationship as

$$u_t = b^u \epsilon_t^u + B^* \epsilon_t^*, \tag{2.3}$$

where b^u is the impulse response associated with the uncertainty shock and B^* represents the impulse responses for the remaining structural shocks. We impose the relevance and the exogeneity conditions as

$$E(\epsilon_t^u U_t) = \phi^u \neq 0 \tag{2.4}$$

$$E(\epsilon_t^* U_t) = \phi^* = 0. \tag{2.5}$$

These assumptions allow us to use our instrument to identify the uncertainty shock as we impose the exogeneity restriction in the case when our instrument is correlated with other structural shocks. In order to prevent the estimated shock being contaminated by other shocks we impose that the correlation is exactly zero.

2.3.3 Identification

We impose that the uncertainty shock is more correlated with uncertainty, with similar restrictions imposed for a news shock. As argued in Piffer and Podstawski (2018), these restrictions provide a set of assumptions which allow us to identify the structural shocks without imposing a direct restriction on the impulse response functions. We rewrite equation (2.3) to incorporate the instrument for news shocks as

$$u_t = b^u \epsilon_t^u + b^n \epsilon_t^n + B^* \epsilon_t^*. \tag{2.6}$$

We define variance-covariance matrices as $\zeta_t = (\epsilon_t^u \epsilon_t^n)'$, $X_t = (U_t N_t)'$ and $E(\zeta_t X_t') = \Phi$. Based on our assumptions, Φ represents the correlations between the shock of interest and our instruments, where $\phi_{i,j}$ is the i, j entry of the matrix. The set identification approach imposes restrictions on this matrix.

The set identification requires:

$$\phi_{11} > 0; \phi_{22} > 0, \tag{2.7}$$

and

$$\phi_{11} - \phi_{21} > \varphi; \phi_{22} - \phi_{12} > \varphi. \tag{2.8}$$

Equation (2.7) implies that each instrument is correlated to the shock that it is trying to capture, while equation (2.8) imposes that the instrument is more correlated with the shock it is trying to capture when compared to the other shock. The restrictions in equation (2.7) need to be statistically significant in order to ensure a sufficiently strong relationship between the instrument and the shock. We set $\varphi = 0.1$.

For robustness, and to give context to the impact of uncertainty shocks net of news, we estimate an alternate model introduced by Favero and Giavazzi (2012). Specifically, we take the uncertainty shock instrument and embed it as an exogenous regressor within our larger VAR framework. The main benefit of the approach is that it is easily applied to the non linear case, allowing us to compare results from the linear case to the results generated in the non linear model.

2.3.4 Data

We consider an eight variable VAR model defined by the vector (S_t, unc_t, r_t, τ_t, π_t, c_t, cdt_t, hp_t). S_t and unc_t measure the log difference of the S&P 500 index and the VXO uncertainty index. The shadow rate developed by Wu and Xia (2016) is used for the measure of interest rates, r_t. The shadow rate follows the normal Federal Funds rate for positive values, but is not bounded by zero. Once the shadow rate passes zero it is assumed to be a linear function of three latent variables which follow a VAR(1) process. The latent factors and the shadow rate are estimated with the extended Kalman filter. We introduce this into the VAR in levels. We define hours worked and the GDP deflator by τ_t and π_t respectively. Our unemployment measure enters the VAR in levels while we take a log difference of inflation. We measure economic activity by including consumption, c_t, in log differences. Finally, cdt_t, hp_t, represent the variables we introduce into the VAR in order to explain the response of credit. They correspond to the log difference of total private credit and the log difference of the Federal Reserve house price index. For our monthly model we include 6 lags as informed by the AIC and BIC.

Our data runs from 1990 until 2019 in monthly observations. We choose not to include observations from 2020 because of the impact COVID-19 had on the data series. Across all macro variables there is a structural break, caused by the impact of lockdowns, which makes our econometric estimation infeasible. In order to combat this we could assume that COVID-19 represents a third regime of uncertainty dynamics characterised by both a high frequency and level of uncertainty shocks. This assumption leads one to the conclusion that COVID-19 needs to be examined as an isolated event.[10]

We also build a quarterly model to allow us to examine the dynamics of GDP, which we then estimate by our alternative identification strategy. The endogenous variables included in the baseline VAR are given by (y_t, π_t^*, r_t^*, cdt_t^*, hp_t^*). Variables denoted by a star correspond to the related monthly variables aggregated to a quarterly level, while y_t is the log difference of GDP. We also estimate two additional augmented models in order to decompose the channels of an uncertainty shock. Our first model decomposes GDP by the vector (c_t^*, I_t, s_t, ip_t), where the variables I_t, s_t and ip_t denote the log difference of non housing investment, savings as a percentage of GDP and the log difference of industrial production respectively. The final model introduces an extended set of housing variables such that alongside house prices we also introduce housing investment, hi_t, measured as the log difference in total private housing purchases and the log difference of total mortgage loans, m_t. The quarterly model is estimated with 2 lags.

2.3.5 Estimation

The reduced form model is estimated equation by equation using Ordinary Least Squares. In order to compute confidence intervals, we utilise the work of Gertler and Karadi (2015) in using the wild bootstrap developed by Gonçalves and Kilian (2004) and extend the bootstrap to account for set-identification following Piffer and Podstawski (2018). The wild bootstrap changes the sign of both the reduced form shocks and the instrument at randomly selected periods in order to generate a psuedo data set. For each draw of pseudo data, we identify the model as discussed above,

[10] Examining the literature, the impact of COVID-19 is taken in isolation as a singular event or by using theoretical SIR models in order to generate data. For example McKibbin and Fernando (2020) estimate the economic cost of COVID-19. Using a Hybrid DSGE/CGE global model, the authors model COVID-19 as a negative shock to labor supply, consumption, financial markets, and as a positive shock to government expenditure, particularly stemming from health-related expenditures. In the case of the most contained outbreak, the reduction in global GDP is around \$2.4 trillion in 2020. See Brodeur et al. (2020) for a complete summary of this literature.

drawing a single orthogonal matrix Q from the uniform distribution. If the estimated reduced form model generated from this pseudo data satisfy the restrictions imposed by our set identification we keep the draw. This procedure is repeated until 1000 draws satisfy our restrictions. From this, we compute the median target model of Fry and Pagan (2011), in order to estimate the median impulse response to the uncertainty shock from our proxy SVAR. We report 68% confidence intervals drawn from our 1000 models generated.

2.3.6 Results

Testing the Strength of the Instrument

We run Gertler and Karadi (2015) tests in order to assess the suitability of our instrument. This approach tests the correlation between our proxy and the corresponding estimated reduced form shocks. Let $V_{i,t}$ be the estimated reduced form shocks, we run the regression,

$$V_{i,t} = \alpha + \beta_i U_{i,t} + \eta_{i,t}, \tag{2.9}$$

where $i = i, 2, ..., k$. Table 2.1 reports the results from this exercise. The statistical significance is constructed using the asymptotic distribution of the OLS estimator.

As indicated, the VXO is highly positive and statistically significant which implies that uncertainty rises when the price of gold increases suggesting that our proxy is capturing the increases in uncertainty. Most importantly, we show that there is zero statistical significance between the stock market and our uncertainty proxy. As shown in Piffer and Podstawski (2018), there is a high degree of statistical significance between a news proxy and financial markets, which implies that our proxy is not capturing information from news shocks.[11] In order to confirm this result, we run an F test of $\beta_i = 0$. The F stat on uncertainty is shown to be bigger than 10 and much higher in magnitude when

[11]Running the same exercise, but replacing our uncertainty proxy with the news proxy, we find similar results to this. The table is documented in the Appendix.

Table 2.1 Testing the Strength of the Instrument

	SP 500	VXO	Fed Funds	Hours	CPI
β	-0.5143	78.1690***	-3.0705***	-1.307	-0.0408**
F	1.799	11.4161	6.9535	0.7231	4.3461
R^2	0.0046	0.0237	0.0176	0.0019	0.011
	House Prices	Consumption	Credit		
β	-0.0015	0.0723**	0.0823**		
F	0.0107	4.6327	4.6647		
R^2	0.0027	0.012	0.012		

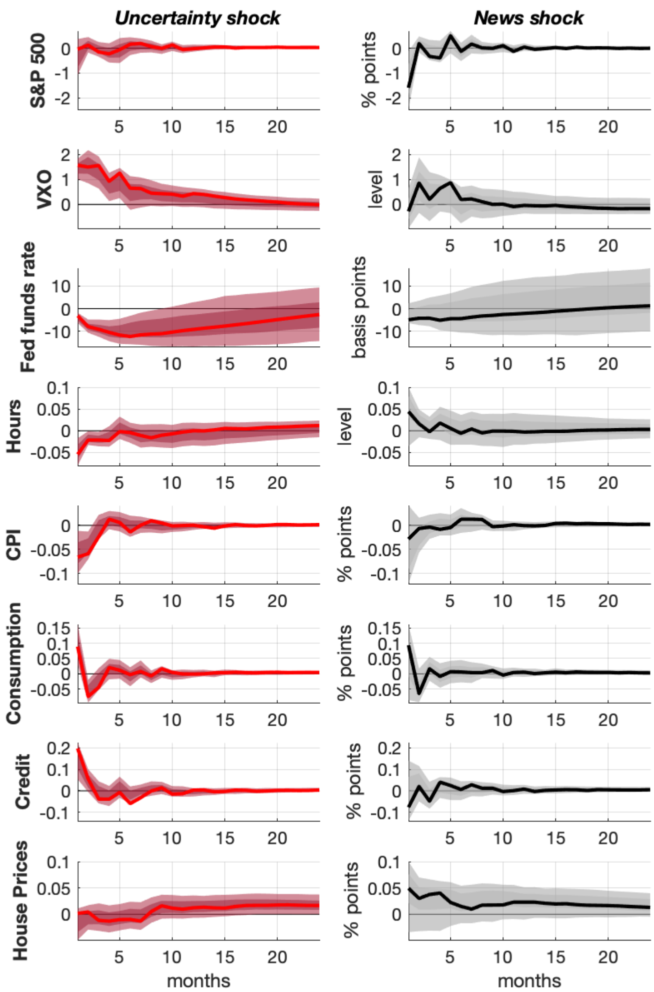
Notes: We report the coefficients from the estimated regression, the test statistic from the F test and the R^2 value. Two stars indicate significance at the 10% level, while 3 stars indicate significance at the 5% level.

compared to the other variables in our model indicating that we can conclude that our proxy is a strong instrument.

Impulse Responses

Figure 2.4 plots the responses estimated from our proxy SVAR following a one standard deviation shock to uncertainty and news. Estimating the model in such a way allows us to quantify the responses following a pure uncertainty shock because we are able to draw comparisons between the two shocks and gather a more complete picture of the propagation mechanism of the two shocks. In general, results from our linear analysis provide evidence of recessionary impacts. Despite our proxy SVAR finding a significant rise in consumption on impact, this is followed by a negative bounce back which lasts for up to a year and a half. Intuitively, this makes sense as agents 'panic' driving up a short term increase in purchases based on the fear that the economic outlook is going to get worse, before precautionary motives dominate as time passes. On the firm side, our results suggest that firms hire less, as hours are significantly negative for 5 quarters. This result is likely driven by the risk averse decision of the firm to be more cautious in delaying employment decisions until the period of uncertainty has dissipated, as well as potentially offering more temporary work (Bloom et al., 2018).

Fig. 2.4 The Proxy SVAR: Uncertainty and News

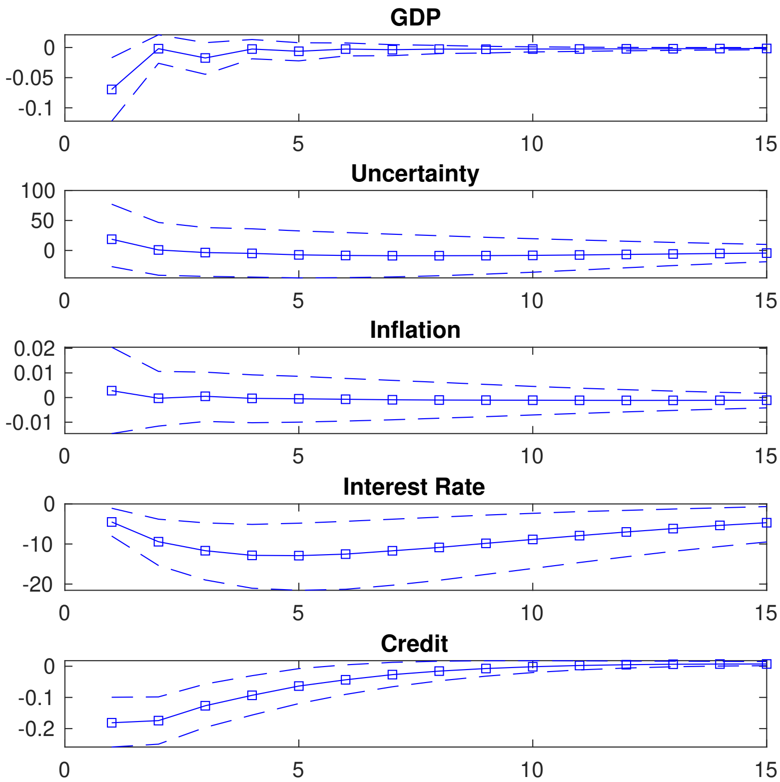


Notes: We report the impulse responses following a one standard deviation increase in uncertainty (red) and a bad news shock (grey) of similar magnitude. See section 2.3.2 for how the y axis should be interpreted (we indicate this on the y axis of the news shock). 64% confidence bands (dark red/grey) and 90% (light red/grey) are calculated using a wild bootstrap procedure.

Introducing credit into the model also plays an important role, specifically as credit only increases following the uncertainty shock. Credit increases by 20% on impact which allows for an effect which conflicts with the wait and see narrative. As discussed in Balke et al. (2017), this channel operates as individuals are faced with a number of possible directions of the economy. Wait and see behaviour depends crucially on the assumption that the economy is going to return to a certain level of 'normal'. Hence, when agents are able to access credit markets, it may be possible that the optimal decision is to consume today as opposed to risking consuming at a later date, when the outcome of uncertainty may be unclear. These contrasting channels are apparent as the initial increase in consumption is driven by the availability of credit, while traditional precautionary saving carries more weight as time passes. The initial increase in consumption is not found if credit is excluded from the model. Overall, this precautionary saving motive leads to a four month recession which is significant at the 68% level. The recessionary impact caused by low investment demand and lower relative employment leads to lower inflationary pressures and we document a significant reduction in inflation.

In terms of news, we provide evidence which supports a number of key findings. First, we show that there are limited impacts on financial markets following an increase in uncertainty as results are insignificant. In contrast, there is a short lived significant fall following the news shock. Although Caldara et al. (2016) show that uncertainty has a significant adverse effect on the stock market, we argue that this result is driven by the methodological approach adopted by the paper which conditions on financial conditions as opposed to news. Our results follow Alessandri and Mumtaz (2019) and suggest that news is the most important mechanism for negative responses on financial markets. Net of news, uncertainty has limited impacts on the stock market such that it is essential that future studies account for news. Second, news shocks find similar 'demand shock' effects as an uncertainty shock at the median response level, yet all these responses are insignificant. Our evidence still suggests that uncertainty is the driving force behind the similarities to the propagation of a demand shock. Finally, in terms of uncertainty, shocks to uncertainty lead to prolonged periods of uncertainty, while news shocks also increase uncertainty but at a lower magnitude and with a delay which is consistent with Faccini and Palombo (2021).

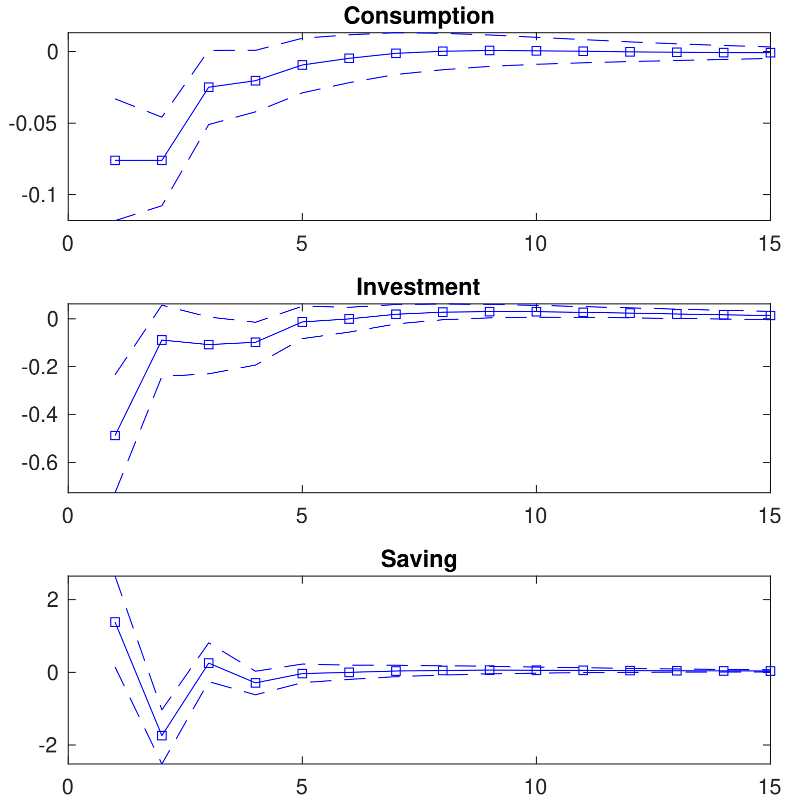
Fig. 2.5 Our Alternative Identification scheme: Baseline Model



Notes: We present impulse responses using our alternative identification scheme based on narrative restrictions as introduced Favero and Giavazzi (2012). Within this we take our instrument of uncertainty shocks and embed it as an additional regressor. 68% confidence intervals are estimated using a wild bootstrap procedure. We present impulse responses for the full model.

We provide complimentary evidence in our alternative identification scheme of recessionary behaviour following an uncertainty shock. The results from our proxy SVAR are robust to our alternative identification scheme. As presented in Figure 2.5, we show that increases in exogenous uncertainty leads to a significant contraction in GDP lasting 5 quarters. In our baseline model credit now falls, however, once we include housing within the model we are able to capture the positive response of credit. We also replicate the loose and persistent monetary policy stance. Once we decompose

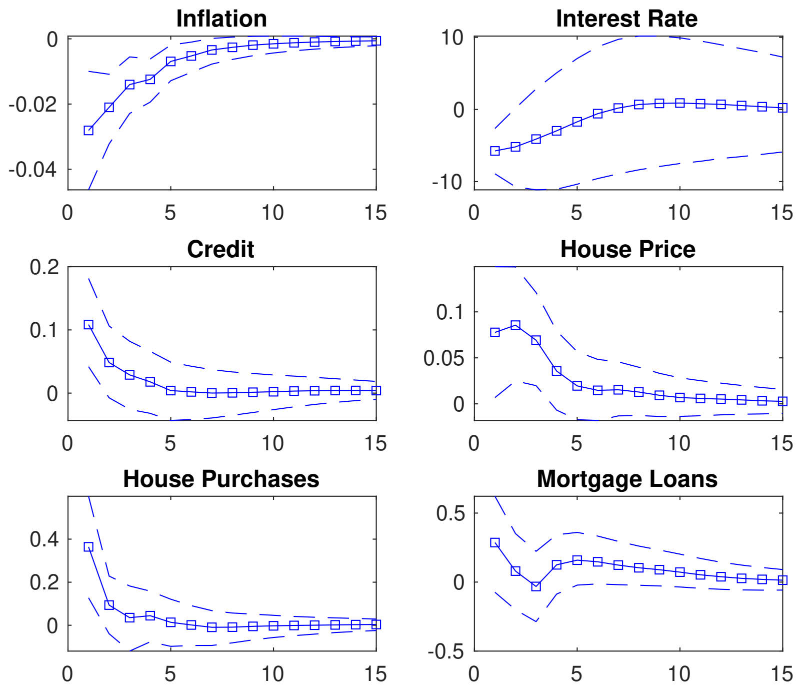
Fig. 2.6 Our Alternative Identification scheme: Extended Model



Notes: We present impulse responses using our alternative identification scheme based on narrative restrictions as introduced Favero and Giavazzi (2012). Within this we take our instrument of uncertainty shocks and embed it as an additional regressor. 68% confidence intervals are estimated using a wild bootstrap procedure. We present impulse responses only for the decomposed GDP variables.

the components of GDP, we show that both precautionary saving and the real option channel are present, but we do not observe the initial increase present in the proxy estimation. We capture a prolonged reduction in consumption consistent with wait and see behaviour. Further, saving increases by a relatively large magnitude, yet this is comparably short lived. This links closely to the response of investment which falls significantly for a similar duration, consistent with the work of Basu and Bundick (2017). Extending our baseline model, we are able to capture a housing uncertainty channel through a combination of including housing purchase variables and increases in credit. That is, in order to limit the risk associated with uncertainty, agents invest in safe assets which drives up demand for house purchases which are positive and significant for 3 quarters respectively. This increase in housing demand, in turn, causes an increase in house prices. These results are presented in Figures 2.6 and 2.7 and lend support to the conclusions presented in Chapter 1 for the UK.

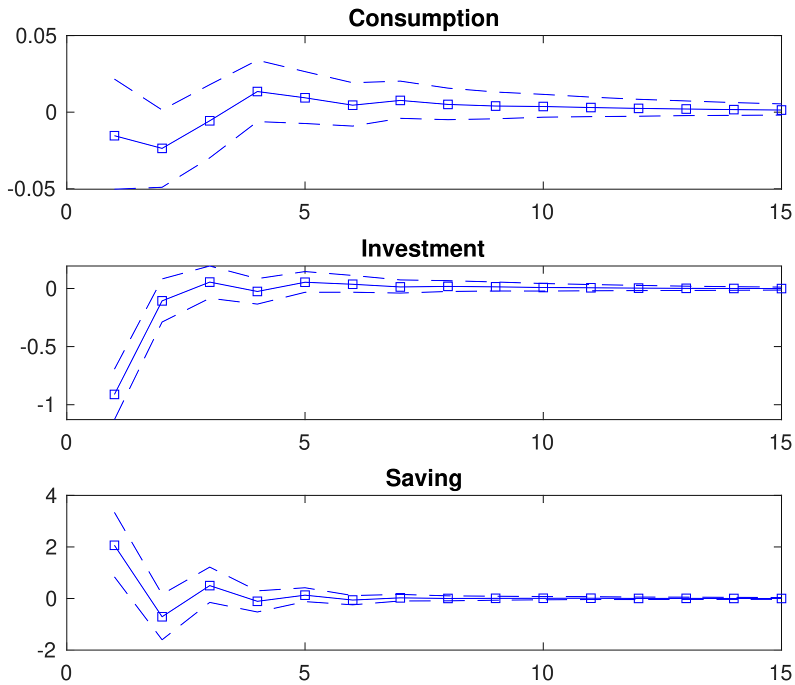
Fig. 2.7 Our Alternative Identification scheme: Extended Model Housing



Notes: We present impulse responses using our alternative identification scheme based on narrative restrictions as introduced Favero and Giavazzi (2012). Within this we take our instrument of uncertainty shocks and embed it as an additional regressor. 68% confidence intervals are estimated using a wild bootstrap procedure. We present impulse responses only for the additional variables.

Central to this impact is the availability of credit driven by a loose monetary policy stance which is highly persistent. Our results are broadly consistent when compared to those estimated in Piffer and Podstawski (2018). We similarly find that real variables revert back to trend after approximately one year which is supported by monetary policy, which takes up to two years to revert back to pre shock levels. Compared to other studies utilising recursive orderings, Cesa-Bianchi et al. (2014) finds the response takes 13 months, while Caldara et al. (2020) finds it takes 18 months for monetary policy to return to baseline. Although we find the sign and duration of the responses of real variables to be similar to Piffer and Podstawski (2018), the magnitude of our responses are lower. For example, the Fed Funds Rate falls by 10 basis points, while Piffer and Podstawski (2018) find the magnitude to be closer to 30 basis points. Similarly, employment falls by 0.05% compared to 0.08% with this relatively limited response consistent across our estimated results. This is driven by the introduction of credit, which acts to mitigate the recessionary impacts associated with uncertainty shocks and precautionary saving.

Fig. 2.8 Our Alternative Identification scheme: Extended Model Housing



Notes: We present impulse responses using our alternative identification scheme based on narrative restrictions as introduced Favero and Giavazzi (2012). Within this we take our instrument of uncertainty shocks and embed it as an additional regressor. 68% confidence intervals are estimated using a wild bootstrap procedure. We present impulse responses only for the decomposed GDP variables.

In terms of the housing market we find two important results. First, decomposing investment into non housing and housing aggregates, we present an amplified real option channel for non housing investment, but a response characterised by housing uncertainty for housing investment. Second, the corresponding increase in house prices leads to a wealth effect (Iacoviello, 2011). In a theoretical setting increases in house prices lead to a substitution effect which causes an increase in consumption. This offers an explanation for the insignificance to the response of consumption as presented in Figure 2.8. While the amplified real option channel creates a larger on impact response for GDP, both the wealth effect and the housing uncertainty channel lead to an uncertainty in the response of GDP.

2.4 The Impact of Non-Linearity

2.4.1 The Threshold VAR model

For the non linear empirical analysis, we use a Threshold VAR model introduced by Balke (2000). It is an extension of standard VAR models as it can capture possible nonlinearities, such as asymmetric reactions to shocks, driven by the level of an external threshold variable. This potential to shift regime has shown to be crucial in the propagation of macroeconomic shocks. In addition, a TVAR allows uncertainty regimes to switch as a result of shocks to other variables besides uncertainty, so that uncertainty regimes are themselves endogenous (Afonso et al., 2018). Following the financial crisis, the standard approach has been to look at regimes which capture financial stress. Employing a TVAR, Alessandri and Mumtaz (2019), Caggiano et al. (2014b) and Caggiano et al. (2014a) show that the real effects of uncertainty shocks strongly depend on the state of the economy. In particular, Alessandri and Mumtaz (2019) show that the effects depend on the state of financial markets and estimate that the impact on output is five times larger in periods of financial stress than in tranquil periods. Similarly, both papers by Caggiano capture recession and expansion phases and show that uncertainty shocks are substantially more costly under recessions than under expansions. In an alternative approach, Basu and Bundick (2017), Cuaresma et al. (2019) and Lhuissier and Tripier (2019) examine the impact at the zero lower bound. Our approach uses an alternative method where we condition explicitly on uncertainty in order to mimic the defining feature of events which have occurred in recent times.

