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The Great Moderation and the Great Recession

Macroeconomic Volatility in the United States, the United Kingdom, and Sweden

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Abstract. During the Great Recession between 2007 and 2009, the economies of the United States, the United Kingdom, and Sweden experienced increased levels of macroeconomic volatility. This same volatility had undergone a marked decrease in the United States and the United Kingdom beginning in the 1980s – a phenomenon known as the Great Moderation. In this thesis, we investigate (i) whether Sweden has also experienced a Great Moderation, (ii) whether the Great Recession marks the end of the Great Moderation in the three countries, and (iii) what the causes of increased volatility during the Great Recession are. First, we employ a series of break tests to identify structural changes in macroeconomic time series. To analyze the causes of increased variability, we calculate instantaneous standard deviations and employ a TVP-VAR with stochastic volatility to estimate a macroeconomic model. We find clear evidence of a Great Moderation in Sweden, demonstrated by lower volatility of output, consumption, and inflation. Furthermore, we show that the Great Moderation in all three countries is intact, with the Great Recession only representing a transitory period of increased volatility. Finally, our results suggest that this increase in volatility was largely caused by shocks in the financial systems.

Keywords: business cycle, volatility, structural change, Great Moderation, Great Recession, Bayesian estimation

JEL classification: C11, C32, E20, E32

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Glossary

Abbreviations of Macroeconomic Variables

GDP	Gross Domestic Product
CONS	Private Consumption
INVST	Investment
GOV	Government Expenditure
EXP	Exports of Goods and Services
IMP	Imports of Goods and Services
PICORE	Inflation (measured by the core personal consumption expenditure price index)
CBR	Central Bank Rate
TB3M	3-month Treasury Bill Rate
UR	Unemployment Rate
TWEXR	Trade-Weighted Exchange Rate Index
TED	Interest Rate Spread (between the interest on an interbank loan and the interest on a treasury bill with 3-month maturity)
FSI	Financial Stress Index
HPI	House Price Index
OIL	Crude Oil Price

Countries

United Kingdom (U.K.)	United Kingdom of Great Britain and Northern Ireland
United States (U.S.)	United States of America

Econometric Terms

ADF Test	Augmented Dickey-Fuller test; designed to test for the presence of a unit root process
HAC Estimator	Heteroscedasticity and autocorrelation consistent estimator for the variance covariance matrix of OLS coefficients
MCMC Algorithm	Markov Chain Monte Carlo algorithms; a class of algorithms for sampling from a probability distribution
MSE	Mean Squared Error
OLS	Ordinary Least Squares
SBC	Schwarz Bayesian Information Criterion
SSR	Sum of Squared Residuals
TVP-AR	Time-Varying Parameter Autoregressive Model
TVP-VAR	Time-Varying Parameter Vector Autoregressive Model; extension of the VAR model with parameters that are allowed to vary between time periods
Unit Root	Feature of a non-stationary time series; a series whose mean and variance are not constant over time
VAR Model	Vector Autoregressive Model

1 Introduction

During the years 2007 to 2009 many countries around the world experienced a large increase in macroeconomic volatility. The growth of the gross domestic product (GDP) plunged, unemployment rose, and many countries experienced deep recessions. This worldwide event is now known as the *Great Recession*. Among the countries affected were the United States, the United Kingdom, and Sweden. In 2009, annual growth of real GDP dropped to -2.8% in the U.S., -4.3% in the U.K., and -5.1% in Sweden. Other variables – such as investment, imports, and exports – often dropped by more than 10%.[1] By contrast, the decades leading up to the Great Recession were marked by long periods of low macroeconomic volatility and muted business cycles in many developed countries – a phenomenon that has become known as the *Great Moderation* (Stock and Watson, 2003).