The TVAR model can be written as follows:

$$\begin{gathered} Y_t = c_{low} + B_{low}(L)Y_{t-1} + \sigma^{1,n}e_t^n + \sigma^{1,p}e_t^p + \\ (c_{high} + B_{high}(L)Y_{t-1}\sigma^{2,n}e_t^n + \sigma^{2,p}e_t^p)In_{[s_{t-d}>\gamma]} + U_t, \end{gathered} \tag{2.10}$$

where Y_t is the vector of endogenous variables, In is an indicator function that takes value 1 if the conditioning variable is above the fixed threshold and 0 otherwise, and U_t are multivariate white noise errors. In our chapter, the indicator function will take value 1 in the high uncertainty regime. In general it is possible to obtain more than one critical threshold value and therefore more than two regimes, however we argue that two regimes better match the dynamics of uncertainty. We set d as the number of lags imposed on the switching variable to define the regimes. This value will be set to one, in order to minimise feedback effects of the economic aggregates on the definition of the regime via their possible contemporaneous impact on the uncertainty measure. It also allows us to take into account that changes in the macroeconomic dynamics require some time (Bertolotti and Marcellino, 2019).[12] The threshold γ is determined by grid search and is chosen as the value which minimises the sum of squared residuals of the estimated model. $B_{low}(L)$ and $B_{high}(L)$ are the lag polynomials that regulate the dynamics of the system in the two regimes and c_{low} and c_{high} are vectors of intercepts. We define e_t^i, for i = n,p, as positive and negative shocks to uncertainty. Based on the distribution of realisations in our proxy we focus on positive shocks to uncertainty

[12] A separate literature exists which tests for the significance of the number of lags of the indicator variables. We choose not to examine this, as the focus of our chapter is applied rather than methodological. The current literature which examines non linear VARs take the value d equal to one as given.

which represent an increase in uncertainty. The vectors $\sigma^{1,n}$ and $\sigma^{1,p}$ are the on impact effect in the low uncertainty regime, while $\sigma^{1,n} + \sigma^{2,n}$ and $\sigma^{1,p} + \sigma^{2,p}$ are the effects for the high uncertainty regime.

2.4.2 Identification and Estimation

The model is estimated using the alternate quarterly dataset outlined in section 3.4. Likewise, the model is estimated using two lags based on the AIC and BIC criteria. For our indicator function we use a smoothed measure of the Jurado et al. (2015) macro uncertainty index.[13] In order to calculate this, we compute a standardised moving average of the index using six realisations following Bachmann and Sims (2012). As a test of robustness, we alter the threshold variable across policy uncertainty, financial uncertainty and the VXO index. Results are presented in the Appendix.

For the identification, we build on the narrative identification we use in the linear model and introduce restrictions developed for a non linear setting by Favero and Giavazzi (2012) and Bertolotti and Marcellino (2019). Under this approach, shocks remain completley exogenous and allow us to map the dynamics of the macroeconomic variable of interest by imposing an exogenous change in uncertainty. We account for any possible endogeneity problems from our identification by computing regime specific generalised impulse response functions (GIRFs) as in Koop et al. (1996). GIRFs are essential in our context because they plot the dynamic responses of all the variables in the system conditional on the entire history of the system up to the point when the shock occurs. This is important because an unexpected increase in uncertainty has the potential to drive the economy from low to high uncertainty. GIRFs enable us to keep track of the dynamic responses of all the endogenous variables and depend on the sign and size of the shock, and initial conditions of the system. Formally, the

[13]The key benefit of the Jurado approach, when compared to other measures, is that it gives a broader definition as it measures uncertainty that may be observed in many economic indicators at the same time, across firms, sectors, markets, and geographic regions. For the means of our research question, a broader definition is preferred as we wish to study the effect originating across a wide range of sources, not just policy as in Baker et al. (2016a) or financial markets with the VIX index.

impulse response at horizon h of the vector y_t to a one percent shock, σ, computed conditional on an initial history γ_{t-1} of observed histories of y is given by the difference in conditional means:

$$GIRF_y(h, \sigma, \gamma_{t-1}) = E[y_t + h|\sigma, \gamma_{t-1}] - E[y_t + h|\gamma_{t-1}]. \tag{2.11}$$

Due to threshold models implying that the predicted responses from the model to a shock depend on a particular history, we can simulate the responses for the evolving model for a particular history of interest, or averaging over all histories when the threshold variable is above or below the estimated threshold. The complete estimation procedure for our GIRFs is presented in the Appendix.

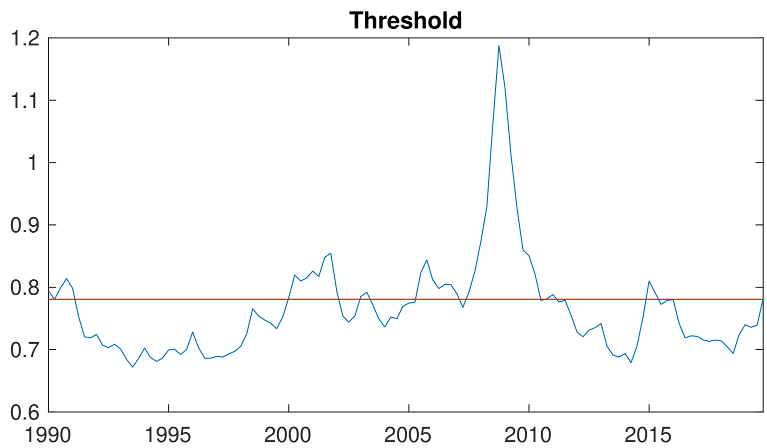
2.4.3 Testing the Model

Threshold

Figure 2.9 shows the uncertainty variable together with a horizontal line which is the threshold value identified by grid search in our TVAR model. When the plotted uncertainty variable is above this line, the system is considered in the high-uncertainty regime. When it is below, the system is in the low uncertainty regime. In particular, we identify three main periods of high uncertainty. The first occurs from 1990 Q1 until 1991Q3, which coincides with the 1990 recession and the start of the Gulf War. The second starts in 2000 and concludes in 2002 Q3, corresponding to the high-uncertainty caused by the 9/11 attack, the Bush election victory and the WorldCom scandal. Finally, we define a high uncertainty regime from 2007 Q1 until 2010 Q4 which is caused by the financial crisis. This is in line with the findings of Jurado et al. (2015), who state that the economy becomes harder to predict in recessions. We also document a spike from mid 2015 until early 2016 following various terror attacks in Europe. The remaining periods covered in the dataset are classed as low uncertainty. We find that the average length of the low uncertainty regime to be 20 quarters, while a high uncertainty regime stays in place for approximately 8 quarters. When compared to

Bertolotti and Marcellino (2019), our results suggest that high uncertainty is similar in persistence.[14]

Fig. 2.9 Our Estimated Regimes



Notes: The blue line plots the level of the macro uncertainty index, while the horizontal red line equates to our estimated threshold as defined by our grid search.

Our threshold value is somewhat arbitrary and thus one can argue that our two regimes also become arbitrary. However, as discussed by Schmidt (2013), the threshold can be set by the econometrician, or can be trimmed at a lower and upper bound in order to ensure a sufficient number of data points in each regime. We take an alternative view in order to not drive our results by the choice of threshold and simply rely on the value as computed by the grid search of all possible threshold variables corresponding to the the smallest sum of squares. Our rationale is to allow our regimes to be set according to what is identified by the data.

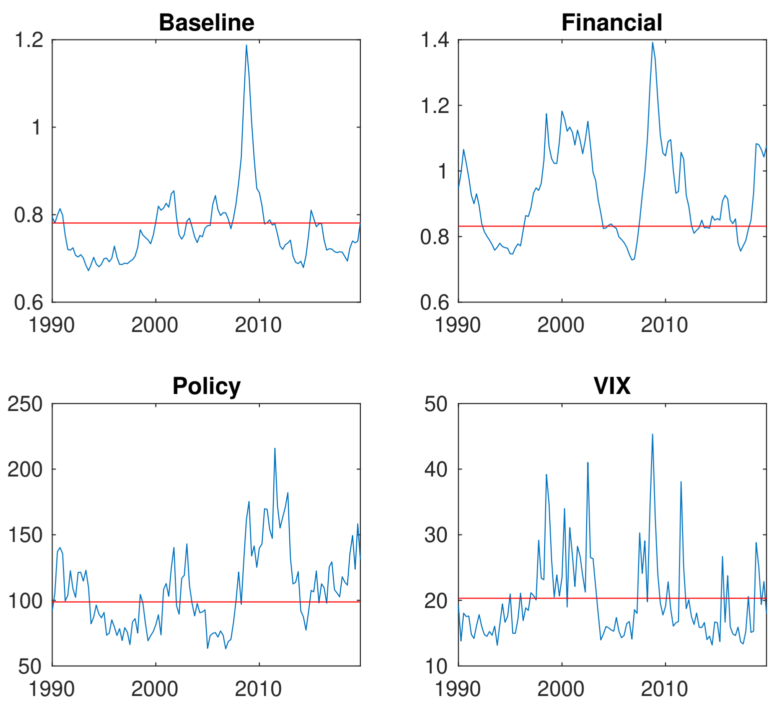
Non-Linearity

We draw confidence that our regimes are well defined by a combination of descriptive statistics and other alternative statistical tests that we undertake. First, our high

[14]These results are purely descriptive and have no bearing on our impulse response functions and instead are intended to allow us to compare the length of regimes to previous results in the literature. Our results are calculated as the average length of each regime, and are likely heavily influenced by one or two key periods for both the low and high regimes.

uncertainty regime occurs broadly in line with recessions which is consistent with Afonso et al (2011) who suggest that peaks in indexes of uncertainty coincide with economic recessions. Second, in a test of robustness there are similarities between the regimes identified from the macro uncertainty index and the policy index, while the VIX index and financial uncertainty identify similar regimes. Capturing similar regimes with alternative uncertainty indexes makes us confident that we have correctly identified regimes. We present our robustness test in Figure 2.10.

Fig. 2.10 Our Estimated Regimes: Robustness



Notes: The blue line plots the level of the various uncertainty index, while the horizontal red line equates to our estimated threshold as defined by our grid search.

Finally, running various tests of the suitability of our model also provides additional evidence that our threshold is well defined.[15] We implement two statistical tests

[15]There are a number of differing approaches proposed within the literature such as the local projection implemented by Jordà (2005). Alternatively, Lhuissier and Tripier (2019) use a Markov switching VAR model to model uncertainty within a non linear setting. Again this is a convenient

proposed by Olivei and Tenreyro (2010) in order to assess whether the impulse responses found for the nonlinear model are statistically different from those of the linear model. The two tests are based on statistics obtained from the comparison of the impulse responses of the linear and nonlinear models with bootstrapped critical values. The first test considers the maximum difference in absolute value between the impulse responses relative to different regimes. In particular, the first statistic is:

$$S_1 = sup|y_t^1 - y_t^0|, \tag{2.12}$$

where the arguments of the absolute value are the responses of variable y in the high and low regimes and the supremum is taken over the time horizon for which impulse responses are computed (10 quarters). The second test statistic considers the cumulated difference between the impulse responses of a given variable in the two different linear and nonlinear specifications. The sum of the impulse response is calculated over the whole time horizon considered. In formulae, the statistic is:

$$S_2 = |\sum_{t=1}^{10}(y_t^1 - y_t^0)|. \tag{2.13}$$

For both statistics, empirical distributions are obtained by bootstrapping the residuals generated from model estimation, re-estimating the model and the impulse responses on the simulated data, and computing the value of the test statistic for that draw. 1,000 repetitions are used, as in Olivei and Tenreyro (2010). Bootstrapped p-values are the percentage of simulated test statistics with a value exceeding the one estimated

method to measure non linearity, however, the state variable is generally not observed and so suffer from a lack of tractability because the underlying regime switching process cannot be identified (Schmidt, 2013). The Interacted VAR (IVAR) model is also a popular method to address questions similar to ours. The IVAR has a non linear interaction term to capture different changes in regime. The estimation takes place across two distinct samples, which is useful when examining periods like the zero lower bound. The issue in our context from the IVAR model is inefficient estimation due to limits in observations given that uncertainty is more volatile. Another approach is the smooth transition VAR model which is designed to study gradual transitions from a regime to another and vice versa. This is governed by a logistic function which assigns a certain probability to being in each regime (Auerbach and Gorodnichenko, 2012; Caggiano et al., 2014a). However, uncertainty changes regimes abruptly in line with new events. Thus, a smooth transition does not match the dynamics witnessed in the uncertainty data.

from the original data.

Table 2.2 P-values from Non Linearity Tests

Description	Baseline	Baseline 2	Housing	M. Policy
+ Lin. vs. Low	**0.044**	**0.024**	**0.041**	**0.063**
+ Lin. vs. High	**0.012**	**0.012**	**0.011**	**0.068**
- Lin. vs. Low	0.778	0.463	0.273	**0.049**
- Lin. vs. High	0.119	0.103	0.117	**0.071**
+ High vs. Low	**0.021**	0.434	**0.063**	**0.086**
- High vs. Low	**0.098**	**0.1**	**0.054**	**0.087**

Notes: Bootstrapped p-values are the percentage of simulated test statistics with a value exceeding the one estimated from the original data. Bold values correspond to significance at least the 10% level.

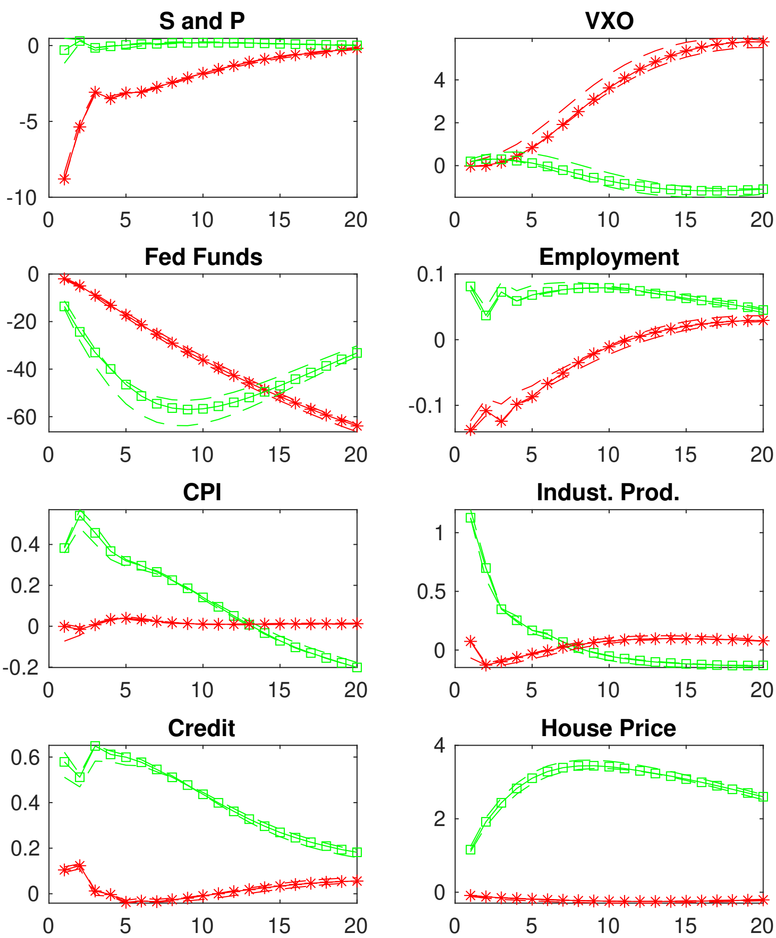
We find strong evidence of non linearity across our impulse response functions. Table 2.2 presents p-values from our non linearity tests described above. We compute these statistics for our baseline model and our model with housing described in section 2.2 in terms of the response of GDP. For our baseline model we show that the responses are different between a linear model and across regimes. We fail to reject that the responses are the same at the 5% level for low uncertainty, but are able to conclude at a 5% level that responses are different between high uncertainty and a linear model. Across regimes we also find evidence of non linearity because we reject at the 5% level that responses are the same. Results are similar once we include housing. That is, we are able to reject at the 5% level that impulse response functions are different following a positive shock in the linear model and across regimes at the 10% level.

2.4.4 Results

Monetary Policy

As presented in Figure 2.11, the responses following an unexplained expansionary policy representing a cut in the policy instrument are highly sensitive to the regime. In a low uncertainty regime, the cut in policy rates propagates according to traditional theory, in that we document an expansionary impact on employment, industrial production and inflation.

Fig. 2.11 Non Linear Monetary Policy Shock



Notes: Generalised impulse responses to a one standard deviation shock to the narrative monetary policy series. The low uncertainty is presented in green while the high uncertainty is presented in red. We also document 68% confidence intervals computed using the bootstrap procedure outlined in Appendix B.2.

Specifically, employment increases by 0.05% with the expansion lasting close to two years. Industrial production returns to baseline after a year, while inflation takes just over a year to return to pre cut levels. In contrast, a high uncertainty environment leads to less effective monetary policy which has the potential to become recessionary. This is a result consistent with Bertolotti and Marcellino (2019), Aastveit et al. (2017), Caggiano et al. (2017) and Pellegrino (2018). When ex-ante macroeconomic uncertainty is high, the responses of employment fall by 0.15%, industrial production remains close to zero and credit responds negatively with a two period lag which is highly persistent. This leads to a negative response which is close to zero for inflation. This has the implication that while monetary stimuli carried out via policy rate cuts are effective, when the future developments of the economy are subject to low macro uncertainty, the same policies carried out when the economic outlook is more uncertain, are ineffective or even harmful. From a firm perspective the limited pass through to employment aggregates can be explained by the presence of wait and see behaviour in labour demand decisions, which suggests a weaker response during uncertain times (Bloom, 2009). On the consumer side, despite the policy cut, saving remains high which limits the effectiveness of the policy. This follows from the theoretical results that uncertainty induces people to adopt wait and see behaviour.

A key driver of our results is the dynamics of the policy cut, which are equally impacted by the level of uncertainty. When the macroeconomic outlook is characterised by low uncertainty, the policy cut has zero impact on the VXO, while for the high uncertainty regime the policy cut leads to an increase in the VXO indicating a worsening of uncertainty conditions. This suggests that the monetary policy acts as a signal for the future direction of the economy, and agents interpret this as a worsening of conditions. Our results are consistent with both the information and signalling effect discussed in the theoretical literature. For example, Nimark (2008), Melosi (2017) and Andrade and Ferroni (2021) suggest that there is imperfect common knowledge due to the advantage the central bank has in processing information, while Romer and Romer (2000) and Nakamura and Steinsson (2018) suggest that rational agents are able to gain information from the observation of monetary policy and thus are able to update their beliefs about the future path of the economy.

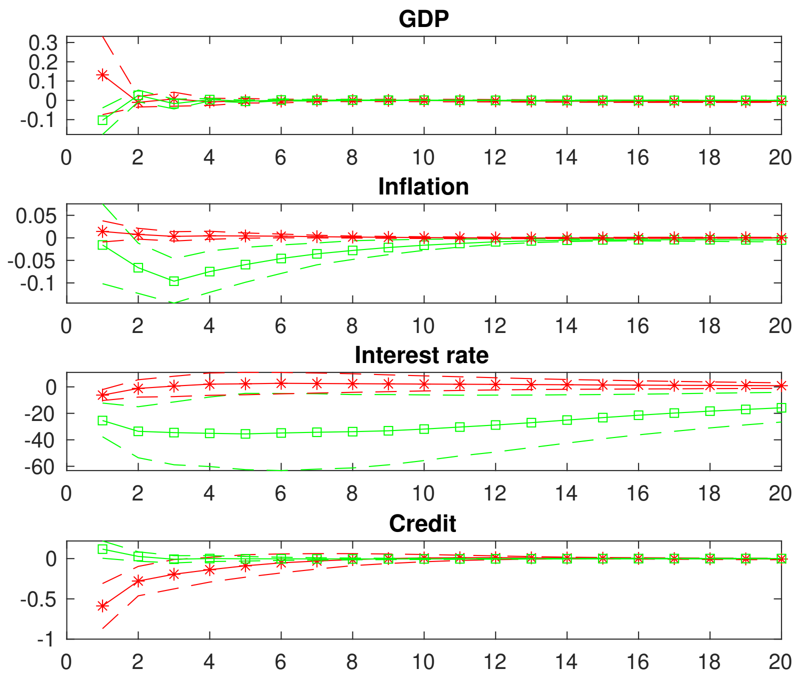
We provide additional evidence to support the empirical signalling effect as financial markets respond negatively in response to the shock in the monetary policy series. Through deepening the scale of uncertainty in the economy, there is an exacerbated precautionary saving motive which reduces the effectiveness of policy. In line with this, in a low uncertainty regime, the policy returns to pre cut levels after two years, while a more aggressive and persistent policy stance is required in the high uncertainty regime in order to combat the increased level of uncertainty. The implication from this result is that central banks must ensure consistency in policy once uncertainty is high otherwise there is the potential for policy interventions to lead to a worsening of conditions.

In terms of the housing market, we show the distinction across regimes. There is almost zero impact on houses in the high uncertainty regime. This follows from the increase in financial frictions as discussed by Arellano et al. (2019) and Gilchrist et al. (2014). High uncertainty regimes, i.e. the financial crisis, have been accompanied by a tightening in credit conditions, such that in this regime agents are unable to adequately access credit markets. The resulting impact is both credit and house prices fall, with agents instead choosing to save more by delaying decisions. This is consistent with wait and see behaviour because purchases which have a large cost associated with them are likely to be sensitive to precautionary thinking. In contrast, the low uncertainty regime has relatively more favourable lending conditions. The result is that we witness an increase in credit and an expansion in investment and house prices consistent with Barnett and Thomas (2013) and Iacoviello and Neri (2010) who suggest that house price booms are caused by unexpected monetary policy.

Uncertainty

We show that uncertainty shocks have a negative impact on real variables only in low uncertainty regimes in Figure 2.12. In the low uncertainty regime, the shock propagates as discussed in section 3.6.2 for the linear case.

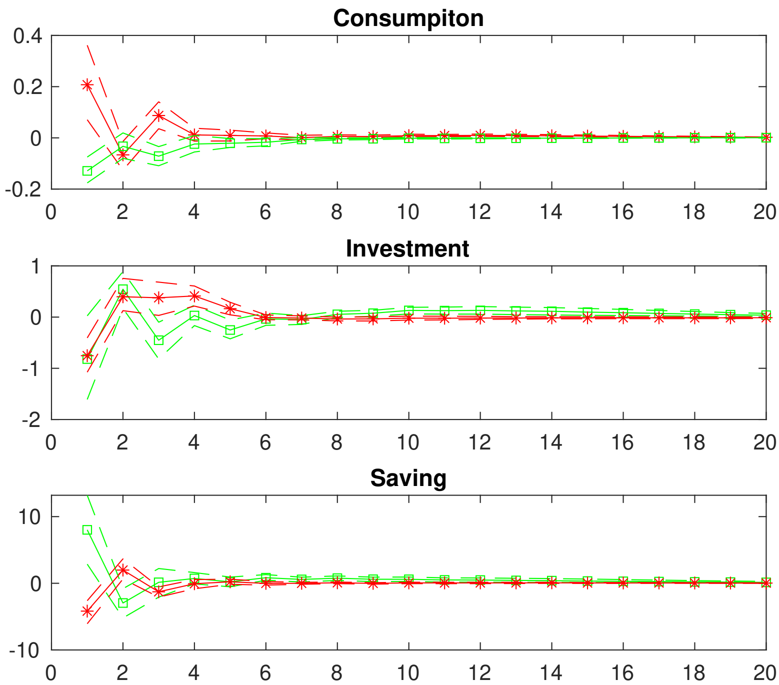
Fig. 2.12 Non Linear Uncertainty Shock (1)



Notes: Generalised impulse responses to a one standard deviation shock to the narrative uncertainty series. The low uncertainty is presented in green while the high uncertainty is presented in red. We also document 68% confidence intervals using the bootstrap procedure outlined in Appendix B.2. We use the baseline model.

Specifically, we present a contraction in GDP driven by wait and see behaviour, a corresponding reduction in inflation and a persistent loose monetary policy stance. In contrast, additional shocks to uncertainty have relatively limited impact when macroeconomic uncertainty is already high such that the response on GDP becomes neutral. Impatient behaviour and the real option channel providing conflicting responses, which provides an explanation for the limited effect on output. The distinction across regimes is that precautionary saving is highly significant when uncertainty is low, but this carries less weight the longer or deeper the level of uncertainty gets. As highlighted in Figure 2.13, we document a reversal in the response of saving during high uncertainty, which plays a significant role on impact of the increase in uncertainty. While this response is short-lived, it represents a shift in attitude towards uncertainty and helps fuel an increase in consumption which lasts for up to one year. Overall, once uncertainty has reached a certain level, it is undesirable to continue to delay consumption decisions, the precautionary saving is reversed and agents undertake consumption.

Fig. 2.13 Non Linear Uncertainty Shock (2)



Notes: Generalised impulse responses to a one standard deviation shock to the narrative uncertainty series. The low uncertainty is presented in green while the high uncertainty is presented in red. We also document 68% confidence intervals computed by the bootstrap procedure outlined in Appendix B.2. We use the baseline model.

The dynamics of saving also play an important role in driving the response of investment. Responses of non housing investment are negative suggesting that the real option channel holds across regimes. However, we also document a delayed positive response which lasts for three quarters in the high uncertainty regime. This is analogous to impatient behaviour witnessed in the response of consumption. We posit that saving, and a potential accumulation of saving is crucial in driving this behaviour. In line with this argument, we document a reduction in credit for the high uncertainty regime which represents that high uncertainty regimes are highly correlated with periods of tight credit conditions and financial frictions. Agents are unable to fund investment through credit markets, but instead use the accumulation of saving they have accrued through precautionary saving in response to the high level of uncertainty that characterises the regime. In contrast, a low uncertainty environment is unable to capture this mechanism as the excess saving has not occurred and financial frictions also are less prevalent. The responses can therefore be defined through a strong precautionary motive which maintains low consumption and investment and the ability to access credit markets. Although we present an increase in credit markets, the impact on non housing investment is relatively small as the wait and see motive incentivises agents to wait until the period of uncertainty has dissipated.

Our results are consistent with both the theoretical and empirical literature. Theoretically, altering consumption behaviour is in line with the theory of consumption smoothing (Gilchrist et al., 2014). Empirically, our results are similar to mean reverting behaviour introduced by Bloom (2009). Specifically, mean reverting behaviour implies that when looking at the impact of long run uncertainty, there is a tendency for the impact on investment to become diluted once longer horizons of uncertainty are considered. Similarly Bonciani and Oh (2019) and Barrero et al. (2017) find that the real option channel is highly sensitive to long run uncertainty, reflecting a more myopic focus and a belief that long run uncertainties will not impact agents today. These papers focus on the impact of long term uncertainty and the interaction with investment. The benefit of our results is that we are able to capture the short term response of uncertainty conditional on prevailing conditions and so the 'long run' impact propagates through impatient behaviour and an accumulation of excess saving.

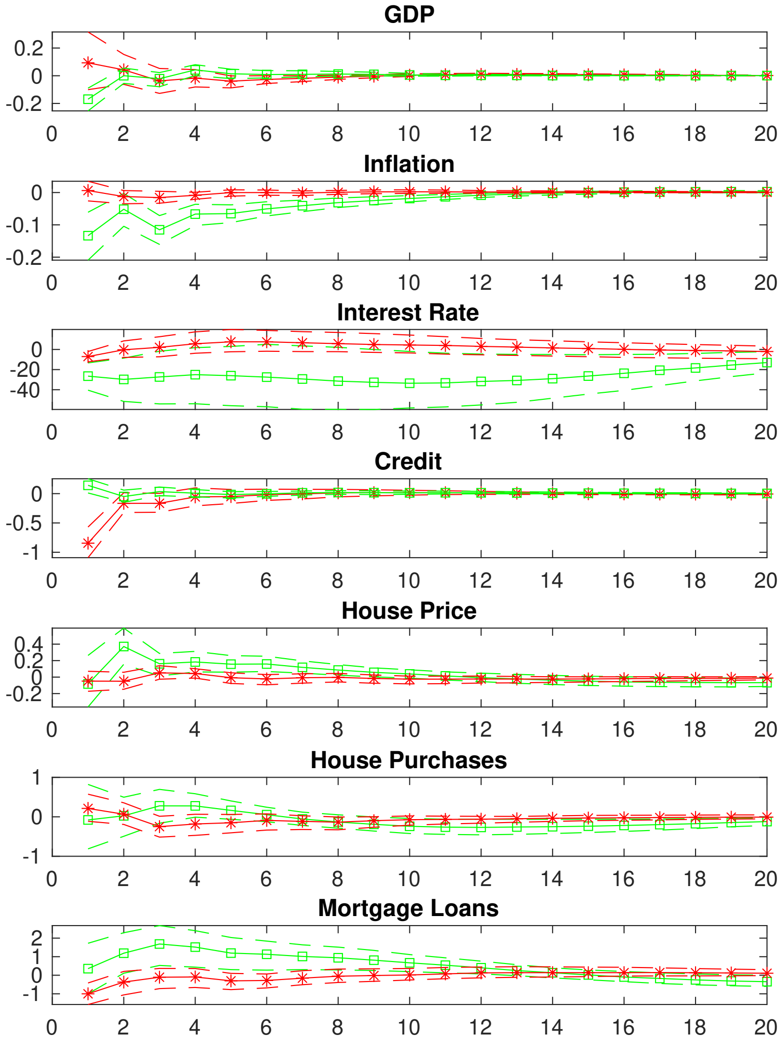
In terms of the interest rate, the amplified and conflicting uncertainty mechanisms lead to limited dynamics in inflation during a high uncertainty regime and so there is only a small movement in the interest rate. In the low uncertainty regime, the uncertainty shock propagates as shown in the linear case, and the magnitude and persistence of the monetary policy stance is matched to our linear results.

Housing

Figure 2.14 presents the TVAR model, following a 1% increase in the standard deviation of uncertainty, in a model which includes housing variables. Similarly to a monetary policy shock, we demonstrate that the response of the housing market is highly sensitive to regime. As discussed previously, we document a significant fall in credit which is representative of financial frictions and a reluctance from lenders to lend in high risk conditions. Although there is an accumulation of saving, housing purchases are highly dependant on the availability of credit. When investment projects are irreversible (they cannot be 'modified' without very high costs) there exists a trade-off for investors between additional returns, and the benefits of waiting to gather more information in the future (Baker et al., 2016a). In this case, the wait and see motive is exacerbated and we document a fall in mortgage loans, house purchases and house prices.

The picture is different for a shock realised in a low uncertainty regime. Economic conditions allow for agents to access credit, which responds positively as agents look to undertake investment to insure against the risk of higher uncertainty. Although premiums may rise as financial intermediaries protect themselves against default risk by charging a premium to cover the costs of default, the motive to insure against the negative impacts of uncertainty is more important (Jackson et al., 2019). As previously discussed, there is limited impact on non housing investment. Alternatively, agents look to 'safe haven' assets which represent a safe investment. This facilitates an increase in mortgage loans and housing purchases which represent a housing uncertainty channel. This result is in line with the work of Belke and Osowski (2017), who argue that as

Fig. 2.14 Non Linear Uncertainty Shock (3)



Notes: Generalised impulse responses to a one standard deviation shock to the narrative uncertainty series. The low uncertainty is presented in green while the high uncertainty is presented in red. We also document 68% confidence intervals computed by the bootstrap procedure outlined in Appendix B.2. We use the extended model.

uncertainty creates several possibilities for the direction of the economy, the decision to invest today becomes more attractive on the belief that the outcome of the economy is going to be more favourable.

2.5 Conclusion

The key aim of this chapter is to bridge a gap in the literature by examining the non linear effects of uncertainty shocks. We provide an explanation to the question raised by Coibon et al (2020) which asks when uncertainty is already at a high level, how do macroeconomic shocks propagate into the economy? As our empirical results suggest that traditional channel of uncertainty hold when uncertainty about the macroeconomic outlook is low. However, we offer an alternative interpretation of an uncertainty shock once uncertainty is high which departs from the precautionary saving narrative and reflects the idea that agents cannot continue to save forever. The key takeaway from our model is that there is an impatience effect which causes an increase in consumption generated from an accumulation of precautionary saving which represents business as usual behaviour.

Our non linear results lead to the conclusion that it is better for the policy maker to implement changes in monetary policy when uncertainty about future developments of the economy are low. This links closely to the work presented Caggiano et al (2017) and Pellegrino (2018), however we extend the analysis by suggesting that unexplained changes in policy act as a signal. Specifically, in a high uncertainty regime, we show that unexplained monetary policy negatively impacts stock markets which further increases macroeconomic uncertainty, This, in turn, amplifies wait and see behaviour which consequently leads to precautionary saving and a limited impact following expansionary monetary policy. Our results support the need for consistency in monetary policy once uncertainty is high.

We also make an important contribution to the discussion about the linear propagation of uncertainty shocks. The novel aspect of our work is to examine the interaction between housing and credit in an empirical setting. We find that the introduction of credit facilitates a housing uncertainty channel and an increase in housing investment.

The latter allows us to reconcile our empirical model with the theoretical work discussed in Balke et al (2017). Overall, the results presented in this chapter suggest that the housing uncertainty channel acts to mitigate the negative responses associated with shocks to uncertainty.

One of the current issues regarding uncertainty is how the COVID-19 pandemic has been able to impact the relationship between macroeconomic aggregates and uncertainty. Although we do not address this question explicitly, we argue that the model proposed in this chapter is well suited to be able to account for the pandemic. First, we estimate a time series to proxy the level of uncertainty in the economy by utilising variations in the price of gold around the timings of exogenous uncertain events. This methodology allows us to capture COVID-19 related uncertainty. Second, we suggest that the pandemic introduced an unprecedented level and scope of uncertainty which could be represented as an additional uncertainty regime. We suggest that an examination similar to Caggiano et al (2017) for the zero lower bound period could accurately account for the impact of the pandemic. However due to data limitations, we leave this exercise to future work.

Chapter 3

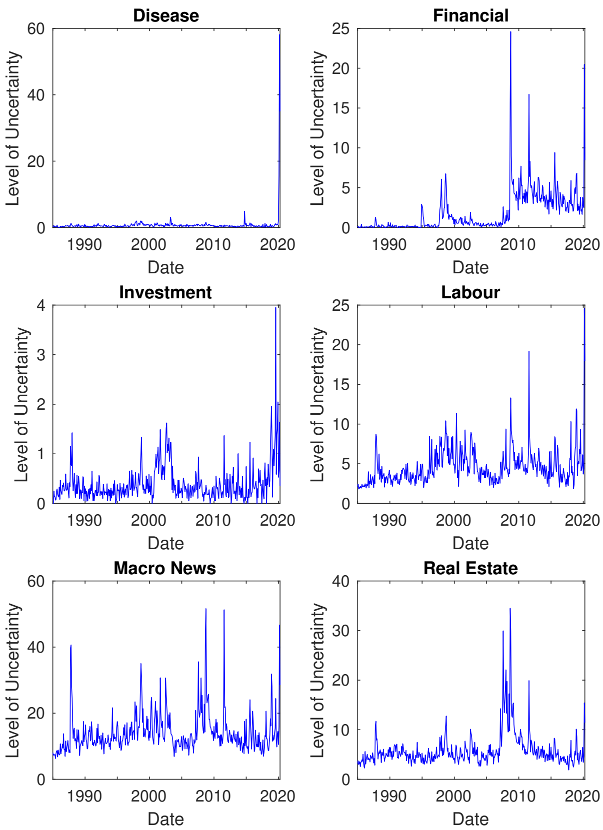
Uncertainty, Financial Frictions and the Housing Market

Abstract We develop a real business cycle model characterised by credit frictions, a banking sector, heterogenous households and the housing market which facilitates the study of uncertainty shocks. Within our framework, we document i) a credit channel which limits access to external funds for the credit dependant sector of the economy, and ii) a housing demand channel, which leads to tighter constraints for households and entrepreneurs and lowers the return on capital. Together, both channels amplify precautionary saving for household borrowers. The credit channel creates a real option channel for entrepreneurs, while the housing demand channel impacts households savers by amplifying their reduction in investment. We show that impulse responses generated by the model are consistent with the empirical evidence on the effect of uncertainty shocks on macroeconomic aggregates.

3.1 Introduction

Following the 2008 financial crisis, the consensus was that the increased uncertainty experienced in the US amplified the ensuing recession. Stock and Watson (2012) find support for this claim, citing that uncertainty shocks accounted for two thirds of the decline in US GDP over this time; while Bloom et al. (2018), Baker et al. (2016b), Altig et al. (2020) and Fernández-Villaverde et al. (2015) also provide evidence that uncertainty acts as a driver of macro economic aggregates.

Fig. 3.1 Components of the Jurado et al. (2015) Macro Uncertainty Index



Notes: We document the various components of the Jurado et al. (2015) macro uncertainty index. The y axis is measured as the index of uncertainty as produced by the factor model methodology. We present the data from 1990 until 2020 for the US. We take the data from Sydney Ludvigson's personal website.

As Figure 3.1 presents, uncertainty continues to be at the forefront of the issues facing the US economy. Specifically, the outbreak of the COVID-19 pandemic has led to a large rise in all of the components of the macro uncertainty index developed by Jurado et al. (2015). Most notably, we document sharp rises in uncertainty over investment, labour market decisions and macro aggregates which are greater than the level witnessed following the 2008 financial crisis. As a result of the prevalent nature of uncertainty since the crisis, there has been substantial interest in understanding what impact uncertainty has on the macroeconomy. This chapter contributes to the growing literature which aims to address this question by modelling the dynamic links between uncertainty and macroeconomic fluctuations in a general equilibrium framework.

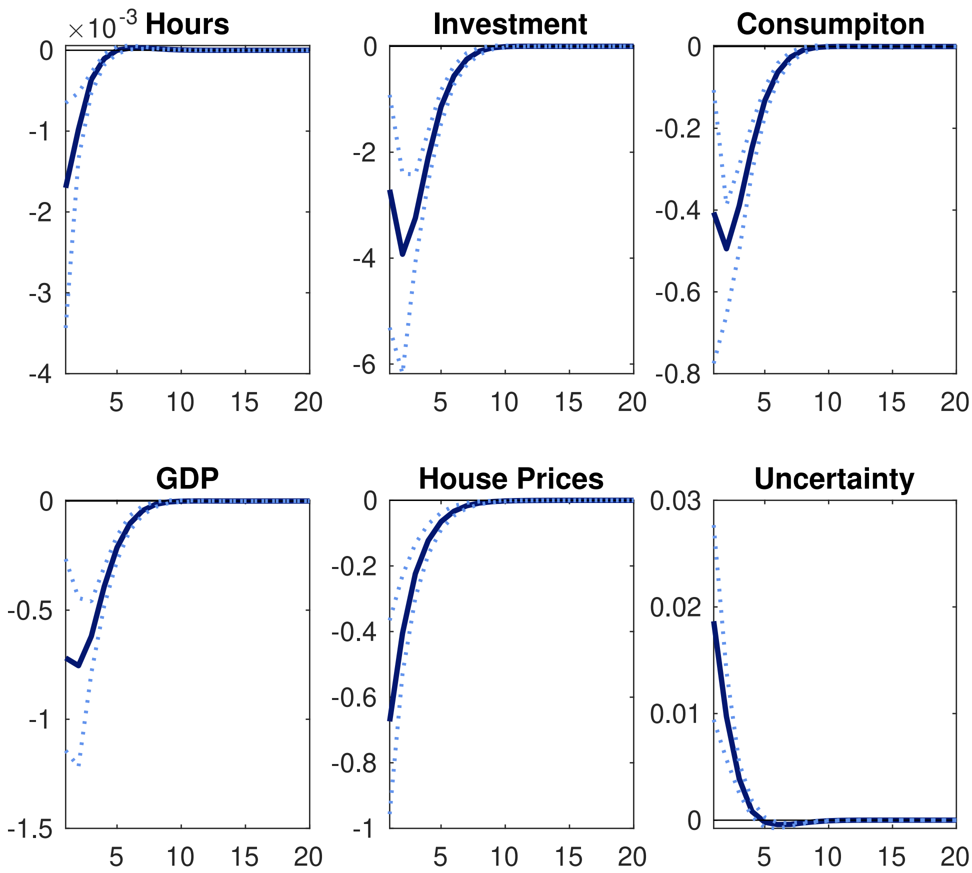
In line with both precautionary saving and the real option channel, we establish several stylised facts following an increase in uncertainty.[1] Uncertainty has a negative impact on real activity and is characterised by a co-movement of key economic variables over the period from 1985 to 2020 in the US. As argued by Basu and Bundick (2017), this co-movement is the most significant feature of the response of macro variables to increased uncertainty. Figure 3.2 displays impulse response functions of investment, consumption, output, house prices and labour hours following a shock to the macro uncertainty series. These impulse responses are estimated from an SVAR using a sign restriction approach similar to the one proposed in Chapter 1. We impose restrictions which satisfy an increase in uncertainty, a reduction in consumption and a reduction in investment, while we leave the other variables in the model unrestricted in order to allow these responses to be solely driven by the dynamics of the VAR model.[2] An

[1]Leland (1978), Kimball (1990), and Carroll and Kimball (1996) show the theoretical conditions needed for (future) uncertainty to affect consumption, later quantified empirically by Carroll and Samwick (1998). Hartman (1976), Abel (1983), Caballero (1991), and Dixit et al. (1994) show the theoretical conditions needed for uncertainty to affect investment. Recently, Bloom (2009) has shown that uncertainty can have sizeable effects on firms' demand for factor inputs. Additionally, when the relationship between lender and borrower is subject to to asymmetric information, caused by moral hazard problems, an increase in uncertainty will raise the cost of external finance (Christiano et al., 2014).

[2]This procedure follows from the evidence in Basu and Bundick (2017) and is consistent with precautionary saving and the real option channel.

increase in uncertainty leads to a persistent decline in all the macroeconomic variables. However, we document a large negative response for investment which suggests that the real option channel dominates following an uncertainty shock. There is also evidence of precautionary behaviour for the labour and consumption decisions, yet the responses are at a lower magnitude to the investment response.

Fig. 3.2 Impulse Responses to a Shock to Uncertainty from a Sign Restriction SVAR Model



Notes: Impulse responses estimated from a sign restriction SVAR model. We impose restrictions which satisfy an increase in uncertainty, a reduction in consumption and a reduction in investment all which last for 4 periods after the shock. 68% confidence intervals are drawn from the distribution we generate from our sign restriction routine. Data is transformed to be stationary, so we take the log first differences of all variables.

Despite precautionary saving being present in the standard real business cycle (RBC) model, the model is unable to produce responses which are consistent with the stylised facts presented in our empirical work (see also Cesa-Bianchi and Fernandez-Corugedo (2018)). In the RBC framework, households are subject to the precautionary saving channel, which implies a reduction in consumption and an increase in hours worked. Higher uncertainty increases the marginal utility of wealth, which shifts the household labor supply curve outward. Firms labor demand depends on the level of the capital stock and technology, neither of which changes in response to higher uncertainty. Through the production function, higher labor supply with unchanged capital and technology means that output must rise. Higher output with lower consumption implies that investment must increase via the national income accounts identity. Thus, higher uncertainty, under flexible prices, lowers consumption but causes an expansion in output, investment and hours worked.

In order to match both the salient features of the data, and the well established channels of an uncertainty shock, we extend the standard RBC model with two additional elements. Firstly, we introduce a real estate sector as in Iacoviello (2005), and secondly we introduce banks and financial frictions.[3] A real estate sector is included in our model, because housing is assumed to be particularly sensitive to changes in uncertainty. Following from Liu et al. (2013), it is widely accepted that the housing market is an important influence on macroeconomic fluctuations, however, no study includes both housing and uncertainty in a DSGE framework.[4] Therefore, an additional aim of the chapter is to establish an empirically consistent framework between uncertainty and the real estate market, whilst also exploring how housing impacts the propagation of

[3]The Iacoviello (2005) model introduces housing into a DSGE model. Housing enters the maximisation problem of households and is the only asset in which consumption can be smoothed. The key aspect of this model is that households are differentiated in terms of their discount factor, with borrowers having a lower discount factor than savers.

[4]Housing and uncertainty have been studied in heterogeneous agent models. In these models aggregate uncertainty is specified by a probability matrix from which one can simulate the path of housing. Iacoviello and Pavan (2013) study both individual and aggregate risk and match the dynamics of the housing market to the great recession. However, the issue with these models is that you are unable to examine the interactions of several variables.

an uncertainty shock. We show that housing amplifies both precautionary saving and the real option channel, thus allowing us to match the model with the negative impact of investment.

The response of investment is also a crucial aspect of an uncertainty shock and so we choose to focus on financial frictions in order to capture additional channels that influence the investment decisions of agents. However, the literature investigating the connections between financial frictions and uncertainty is scarce, despite the two being intuitively linked. The most notable example is Bloom et al. (2007) who introduces credit frictions into an otherwise standard RBC model. Within this framework uncertainty is costly for bond holders because it leads to a rise in the cost of external finance. This is a view shared by Gilchrist et al. (2014) and Balke et al. (2017) who state that uncertainty leads to an increase in credit spreads. As a consequence, financial frictions prevent firms from buffering uncertainty without cost via financial channels.[5] Bonciani and van Roye (2015) take a different approach by investigating an environment where banks operate under monopolistic competition, so that there is imperfect pass through of the policy instrument to the commercial sector. Within this framework, the central bank is unable to directly counteract the negative effects of uncertainty and so the impact is more prolonged. This echoes the work of Basu and Bundick (2017) who examine the interaction of uncertainty when a central bank is constrained by the zero lower bound.

Cesa-Bianchi and Fernandez-Corugedo (2018) introduce Bernanke et al. (1998) style frictions into the monitoring costs faced by the financial intermediary, in a complimentary study. They show that a large monitoring cost introduces a larger wedge in the banks zero profit condition, inducing banks to raise the spread they charge on lending interest rates. It follows that when credit frictions are more severe the effect of uncertainty is amplified. Although these models are able to generate an increase

[5] These papers find a similar narrative to the one presented here in a New Keynesian setting. However, in these papers, credit frictions only act to amplify the nominal rigidity.

in credit spreads, they still struggle to match the negative co-movement between investment and other macro variables. To overcome this, we assume that there are two sources of financial constraint in the model following Iacoviello (2015).[6] First, bankers are directly credit constrained by how much they can borrow from patient households. Second, entrepreneurs are constrained by how much they can borrow from banks. Although we find that the constraints lead to a similar increase in spreads to that of Cesa-Bianchi and Fernandez-Corugedo (2018), modelling banking in this way allows us to discuss additional channels through which the banking sector is able to amplify the effects of an uncertainty shock. In particular, the constraint on banks leads to a rationing of credit alongside increased credit spreads, which amplifies the real option channel for credit constrained agents and facilitates a reduction in investment.

In our analysis, uncertainty is defined as a mean preserving shock to the variance of total factor productivity. Defining uncertainty in this way allows us to interpret the shock as a 'macro' uncertainty shock. Recent work by Christiano et al. (2014), Balke et al. (2017) and Cesa-Bianchi and Fernandez-Corugedo (2018) consider 'micro' uncertainty shocks. Further Gourio (2012) introduces disaster risk which combines a negative news shock and an increase in uncertainty about the future. The rationale for focusing purely on 'macro' uncertainty shocks is that uncertainty is, by definition, an ex ante concept. Other measures use ex post measures of volatility when forward looking measures are unavailable and so are inconsistent with what we are trying to capture in our model (Basu and Bundick, 2017).

Our work belongs to a burgeoning literature which attempts to reconcile the DSGE model with the stylised facts of the data.[7] In order to replicate the co-movement of

[6]The Iacoviello (2015) model focuses on the first moment effects of the financial market disruption. We extend the analysis to examine the effects of second moment shocks.

[7]Bachmann and Bayer (2013), Gilchrist et al. (2014) and Chugh (2016) find little evidence of uncertainty being a driver of business cycles. In comparison,Bloom et al. (2018) finds large uncertainty shocks to be economically significant, Fernández-Villaverde et al. (2011) finds that an open economy framework leads to business cycle responses in equilibrium, while Fernández-Villaverde et al. (2015)

investment and output witnessed in the data, the key component in the transmission of a macro uncertainty shock is the presence of additional elements within the model. Several New Keynesian models have been proposed as a means to overcome the increase in investment (Basu and Bundick, 2015; Born and Pfeifer, 2014). This strand relies on the time varying markup channel discussed in Born and Pfeifer (2014), Basu and Bundick (2017) and Born and Pfeifer (2021).[8] Within these models a macro uncertainty shock leads to a precautionary saving effect but the presence of nominal rigidities leads to falling marginal costs for firms, which lowers labour demand. This argument is consistent with the seminal paper of Fernández-Villaverde et al. (2011) in that under price stickiness, output becomes demand determined and so lower consumption leads to lower aggregate demand. Demand for both labour and capital fall which leads to a reduction in investment and output. Hence, when prices adjust slowly, the negative impact of uncertainty becomes amplified due to the additional fall in investment.

Leduc and Liu (2016) offer a differing approach by introducing search frictions into the labour market, which gives rise to an option value channel. This channel reinforces the transmission of uncertainty when nominal rigidities are present. With search frictions, the decline in aggregate demand reduces the value of a new match so that firms post fewer jobs, pushing unemployment higher. Income falls further which amplifies the precautionary saving effect and reduces aggregate demand. A job match is seen as a long term employment contract which is often irreversible and so is subject to the real option channel. When times are uncertain, the option value of waiting increases, which leads to an expansion in unemployment and therefore output.

shows policy uncertainty can generate business cycle like responses in an effect analogous to the mark-up channel of Born and Pfeifer (2014).

[8]This channel argues that countercyclical markups through sticky prices generates co-movement. An increase in uncertainty induces precautionary labour supply, which reduces marginal costs for firms. Falling marginal costs with sticky prices imply an increase in firms markups. This higher markup reduces the demand for both consumption and investment goods. As output is demand determined, output and employment must also fall.

Our chapter has a different emphasis than the previous literature. We steer away from the nominal rigidity narrative and instead choose to focus on financial frictions, which have been shown to be as important in the transmission of an uncertainty shock as the real option channel (Bonciani and Van Roye, 2015; Cesa-Bianchi and Fernandez-Corugedo, 2018). Although the current literature share parts of the narrative of what we would expect following an uncertainty shock, it relies on nominal rigidities to generate the co-movement.

The novel feature of our model, and our key result, is that a combination of both financial frictions and a contraction in the real estate market allows us to reconcile the RBC model with all of the channels of an uncertainty shock. We illustrate two channels which reinforce each other. The credit channel leads to a rationing of loans, which implies that credit dependant agents are unable to access loans. Given lower access to loans, credit dependant agents reduce demand for real estate, which leads to downward pressure on house prices. Falling house prices lowers the net worth of all agents and contracts credit constrained agents borrowing capacity. Further, in the benchmark model, households have a heterogenous response as savers follow the desired real option narrative while borrowers undertake investment and consumption purchases. We show that the credit channel reduces this heterogeneity, by creating a psuedo real option channel for the credit dependant. The housing demand channel amplifies this impact by increasing the benefit of waiting until there is a more favourable investment climate. A combination of both effects is sufficient to create an environment where the real option channel dominates such that we are able to match the RBC model with a negative investment response. We also show that the housing demand channel, through the impact on labour decisions leads to a magnified precautionary saving effect. This combination is key in generating the co-movement suggested by our empirical estimations. By quantifying the interaction between housing and financial frictions we are able to generate co-movement following uncertainty even in the absence of nominal rigidities.