Due to the great economic benefits of reduced growth and inflation volatility, the Great Moderation has been the subject of a large body of academic research (Bernanke, 2004). Yet, research has mainly focused on the United States, while studies on other countries such as the United Kingdom and Sweden have remained relatively scarce – a research gap we aim to fill. Although there is no consensus on the causes of the Great Moderation in the literature, three main types of explanations can be identified: (i) good policy, in particular improved monetary policy, (ii) good luck in the form of reduced exogenous macroeconomic shocks, and (iii) good practices in the form of structural changes in inventory management and financial innovation (Ahmed et al., 2004; Dynan et al., 2006; Giannone et al., 2008; McConnell and Perez-Quiros, 2000).

Researchers had different expectations about whether the Great Moderation would last. For instance, Blanchard and Simon (2001) conclude that "the decrease in output volatility appears sufficiently steady and broad based that a major reversal appears unlikely" (p.164). In the light of the Great Recession, however, some economists raised the question whether this economic downturn actually implied the end of the Great Moderation (Canarella et al., 2010; Clark, 2009). Since the state of volatility affects forecasting and policy decisions, it is crucial to know whether the economy has indeed returned to a high-volatility state – equivalent with a reversal of the Great Moderation – or remained in a low-volatility state (Bean, 2010).

[1] The exact timing of the recessionary periods differs between countries. In the remainder of this study, we consistently define the Great Recession period as the time from 2007:Q1 to 2009:Q4. This period includes the recessions in all three countries.

Thus, this empirical study evaluates (i) whether there is evidence of a Great Moderation in Sweden, (ii) whether the Great Moderation in the U.S., the U.K., and Sweden has ended with the Great Recession, and (iii) what the causes of the increased volatility during the Great Recession are. Our choice of countries also allows for comparative conclusions based on different characteristics of the economies. While the United States are a large economy with a prominent financial sector, the economy of the United Kingdom is much smaller with the financial sector playing a relatively even more important role. The Swedish economy, by contrast, is more trade dependent – exports amounted to 44%, imports to 39% of GDP in 2013. In the United States, these ratios were only 13% and 17%, respectively.

In our analysis, we rely on three different empirical methods. First, we employ structural break tests developed by Bai (1997) and Bai and Perron (1998) to detect structural changes in the volatility of a set of macroeconomic time series. Then we estimate a time-varying parameter autoregressive (TVP-AR) process and calculate so called instantaneous standard deviations, which allow a better visual analysis of the changes in volatility and provide preliminary insights into the causes of increased volatility. Eventually, we employ a time-varying parameter vector autoregression (TVP-VAR) with stochastic volatility to estimate a macroeconomic model. At each point of time, we then calculate the forecast error variance decomposition to get further evidence on the causes of the increased fluctuations during the Great Recession.

The results of the empirical analysis support three main findings. First, we observe evidence of the Great Moderation also taking place in Sweden. A number of Swedish macroeconomic series have exhibited clearly decreased variability, partly since the 1980s, partly since the early 1990s. Second, we argue that the Great Moderation has not ended with the Great Recession. In fact, the Great Recession represents only a short-term increase in macroeconomic volatility, with most series stabilizing since 2010. Third, the short-term increased volatility during the Great Recession can mainly be attributed to shocks in the financial system.

The remainder of this study is organized as follows: Section 2 reviews previous findings on the Great Moderation, its relevance, suspected causes, and potential end. Additionally, it provides descriptive statistics on the increased volatility and poses our research questions. In Section 3, we describe the methodology and findings of our structural break tests. Section 4 presents the methods used to analyze the causes of increased volatility and their respective results. In Section 5, we discuss our empirical findings in the context of our research questions. Section 6 concludes.

2 The Great Moderation and the Great Recession

Before we start our analysis, we will review the existing literature regarding the Great Moderation and some descriptive statistics to motivate our research questions. To make clear the importance of the Great Moderation, Section 2.1 will briefly outline how reduced macroeconomic volatility is associated with positive effects on a country's economy. In Section 2.2 we then summarize previous findings on the timing, causes, and potential end of the Great Moderation. Thereafter, Section 2.3 describes our data and gives some preliminary evidence on the Great Moderation in Sweden. Moreover, we find increased volatility across a wide array of variables during the Great Recession in all three countries. Finally, Section 2.4 states our research questions.