The remainder of the chapter proceeds as follows: Section 2 presents the model including a discussion of the choice of the model's parameters, the estimation of the macro-uncertainty shock, and the solution method employed. Section 3 presents and discusses the key results from the impulse response analysis. The last section concludes.

3.2 Model

We consider a discrete-time economy. The economy features three agents: households, bankers, and entrepreneurs. Except for the introduction of the banking sector, the model structure closely follows a flexible price version of the basic model in Iacoviello (2005) (see also Iacoviello (2015), Iacoviello (2010) and Iacoviello and Neri (2010)), where credit-constrained entrepreneurs borrow from households directly. Here, banks intermediate between households and entrepreneurs. The nature of the banking activity implies that bankers are borrowers when it comes to their relationship with households, and are lenders when it comes to their relationship with the credit-dependent sector. The household sector in the aggregate is a net saver. Entrepreneurs accumulate real estate, hire households, and borrow from banks.

There are two sources of friction present in the model: first, bankers are credit constrained in how much they can borrow from the patient savers; second, entrepreneurs are credit constrained in how much they can borrow from bankers. To capture the slow dynamics of many macroeconomic variables, we allow for external quadratic adjustment costs for all assets, for habits in consumption, and for inertia in the borrowing constraints and in the capital adequacy constraint.

3.2.1 Patient Households: Savers

Households work, consume and buy real estate, make one-period deposits into a bank and each agent has unit mass. We split the household sector into two types. Patient households, i.e. savers, accumulate a share $1 - \mu$ of the economy wide capital stock and choose consumption, $C_{H,t}$, housing, $H_{H,t}$, and hours worked, $N_{H,t}$ in order to maximise:

$$\max E_0 \sum_{t=0}^{\infty} \beta_H^t((1-\eta)\log(C_{H,t} - \eta C_{H,t-1}) + j \log H_{H,t} - \tau \log(1 - N_{H,t})). \tag{3.1}$$

Savers face the budget constraint,

$$\begin{aligned} C_{H,t} + \frac{K_{H,t}}{A_{K,t}} + D_t + q_t(H_{H,t} - H_{H,t-1}) + ac_{KH,t} + ac_{DH,t} \\ = (R_{M,t} z_{KH,t} + (1 - \delta_{KH,t}))K_{H,t-1} + R_{H,t-1} D_{t-1} + W_{H,t} N_{H,t}. \end{aligned} \tag{3.2}$$

In the utility function above, the term β_H is the discount factor, η measures external habits in consumption, while j is the weight on housing in the utility function. In the budget constraint, households own physical capital $K_{H,t}$ and rent capital services $z_{KH,t} K_{H,t}$ to entrepreneurs at the rental rate $R_{M,t}$.The utilisation rate is $z_{KH,t}$. The terms $ac_{KH,t}$ and $ac_{DH,t}$ denote convex, external adjustment costs for capital and deposits. The parameter $\delta_{KH,t}$ denotes the depreciation function for physical capital, which assumes that depreciation is convex in the utilisation rate of capital. D_t represents bank deposits which in turn earn a predetermined, gross return $R_{H,t}$. q_t is the price of housing in units of consumption, and $W_{H,t}$ is the wage rate. As is the case in Iacoviello (2005), we assume that housing does not depreciate.

The adjustment cost takes the following form:

$$\begin{aligned} ac_{KH,t} &= \frac{\phi_{KH}}{2} \frac{(K_{H,t} - K_{H,t-1})^2}{K_H} \\ ac_{DH,t} &= \frac{\phi_{DH}}{2} \frac{(D_t - D_{t-1})^2}{D}. \end{aligned} \tag{3.3}$$

The first order conditions (FOC) yield:

$$u_{CH,t}(1 + \frac{\partial ac_{DH,t}}{\partial D_t}) = \beta_H R_{H,t} u_{CH,t+1} \tag{3.4}$$

$$W_{H,t}u_{CH,t} = \frac{\tau_H}{1 - N_{H,t}} \tag{3.5}$$

$$u_{CH,t}(1 + \frac{\partial ac_{KH,t}}{\partial K_{H,t}}) = \beta_H(R_{m,t+1}z_{KH,t+1} + (1 - \delta_{KH,t+1}))u_{CH,t+1} \tag{3.6}$$

$$q_t u_{CH,t} = u_{HH,t+1} + \beta_H q_{t+1} u_{CH,t+1}, \tag{3.7}$$

where $u_{CH,t} = \frac{(1-\eta)}{C_{H,t}-\eta C_{H,t-1}}$ and $u_{HH,t} = \frac{j}{H_{H,t}}$. The optimality conditions yield standard first-order conditions for consumption/deposits, housing, capital demand, and labor supply.

3.2.2 Impatient Households: Borrowers

Alongside patient households, there is a group of impatient households that earns a fraction σ of the total wage income in the economy and borrows against their homes. Borrowers solve:

$$\max E_0 \sum_{t=0}^{\infty} \beta_S^t((1 - \eta)\log(C_{S,t} - \eta C_{S,t-1}) + j \log H_{S,t} - \tau \log(1 - N_{S,t})) \tag{3.8}$$

and their budget constraint is given by:

$$C_{S,t} + q_t(H_{S,t} - H_{S,t-1}) + R_{S,t-1}L_{S,t-1} - \epsilon_{H,t} + ac_{SS,t} = L_{S,t} + W_{S,t}N_{S,t} \tag{3.9}$$

where β_s is their discount factor. $L_{S,t}$ denotes loans made by banks to impatient households, paying a gross interest rate $R_{S,t}$. The term $ac_{SS,t}$ denotes a convex cost of adjusting loans from one period to the next. $\epsilon_{H,t}$ represents a wealth shock that transfers wealth from banks to households and allows for exogenous default risk in the model.[9] Impatient households can pay back less than agreed on their contractual

[9]Default risk is a zero mean, AR(1) process defined as $\log \epsilon_{i,t} = \rho_i \log \epsilon_{i,t-1} + v_{i,t}, v \sim N(0, \sigma_i)$.

obligations when $\epsilon_{H,t}$ is greater than zero.

Impatient households are also subject to a borrowing constraint that limits their liabilities to a fraction of the value of their house:

$$L_{s,t} \leq \rho_S L_{S,t-1} + (1-\rho_S) m_S A_{MH,t} E_t(\frac{q_{t+1}}{R_{S,t} H_s, t}). \tag{3.10}$$

The term ρ_S allows for slow adjustment over time of the borrowing constraint to capture the idea that in practice lenders do not readjust borrowing limits every quarter. The term $AM_{H,t}$ denotes an exogenous shock to the borrowing capacity of the household. This could be due to looser screening practices of the banks that allow them to supply more loans for a given amount of collateral. For impatient households to borrow and to be credit constrained in equilibrium, we need to assume that their discount factor is lower than a weighted average of the discount factors of households and banks.[10]

The adjustment cost is given by:

$$ac_{SS,t} = \frac{\phi_{SS}}{2} \frac{(L_{S,t} - L_{S,t-1})^2}{L_S}. \tag{3.11}$$

The FOC are:

$$u_{CS,t}(1 - \frac{\partial ac_{ss,t}}{\partial L_{S,t}} - \lambda_{S,t}) = \beta_S(R_{S,t} - \rho_s \lambda_{S,t+1}) u_{CS,t+1} \tag{3.12}$$

$$W_{S,t} u_{CS,t} = \frac{\tau_S}{1 - N_{S,t}} \tag{3.13}$$

[10]Credit constraints create a positive wedge between the steady-state output in absence of financial frictions and the output when financial frictions are present. The credit constraint on banks limits the amount of savings that banks can transform into loans. Likewise, the credit constraint on entrepreneurs limits the amount of loans that can be invested for production. Both constraints lead to lower steady-state output.

$$(q_t - \lambda_{S,t}(1-\rho_s)m_s A_{MH,t}\frac{q_{t+1}}{R_{s,t}})U_{CS,t} = u_{HS,t} + \beta_S q_{t+1} u_{CS,t+1}. \tag{3.14}$$

The marginal utilities of consumption and housing are given by $u_{CS,t} = \frac{1}{C_{S,t}}$ and $u_{HS,t} = \frac{j}{H_{HSt}}$.

The optimality conditions yield standard FOC for consumption/deposits, housing demand, and labor supply. For our research question, the presence of the multiplier in the FOC is important, because this is the mechanism through which the housing demand channel is able to impact the capacity to lend for borrowers. The housing demand channel leads to a tighter constraint, i.e, a higher value on $\lambda_{s,t}$. For higher values of the multiplier, we would expect a reduction in both consumption and housing, given the negative relationship documented.

3.2.3 Bankers

The representative banker solves:

$$\max E_0 \sum_{t=0}^{\infty} \beta_B^t (1-\eta)\log(C_{B,t} - \eta C_{B,t-1}) \tag{3.15}$$

subject to the borrowing constraint:

$$\begin{aligned} &C_{B,t} + R_{H,t-1}D_{t-1} + L_{E,t} + L_{S,t} + ac_{EB,t} + ac_{SB,t} \\ &= D_t + R_{E,t-1}L_{E,t-1} + R_{E,t-1}L_{S,t-1} - \epsilon_{E,t} - \epsilon_{H,t}. \end{aligned} \tag{3.16}$$

We assume that banks discount the future more heavily than households by setting $\beta_b < \beta_h$. D_t denotes household deposits, $L_{E,t}$ are loans to entrepreneurs, and $C_{B,t}$ is the banker's consumption.[11] The last two terms denote bank losses caused by default while we introduce three convex adjustment costs for adjusting deposits, loans to

[11] As discussed in Iacoviello (2015), this formulation is equivalent to a formulation where bankers maximise a convex function of dividends (discounted at rate β_B). Thus, $C_{B,t}$ is reinterpreted as the residual income of the banker after depositors have been repaid and loans have been issued.

entrepreneurs and loans to impatient households, respectively. The bank also faces a capital adequacy constraint given by:

$$L_t - D_t - E_t\epsilon_{t+1} \geq \rho_D(L_{t-1} - D_{t-1} - E_{t-1}\epsilon t) + (1-\gamma)(1-\rho_D)(L_t - E_t\epsilon_{t+1}). \quad (3.17)$$

where $L_t = L_{E,t} + L_{S,t}$ are bank loans and $\epsilon_t = \epsilon_{E,t} + \epsilon_{H,t}$ are loan losses. The term can also be interpreted as a redistribution shock that, when positive, transfers resources from the bank to the household. This constraint posits that bank equity, after expected losses, must exceed a fraction of bank assets, allowing for partial adjustment in bank capital given by ρ_D.[12]

This constraint is rewritten as:

$$\begin{aligned} D_t \leq\ & \rho_D(D_{t-1} - (L_{E,t-1} + L_{S,t-1} - (\epsilon_{E,t-1} + \epsilon_{S,t-1}))) \\ & + (1-(1-\gamma))(1-\rho_D)(L_{E,t} + L_{S,t} - (\epsilon_{E,t} + \epsilon_{S,t})). \end{aligned} \quad (3.18)$$

The above constraint of the banker implicitly assumes that deposits can be freely converted into loans. We assume that the bank is constrained in its ability to issue liabilities by the amount of equity in its portfolio.[13] For simplicity, we assume that this ratio is fixed.[14] In this equation, the left-hand side denotes banks liabilities D_t, while the right-hand side denotes the fraction of bank assets that can be used as collateral, once expected losses are taken into account.

[12]As in Iacoviello (2015), the capital to asset ratio of the bank can temporarily deviate from its long-run target, γ, so long as ρ_D is not equal to zero. Such a formulation allows the bank to take corrective action to restore its capital to asset ratio beyond one period.

[13]This constraint can be motivated by standard limited commitment problems or by regulatory concerns. For instance, typical regulatory requirements, such as those agreed by the Basel Committee on Banking Supervision, posit that banks hold a capital to assets ratio greater than or equal to some predetermined ratio.

[14]This assumption echoes the restrictions introduced in Basel I. Although, a more advanced capital requirement is of interest, we chose to keep the model simple in order to discuss the transmission mechanism of uncertainty. A discussion of different macro prudential policies is left to future work.

Adjustment costs are given by:

$$\begin{aligned} ac_{DB,t} &= \frac{\phi_{DB}}{2}\frac{(D_t - D_{t-1})^2}{D} \\ ac_{EB,t} &= \frac{\phi_{EB}}{2}\frac{(L_{E,t} - L_{E,t-1})^2}{L_E} \\ ac_{SB,t} &= \frac{\phi_{SB}}{2}\frac{(L_{S,t} - L_{S,t-1})^2}{L_S}. \end{aligned} \tag{3.19}$$

As for the entrepreneurial problem, the term $ac_{EB,t}$ is a quadratic portfolio loan adjustment cost, assumed to be external to the banker. $m_{B,t} = \beta_B Et(C_{B,t}/C_{B,t+1})$ denotes the banker's stochastic discount factor, while $\lambda_{B,t}$ represents the multiplier on the capital adequacy constraint normalised by the marginal utility of consumption. The optimality conditions for deposits and loans are respectively:

$$(1 - \lambda_{B,t} - \frac{\partial ac_{DB,t}}{\partial D_t})u_{CB,t} = \beta_B(R_{H,t} - \rho_D\lambda_{B,t+1})u_{CB,t+1} \tag{3.20}$$

$$(1 - (\gamma(1-\rho_D) + \rho_D)\lambda_{B,t} + \frac{\partial ac_{EB,t}}{\partial L_{E,t}})u_{CB,t} = \beta_B(R_{E,t+1} - \rho_D\lambda_{B,t+1})u_{CB,t+1} \tag{3.21}$$

$$(1 - (\gamma(1-\rho_D) + \rho_D)\lambda_{B,t} + \frac{\partial ac_{SB,t}}{\partial L_{S,t}})u_{CB,t} = \beta_B(R_{S,t} - \rho_D\lambda_{B,t+1})u_{CB,t+1} \tag{3.22}$$

The FOC are key for discussing the differing impacts in equilibrium following an uncertainty shock and also illustrate the channels through which an uncertainty shock can impact on bank lending. First, from equation (3.21) the banker can consume more today by borrowing from the household, increasing deposits by one unit. In doing so, the bank reduces its equity by one unit, thus tightening its borrowing constraint one-for-one and reducing the utility value of an extra deposit by $\lambda_{B,t}$. Secondly, from equations (3.22) and (3.23), the banker can consume more today by reducing loans by one unit. By lending less, the bank tightens its borrowing constraint, since it reduces its equity. The utility cost of tightening the borrowing constraint through lower loans is equal to $\gamma_E \lambda_{B,t}$. Intuitively, the more loans are used as collateral for the bank activity, i.e. the higher γ_E is, the larger is the utility cost of reducing loans. Given that $R_{H,t}$ is partially determined from the household problem, the banker will be borrowing constrained, and $\lambda_{B,t}$ will be positive, if $m_{B,t}$ is sufficiently lower than the inverse of $R_{H,t}$ (Iacoviello, 2015). In this scenario, as banks pay a higher cost of deposits they require a higher return on loans, which raises the cost of external finance. Both are central to the credit channel of uncertainty. The decision of households to hold more deposits and the banker to consume more are key in creating this channel. If we assume constant losses, then higher uncertainty leads to an increase in deposits and a reduction in loans both of which amplify the impact of uncertainty.[15]

3.2.4 Entrepreneurs

Entrepreneurs accumulate the remaining fraction μ of the capital stock. These agents hire workers and combine labour with capital, in order to produce final good Y_t. They maximise:

$$\max E_0 \sum_{t=0}^{\infty} \beta_E^t (1-\eta) \log(C_{E,t} - \eta C_{E,t-1}) \tag{3.23}$$

subject to:

$$\begin{aligned} Y_t + (1-\delta_{KE,t}) + q_t H_{E,t-1} + L_{E,t} + \epsilon_{E,t} = \\ C_{E,t} + K_{E,t} + q_t H_{E,t} + R_{E,t} L_{E,t-1} + W_{H,t} N_{H,t} \\ + W_{S,t} N_{S,t} + R_{M,t} z_{KH,t} K_{H,t-1} + ac_{KE,t} + ac_{EE,t} \end{aligned} \tag{3.24}$$

The production function is given by:

$$Y_t = A_{z,t} (z_{KH,t} K_{H,t-1})^{\alpha(1-\mu)} (z_{KE,t} K_{E,t-1})^{\alpha\mu} H_{E,t-1}^{\nu} N_{H,t}^{(1-\alpha-\nu)(1-\sigma)} N_{S,t}^{(1-\alpha-\nu)\sigma} \tag{3.25}$$

[15] In turn, if $\lambda_{B,t}$ is positive, the required returns on loans $R_{E,t}$ will be higher, the lower γ_E is. Intuitively, when γ_E is low, the liquidity value of loans is lower, and the compensation required by the bank to be indifferent between lending and borrowing becomes higher. Moreover, loans will pay a return that is higher than the cost of deposits, since, so long as γ_E is lower than one, they are less liquid than deposits.

where $ac_{KE,t}$ and $ac_{EE,t}$ are adjustment costs for capital and loans. This cost penalises entrepreneurs for changing their loan balances too quickly. $A_{z,t}$ denotes a shock to total factor productivity. We introduce the macro uncertainty shock by introducing time varying volatility to this process. Uncertainty is defined as a mean preserving second order shock to total factor productivity,

$$logA_{z,t} = \rho_z logA_{z,t-1} + w_t \sigma^z \varepsilon_t^z \tag{3.26}$$

$$w_t = \rho^w w_{t-1} + \sigma^w \varepsilon_t^w. \tag{3.27}$$

Finally entrepreneurs are subject to a borrowing constraint which acts as a wedge on the capital and labour demand (Iacoviello, 2015):

$$\begin{aligned} L_{E,t} \leq \rho_E L_{E,t-1} + (1-\rho_E)(m_H E_t(\frac{q_{t+1}}{R_{E,t+1}} H_{E,t}) \\ + m_K K_{E,t} - m_N(W_{H,t}N_{H,t} + W_{S,t}N_{S,t})). \end{aligned} \tag{3.28}$$

Entrepreneurs cannot borrow more than a fraction m_H of the expected value of their real estate stock. In addition, the borrowing constraint stipulates that a fraction m_N of the wage bill must be paid in advance, as in Neumeyer and Perri (2005). We assume that entrepreneurs discount the future more heavily than households and bankers.[16] Aliaga-Díaz and Olivero (2010) present a DSGE model of hold-up effects where switching banks is costly for entrepreneurs. Curdia and Woodford (2010) and Goodfriend and McCallum (2007) develop models of financial intermediation with convex portfolio adjustment costs which mimic the functional form adopted here.

[16] Formally, their discount factor satisfies the restriction that $\beta_E < \gamma_E \beta_B + (1-\gamma_E)\beta_H$. This assumption guarantees that the borrowing constraint will bind.

The adjustment costs are given by:

$$
\begin{aligned}
ac_{KE,t} &= \frac{\phi_{KE}}{2}\frac{(K_{E,t}-K_{E,t-1})^2}{K_E} \\
ac_{EE,t} &= \frac{\phi_{EE}}{2}\frac{(L_{E,t}-L_{E,t-1})^2}{L_E}.
\end{aligned}
\tag{3.29}
$$

Finally, denote with $\lambda_{E,t}$ the multiplier associated with the borrowing constraint, normalised by the marginal utility of consumption. The optimisation conditions for loans, real estate and labor are respectively:

$$
(1-\lambda_{E,t}-\frac{\partial ac_{LE,t}}{\partial L_{E,t}})u_{CE,t} = \beta_E(R_{E,t+1}-\rho_E\lambda_{E,t+1})u_{CE,t+1} \tag{3.30}
$$

$$
(1+\frac{\partial ac_{KE,t}}{\partial K_{E,t}}-\lambda_{E,t}(1-\rho_E)m_s A_{ME,t})U_{CE,t} = \beta_E(1-\delta_{KE,t+1}+R_{K,t+1}z_{KE,t+1})u_{CE,t+1}. \tag{3.31}
$$

$$
(q_t-\lambda_{E,t}(1-\rho_E)m_s A_{ME,t}\frac{q_{t+1}}{R_{E,t+1}})U_{CE,t} = \beta_E q_{t+1}(1+R_{V,t+1})u_{CE,t+1}. \tag{3.32}
$$

To complete the model we solve for demand for capital, commercial real estate and labour:

$$
\alpha\mu Y_t = R_{K,t}z_{KE,t}K_{E,t-1} \tag{3.33}
$$

$$
\alpha(1-\mu)Y_t = R_{M,t}z_{KH,t}K_{H,t-1} \tag{3.34}
$$

$$
\nu Y_t = R_{\nu,t}q_t H_{E,t-1} \tag{3.35}
$$

$$
(1-\alpha-\nu)(1-\sigma)Y_t = W_{H,t}N_{H,t}(1+m_N A_{ME,t}\lambda_{E,t}) \tag{3.36}
$$

$$(1-\alpha-\nu)\sigma Y_t = W_{S,t}N_{S,t}(1+m_N A_{ME,t}\lambda_{E,t}) \tag{3.37}$$

As first-order conditions (3.31), (3.32) and (3.33) show, credit constraints, as measured by the multiplier on the borrowing constraint, $\lambda_{E,t}$, introduce a wedge between the cost of factors and their marginal product. This wedge acts as a tax on the demand for credit and the demand for the factors of production. Through this mechanism, first we are able to create a fall in labour demand which allows us to create a reduction in hours worked. Secondly, through reducing demand for capital we are able to impact the investment decision of savers. The wedge is intertemporal in the consumption Euler equation and in the real estate demand equation. It is intratemporal in the case of the labor demand equation (Iacoviello, 2015).

3.2.5 Equilibrium

Market clearing is implied by Walras' law by aggregating all the budget constraints. For housing, we have the following market clearing condition:

$$H_{H,t} + H_{S,t} + H_{E,t} = 1 \tag{3.38}$$

That is, we normalise the total supply of housing to unity. Lagrange multipliers are assumed to be always positive.

3.2.6 Computing Impulse Responses at Higher Orders

DSGE models are normally solved by taking a linear or log-linear, i.e., first-order, approximation around their non-stochastic steady-state equilibrium. However, when using first-order approximations, certainty equivalence holds and the decision rule of the representative agent are independent of second or higher moment shocks. For second order moments to enter the decision rules of economic agents, a higher approximation to the policy functions is needed. In particular, a third-order Taylor series expansion of the solution of the model allows for second moments to play an independent role in the approximated policy function. We compute a third-order Taylor series approximation around the steady state of the model.

When examining high order shocks, such as shocks to uncertainty, two key issues arise with the standard impulse response function (IRF) estimation. First, with higher order perturbations, simulated data generated by decision rules displays explosive behaviour (Cesa-Bianchi and Fernandez-Corugedo, 2018). Secondly, since the solution of the model is at an order higher than one, the ergodic means of the endogenous variables are different to the deterministic steady state. Hence, IRFs need to be computed from the stochastic steady state. The calibration must target the moment of interest generated by the ergodic distributions and not the moments of the deterministic steady state, since the latter are not representative of the stochastic dynamics (Fasani, 2017).[17] We follow Fernández-Villaverde et al. (2011) and compute IRFs as deviations from the ergodic mean. Specifically, we estimate the deterministic simulation of the model in order to compute the level of the endogenous variables after a volatility shock. The IRF's are finally calculated by subtracting the stochastic steady state values from the levels. The estimation procedure is summarised below:

- Simulate the model with third order approximations for the decision rules for 2096 periods starting from the deterministic steady state with all shocks.
- Discard the first 2000 periods to avoid dependance on the initial conditions.
- Use the remaining 96 periods to calculate the ergodic mean of each variable.
- Starting from the ergodic means, conduct two simulations of 20 periods each: one with no shocks and one with a 1 standard deviation shock to volatility.
- The impulse response is calculated as the percentage difference between these two.

[17]The stochastic steady state is the fixed point at which the endogenous variables converge after having set the exogenous shocks to zero and simulated the model for a sufficient number of periods.

3.2.7 Calibrating Model Parameters

Table 3.1 to 3.3 summarises the calibrated parameters of the model. The time period is

Table 3.1 Calibrated Parameters

Parameters		Value
Household-saver discount factor	β_H	0.9925
Household-borrower discount factor	β_S	0.94
Banker discount factor	β_B	0.945
Entrepreneur discount factor	β_E	0.94
Total capital share in production	α	0.35
Loan-to-value ratio on housing	m_S	0.9
Loan-to-value ratio on commercial housing	m_H	0.9
Loan-to-value ratio on capital	m_K	0.9
Wages paid in advance	m_N	1
Liability to asset ratio for bankers	γ_E, γ_S	0.9
Housing preference	j	0.075
Depreciation	δ_{KE}, δ_{KH}	0.035
Labour supply	τ	2
Habit parameter	η	0.46
Capital share of entrepreneur	μ	0.46
Housing share of entrepreneur	ν	0.04
Inertia in borrower capital constraint	ρ_D	0.24
Inertia in entrepreneur borrowing constraint	ρ_E	0.65
Inertia in borrower borrowing constraint	ρ_S	0.7
Borrowers wage share	σ	0.33

a quarter. As is the case in Caldara et al. (2012) the discount factors for the non-credit constrained sector are set at around 0.99 in order to target an annualised risk free interest rate of 2.4%. For the credit constrained sector, we set discount factors as in Iacoviello (2015) in order to ensure that credit frictions bind in the equilibrium. Specifically, we require $\beta_B < \beta_H$ and entrepreneurs to have a discount factor which is higher than a weighted average of the discount factors of households and bankers.

Hence, we set β_B, β_H and β_S to 0.945, 0.9925 and 0.94 respectively.

We set the capital share in production at 0.35, in order to target a labour share of 65%, which is consistent with Cesa-Bianchi and Fernandez-Corugedo (2018) and Basu and Bundick (2017). Capital depreciation is set marginally higher than the standard value in the literature of 0.025 at 0.035. The rationale behind this choice follows from Iacoviello (2015) in that real estate acts as a factor of production which does not depreciate altogether. These numbers imply an investment to output ratio of 0.25 and a variable capital to output ratio of 1.8. Again following the assumptions of Iacoviello (2015), the adjustment costs for loans are set equal to 0.25, while all labour must be paid in advance so that $m_N = 1$.