2.1 Why Does Volatility Matter?

While the Great Moderation – at least in the United States – has been found to imply a decrease in variability in a wide range of macroeconomic series, the term is mostly used to describe the reduced volatility of real output growth and inflation, which will be discussed in the following paragraphs.

For a long time it appeared to be common knowledge that stable output growth is better for the economy and any individual's welfare than a volatile business cycle. Therefore, stabilization of the business cycle has been a policy objective in many developed countries. The United States, for example, passed the Employment Act of 1946 which made macroeconomic stability an objective by law (Yellen and Akerlof, 2006). In his 1987 seminal contribution, however, Lucas (1987) argues that welfare gains from stabilizing output growth and thus consumption would be negligible, given that economic policy can at all be effective in doing so. This notion has led to a large body of research analyzing the issue. While earlier work was able to substantiate his findings, the more recent literature largely agrees that Lucas' approach oversimplified the analysis and conclude that gains from stabilization policy can be substantial (Barlevy, 2004). For instance, Chatterjee and Corbae (2000) argue that reducing business cycle fluctuations also decreases the likelihood of depression. Eliminating recessions can lead to an equivalent of annual consumption gains of about 1 to 7 percent. Storesletten et al. (2000) find a somewhat lower number, but state that an individual would be willing to sacrifice an average of 2.5 percent of lifetime consumption for the elimination of business cycle fluctuations. Similarly, Yellen and Akerlof (2006) argue that stabilization policy can produce substantial welfare gains, but without making an actual estimate of the effect. In a very recent study, Den Haan and Sedlacek (2014) estimate the cost of business cycles between 2 and 13 percent of GDP. Even though an exact estimate of the value of decreased output growth volatility is not obtainable, the cost of business cycles is likely to be significant and reduced volatility – as observed during the Great Moderation – can be associated with a valuable welfare gain.

The same applies to reduced volatility of inflation. The most essential argument against fluctuating inflation rates is the fact that they reduce the transparency of the price mechanism. Individuals find it difficult to account for inflation in their decision-making. Stable prices make it easier for consumers to identify changes in relative prices and thus make informed decisions and allocate resources efficiently (ECB, 2011). Laubach and Mishkin (2001) argue that people start to hedge when inflation is unpredictable, which is naturally associated with cost. Also, most tax and social security systems are not entirely linked to inflation rates. They can be distorted in their effectiveness and may create false incentives. Stable inflation is furthermore crucial for the soundness of financial systems, as sudden revaluations of financial assets can create instabilities (ECB, 2011). Finally, Rother (2004) cites empirical evidence that inflation volatility has negative effects on growth and is positively correlated with output volatility.

2.2 Previous Findings on the Great Moderation and Its Potential Ending

Given this importance of the phenomenon, the Great Moderation in the United States has been studied by numerous researchers. There is also evidence of similar phenomena in other developed countries even though timing and magnitude of the decrease in volatility differ between regions. During the Great Recession in the wake of the 2007/2008 financial crisis, unusual and unexpected levels of macroeconomic volatility arose in most of the developed world. Some studies provide preliminary analysis of this increase in volatility and some evidence on whether the economy in the respective countries has returned to a permanent state of high volatility or whether this increase was only temporary. This section summarizes previous findings on both the Great Moderation and its continuation for the United States, the United Kingdom, and Sweden.

After giving an overview over evidence on its existence and timing, we will discuss potential explanations of the Great Moderation and increased volatility during the Great Recession. Even though findings on the causes of the Great Moderation are still inconclusive, they can provide a natural starting point when analyzing the causes of its potential end.