Table 3.2 Adjustment Cost Parameters

Parameters		Value
Bank deposit adjustment cost	ϕ_{DB}	0.14
Household saver deposit adjustment cost	ϕ_{DH}	0.1
Entrepreneur capital adjustment cost	ϕ_{KE}	0.59
Saver capital adjustment cost	ϕ_{KH}	1.73
Bank loan to entrepreneurs adjustment cost	ϕ_{KH}	1.73
Entrepreneur loan adjustment cost	ϕ_{KH}	1.73
Bank loan to borrowers adjustment cost	ϕ_{KH}	1.73
Borrowers loan adjustment cost	ϕ_{KH}	1.73

Loan to value ratios across all sectors are set to 0.9. This is in line with Van den Heuvel (2008), where the leverage parameter for banks is set to 0.9. This value is consistent with historical data on bank balance sheets that show that capital to asset ratios for banks is often close to 0.1. Together with the discount factors, the leverage parameters imply an annualised steady-state return on deposits of 3% and a steady-state return on loans of 5%.

Table 3.3 Uncertainty Shock Parameters

Parameters		Value
Autocorrelation technology shock	ρ_Z	0.99
Standard deviation technology shock	σ_Z	0.007
Autocorrelation uncertainty shock	ρ_W	0.63
Standard deviation uncertainty shock	σ_W	0.048

In terms of the parameters of the household utility function, the labour supply parameter, which corresponds to the weight placed on leisure, is set to 2. This implies a value of time spent working of about 0.5 and a Frisch labour supply elasticity at around 1, which is consistent with the values presented in Christiano et al. (2014). Although it is common in the literature to set the value of time worked to 0.33, we choose instead to be consistent with the original Iacoviello (2015) model. The share of housing in production is set at 0.05, while the housing preference parameter in the utility function is set to 0.075. As discussed in Iacoviello (2015), these values imply a ratio of real estate wealth to output of 3.1, of which 0.8 is commercial real estate and 2.3 is residential real estate. Adjustment costs are set as in Iacoviello (2015), as are the parameters of the technology shock. Finally, we set the parameters of the uncertainty shock to 0.63 and 0.048 respectively to be consistent with Basu and Bundick (2017).

We calibrate our model purely to be consistent with prior work. The nature of our research question is to establish qualitatively the implied empirical results in an RBC setting. Hence, it is important that our calibration is consistent to avoid artificially inflating our simulated responses by altering parameter values. The novelty of our framework is that is achieved in a parsimonious manner. For interest, altering the parameters, particularly in the FOC which are central lead to an amplified effect. For example, altering the habit function in the FOC of Bankers turns this mechanism off and on. Similarly, changing the parameter values of agents discount factors or the inertia parameters amplifies wait and see behaviour. It is of interest for future work to look into achieving more quantitatively correct impulse responses based on the model framework we present. For example, it could be of interest to examine micro level uncertainties such as real estate uncertainty as opposed to general macro uncertainty in total factor productivity.

3.3 Reconciling the RBC Model with Key Stylised Facts

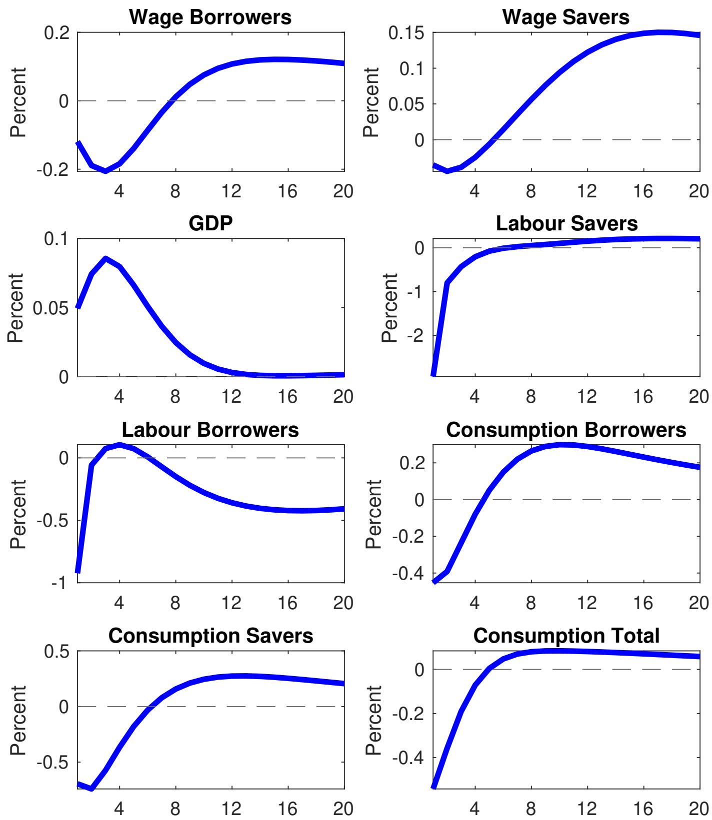
In order to assess the role housing, credit frictions and banks play in transmitting an uncertainty shock, we build our model step by step. First, we estimate impulse response functions in the model of Iacoviello (2005), which we use as the benchmark case. We then estimate the model without banks that retains the financial friction on households and firms. Finally, we estimate the full model with banking and all frictions.

Analysing the model in such a way highlights the importance of incorporating all of the additional components simultaneously in order to successfully generate the responses for investment and output previously found in New Keynesian literature. Our result is driven by two key channels. First, credit frictions and the behaviour of banks creates a credit channel which limits access to credit and emphasises the precautionary saving channel for credit constrained agents. Second, the inclusion of housing is vital as it creates a housing demand channel which impacts the investment decision for both borrowers and savers. These channels make use of the heterogeneity built into the model and are both able to amplify the real option channel for savers and generate a negative investment response for borrowers.

3.3.1 The Benchmark Model: Uncertainty in a Housing Model

As discussed by Cesa-Bianchi and Fernandez-Corugedo (2018), a standard RBC model is unable to generate the desired co-movement of a number of economic variables following a shock to uncertainty.

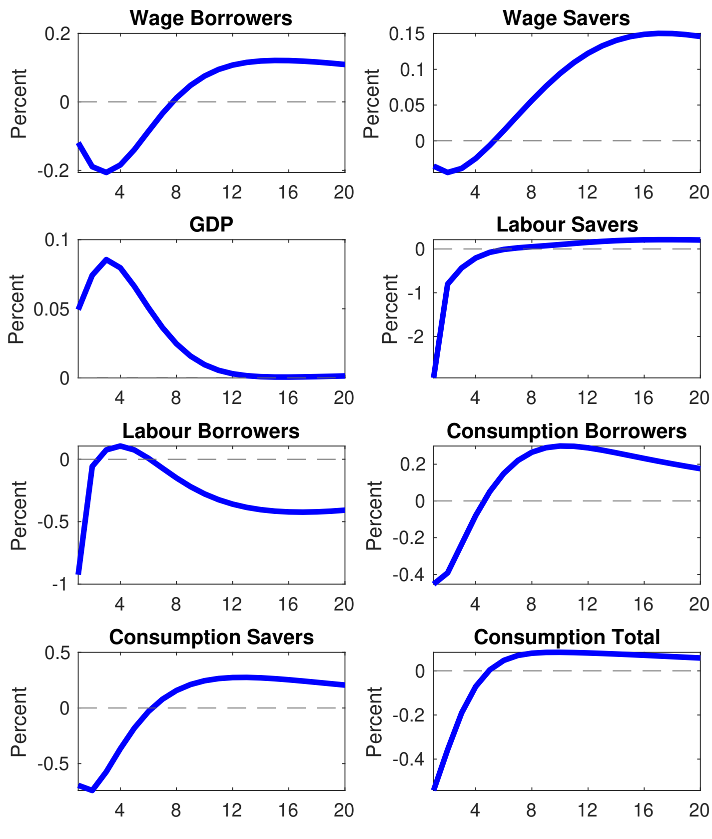
Fig. 3.3 The Benchmark Model: Precautionary Saving



Notes: Impulse responses to a positive (one standard deviation) shock to uncertainty in the Iacoviello (2005) housing model. The responses are computed with respect to the ergodic mean of the variables of interest. All responses are in percent. The unit of the x-axis is quarters.

A key feature of an uncertainty shock is the precautionary saving channel which acts to reduce consumption and increase saving. In the standard model, an increase in saving corresponds to an increase in investment, which is in contrast to the wait and see narrative of the real option channel. Similarly, an increase in uncertainty leads to precautionary labour supply, but a reduction in hours worked due to demand side factors. However, in the benchmark case, uncertainty does not impact the factors of production and so labour demand remains unchanged. Hence, in order to better match results generated by the model to those in the New Keynesian literature we introduce housing and heterogeneity between households by estimating an uncertainty shock in the model of Iacoviello (2005). Figures 3.3 and 3.4 summarise the response of key variables to this exercise.

Fig. 3.4 The Benchmark Model: Precautionary Saving



Notes: Impulse responses to a positive (one standard deviation) shock to uncertainty in the Iacoviello (2005) housing model. The responses are computed with respect to the ergodic mean of the variables of interest. All responses are in percent. The unit of the x-axis is quarters.

Housing plays a key role in propagating uncertainty shocks because it is able to alter the labour demand decision. In this setting which ignores financial markets, savers provide housing to firms. However, an increase in uncertainty leads to a reduction in housing for savers, because housing is subject to the real option channel. As housing enters into the production function, the reduction in commercial real estate leads to a reduction in labour demand and a fall in hours worked across both types of household. Specifically, borrowers reduce labour by 0.8% from trend, while savers reduce labour hours by 2.4% from trend. Hence, including housing allows us to dampen the precautionary labour response and match the stylised fact of a reduction in hours worked following high uncertainty.

However, while housing allows us to better match the desired response for hours worked, we are still unable to generate negative responses for GDP. The heterogeneity between households is significant here as savers follow the expected real option narrative, while borrowers respond by investing in housing (the housing uncertainty channel). Although the housing uncertainty channel is consistent with the empirics, the benchmark model overplays the strength of the mechanism, which gives rise to two problems. Firstly, borrowers are freely able to access cheap credit implied by the reduction in borrowers interest rates. Consequently, through the housing uncertainty channel, there is an incentive to invest in housing, by which housing demand increases and real estate purchases increase by close to 4% from its trend value. Given housing supply is assumed fixed within the model, higher housing demand leads to an increase in house prices. Secondly, as GDP increases following the shock, we can infer that the housing uncertainty channel for borrowers is stronger than the real option channel for savers and an increase in investment is the key mechanism behind the increase in GDP. This highlights the key question with the benchmark model as the increase in uncertainty leads to a positive co-movement of housing and GDP driven by an increase in investment, a point not supported by the empirics.

3.3.2 The Channels of Uncertainty

In order to address the increase in investment we observe in the benchmark case we estimate two additional models. These models are namely the credit friction model, which we estimate with credit frictions and no banks, and the full model which includes all frictions and banks. The rationale is that by introducing credit constraints we correct the over-dominance of the housing uncertainty channel and the positive investment response in the benchmark case and match the co-movements of GDP and its aggregates and housing.

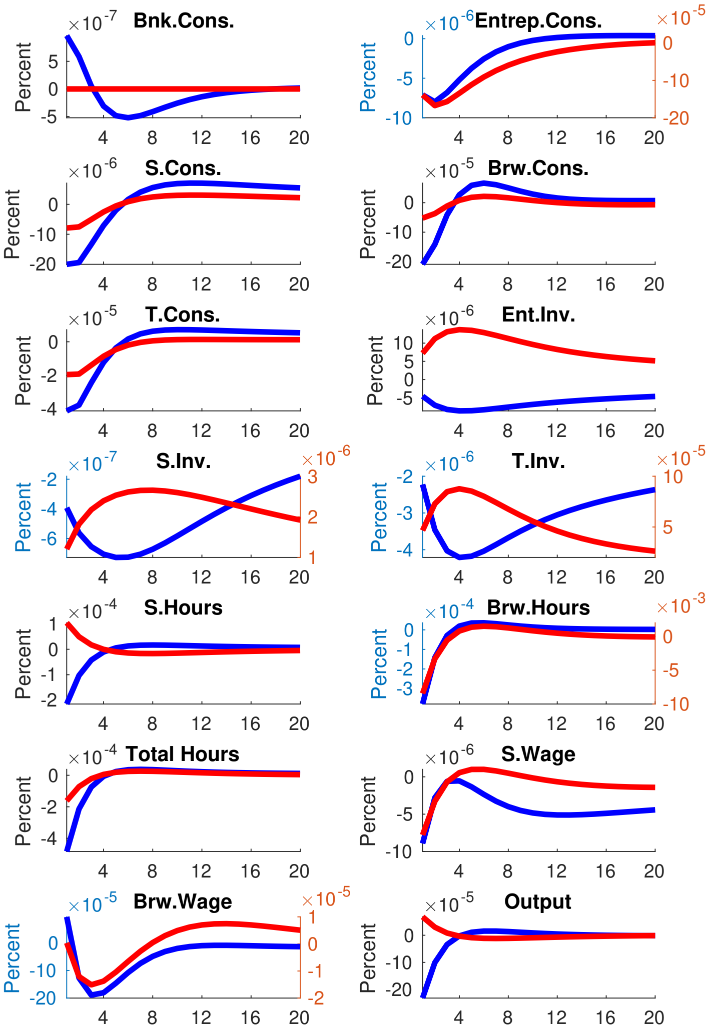
Credit Constraints and Precautionary Saving

Figure 3.5 depicts the response of key business cycle variables in response to an uncertainty shock across the credit friction and the full models. We identify a precautionary saving motive across both models, which is unsurprising given that this is the key component of an uncertainty shock. Households and entrepreneurs reduce consumption on impact of the shock, while bankers respond, negatively with a lag. Lower consumption from the household sector leads to increased saving and hence increased deposits from household savers. From equations (3.21) to (3.23), this increase in deposits directly increases consumption for the banker. Similarly, as banks and credit constrained agents are subject to adjustment costs, the bank further increases consumption as it is reluctant to increase loans. Overtime the bank issues more loans which relaxes the borrowing constraint and leads to a reduction in consumption. Precautionary saving is consistent across all the estimated models and it is instead the response of investment which causes the RBC model to fail to generate the desired co-movement of responses.

How does Banking Impact the Propagation of an Uncertainty Shock?

Figure 3.6 and 3.7 show the response of lending rates and the activity of the housing market across the credit friction and full model respectively. Credit frictions alone are not enough to generate a reduction in investment. In the credit friction model, we

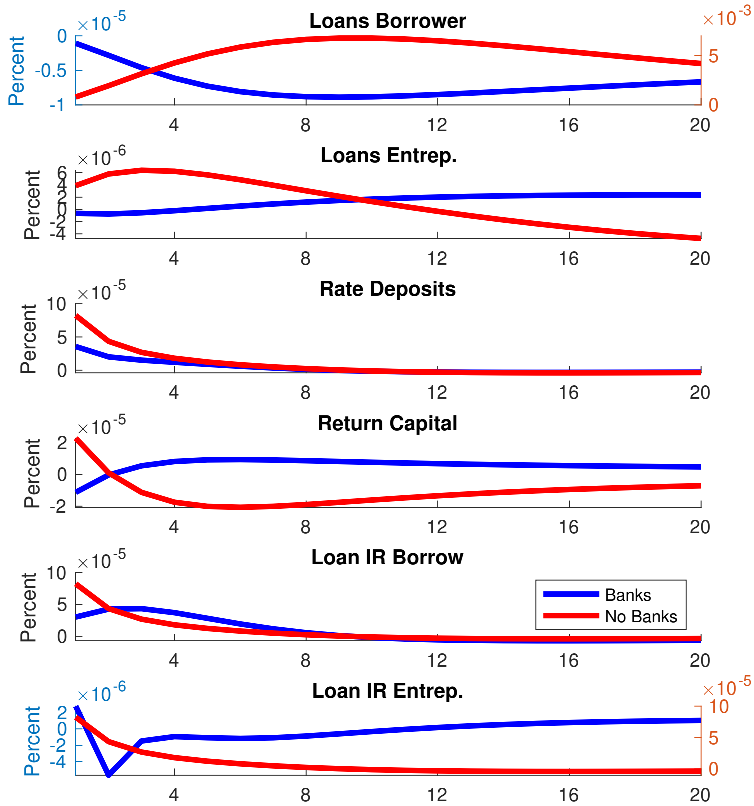
Fig. 3.5 Our Extended Models: Precautionary Saving



Notes: Impulse responses to a positive (one standard deviation) shock to uncertainty in the extended model and full model. The blue line corresponds to the full model with all restrictions, while the red line is the model excluding banks. The responses are computed with respect to the ergodic mean of the variables of interest. All responses are in percent. The unit of the x-axis is quarters.

only impose that borrowers and entrepreneurs are constrained in the amount they can borrow by the value of their stock of real estate and are freely able to access loans supplied by savers. Household borrowers and entrepreneurs increase their demand for loans following an increase in uncertainty in order to fund both consumption and investment respectively. Similarly to the housing uncertainty channel in the benchmark case, an increase in the demand for investment type goods leads to an increase in both house prices and the return on capital. Although introducing credit constraints leads to an additional cost associated with loans, which reflects an additional risk premium, there is no mechanism to force borrowers to reduce investment. Instead, as shown in equation (3.10) an increase in house prices loosens their budget constraint and expands their capacity to lend more through equation (3.14) where we witness an increase in loans.

Fig. 3.6 Our Extended Models: Credit and Lending



Notes: Impulse responses to a positive (one standard deviation) shock to uncertainty in the extended model and full model. The blue line corresponds to the full model with all restrictions, while the red line is the model excluding banks. The responses are computed with respect to the ergodic mean of the variables of interest. All responses are in percent. The unit of the x-axis is quarters.

Investment again plays a key role in driving the observed increase in GDP in the credit friction model. The behaviour of credit constrained agents has an additional impact on savers. That is, the increase in capital returns and the increased capacity to invest through precautionary saving leads to an increase in saver investment, which acts to dampen the wait and see narrative of the real option channel. Overall, all types of agents increase investment which outweighs the weaker precautionary saving channel.[18]

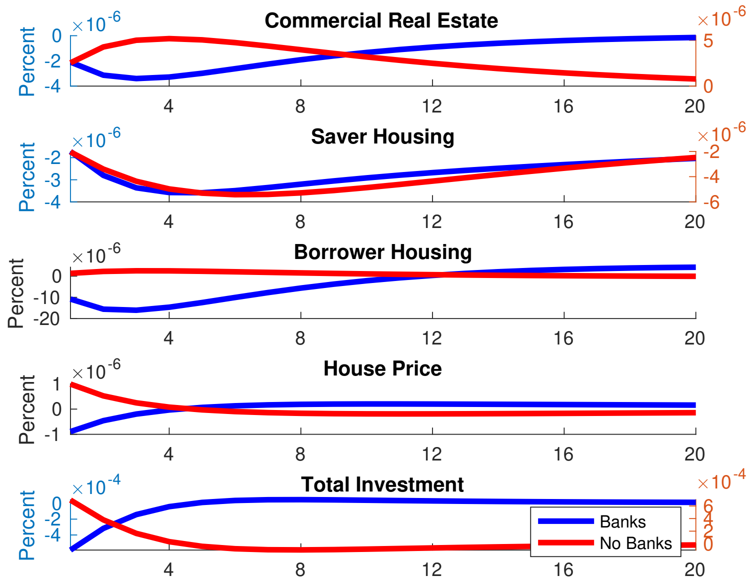
Given that the credit friction model generates a responses analogous to the benchmark case in terms of a positive investment response, the role banks play becomes vital. Financial frictions on banks act by amplifying shocks which affect a banks net worth. The capital requirement on banks constrains the amount of savings that can be transformed into investment goods. This constraint is absent in the model without banks, which implicitly assumes that all savings can be transformed into investment goods at no cost, except for the standard quadratic adjustment costs.[19] Practically, as shown in equations (3.22) and (3.23), the inclusion of a financial intermediary who is constrained in the amount of funds they can generate leads to a reduction in loans offered to the credit dependant sector.[20] As these agents are now unable to access all the funds they may demand, we are able to reverse the channels that dominate the benchmark and credit friction models.

[18]This links closely to the Oi-Hartmann-Abel effects discussed within the literature. This suggests that if the marginal revenue product of capital is a strictly convex function of the price of output, then investment is an increasing function of the variance of total factor productivity (Bonciani and van Roye, 2015). Hence, any uncertainty shock, measured as an increase in the variance of productivity, directly impacts investment.

[19]Adjustment costs are assumed quadratic to represent a symmetric impact from uncertainty, that is high uncertainty is equally as costly to agents as low uncertainty. Estimating a negative uncertainty shock we get impulse responses that match those from a positive uncertainty shock. This is significant as it shows adjustment costs are not driving the results generated. Results are presented in the appendix.

[20]In terms of the effect on bank capital, we assume constant losses which allows us to generate the increase in spreads which is central to the result generated here. In the absence of loan losses, precautionary saving leads to more deposits, while interest rates to credit constrained agents increases which reflect an unwillingness from the bank to lend due to external factors such as uncertainty. If we introduce defaults as an exogenous shock, then bank capital further falls which acts to increase spreads and would amplify the transmission discussed here.

Fig. 3.7 Our Extended Models: Housing



Notes: Impulse responses to a positive (one standard deviation) shock to uncertainty in the extended model and full model. The blue line corresponds to the full model with all restrictions, while the red line is the model excluding banks. The responses are computed with respect to the ergodic mean of the variables of interest. All responses are in percent. The unit of the x-axis is quarters.

The Credit Channel of Uncertainty

The introduction of banks drastically impacts the response of the credit constrained sector to an increase in uncertainty. As before, on the demand side, entrepreneurs would like to borrow more. Given their high discount factor, the drop in consumption growth increases their loan demand. In order to maintain its leverage position, the bank demands more deposits. In the benchmark model this directly raises supply and leads to a fall in interest rates on deposits. However, in the full model, we introduce the second credit constraint in that banks are also constrained in the amount of deposits they are able to receive from household savers. Given this constraint, the supply of deposits is unable to shift as much when compared to the benchmark case. Following Iacoviello (2005), the increase in demand is larger than the decrease in supply of deposits because there are two types of agents who demand loans, where only one type of agent supplies deposits. Consequently, we see an increase in the cost of deposits, which raises costs for the bank. Banks are additionally subject to adjustment costs which penalise changing loans quickly which causes rigidity in supply.

Additionally, given that the bank is unable to effectively generate as much capital, in order to maintain its leverage ratio the bank is forced to contract its assets by a multiple of its capital. From the first order conditions of the banker, this can be achieved by either raising new capital or reducing consumption. However, by assumption the bank is impatient which makes both options unattractive. Therefore, on the supply side, as bankers are forced to deleverage, they reduce the supply of loans. Hence, high demand for loans, reductions in supply and the additional cost in deposits both drives up the cost of loans and reduces the amount of total loans.

When compared to the benchmark and credit friction model, this mechanism directly impacts the decision of the credit dependant sector. The response of loans for borrowers switches across model. Faced with lower capacity to lend, household borrowers further reduce consumption from the trend value and we amplify the precautionary saving channel for these agents. As Figure 3.6 shows, we also witness the same switch in response in the amount of loans to entrepreneurs. The implication for entrepreneurs is a higher cost, and lower access, to loans. This creates a real option style channel for the entrepreneur who, in contrast to the credit friction model, reduces investment.

The Housing Demand Channel of Uncertainty

Figure 3.7 presents results from an estimated uncertainty shock in real estate markets. Following the credit channel, the reduction in loans leads to a reduction in demand for housing. Alongside reducing investment, limited access to loans forces entrepreneurs to reduce their holdings of real estate from the trend value through equation (3.31). Consequently, the reduction in demand acts to put downward pressure on house prices and further constrains the entrepreneur through the capital adequacy constraint. This creates a cycle through which the entrepreneur is continually unable to access loans and reinforces the impact on investment caused through the credit channel. For borrowers, downward pressure on house prices similarly leads to a tighter credit constraint and consequently they are unable to access credit in order to finance both consumption and housing purchases. As a result, we reverse the housing uncertainty channel we witness in the benchmark and credit friction model, because housing purchases for borrowers decrease from trend. This is a key result of the chapter because by reversing this channel we reduce demand for housing from the credit constrained sector. Hence, all types of agents reduce purchases of housing and we witness a reduction in house prices, as shown in Figure 3.7.

Capital Markets

The conclusion we reach is that if the productive sector of the economy depends on bank credit to run activities, then the contraction in bank credit can lead to a reduction in output. This is the crucial channel which impacts the response of investment. In the full model, the reduction in lending to entrepreneurs corresponds to a reduction in entrepreneur investment because firms are unable to access funds to finance investment. That is, in the market for capital, as equilibrium borrowing drops, entrepreneurs are less able to supply funds to final good firms, and the supply of capital drops. However, falling real estate demand and utilisation rates lowers the marginal product of capital and overall, capital demand drops in response to lower capital returns. This downward pressure outweighs the upward pressure on prices from falling supply.

In comparison to the credit friction model and the benchmark case, we are able to generate a fall in investment from savers. We see a reversal in the response of investment as total capital investment falls from trend. Similarly, although total factor productivity remains unchanged, both the reduction in real estate demand and lower capital investment leads to a further reduction in labour demand. The result is the precautionary labour supply carries little weight as we observe a reduction in hours worked. Together, both the credit channel and the housing demand channel are significant and crucial to generating the co-movement of hours worked, consumption, investment and output.

3.4 Conclusion

In this chapter we develop a framework for analysing uncertainty shocks, which offers an alternative approach to those introduced by Born and Pfeifer (2014), Basu and Bundick (2015) and Cesa-Bianchi and Fernandez-Corugedo (2018). The novel feature of our model is the interaction between credit constraints, a banking sector and the housing market. The current literature has stressed the need for nominal rigidities in order to generate the co-movement of several economic variables that match the stylised facts present in the data. The key takeaway from our model is that a cost and housing demand channel generated through the interaction between all the elements of our model is sufficient to generate a fall in investment, even in the absence of nominal rigidities.