2.2.1 The Existence and Timing of the Great Moderation

United States One of the first studies on the Great Moderation in the United States was published by Kim and Nelson (1999). They use a Markov-switching model to study the decline in volatility of real GDP growth and find a break in the beginning of 1984. This dating of the break in output growth volatility is confirmed by McConnell and Perez-Quiros (2000), who employ a series of structural break tests to analyze the decline in GDP volatility. They note that the variance of output fluctuations before the break is more than four times as large as the variance after the break. These results are also verified by Stock and Watson (2003), who expand the analysis to a much larger set of variables and test for a one-time break in each of those. They find that the reduction of volatility is wide-spread throughout many macroeconomic measures, including most GDP components (consumption, investment, government spending, exports, imports), employment, as well as wage and price inflation. Similar evidence is brought forward by Sensier and van Dijk (2004) who also study a large set of series and find breaks in the majority of those. Most of the breaks are found to be centered around the early 1980s and decreases in volatility are estimated to be around 50%. Conducting Bayesian analysis, Kim et al. (2004) further support these findings. They find evidence of a volatility reduction in the cyclical component of real GDP during the mid-1980s, while this reduction is not found for the trend component of real GDP. Also, they further support the evidence for reduced volatility in inflation.

Overall, there is broad agreement on the fact that macroeconomic volatility in the United States has been markedly reduced since the mid-1980s. Blanchard and Simon (2001), however, propose a different interpretation of the decrease in output volatility. Rather than identifying a one-time break in volatility, they argue that there has been a steady decline in volatility since the 1950s, which was interrupted in the 1970s and early 1980s. While the question whether there has been a long-time downward trend or a one-time decrease in variability has not been finally answered, both Stock and Watson (2003) and Sensier and van Dijk (2004) argue that the volatility changes are better characterized by discrete breaks.

More recently, the debate arose whether the 2008-2009 recession in the United States and the significantly increased macroeconomic volatility during this period marks the end of the Great Moderation and whether the economy has returned to a state of higher variability. The earliest evidence is provided by Canarella et al. (2010) who use data only until the second quarter of 2007. Using a Markov-switching model they allow for a switch between a low-volatility and a high-volatility state of GDP growth. They find preliminary indications that the economy has switched to a high-volatility state and interpret this as the end of the Great Moderation. Chen (2011) employs a similar methodology to a longer data set and finds a switch to the high volatility state in the end of 2007, but also shows that output growth had returned to a low-volatility state by the beginning of 2010.

Looking at data through the second quarter of 2009, Clark (2009) finds that volatility of the growth of GDP and its components, inflation, and interest rates is significantly higher at the end of his sample than in 2003, but argues that this increase is temporary. This view is shared by Gadea et al. (2013), who find no structural break in output growth volatility during the Great Recession.

United Kingdom and Sweden Research on the Great Moderation in the United Kingdom and Sweden is relatively scarce and mostly exists in the context of international comparative studies. Studying the United Kingdom, Benati (2004) finds significant reductions in the volatility of output growth and inflation, with the latest breaks coinciding with the introduction of an inflation targeting regime in 1992. Fang et al. (2008) identifies a similar timing for the decrease in output growth volatility, while Summers (2005) and Stock and Watson (2005) place it about a decade earlier. Analyzing a somewhat larger set of variables, van Dijk et al. (2002) find volatility reductions in industrial production, imports, exports, inflation and interest rates, with break dates ranging from the late 1970s to the early 1990s. Ćorić (2012), who studies a large set of countries through 2007, finds decreases in output growth variability for both Sweden and the United Kingdom during the early 1990s. This result is confirmed by Cecchetti et al. (2006). In summary, there appears to be evidence of decreased volatility since the early 1990s. Yet, research is all but limited to output growth and inflation variability.

To the best of our knowledge, there exist no studies concerning the end of the Great Moderation in Sweden. Two of the studies cited with respect to the United States, however, also include research on the United Kingdom. The findings for the United Kingdom in Canarella et al. (2010) and Chen (2011) are equivalent to those in the United States. The former identify the preliminary end of the Great Moderation in 2007, while the latter shows that output growth had returned to a low-volatility state by 2010.