We show that in the benchmark housing model of Iacoviello (2005), uncertainty impacts agents heterogeneously, with the response of credit dependent agents driving investment and output up. This reflects the fact that there is no mechanism built into the model to incentivise the agent to behave as the real option channel would suggest. It is, in fact, access to external funds which is vital to reversing the investment decisions of those credit dependant agents. Through the credit channel of uncertainty, we limit access to funds which amplifies precautionary saving for impatient households, who are unable to use these funds to finance consumption. We are also able to reconcile the real option channel for entrepreneurs. That is, when faced with a higher cost and lower access to loans, the option value associated with waiting is amplified. Consequently, credit constrained agents act more in line with savers. Our results mirror the narrative presented in Balke et al. (2017), however we show that frictions not only amplify nominal rigidities, but are enough to generate a fall in investment.

Housing also plays a vital role in propagating the effects of an uncertainty shock. Uncertainty is able to impact both types of agents through the housing demand channel. Lower demand for commercial real estate drives down house prices. Through the capital adequacy constraint for credit dependant agents, a lower value of the housing stock leads to a tighter constraint and a further amplification of precautionary saving for household borrowers. For entrepreneurs, this creates a cycle in which they continuously have access to less loans. Indirectly, through capital markets the housing demand channel is able to influence and amplify the real option effect for savers. Commercial real estate enters into the production function and so lower demand for housing leads to lower utilisation rates for capital which lowers the return of capital. Therefore, savers who previously may have be incentivised to take advantage of high investment returns are discouraged from investing. This channel also allows us to better match the dynamics of the housing market. As borrowers are constrained by the value of their house, these agents simultaneously are unable to access credit and we see a reversal of the housing uncertainty channel. This in turn drives down house prices. The significance of our results is that we are able to reconcile the RBC model with the narrative expected from an uncertainty shock.

References

Aastveit, K. A., Natvik, G. J., and Sola, S. (2017). Economic uncertainty and the influence of monetary policy. *Journal of International Money and Finance*, 76:50–67.

Abel, A. B. (1983). Optimal investment under uncertainty. *The American Economic Review*, 73(1):228–233.

Afonso, A., Baxa, J., and Slavík, M. (2018). Fiscal developments and financial stress: a threshold var analysis. *Empirical Economics*, 54(2):395–423.

Albrizio, S., Buesa, A., and Viani, F. (2021). The real effects of trade uncertainty. *Working Paper*.

Alessandri, P. and Mumtaz, H. (2019). Financial regimes and uncertainty shocks. *Journal of Monetary Economics*, 101:31–46.

Aliaga-Díaz, R. and Olivero, M. P. (2010). Macroeconomic implications of “deep habits” in banking. *Journal of Money, Credit and Banking*, 42(8):1495–1521.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., Mihaylov, E., et al. (2020). Economic uncertainty before and during the covid-19 pandemic. *Journal of Public Economics*, 191:104274.

Andrade, P. and Ferroni, F. (2021). Delphic and odyssean monetary policy shocks: Evidence from the euro area. *Journal of Monetary Economics*, 117:816–832.

André, C., Bonga-Bonga, L., Gupta, R., Mwamba, M., and Weirstrasd, J. (2015). The impact of economic policy uncertainty on US real housing returns and their volatility: A nonparametric approach. *Journal of Real Estate Research*.

Antolin-Diaz, J. and Rubio Ramírez, J. (2016). Narrative sign restrictions for SVARs. *FRB Atlanta Working Paper 2016-16, Federal Reserve Bank of Atlanta*.

Arellano, C., Bai, Y., and Kehoe, P. J. (2019). Financial frictions and fluctuations in volatility. *Journal of Political Economy*, 127(5):2049–2103.

Arellano, C. and Ramanarayanan, A. (2012). Default and the maturity structure in sovereign bonds. *Journal of Political Economy*, 120(2):187–232.

Aron, J. and Muellbauer, J. (2016). Modelling and forecasting mortgage delinquency and foreclosure in the uk. *Journal of Urban Economics*, 94:32–53.

Auerbach, A. J. and Gorodnichenko, Y. (2012). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 4(2):1–27.

Bachmann, R. and Bayer, C. (2013). ‘wait-and-see’business cycles? *Journal of Monetary Economics*, 60(6):704–719.

Bachmann, R. and Sims, E. R. (2012). Confidence and the transmission of government spending shocks. *Journal of Monetary Economics*, 59(3):235–249.

Bai, J. and Ng, S. (2007). Determining the number of primitive shocks in factor models. *Journal of Business & Economic Statistics*, 25(1):52–60.

Baker, S. R., Bloom, N., and Davis, S. J. (2012). Has economic policy uncertainty hampered the recovery? *Becker Friedman Institute for Research In Economics Working Paper*, (2012-003).

Baker, S. R., Bloom, N., and Davis, S. J. (2016a). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Baker, S. R., Bloom, N., and Davis, S. J. (2016b). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Balke, N. S. (2000). Credit and economic activity: Credit regimes and nonlinear propagation of shocks. *Review of Economics and Statistics*, 82(2):344–349.

Balke, N. S., Martínez-García, E., and Zeng, Z. (2017). Understanding the aggregate effects of credit frictions and uncertainty. *Globalization and Monetary Policy Institute Working Paper*, (317).

Barnett, A. and Thomas, R. (2013). Has weak lending and activity in the united kingdom been driven by credit supply shocks?

Barrero, J. M., Bloom, N., and Wright, I. (2017). Short and long run uncertainty. *No. w23676. National Bureau of Economic Research.*

Barsky, R. B. and Sims, E. R. (2011). News shocks and business cycles. *Journal of Monetary Economics*, 58(3):273–289.

Basu, S. and Bundick, B. (2015). Endogenous volatility at the zero lower bound: Implications for stabilization policy. Technical report, National Bureau of Economic Research.

Basu, S. and Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica*, 85(3):937–958.

Beaudry, P. and Portier, F. (2014). News-driven business cycles: Insights and challenges. *Journal of Economic Literature*, 52(4):993–1074.

Belke, A. and Göcke, M. (2005). Real options effects on employment: Does exchange rate uncertainty matter for aggregation? *German Economic Review*, 6(2):185–203.

Belke, A. and Osowski, T. (2017). International effects of Euro area versus US policy uncertainty: A FAVAR approach. *Ruhr Economic Papers. No. 689.*

Benzarti, Y. and Carloni, D. (2019). Who really benefits from consumption tax cuts? evidence from a large vat reform in france. *American Economic Journal: Economic Policy*, 11(1):38–63.

Bernanke, B., Gertler, M., and Gilchrist, S. (1998). The financial accelerator in a quantitative business cycle framework. Technical report, National Bureau of Economic Research.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1):85–106.

Bernanke, B. S., Boivin, J., and Eliasz, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics*, 120(1):387–422.

Bernanke, B. S. and Gertler, M. (1995). Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4):27–48.

Bertolotti, F. and Marcellino, M. (2019). Tax shocks with high and low uncertainty. *Journal of Applied Econometrics*, 34(6):972–993.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3):623–685.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2):153–76.

Bloom, N., Bond, S., and Van Reenen, J. (2007). Uncertainty and investment dynamics. *The Review of Economic Studies*, 74(2):391–415.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., and Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, 86(3):1031–1065.

Bonciani, D. and Oh, J. J. (2019). The long-run effects of uncertainty shocks.

Bonciani, D. and van Roye, B. (2015). Uncertainty shocks, banking frictions and economic activity. *European Central Bank Working paper No.1825.*

Bordo, M. D., Duca, J. V., and Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level US evidence over several decades. *Journal of Financial Stability*, 26:90–106.

Born, B. and Pfeifer, J. (2014). Policy risk and the business cycle. *Journal of Monetary Economics*, 68:68–85.

Born, B. and Pfeifer, J. (2021). Uncertainty-driven business cycles: Assessing the markup channel. *Quantitative Economics*, 12(2):587–623.

Brodeur, A., Gray, D. M., Islam, A., and Bhuiyan, S. (2020). A literature review of the economics of covid-19.

Brunnermeier, M., Palia, D., Sastry, K. A., and Sims, C. A. (2017). Feedbacks: Financial markets and economic activity. *Working Paper.*

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421.

Bu, C., Rogers, J., and Wu, W. (2020). A unified measure of fed monetary policy shocks. *Journal of Monetary Economics*.

Caballero, R. J. (1991). Earnings uncertainty and aggregate wealth accumulation. *The American Economic Review*, pages 859–871.

Caggiano, G., Castelnuovo, E., Colombo, V., Nodari, G., et al. (2014a). Estimating fiscal multipliers: evidence from a nonlinear world. Technical report, Dipartimento di Scienze Economiche" Marco Fanno".

Caggiano, G., Castelnuovo, E., and Groshenny, N. (2014b). Uncertainty shocks and unemployment dynamics in us recessions. *Journal of Monetary Economics*, 67:78–92.

Caggiano, G., Castelnuovo, E., and Pellegrino, G. (2017). Estimating the real effects of uncertainty shocks at the zero lower bound. *European Economic Review*, 100:257–272.

Caldara, D., Fernandez-Villaverde, J., Rubio-Ramirez, J. F., and Yao, W. (2012). Computing dsge models with recursive preferences and stochastic volatility. *Review of Economic Dynamics*, 15(2):188–206.

Caldara, D., Fuentes-Albero, C., Gilchrist, S., and Zakrajšek, E. (2016). The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, 88:185–207.

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., and Raffo, A. (2020). The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, 109:38–59.

Carriero, A., Clark, T. E., and Marcellino, M. (2015a). Bayesian vars: Specification choices and forecast accuracy. *Journal of Applied Econometrics*, 30(1):46–73.

Carriero, A., Mumtaz, H., Theodoridis, K., and Theophilopoulou, A. (2015b). The impact of uncertainty shocks under measurement error: A proxy SVAR approach. *Journal of Money, Credit and Banking*, 47(6):1223–1238.

Carroll, C. D. and Kimball, M. S. (1996). On the concavity of the consumption function. *Econometrica*, pages 981–992.

Carroll, C. D. and Samwick, A. A. (1998). How important is precautionary saving? *Review of Economics and Statistics*, 80(3):410–419.

Carter, C. K. and Kohn, R. (1994). On gibbs sampling for state space models. *Biometrika*, 81(3):541–553.

Castelnuovo, E. and Pellegrino, G. (2018). Uncertainty-dependent effects of monetary policy shocks: A new-keynesian interpretation. *Journal of Economic Dynamics and Control*, 93:277–296.

Cesa-Bianchi, A. and Fernandez-Corugedo, E. (2018). Uncertainty, financial frictions, and nominal rigidities: A quantitative investigation. *Journal of Money, Credit and Banking*, 50(4):603–636.

Cesa-Bianchi, A., Pesaran, M. H., and Rebucci, A. (2014). Uncertainty and economic activity: A global perspective. *CESifo Working Paper Series 4736. CESifo Group Munich.*

Christiano, L. J., Eichenbaum, M., and Evans, C. (1994). The effects of monetary policy shocks: some evidence from the flow of funds. Technical report, National Bureau of Economic Research.

Christiano, L. J., Motto, R., and Rostagno, M. (2014). Risk shocks. *American Economic Review*, 104(1):27–65.

Christidou, M. and Fountas, S. (2017). Uncertainty in the housing market: Evidence from US states. *Studies in Nonlinear Dynamics & Econometrics*, 22(2).

Chudik, A. and Pesaran, M. H. (2011). Infinite-dimensional VARs and factor models. *Journal of Econometrics*, 163(1):4–22.

Chugh, S. K. (2016). Firm risk and leverage-based business cycles. *Review of Economic Dynamics*, 20:111–131.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. Technical report, National Bureau of Economic Research.

Colombo, V. (2013). Economic policy uncertainty in the US: Does it matter for the Euro area? *Economics Letters*, 121(1):39–42.

Cuaresma, J. C., Huber, F., and Onorante, L. (2019). The macroeconomic effects of international uncertainty.

Curdia, V. and Woodford, M. (2010). Credit spreads and monetary policy. *Journal of Money, Credit and Banking*, 42:3–35.

Dixit, A. K., Dixit, R. K., and Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton university press.

Dovern, J., Fritsche, U., and Slacalek, J. (2012). Disagreement among forecasters in G7 countries. *Review of Economics and Statistics*, 94(4):1081–1096.

Elbourne, A. (2008). The uk housing market and the monetary policy transmission mechanism: An svar approach. *Journal of Housing Economics*, 17(1):65–87.

Ellis, C., Mumtaz, H., and Zabczyk, P. (2014). What lies beneath? A time-varying FAVAR model for the UK transmission mechanism. *The Economic Journal*, 124(576):668–699.

Faccini, R. and Palombo, E. (2021). News uncertainty in brexit united kingdom. *American Economic Review: Insights*, 3(2):149–64.

Fasani, S. (2017). Uncertainty shocks and monetary smoothness in a dsge model.

Favero, C. and Giavazzi, F. (2012). Measuring tax multipliers: The narrative method in fiscal vars. *American Economic Journal: Economic Policy*, 4(2):69–94.

Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., and Rubio-Ramírez, J. (2015). Fiscal volatility shocks and economic activity. *American Economic Review*, 105(11):3352–84.

Fernández-Villaverde, J., Guerrón-Quintana, P., Rubio-Ramírez, J. F., and Uribe, M. (2011). Risk matters: The real effects of volatility shocks. *American Economic Review*, 101(6):2530–61.

Fernandez-Villaverde, J., Guerron-Quintana, P. A., Kuester, K., and Rubio-Ramírez, J. (2011). Fiscal uncertainty and economic activity. *Manuscript, Duke University.*

Ferrara, L. and Guérin, P. (2018). What are the macroeconomic effects of high-frequency uncertainty shocks? *Journal of Applied Econometrics*, 33(5):662–679.

Fry, R. and Pagan, A. (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature*, 49(4):938–60.

Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Gilchrist, S., Sim, J. W., and Zakrajšek, E. (2014). Uncertainty, financial frictions, and investment dynamics. Technical report, National Bureau of Economic Research.

Gonçalves, S. and Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123(1):89–120.

Goodfriend, M. and McCallum, B. T. (2007). Banking and interest rates in monetary policy analysis: A quantitative exploration. *Journal of Monetary Economics*, 54(5):1480–1507.

Gourio, F. (2012). Disaster risk and business cycles. *American Economic Review*, 102(6):2734–66.

Haddow, A., Hare, C., Hooley, J., and Shakir, T. (2013). Macroeconomic uncertainty: What is it, how can we measure it and why does it matter? *Bank of England Quarterly Bulletin*, 53(2):100–109.

Handley, K. and Limao, N. (2015). Trade and investment under policy uncertainty: Theory and firm evidence. *American Economic Journal: Economic Policy*, 7(4):189–222.

Hartman, R. (1976). Factor demand with output price uncertainty. *The American Economic Review*, 66(4):675–681.

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review*, 95(3):739–764.

Iacoviello, M. (2010). Housing in dsge models: Findings and new directions. In *Housing markets in Europe*, pages 3–16. Springer.

Iacoviello, M. (2011). Housing wealth and consumption. *FRB International Finance Discussion Paper*, (1027).

Iacoviello, M. (2015). Financial business cycles. *Review of Economic Dynamics*, 18(1):140–163.

Iacoviello, M. and Neri, S. (2010). Housing market spillovers: evidence from an estimated dsge model. *American Economic Journal: Macroeconomics*, 2(2):125–64.

Iacoviello, M. and Pavan, M. (2013). Housing and debt over the life cycle and over the business cycle. *Journal of Monetary Economics*, 60(2):221–238.

Ilut, C. L. and Schneider, M. (2014). Ambiguous business cycles. *American Economic Review*, 104(8):2368–99.

Jackson, L. E., Kliesen, K. L., Owyang, M. T., et al. (2019). A bad moon rising? uncertainty shocks and economic outcomes. *Economic Synopses*, (6).

Jo, S. and Sekkel, R. (2019). Macroeconomic uncertainty through the lens of professional forecasters. *Journal of Business & Economic Statistics*, 37(3):436–446.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

Kimball, M. S. (1990). Precautionary saving and the marginal propensity to consume. Technical report, National Bureau of Economic Research.

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Kurmann, A. and Otrok, C. (2013). News shocks and the slope of the term structure of interest rates. *American Economic Review*, 103(6):2612–32.

Leduc, S. and Liu, Z. (2012). Uncertainty, unemployment, and inflation. *FRBSF Economic Letter*, 28.

Leduc, S. and Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82:20–35.

Leland, H. E. (1972). Theory of the firm facing uncertain demand. *The American Economic Review*, 62(3):278–291.

Leland, H. E. (1978). Saving and uncertainty: The precautionary demand for saving. In *Uncertainty in Economics*, pages 127–139. Elsevier.

Lhuissier, S. and Tripier, F. (2019). Regime-dependent effects of uncertainty shocks: A structural interpretation.

Liu, Z., Wang, P., and Zha, T. (2013). Land-price dynamics and macroeconomic fluctuations. *Econometrica*, 81(3):1147–1184.

Luciani, M. (2015). Monetary policy and the housing market: A structural factor analysis. *Journal of Applied Econometrics*, 30(2):199–218.

Ludvigson, S. C., Ma, S., and Ng, S. (2015). Uncertainty and business cycles: Exogenous impulse or endogenous response? Technical report, National Bureau of Economic Research.

Ludvigson, S. C., Ma, S., and Ng, S. (2020). Covid19 and the macroeconomic effects of costly disasters. Technical report, National Bureau of Economic Research.

McKibbin, W. J. and Fernando, R. (2020). The global macroeconomic impacts of covid-19: Seven scenarios.

Melosi, L. (2017). Signalling effects of monetary policy. *The Review of Economic Studies*, 84(2):853–884.

Mertens, K. and Ravn, M. O. (2013). The dynamic effects of personal and corporate income tax changes in the united states. *American Economic Review*, 103(4):1212–47.

Mumtaz, H. and Surico, P. (2013). Policy uncertainty and aggregate fluctuations. *Journal of Applied Econometrics*, 33(3):319–331.

Mumtaz, H. and Theodoridis, K. (2017). Common and country specific economic uncertainty. *Journal of International Economics*, 105:205–216.

Nakamura, E. and Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330.

Neumeyer, P. and Perri, F. (2005). Business cycles in emerging economies: The role of interest rates. *Journal of Monetary Economics*, 52(2):345–380.

Nevo, A. and Rosen, A. M. (2012). Identification with imperfect instruments. *Review of Economics and Statistics*, 94(3):659–671.

Nimark, K. (2008). Dynamic pricing and imperfect common knowledge. *Journal of Monetary Economics*, 55(2):365–382.

Olivei, G. and Tenreyro, S. (2010). Wage-setting patterns and monetary policy: International evidence. *Journal of Monetary Economics*, 57(7):785–802.

Onatski, A. (2009). Testing hypotheses about the number of factors in large factor models. *Econometrica*, 77(5):1447–1479.

Pellegrino, G. (2018). Uncertainty and the real effects of monetary policy shocks in the euro area. *Economics Letters*, 162:177–181.

Piffer, M. and Podstawski, M. (2018). Identifying uncertainty shocks using the price of gold. *The Economic Journal*, 128(616):3266–3284.

Popescu, A. and Smets, F. (2010). Uncertainty, risk-taking, and the business cycle in Germany. *CESifo Economic Studies*, 56(4):596–626.

Ramey, V. A. and Shapiro, M. D. (1998). Costly capital reallocation and the effects of government spending. In *Carnegie-Rochester conference series on public policy*, volume 48, pages 145–194. Elsevier.

Ramey, V. A. and Zubairy, S. (2018). Government spending multipliers in good times and in bad: Evidence from us historical data. *Journal of Political Economy*, 126(2):850–901.

Redl, C. (2017). The impact of uncertainty shocks in the United Kingdom. *Bank of England Staff Working Papers No.695*.

Ricco, G., Callegari, G., and Cimadomo, J. (2016). Signals from the government: Policy disagreement and the transmission of fiscal shocks. *Journal of Monetary Economics*, 82:107–118.

Romer, C. D. and Romer, D. H. (2000). Federal reserve information and the behaviour of interest rates. *American Economic Review*, 90(3):429–457.

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084.

Rossi, B. and Sekhposyan, T. (2015). Macroeconomic uncertainty indices based on nowcast and forecast error distributions. *American Economic Review*, 105(5):650–55.

Schmidt, J. (2013). Country risk premia, endogenous collateral constraints and non-linearities: A threshold var approach. Technical report, Working paper.

Scotti, C. (2016). Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. *Journal of Monetary Economics*, 82:1–19.

Stock, J. H. and Watson, M. W. (2012). Disentangling the channels of the 2007-2009 recession. Technical report, National Bureau of Economic Research.

Stock, J. H. and Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In *Handbook of macroeconomics*, volume 2, pages 415–525. Elsevier.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

Valletta, R., Bengali, L., et al. (2013). What's behind the increase in part-time work? *FRBSF Economic Letter*, 24(aug26).

Van den Heuvel, S. J. (2008). The welfare cost of bank capital requirements. *Journal of Monetary Economics*, 55(2):298–320.

Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.

Appendix A

Uncertainty and the UK Housing Market: A Structural Analysis

A.1 Robustness

The general idea of our alternative restriction scheme SR1 is to take a less agnostic view about the response of investment because of the prevalence of the real option narrative in the transmission of an uncertainty shock. Results presented in Figure A.1 indicate that results closely mirror those in our baseline case in terms of sign and magnitude. Similarly, for sign restriction scheme SR2 we impose a negative response of our measure of mortgages. The intuition follows as we aim to test the conjecture that financial conditions deepen or worsen the effects of uncertainty shocks. Results from this exercise are presented in Figure A.2. We show results are slightly muted when financial conditions do not worsen, but the general effects of precautionary saving and the real option channel is consistent.

As Figure A.3 shows, once we include global uncertainty we find more modest effects on consumption, a result consistent with those of Cesa-Bianchi et al. (2014). However, while the effect is reduced we still find the same precautionary saving narrative as in the baseline FAVAR. Specifically, firm results are more apparent as total production and production across all industries falls as firms delay decisions following higher uncertainty. We also find that results for capital are consistently negative across both specifications indicating the real option channel is robust. In terms of the housing uncertainty channel, the main conclusion still holds as we see an expansion of mortgage approvals and housing transactions. However, for the latter this result is to a much lower magnitude. Similarly, household lending and total mortgage debt are now insignificant. Redl (2017) finds that global uncertainty is highly correlated with financial conditions within the UK. Intuitively, worsening financial conditions limits the amount of agents who are willing to invest in housing and, thus, the strength of the channel is smaller. Finally, the response of GDP is slightly lower, but this is driven by the reduction in consumption.

A.2 Data

Table A.2 and A.3 document a description of the dataset used for the FAVAR estimation. The majority of the data is sourced from the ONS, data for housing risk variables comes from the Bank of England statistical database while financial data is obtained from Datastream. In order to standardise the dataset, outliers are defined as those entries that have a difference of more than six times the interquartile difference from the median value. These outliers are replaced by the median of the previous five results. The below key in Table A.1 explains the interpretation of our dataset.

Table A.1 Key

Transformation	Category	Fast/Slow
1 = Log Difference.	1 = GDP and Components	0 = Slow
2 = No Transformation.	2 = Manufacturing and Production	1 = Fast
3 = First Difference.	3 = Inflation	
	4 = Monetary Aggregates	
	5 = Housing Variables	
	6 = Housing Risk	
	7 = Financial	
	8 = Exchange Rates	

Table A.2 Data (1)

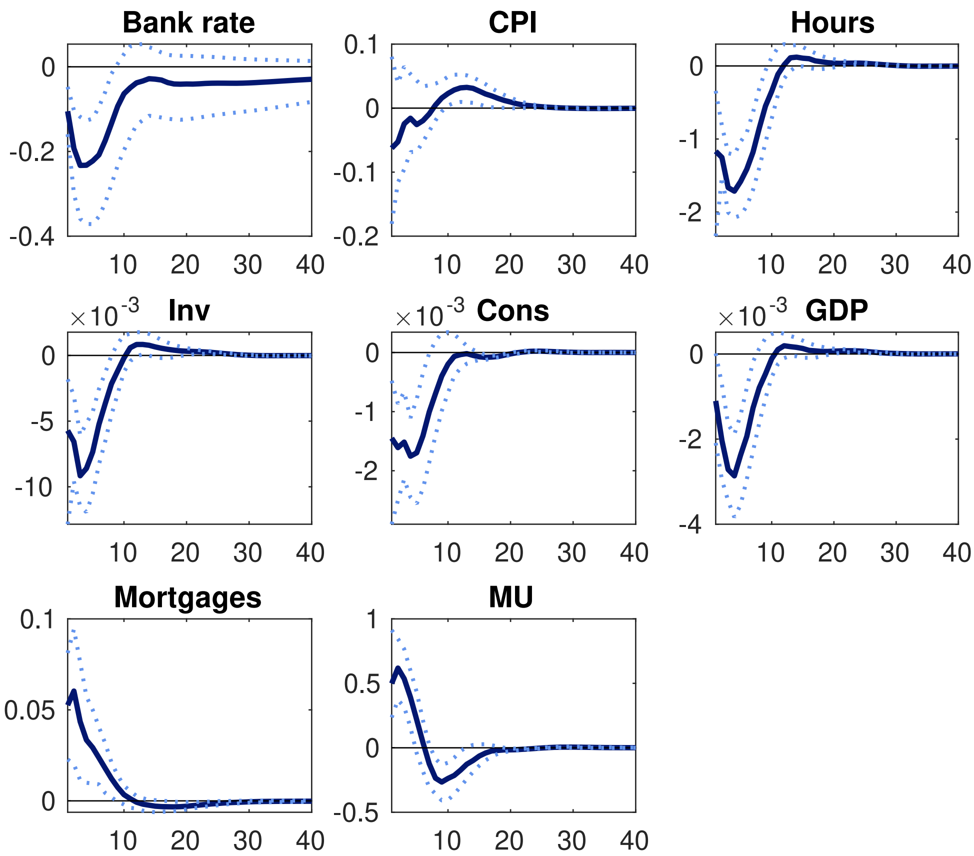
Series	Transformation	Category	Fast/Slow
Consumption	1	1	0
Government Consumption	1	1	0
Construction	1	1	0
Exports	1	1	0
Imports	1	1	0
Capital	2	1	0
GDP	1	1	0
Manufacturing	1	2	0
Transport Storage, Communication	1	2	0
Total Output	1	2	0
All Production Industries	1	2	0
Electricity, Gas and Water supply	1	2	0
Manuf. of Food, Drink and Tobacco	1	2	0
Manuf. Coke/petroleum, Prod/nuclear fuels	1	2	0
Manuf of Chemicals and Man-made Fibres	2	2	0
Total Production	1	2	0
RPI Total Food	1	3	0
RPI Total Non-Food	1	3	0
RPI All items other than Seasonal Food	1	3	0
CPI	1	3	0
GDP Deflator	1	3	0
Wages	1	3	0
RPIX	1	3	0
RPI	1	3	0
M4 Total	1	4	0
M4 Households	1	4	0
M4 PNFCs	1	4	0
M4 OFCs	3	4	0
M0	1	4	0
M4 Lending	1	4	0
M4L Households	1	4	0

Table A.3 Data (2)

Series	Transformation	Category	Fast/Slow
M4L PNFCs	1	4	0
Interest Rates	1	4	0
House Prices	1	5	1
Housing Starts	1	5	1
Housing Completions	1	5	1
House Price FTB	3	5	1
Household Credit Growth	1	6	1
HouseHold Debt to Income	1	6	1
Total Mortgage Debt	1	6	1
Mortgage Approvals	1	6	1
Housing Transactions	1	6	1
House Price to Disposable Income	1	6	1
Rental Yield	1	6	1
Spread LTV on New Mortgages	3	6	1
Commercial Real Estate	1	6	1
Price to Rent	1	6	1
Dividend Yield	1	7	1
FTSE ALL Share Index	1	7	1
Pounds/dollar	1	8	1
Pounds/euro	1	8	1
Pounds/yen	1	8	1

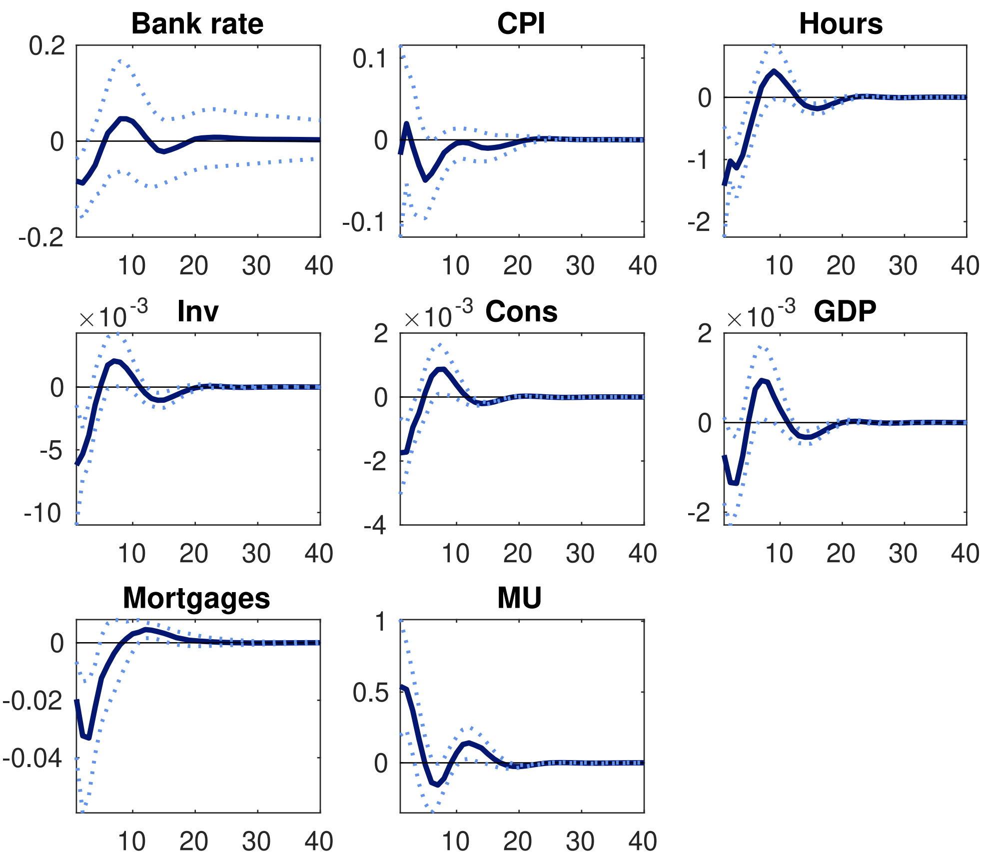
A.3 Additional Graphs

Fig. A.1 Robustness: SR1 Restrictions



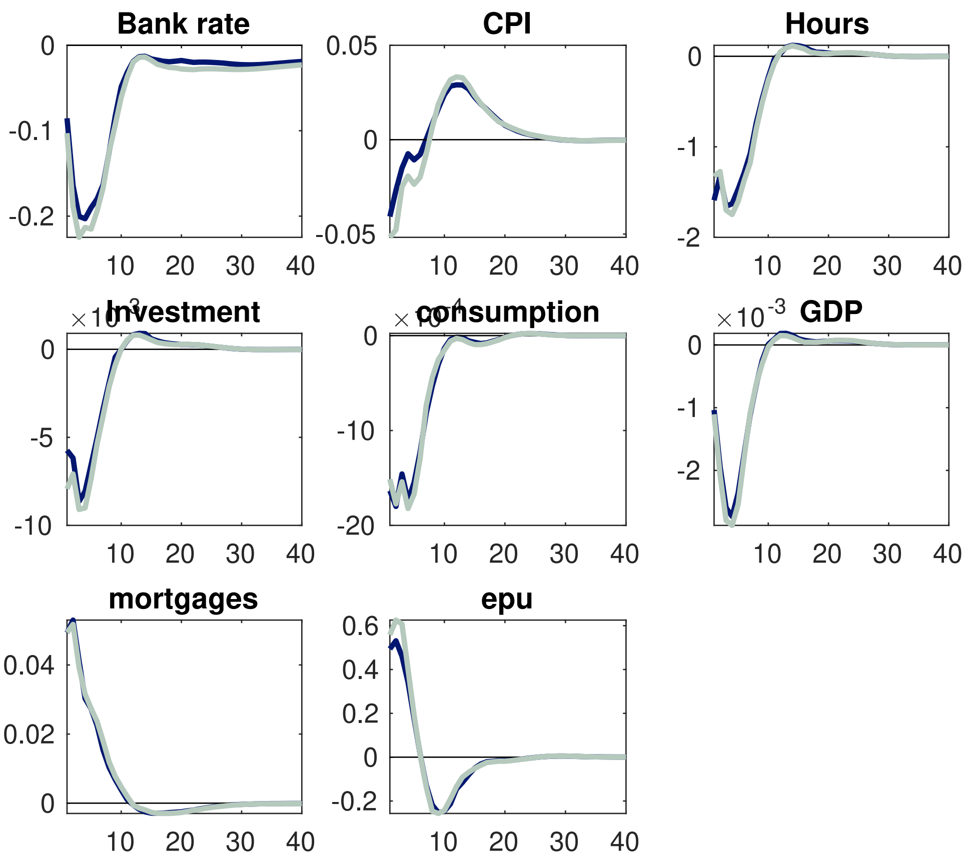
Notes : Median impulse responses from a one standard deviation shock to uncertainty from the SVAR model. Identification is achieved by imposing the SR1 restrictions as outlined in Table 1.1. Our sign restriction method accepts draws which conform to our restriction matrix and creates a distribution based on these accepted draws. We compute 68% confidence intervals from this distribution. The y axis is percentage deviation from trend. The data included is bank rate, CPI, hours worked, investment, consumption, GDP, mortgage credit spreads and macro uncertainty.

Fig. A.2 Robustness: SR2 Restrictions



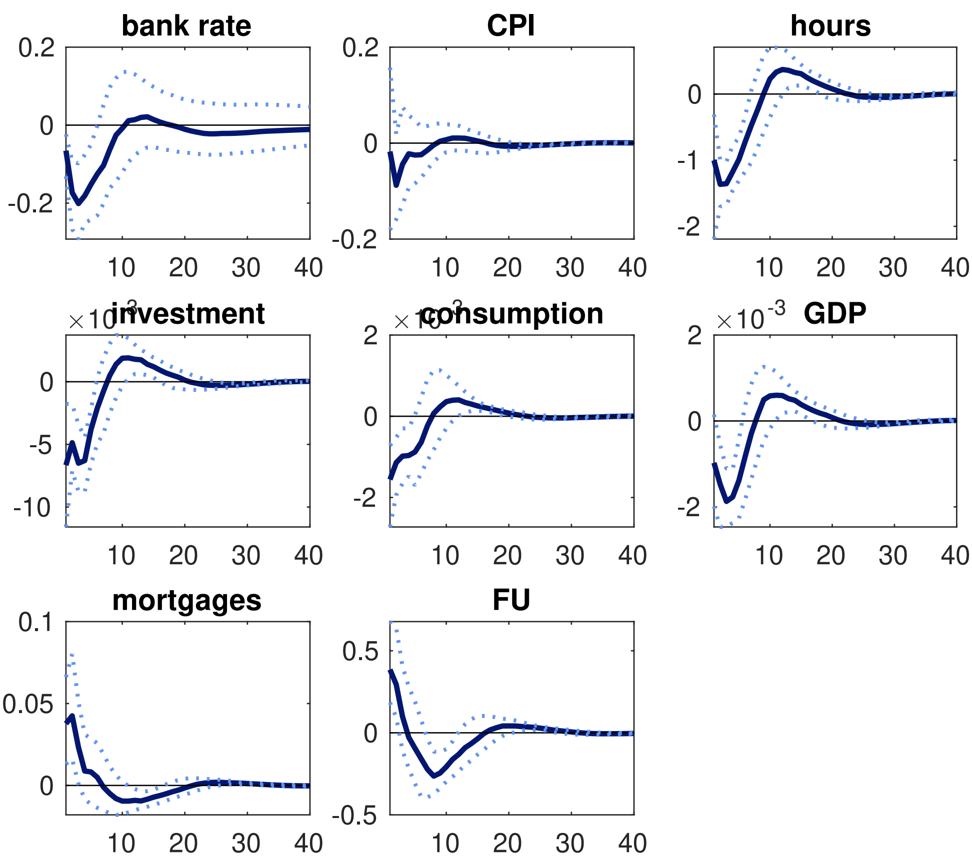
Notes: Median impulse responses from a one standard deviation shock to uncertainty from the SVAR model. Identification is achieved by imposing the SR2 restrictions as outlined in Table 1.1. Our sign restriction method accepts draws which conform to our restriction matrix and creates a distribution based on these accepted draws. We compute 68% confidence intervals from this distribution. The y axis is percentage deviation from trend. The data included is bank rate, CPI, hours worked, investment, consumption, GDP, mortgage credit spreads and macro uncertainty.

Fig. A.3 Baker et al (2016) vs Jurado et al (2015)



Notes: We present median results from the SVAR using sign restriction routine SR1 and the policy uncertainty index of Baker et al. (2016). For comparison, the blue line is the original results from the SVAR, while the grey line corresponds to the results from this estimation. Results are largely similar, indicating that shocks to policy and macro uncertainty act similarly. This is likely due to the high correlation between the two indexes.

Fig. A.4 Financial Uncertainty



Notes: Median impulse responses from a one standard deviation shock to uncertainty from the SVAR model. Identification is achieved by imposing the SR1 restrictions as outlined in Table 1.1. Our sign restriction method accepts draws which conform to our restriction matrix and creates a distribution based on these accepted draws. We compute 68% confidence intervals from this distribution. The y axis is percentage deviation from trend. The data included is bank rate, CPI, hours worked, investment, consumption, GDP, mortgage credit spreads and financial uncertainty.

Appendix B

The Non Linear Effects of Uncertainty, the Housing Uncertainty Channel and Monetary Policy

B.1 Robustness

In order to test the robustness of our results, we estimate the impact on GDP using the various measures of uncertainty as our threshold variable. Figures B.1 and B.2 plot the responses of GDP across high and low regimes respectively. Focusing on policy uncertainty, we show that the amplification impact holds and is of a similar magnitude to what we capture using the macro uncertainty index. This likely follows from the two indexes capturing similar regimes and so it is unsurprising that similar dynamics are present in the response of GDP. Utilising both the VIX and the financial uncertainty index also present a similar story. A shock to uncertainty in a low regime leads to a negative impact on GDP. In a high uncertainty regime, results are of similar magnitude but are insignificant. As discussed in Bertolotti and Marcellino (2019), using financial uncertainty is difficult as there is no theoretical benchmark to discuss the results. They argue that the apparent difference from using financial uncertainty derives from the the index capturing alternative sources of uncertainty.

B.2 Computation of the GIRFs

We follow Bertolotti and Marcellino (2019) in the computation of the GIRFs. The algorithm to compute regime specific impulse responses with a time horizon h follows:

- Choose a history $(\Omega_{t-i})_{i=0}^{p}$ from the original Y data. P defines the lag order of the VAR.
- Choose a sequence of shocks with length h from a random starting point.
- Given the history, the estimated coefficients from the original model and a chosen sequence of residuals, simulate the evolution of the model over the desired time horizon in the absence of exogenous shocks.
- Repeat step 3, yet at time 0 add to the variables the estimate impact of a 1% narrative shock.
- Repeat steps 2 to 4 for 200 replications.
- Compute the average difference between the shocked path and the non shocked one.
- Repeat steps 1 to 6 considering all histories.
- The average GIRF associated with a specific regime is the average of the GIRFs obtained considering starting conditions from which the regime at time 0 was the one of interest.

Once we obtain our GIRFs, confidence bands are obtained by bootstrapping as follows:

- Simulated data are generated recursively using the estimated coefficients and the bootstrapped residuals from our non linear model.

- Using the new dataset, the non linear model is re-estimated keeping the threshold fixed. We store the new residuals.

- With the original data set for starting conditions and the newly computed coefficients and errors, GIRFs are computed as above.

- The above steps are repeated 300 times to generate a sample distribution of the GIRFs from which confidence bands are drawn at the respective significance levels.

B.3 List of Events

January

The Assassination of Qasem Suleimani

A bombing of Kata'ib Hezbollah in late December 2019 occurred as part of increasing tensions between Iran and the US. At a security briefing at the Mar-a-lago estate the killing was presented as "the most extreme option". These extreme options are used by security officials to rationalise other options presented to the President. Trump decides to take this option, and did not advise anyone outside of the estate of the strike. Congress members are cited as claiming that nothing of the strike was indicated to them. This was a huge escalation in the Persian Gulf crisis with high uncertainty about the potential for war between the two nations. Tensions continue throughout 2020 with a number of bombings and attacks.

China Quarantines Wuhan

Mystery disease had previously had isolated cases. China takes the decision to impose harsh restrictions on the city of Wuhan following the first death outside of the Hubei region. This led to increases in uncertainty as it indicated an increasing dire situation around the disease.

Other Events

- Donald Trump has articles of impeachment delivered. This is not included as this was an expected event, had been extensively discussed in prior to January 2020.

- Global emergency declared by WHO. This is not included due to an expected announcement due to the events in China.

- UK leaves the EU. Long set date and expected to occur following the Brexit vote.

February

European Lockdown

Italy introduce roadblocks and more significant restrictions across several cities in the Lombardy region. This lead to increases in uncertainty as it is the first instance of lockdown outside of china and that the COVID disease had the potential to hit European countries.

Dow Jones Crashes The world stock market crashes in response to the transmission of COVID across the world and outside of China. Increases in uncertainty due to the potential for economic fallout from Covid.

US COVID Task Force Donald Trump takes charge of the Corona Virus task force. Previously Vice President Mike Pence had been put in charge. Trump announces this and signals that coronavirus was a bigger issue than previously thought for the US. Previously had been played down and although there was no change in rhetoric, the move to place Trump in direct control of the Coronavirus lead to increased uncertainty about the seriousness of the pandemic in the US.

Other Events

- First COVID death in the US. This is not included as once COVID is in the US the death is almost expected.

- Risk level raised by WHO. This is not included due to an expected announcement due to the events around the world.

March

UK Lockdown The UK had previously been taking a non lockdown approach with limited social distancing guidelines. In a u-turn of policy the UK announce a full lockdown in order to prevent hospitals from becoming overwhelmed. Increased uncertainty over how the reversal in policy would play out.

Black Thursday Stock markets have their largest single day drop since the stock market crash in 1987. This signalled a loss of confidence in Donald Trump's ability to deal with the COVID crisis alongside the travel ban to the Schengen area. Increased uncertainty over how the US would deal with COVID and in terms of the fall in integration in Western markets.

Other Events

- Fed cuts rate on the 3rd. Although the cut in rates was the first time since 2008 and represented the dire economic situation in the US economy, world economies had recognised the need to alter policy to impact COVID and so the policy was expected and so not included.

- Black Monday. This relates heavily to the oil price war between Saudi Arabia and Russia, linking closely to the oil price shock we do not include it.

- Fed Cuts rates on the 15th. Although the rate cut again is a shock, Trump had tweeted extensively and there had been large media coverage prior calling for additional measures so we do not include it.

- 2 trillion dollar COVID Relief Passed. Not included as virus relief package had been discussed as early as January. However the scale of the bill was a shock and a hugely inflated figure demonstrates the scale of the issues of COVID. We choose not to include it as we argue that the size of the bill is not a big enough event to warrant inclusion, alongside being heavily linked to the economic situation.

- Fallout from COVID. Various issues in the US, New York hospitals are full, deaths, government aids test positive. Not included as the fallout is response to the coronavirus and almost is expected.

- Boris Johnson tests positive. Although this represented the first time a world leader tested positive, we argue that the event should not be included as again is a response to coronavirus.

April

Other Events

- Boris Johnson in intensive care. We choose not to include as there is no bad outcome and is highly linked to the fallout from COVID.

- Confusion over US guidelines. The US announce that they suggest wearing masks before Trump claims they are "not for him". Although there is uncertainty about the approach and the message it is not deemed an event.

- Europe begin to ease lockdowns. Always expected to occur with clear dates set prior, expected so not included.

- WHO warn against lifting restrictions. Against the backdrop of world economies discussing lockdowns, this again is expected given the scale of the deaths and continued cases of COVID-19.

May

George Floyd dies George Floyd is killed at the hands of police officers. This leads to nationwide outrage and the fallout is huge and worldwide. Protests erupt across the US, The White House is placed on Lockdown and there is calls for the National Guard to be deployed nationwide. High uncertainty due to increasing tensions in the US.

Other Events

- Failed attempt to oust Maduro in Venezuela.. US not involved so isn't a huge impact and therefore is not an event we consider.

June

Other Events

- News breaks of Russia offering bounties to Afghanistan to kill US military. The news is quickly debunked and US had been told around 2019. No lasting impact so not considered.

July

Other Events

- Hong Kong Autonomy Act. Passed early July and accompanies an executive order to not recognise Hong Kong as an independent state due to the increase in influence from China. The first big event of increasing tensions with China. Almost expected given the press releases and rhetoric displayed by President Trump in news briefings prior.

- Rockets fired at US Iraq embassy from Iran backed Militia - part of operation Martyr starting with the assassination. Among a number of events including Gulf Sea events between US and Iran. Choose not to include as nothing linked to Iran. With the War ship incident it goes no further than that and we argue is a response to the assassination from the US and so is almost expected.

August

Other Events

- End of Jobs benefit scheme, long published end date and debate starts over extending, we argue isn't a conclusive event.

- Arab Israel peace talks. Long term discussions with the countries involved that was discussed and mentioned in terms of the possibility of it occurring. Not included.

September

Other Events

- Serbia Kosovo economic normalisation agreement. Although everything prior indicated a deal could not be struck, news is available to point to the two countries attending The White House, alongside the role Trump plays prior so we do not include.
- UK breaks international law. Part of Brexit negotiations, through the possibility of no deal become more of a reality, all part of news releases about the struggles of the negotiations and were widely reported and so is not an isolated event.
- Armenia- Azerbijan War. Long held tensions between two two nations end in conflict which receives little attention in the US. Commentators for a prolonged period argue that it was going to be a reality and so we do not include.

October

European Terror Attacks Terror attacks in NiceFour weeks prior to this attack, French President Emmanuel Macron described Islam as a religion "in crisis" worldwide, prompting backlash from Muslims. He vowed to present a bill to strengthen a 1905 law that officially separated church and state in France. September 25 stabbings in Paris, Murder of Samuel Patys. All part of a backlash from the extremist side of the muslim religion. Attacks in Nice most high profile, reach America.

Other Events

- Donald Trump tests positive and is hospitalised. To be consistent with Boris not included is not a big event more a response to COVID.

November

Other Events

- Biden declared winner. Not included.

December

Other Events

- Vaccines approved in the US.
- New strain of COVID - Uncertainty over vaccines. Would this extend the pandemic? Included.

Table B.1 The Full List of Events

Number	Date	Event	Gold Price
1	13 Nov 2015	Paris terrorist attack	1.2
2	22 Mar 2016	Suicide bomb in Belgium	-0.55
3	24 Jun 2016	Brexit	4.1
4	14 Jul 2016	Terror attacks in Nice	0.52
5	19 Dec 2016	Terror attacks in Berlin	-0.31
6	22 May 2017	Terror attacks in Manchester	0.08
7	3 June 2017	Terror attacks in London	0.43
8	17 Aug 2017	Terror attacks in Barcelona	0.79
9	31 Oct 2017	Terror attacks in New York	0.72
10	23 Mar 2018	US/China trade war	0.72
11	11 Dec 2018	Strasbourg terror attack	-0.04
12	15 Mar 2019	Christchurch shooting	0.55
13	5 May 2019	Persian Gulf tensions	0.22
14	3 Jan 2020	Operation Matyr	1.33
15	23 Jan 2020	China quarantines Wuhan	0.57
16	24 Jan 2020	First COVID cases in Europe	1.22
17	23 Feb 2020	European lockdown	2.38
18	26 Feb 2020	US Task Force	0.72
19	12 Mar 2020	Black Thursday	1.11
20	17 Mar 2020	EU travel ban	4.34
21	23 Mar 2020	UK lockdown	4.86
22	4 Apr 2020	Boris Johnson hospitalized	0.24
23	27 May 2020	George Floyd murder	1.69
24	5 Aug 2020	Explosion in Lebanon	2.86
25	29 Oct 2020	Nice Beheading	0.37
26	29 Oct 2020	New COVID strain	0.72

B.4 Significance of News

Testing the significance of news as in Piffer and Podstawski (2018), we broadly replicate the results shown in the original paper.

Table B.2 P-values from Non Linearity Tests - Revisited

	SP 500	VXO	Fed Funds	Hours	CPI
β	-0.004^{***}	0.2933^{***}	-0.001	-0.0004	-0.0072^{**}
F	103.72	11.12	0.562	0.456	14.463
R^2	0.524	0.207	0.002	0.112	0.011
	House Prices	Consumption	Credit		
β	-0.005	0.000	0.0823^{**}		
F	3.334	0.115	4.33		
R^2	0.019	0.002	0.015		

Notes: The models estimated are $V_{i,t} = \alpha + \beta_i U_{i,t} + \eta_{i,t}$ .The null hypothesis refers to $\beta_i = 0$.

The residual on the stock market index has a strong and negative correlation with the proxy for the news shock, delivering an F-statistic as high as 103. This finding indicates that unfavourable news, as captured by an increase in the proxy for the news shock, is associated with decreases in the S&P500. While we find that increases in the proxy for the news shock are also associated with increases in the residuals in the VXO, the F-statistic corresponding to the latter equation equals one tength of the F-statistic related to the residual of the stock market index.

B.5 Altering the Choice of Events

The key results from our paper hold when we alter our uncertainty instrument as documented in Figures B.3 and B.4, suggesting that results are not dependant on the choice of event. We capture a precautionary saving response in the low uncertainty regime for both the Albrizio et al. (2020) and the updated Piffer and Podstawski (2018) instruments, which is similar in magnitude to the responses found using our instrument.

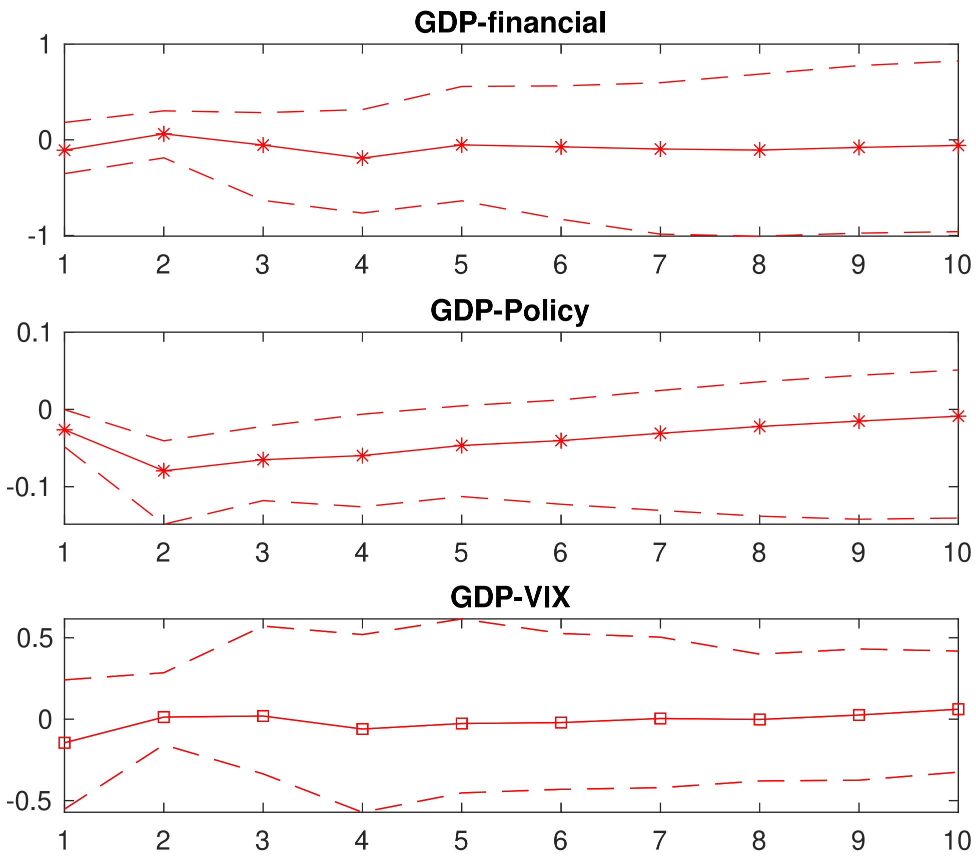
We similarly capture the flip in consumption response in the high uncertainty regime which is more pronounced in for the Albrizio et al. (2020) measure. In comparison, using the Piffer and Podstawski (2018) measure we capture a stronger real option channel and credit response. The saving response is consistent between our measure and the updated Piffer and Podstawski (2018), while results become insignificant using the Albrizio et al. (2020) measure. Both measures capture the inflationary response we estimate, however, the policy response in a low regime becomes insignificant.