2.2.2 Potential Causes of the Great Moderation

United States The research regarding the causes of the Great Moderation in the United States can largely be clustered into three different categories: (i) good policy, (ii) good luck, and (iii) structural changes in the economy. Regarding the decreased volatility of inflation, there is wide agreement that this has largely been a result of better monetary policy (Ahmed et al., 2004; Bernanke, 2004; Leduc and Sill, 2007; Nakov and Pescatori, 2010; Stock and Watson, 2003; Summers, 2005). For instance, Clarida et al. (2000) find systematic differences in policy between the Volcker-Greenspan era (beginning in 1979) and previous periods and conclude that better policy rules helped decreasing inflation and inflation volatility.

Despite a large body of research there is still no agreement on the causes of the decrease in output volatility. Most researchers refrain from attributing the Great Moderation to one of the potential causes, but put different emphasis on the competing explanations. Blanchard and Simon (2001) note that inflation volatility and growth volatility exhibit a strong co-movement, indicating that the reduced variability of growth may to some extent be a result of the policy-induced reduction in inflation variability. This view is supported by Bernanke (2004) and Stock and Watson (2003), who find that monetary policy plays some role moderating output volatility.

Yet, Stock and Watson (2003) argue that much of the volatility reduction is still a result of good luck. By good luck they mean that there have been smaller economic disturbances, such as oil price or productivity shocks, hitting the economy. This result is supported by the findings of Ahmed et al. (2004), Benati and Mumtaz (2007), and Canova (2009), all of whom conclude that better policy and structural changes played a minor role in output stabilization compared to the absence of shocks. Both Leduc and Sill (2007) and Nakov and Pescatori (2010) note that these decreased disturbances can indeed mostly be identified as reductions in shocks to total factor productivity (TFP). Looking into the causes of reduced shocks to TFP, Dhawan et al. (2010) find that shocks to energy prices spilled over into TFP until around 1982, but that this spillover has since disappeared. They argue that this change can explain the majority of the moderation in growth volatility.

Giannone et al. (2008) argue that the models providing evidence in favor of the good luck hypothesis are too small and overly naïve. Estimating a large macroeconomic model, they find that the Great Moderation can be explained by structural changes of the economy, without specifying what these changes are. Other researchers identify a number of structural changes, also referred to as good practices, that may serve as explanations of the Great Moderation. McConnell and Perez-Quiros (2000) note that the volatility reduction is concentrated in the production of durable goods and can be explained by improved inventory management by firms. This improvement is then attributed to better information technology systems by Kahn et al. (2002). A role of improved inventory management is also recognized by Cecchetti et al. (2006), who further suggest improved financial systems as a possible explanation. Financial innovations are also identified as a potential cause of the Great Moderation by Dynan et al. (2006). Examples of such innovation are for instance improved lending practices and loan markets which have improved the borrowing ability of both households and firms as well as changes in government policy. The view of Dynan et al. (2006), however, is rejected by Den Haan and Sterk (2011), who find that borrowing behavior has changed less than previously believed.

United Kingdom and Sweden Again, research on the United Kingdom and Sweden is relatively scarce and inconclusive. For the United Kingdom, Summers (2005) suggests that both improved monetary policy and better inventory management may serve as explanations for reduced macroeconomic volatility. His conclusions, however, are solely based on a similar timing of the Great Moderation and reductions in inflation volatility and inventory investment volatility. Estimating a macroeconomic model, Benati (2008) finds that the Great Moderation in the United Kingdom is mostly the result of good luck, even though its timing coincides with the introduction of inflation targeting. Cecchetti et al. (2006), however, argue that for both the United Kingdom and Sweden evidence suggests that reduced output volatility may be the result of financial innovations and improved inventory management. Studying a large set of countries, Ćorić and Mustra (2014) find that the Great Moderation around the world, including the United Kingdom and Sweden, is not just the result of decreased macroeconomic volatility in the United States, but has domestic causes.