B.6 Testing the Proxy SVAR Model

We present the estimated shocks from the proxy SVAR in Figure B.6. The estimated shock shares a number of peaks, notably Black Monday and the 9/11 terrorist attack. We show that Brexit only increased exogenous uncertainty by about 0.8 standard deviations and was realised in combination with a news shock of 1.7 standard deviations in magnitude. Post, 2015, the estimated shock does not present any events not captured by our proxy, indicating that we have sufficiently represented the dynamics of uncertainty.

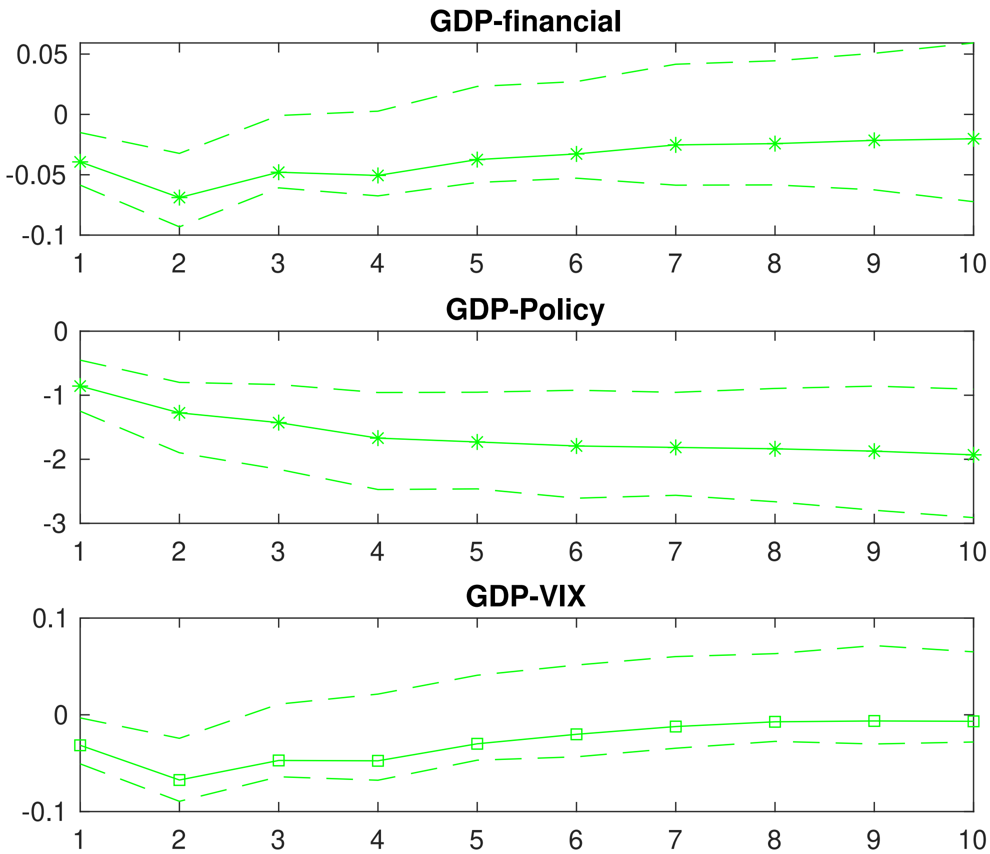
B.7 Additional Graphs

Fig. B.1 Altering the Threshold Variable (1)



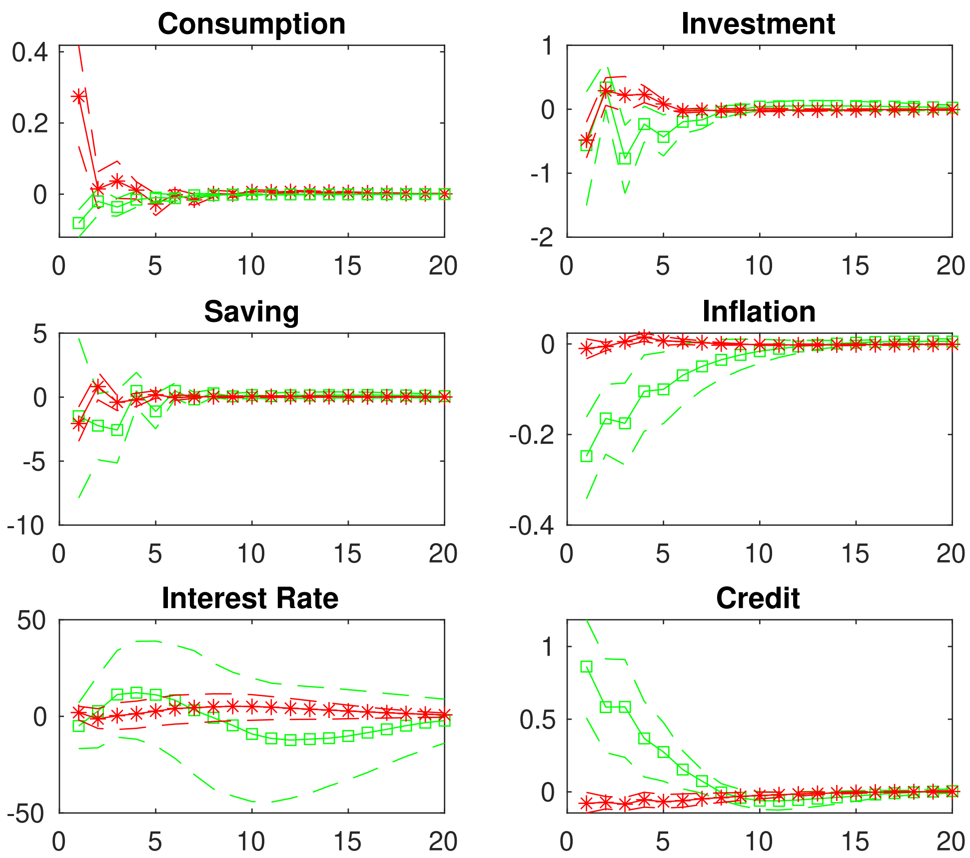
Notes: We document generalised impulse response functions to a 1 standard deviation shock to our narrative series, altering the transition variable we measure use in the threshold estimation. Results are presented for a high uncertainty regime. We also present 68% confidence intervals computed by a bootstrapping procedure outlined in appendix 3.2.

Fig. B.2 Altering the Threshold Variable (2)



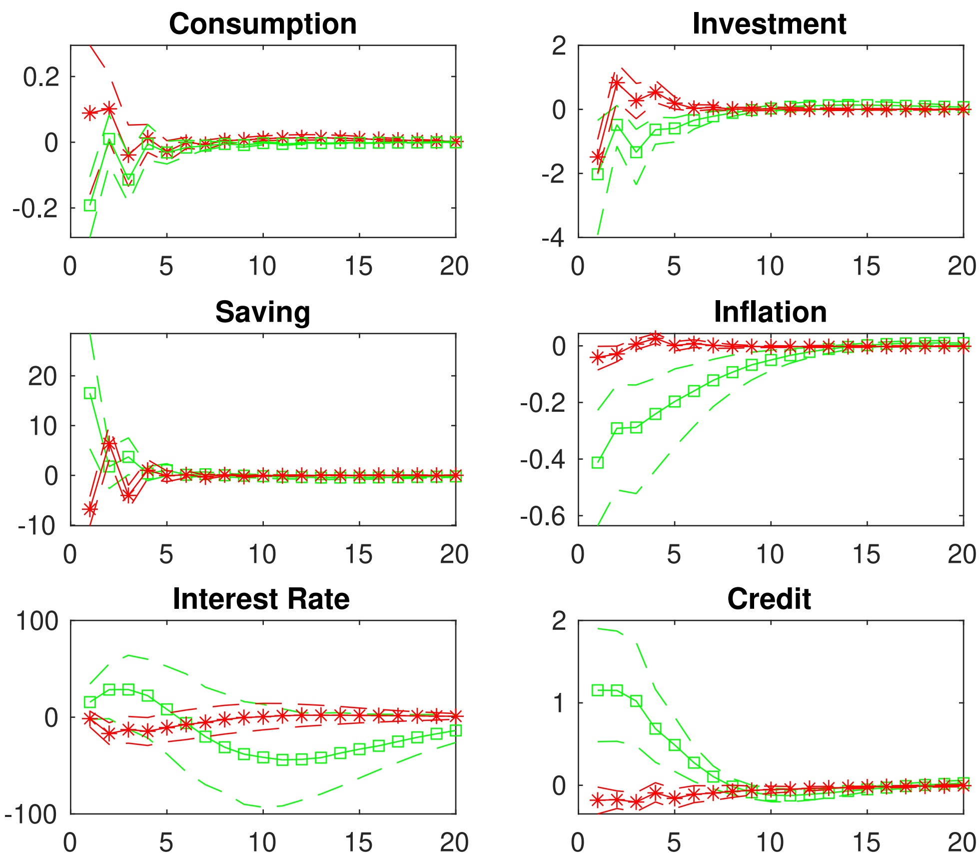
Notes: We document generalised impulse response functions to a 1 standard deviation shock to our narrative series, altering the transition variable we measure use in the threshold estimation. Results are presented for a low uncertainty regime. We also present 68% confidence intervals computed by a bootstrapping procedure outlined in appendix 3.2.

Fig. B.3 Albrizio Narrative Measures



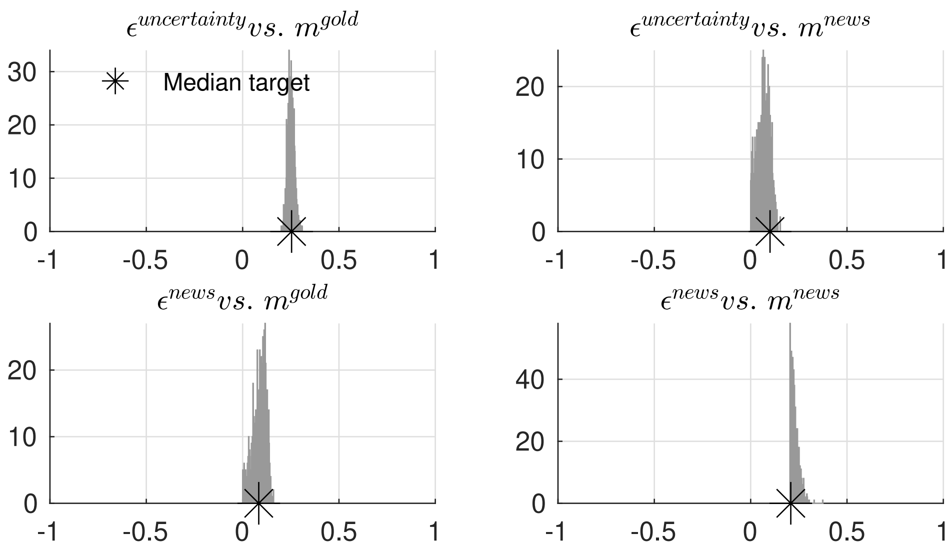
Notes: Generalised impulse response functions from our TVAR model estimated using the narrative uncertainty shocks of Albrizio et al. (2020). The low uncertainty is presented in green while the high uncertainty is presented in red. We also document 68% confidence intervals computed by the bootstrap procedure outlined in Appendix B.2. We use the extended model.

Fig. B.4 Piffer Narrative Measures



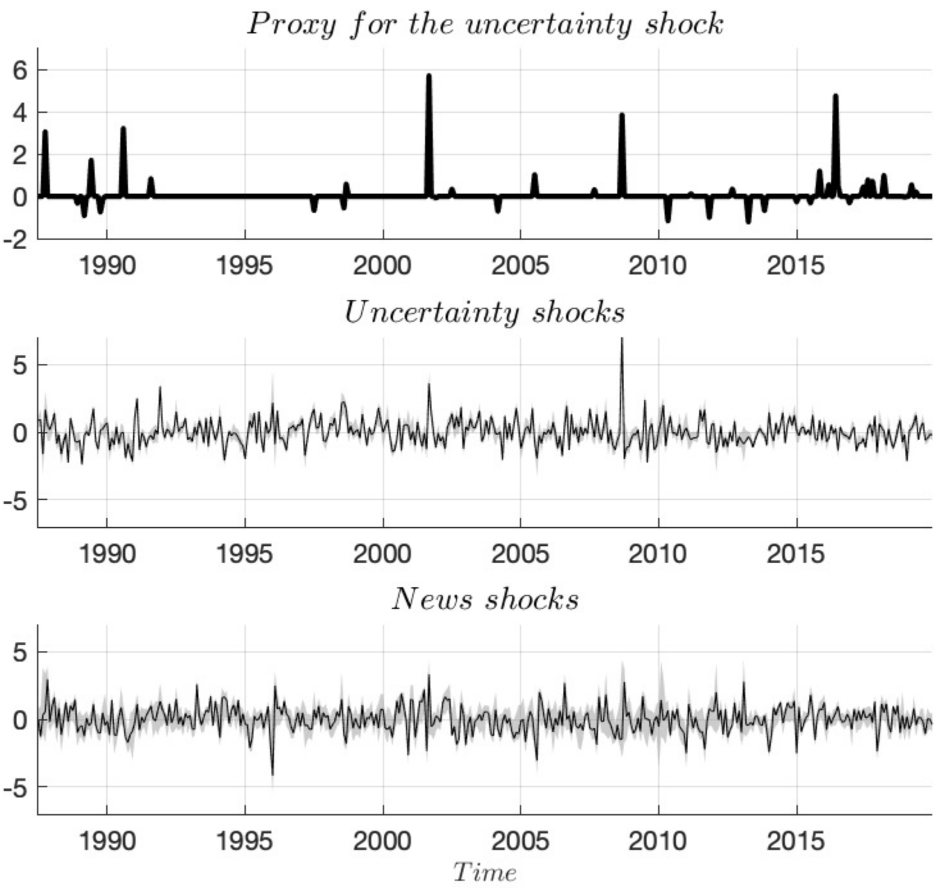
Notes: Generalised impulse response functions from our TVAR model estimated using the narrative uncertainty shocks of Piffer and Podstawski (2018). The low uncertainty is presented in green while the high uncertainty is presented in red. We also document 68% confidence intervals computed by the bootstrap procedure outlined in Appendix B.2. We use the extended model.

Fig. B.5 Correlation Structure



Notes: The estimated correlation structure, Φ. The diagonal plots represent the restriction outlined in equation (2.7) in that the correlations are positive and statistically different from zero. In line with the restrictions in equation (2.8), the off diagonal plots highlight that for each draw, the difference between the correlation shown in the diagonal plots, and the correlation in the off diagonal from the same column is never below the stated threshold.

Fig. B.6 Estimated Shocks



Notes: The top panel shows the proxy for the uncertainty shock, which the middle and bottom document the estimated shock corresponding to the median target specification and 90% confidence bands for uncertainty and news respectively.

Appendix C

Uncertainty, Financial Frictions and the Housing Market

C.1 Estimating Uncertainty

Fig. C.1 Estimating Uncertainty

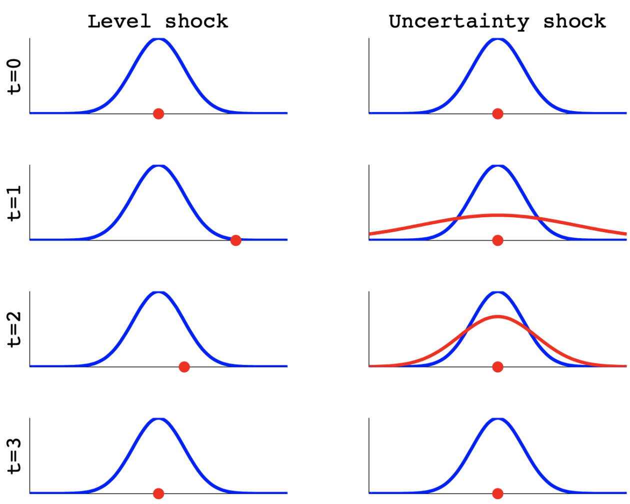


Figure C.1 offers a graphical representation of both a level shock and an uncertainty shock. A macro uncertainty shock works by allowing the variance of total factor productivity shocks to rise, which in turn can be interpreted as the probability of events that are distant from the mean increasing. In the face of higher uncertainty, agents are likely to modify their behaviour, even though there has been no first moment shocks and so the mean outcome remains unchanged.

C.2 Steady State

From the Euler equation of savers, we derive the steady state level of the real interest rate:

$$R_h = \frac{1}{\beta_h} \tag{A1.1}$$

Where the rental rate of capital follows:

$$R_m = R_h - (1 - \delta) \tag{A1.2}$$

Banks are subject to an additional constraint, which ensures that bank equity exceeds a fraction of bank assets, allowing for partial adjustment given by ρ_D. The steady state of the multiplier is given by:

$$\lambda_b = \frac{(1 - \beta_b R_h)}{(1 - \beta_h \rho_D)} \tag{A1.3}$$

As discussed in Iacoviello (2015), we assume that bankers are impatient which implies that as long as $\beta_b > \beta_h$ bankers are credit constrained.

From the Euler equation of entrepreneurs and borrowers we get the corresponding interest rates on loans and gross interest rate respectively:

$$R_e = \frac{1}{\beta_b} - \frac{(1 - \beta_b)\rho_D(1 - \rho_D)\gamma_e}{\beta_b}\lambda_b \tag{A1.4}$$

$$R_s = \frac{1}{\beta_b} - \frac{(1-\beta_b)\rho_D(1-\rho_D)\gamma_s}{\beta_b}\lambda_b \tag{A1.5}$$

The steady state of the credit constraints on entrepreneurs and borrowers is given by:

$$\lambda_e = \frac{(1-\beta_e R_e)}{(1-\beta_e\rho_e)} \tag{A1.6}$$

$$\lambda_s = \frac{(1-\beta_s R_s)}{(1-\beta_s\rho_s)} \tag{A1.7}$$

These act as a wedge between the cost of production and their marginal product and thus act as a tax on the demand for credit and factors of production.

Finally, the return on capital used by entrepreneurs and housing is given by:

$$R_k = \frac{1}{\beta_e} - (1-\delta) - \lambda_e \frac{m_k}{(1-\lambda_e)} \tag{A1.8}$$

$$R_v = \frac{1}{\beta_e} - 1 - \lambda_e \frac{(1-\rho_e)m_h}{\beta_e R_e} \tag{A1.9}$$

We have several restrictions that must hold in order for the credit constraints to be positive.

In order to define the steady state of variables in the model, we follow Iacoviello (2005) by starting with ratios and then moving to levels. As shown in Iacoviello (2005), we have the following constants:

$$\omega_1 = \frac{j}{(1-\beta_h})) \tag{A1.10}$$

$$\omega_2 = \frac{j}{1-\beta_s-\lambda_s(1-\rho_s)m_s/R_s} \tag{A1.11}$$

$$\omega_3 = \frac{1}{1+(1-1/R_s)m_s\omega_2} \tag{A1.12}$$

$$\omega_4 = \gamma_e(R_h - 1)(\frac{\nu m_h}{R_v R_e} + \frac{\mu\alpha m_k}{R_k R_e} - \frac{1-\alpha-\nu}{1+m_n\lambda_e}m_n) \tag{A1.13}$$

$$\omega_5 = \gamma_s \frac{m_s}{R_s}\omega_2\omega_3(R_h - 1) \tag{A1.14}$$

$$\omega_6 = R_m - \delta \tag{A1.15}$$

$$\omega_7 = \frac{(1-\alpha-\nu)(1-\sigma)}{1+m_n\lambda_e} \tag{A1.16}$$

$$\omega_8 = (1-\mu)\frac{\alpha}{R_m} \tag{A1.17}$$

Then the housing consumption ratios are given by:

$$qH_h = \omega_1 C_h \tag{A1.18}$$

$$qH_s = \omega_2 C_s \tag{A1.19}$$

$$qH_E = \frac{\nu}{R_v}Y \tag{A1.20}$$

From the households we have:

$$C_h = (R_m - \delta)K_h + (R_h - 1)D + W_h N_h \tag{A1.21}$$

$$C_s = W_s N_s - (1 - 1/R_s)m_s q H_s \tag{A1.22}$$

Which we can rewrite as:

$$C_s = \omega_3 W_s N_s \tag{A1.23}$$

Following Iacoviello (2015), we define from the FOC of labour supply:

$$z_1 = \omega_6 \frac{\omega_8}{\omega_7} + 1 + \frac{\omega_4}{\omega_7} + \omega 5 \frac{\sigma}{1-\sigma} \tag{A1.24}$$

which allows us to define labour as:

$$n_s = \frac{1}{1 + \omega_3 \tau_s} \tag{A1.25}$$

$$n_h = \frac{1}{1 + z_1 \tau_h} \tag{A1.26}$$

In order to solve for housing we define to consumption to output ratios as:

$$cy_s = \frac{\omega 3(1-\alpha-\nu)\sigma}{1+\lambda_e} \tag{A1.27}$$

$$cy_h = z_1 \omega_7 \tag{A1.28}$$

Therefore,

$$H_h = \omega_1 cy_h Y \tag{A1.29}$$

and,

$$H_s = \omega_2 cy_s Y \tag{A1.30}$$

$$H_e = \frac{\nu}{R_v} Y \tag{A1.31}$$

Using the equation for real estate we can determine steady state q.

The equilibrium is also given as,

$$H_h + H_s + H_e = 1 \tag{A1.32}$$

To complete the steady state equations we have:

$$Y = (\frac{\alpha(1-\mu)}{R_m})^{\frac{\alpha(1-\mu)}{(1-\alpha)}} (\frac{\alpha\mu}{R_k})^{\frac{\alpha\mu}{1-\alpha}} H_e^{\frac{\nu}{1-\alpha}} (N_h^{1-\sigma} N_s^{\sigma})^{\frac{1-\alpha-\nu}{1-\alpha}} \tag{A1.33}$$

$$K_e = \mu\alpha \frac{Y}{R_k} \tag{A1.34}$$

$$K_h = (1-\mu)\alpha \frac{Y}{R_m} \tag{A1.35}$$

$$q = \nu \frac{Y}{R_v} \frac{1}{h_e} \tag{A1.36}$$

$$L_e = m_h q \frac{h_e}{R_e} + m_k \frac{K_e}{R_e} - m_n \frac{1-\alpha-\nu}{1+m_n\lambda e} Y \tag{A1.37}$$

$$L_s = \frac{m_s}{R_s} \omega_2 C_s \tag{A1.38}$$

$$W_h = \frac{1-\alpha-\nu}{1+m_n\lambda e} \frac{(1-\sigma)Y}{N_h} \tag{A1.39}$$

$$W_s = \frac{1-\alpha-\nu}{1+m_n\lambda e} \frac{\sigma Y}{N_s} \tag{A1.40}$$

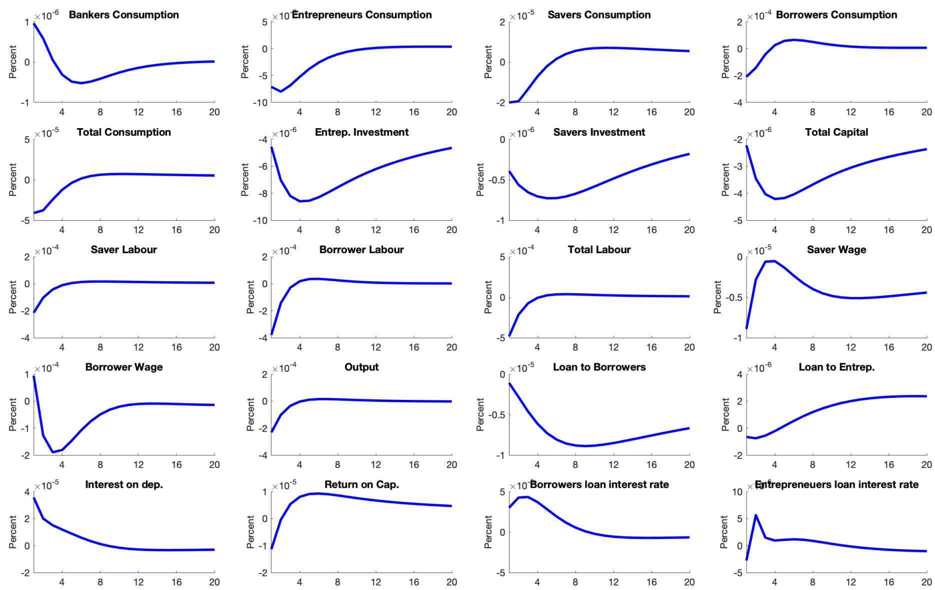
$$D = \gamma_e L_e + \gamma_s L_s \tag{A1.41}$$

$$C_b = (R_e - 1)L_e + (R_s - 1)L_s - (R_h - 1)D \tag{A1.42}$$

C.3 Adjustment Costs

Adjustment costs are assumed quadratic to represent a symmetric impact from uncertainty, that is high uncertainty is equally as costly to agents as low uncertainty. Estimating a negative uncertainty shock we get impulse responses as shown in Figure C.2.

Fig. C.2 Negative Uncertainty and Adjustment Costs



Notes: Estimating impulse response functions from a 1 standard deviation shock to uncertainty which is negative. We utilise our benchmark model. The responses are computed with respect to the ergodic mean of the variables of interest. All responses are in percent. The unit of the x-axis is quarters.

We generate impulse responses that match the results from a positive uncertainty shock across the majority of the variables.