2.2.3 Causes of Increased Volatility During the Great Recession

United States For the United States, there already exists a significant amount of literature on the Great Recession and its causes which is closely related to the notion of increased volatility during this period. There is wide agreement that the single most important factor causing the large drop in GDP growth are shocks in the financial system and financial frictions (Arellano and Kehoe, 2012; Caldara et al., 2014; Christiano et al., 2014). Clark (2009) additionally attributes some of the volatility during the recession to oil price shocks, while housing prices and residential investment only play a minor role. Similarly, Stock and Watson (2012) find that the recession was mostly caused by shocks to the financial system, with oil price shocks and monetary policy shocks playing a secondary role. Bean (2010) suggests that the meltdown of the financial system may actually have been a result of the Great Moderation. He argues that the reduced volatility of the economy shifted risk perceptions of participants in financial markets and subsequently led them to take on excessive risks and invest into complex financial instruments.

United Kingdom and Sweden To the best of our knowledge, there exists very little published academic work that disentangles the causes of the Great Recession and increased macroeconomic volatility in the United Kingdom and Sweden. Hills et al. (2010) note that the recession in the United Kingdom was most likely a result of shocks to the financial system. Benati (2012) argues that the Swedish economy did not stand at the epicenter of the financial crisis. He hypothesizes that it has mostly been affected through trade channels.

2.3 Volatility Throughout the Decades

To start our analysis of macroeconomic volatility in the United States, the United Kingdom and Sweden, we first study some descriptive statistics. The following sections describe our data and its properties and summarize the most important findings when looking at standard deviations – a simple measure of volatility – throughout the decades.

2.3.1 Data and Data Properties

In our analysis, we consider data on quarterly macroeconomic time series from 1960:Q1 to 2014:Q2 for all three countries. For reasons of clarity and data availability, we restrict our analysis to 15 variables. Yet, as customary in the literature, we systemically cover many macroeconomic categories. These categories include (1) real GDP and its decomposing variables, (2) private consumption expenditure and house price inflation, (3) interest rates and the TED spread, (4) employment, (5) exchange rates, (6) an index of financial stress, and (7) the real price of oil. We use seasonally adjusted series where available. For variables which are not reported quarterly, we rely on monthly data and use the average as aggregation method. Data sources include national central banks, national statistical agencies and the OECD StatExtracts database, but vary greatly across countries. Financial stress indices for the United Kingdom and Sweden are not readily available and are therefore constructed as described in Appendix B. Other time series are not available for the entire period under consideration in all countries. A detailed overview of the data sources and data availability can be found in Appendix A.1.

Given the data at hand, we face a trade-off between stationarity and reduced volatility. Testing for a unit root is essential, since stationarity is a desirable data property in our analysis. Suppose a time series contains a unit root. In such a case, the series will not revert to a long-run mean. And without a long-run mean, it is difficult to assess whether the volatility of the series has changed or not, since we are following Stock and Watson (2003) in using the absolute value of the demeaned series as a raw estimate of volatility. The data transformation, however, comes at the cost of reduced variation in the data – a fact of particular importance when testing for structural breaks. Moreover, Enders (2010) advises to be cautious in performing augmented Dickey-Fuller (ADF) tests for the detection of unit roots if one suspects a structural change. In such cases, the ADF test is biased toward the nonrejection of the unit root – a finding confirmed by a Monte Carlo experiment by Perron (1989).

Relying on economic reasoning, we choose to transform the data to growth rates and first differences, respectively. Real GDP and its components clearly follow a trend and are therefore transformed to quarterly growth rates by taking logged first differences. Given the original series Y_t, the transformation is $\log(Y_t/Y_{t-1})$. The price indices and oil prices are converted to quarterly inflation rates using the same transformation. For the inflation rate, interest rates and TED spread, unemployment rate, the exchange rate index, and the financial stress index we then take first differences using the transformation $Y_t - Y_{t-1}$. We test the transformed data for a unit root to make sure we can calculate proper descriptive statistics and meaningfully test for breaks in volatility in the next section.

In doing so, we perform ADF test to check for a unit root (Dickey and Said, 1984). Allowing for a drift, we apply the following form of the ADF test to the transformed variable y_t:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=1}^{p} \Delta y_{t-p} + \varepsilon_t, \qquad (2.1)$$

where Δy_t is the first difference of y_t, a_0 is the drift term and ε the white-noise error term. The drift component is included to control for the possibility of a volatility drift captured by the transformed series y_t. The appropriate number of lags p to be included in the ADF test (2.1) is determined by the Schwartz Bayesian Information Criterion (SBC) for each variable y_t. By calculating the Ljung-Box Q-statistic, we check for remaining serial autocorrelation and add further lags if necessary. Given the data and final lag selection p, the ADF test then evaluates the null hypothesis of a unit root $H_0 : \gamma = 0$ against the alternative $H_1 : \gamma < 0$. As shown in Appendix A.2, we are able to reject the null of a unit root for each of the transformed series at the 1% significance level and can proceed with our analysis.

2.3.2 Descriptive Statistics

Table 2.1 reports sample standard deviations for each of the time series by decade and for the recession period, which we define to last from 2007:Q1 to 2009:Q4. It provides preliminary evidence of considerably increased volatility across a wide range of variables during this period and of the existence of a Great Moderation in Sweden.

United States In the United States, volatility during the Great Recession was higher than in the preceding ten years for all variables except government expenditure. GDP growth was 1.81 times as volatile as previously, inflation 1.7 times. Volatility of the Federal Funds Rate and the Treasury Bond Rate was only slightly elevated. The largest volatility increases, however, can be seen in variables that indicate stress in financial markets, namely the TED spread and the financial stress index, which fluctuate four to five times as much as before. The house price index was also much more volatile than previously, with a standard deviation 2.65 times as high as before.

United Kingdom For the United Kingdom, the picture looks a little different. While we clearly observe increased variability in the growth rates of GDP, consumption, and investment, volatility for some other series stayed level or even decreased. For instance, growth of trade components of GDP did not become more volatile and inflation variability slightly decreased. Similar to the United States, the largest volatility increases are observed for the TED spread and the financial stress index, which were six and four times as volatile as before, respectively.

Table 2.1: Standard Deviation of Time Series by Decade and During The Great Recession

	Full Sample	1960s	1970s	1980s	1990s	2000s	2010s	Recession	*Recession relative*
United States									
GDP	0.85	0.85	1.08	0.97	0.53	0.73	0.47	0.93	*1.81*
CONS	0.68	0.69	0.81	0.80	0.53	0.58	0.23	0.55	*1.34*
INVST	4.12	4.38	5.02	4.91	2.57	3.69	2.48	5.09	*2.13*
GOV	1.02	1.37	0.93	0.98	0.76	0.65	0.72	0.58	*0.85*
EXP	3.66	6.50	3.78	2.32	1.66	2.88	1.29	3.99	*1.81*
IMP	3.38	4.38	4.52	3.46	1.43	2.82	1.40	3.92	*2.17*
PICORE	0.21	0.13	0.31	0.30	0.11	0.18	0.13	0.24	*1.70*
HPI	1.03	–	–	0.89	0.58	1.05	1.27	1.63	*2.65*
UR	0.34	0.25	0.43	0.40	0.21	0.36	0.16	0.44	*2.22*
TWEXR	2.28	–	1.84	3.07	2.02	2.25	1.37	3.04	*1.52*
CBR	0.93	0.49	1.22	1.58	0.41	0.57	0.03	0.55	*1.17*
TB3M	0.74	0.37	0.81	1.33	0.37	0.53	0.03	0.49	*1.10*
TED	0.22	–	–	–	0.14	0.30	0.11	0.54	*4.25*
FSI	0.51	–	–	–	0.25	0.74	0.24	1.33	*4.91*
OIL	18.21	–	–	–	19.09	21.30	11.75	32.71	*2.25*
United Kingdom									
GDP	0.97	1.02	1.51	0.88	0.60	0.78	0.39	1.08	*2.85*
CONS	1.09	1.17	1.61	1.06	0.79	0.80	0.38	0.92	*1.66*
INVST	2.98	3.43	2.56	3.61	2.03	3.36	1.87	4.06	*1.51*
GOV	1.21	1.51	1.15	1.22	1.09	1.02	1.22	0.71	*0.56*
EXP	3.38	3.38	5.03	2.15	1.80	3.97	2.46	2.74	*0.73*
IMP	3.08	2.95	3.90	3.52	1.87	3.36	1.81	3.00	*1.01*
PICORE	1.50	–	2.14	1.63	1.41	0.92	0.84	0.89	*0.89*
HPI	1.38	–	–	1.35	1.13	1.79	0.82	2.09	*1.41*
UR	0.25	–	–	0.23	0.26	0.23	0.22	0.33	*2.29*
TWEXR	2.69	–	–	3.41	2.59	2.40	1.46	3.31	*1.92*
CBR	0.95	–	–	1.22	0.60	0.51	0.00	0.81	*2.33*
TB3M	0.94	–	–	1.19	0.63	0.54	0.05	0.86	*2.45*
TED	0.22	–	–	–	0.14	0.31	0.10	0.57	*6.10*
FSI	0.49	–	–	–	0.24	0.69	0.32	1.20	*4.07*
OIL	19.71	–	–	–	21.69	21.80	9.22	32.46	*1.97*
Sweden									
GDP	1.30	1.69	1.26	1.51	0.94	1.05	0.99	1.46	*2.44*
CONS	1.66	2.62	2.11	1.39	1.12	0.71	0.63	0.89	*1.32*
INVST	2.95	2.20	3.36	2.54	3.35	3.06	2.82	3.72	*1.51*
GOV	0.89	0.61	1.18	0.86	0.85	0.37	0.24	0.41	*0.62*
EXP	3.70	4.84	4.18	4.19	2.59	2.88	2.13	3.75	*1.82*
IMP	4.00	3.86	6.65	3.53	2.58	2.98	1.85	4.12	*2.01*
PICORE	1.38	–	1.50	0.96	1.25	1.51	1.91	1.65	*1.18*
HPI	2.32	–	–	–	2.82	2.30	1.40	3.13	*1.67*
UR	0.34	–	–	0.11	0.47	0.33	0.17	0.38	*1.20*
TWEXR	3.24	–	–	2.49	3.91	3.30	2.63	4.92	*1.90*
CBR	0.63	0.43	0.56	0.75	0.79	0.68	0.24	0.82	*1.48*
TB3M	0.90	–	–	1.07	1.23	0.49	0.25	0.78	*2.71*
TED	0.19	–	–	–	0.25	0.16	0.18	0.28	*4.49*
FSI	0.50	–	–	–	0.50	0.50	0.50	0.84	*2.74*
OIL	20.20	–	–	–	22.71	22.03	9.94	33.00	*2.01*

Note: In percentage points, TWEXR and FSI in index points. Recession period defined as 2007:Q1-2009:Q4. The last column gives the standard deviation during the Great Recession relative to the 10 years prior to the crisis. 2010s only refers to the period 2010:Q1 to 2014:Q2.

Sweden First of all we notice some preliminary hints toward the existence of the Great Moderation in Sweden. Despite the financial crisis in the early 1990s and in the second half of the 2000s, we observe that the volatility of GDP, consumption, and the trade components of GDP is markedly lower in these two decades. This trend continues throughout the 2010s. Such a reduction, however, cannot be observed for the variability of investment, inflation, unemployment, or the exchange rate. There appears to be a stabilization of output, that is not evident throughout other macroeconomic time series.

With respect to the Great Recession, we note that – as in the United States – volatility has increased in all variables under consideration except for government expenditure. GDP growth was 2.44 times as variable as in the previous ten years, while volatility of inflation and unemployment increased only by about 20 percent. We observe, however, a notable increase in the volatility of exports and imports. As in the other two countries the highest volatility increases occurred in measures of financial market stability – the TED spread and the financial stress index.

2.4 Research Questions

This section has shown that the Great Moderation is a highly relevant phenomenon, which has received a lot of attention in academic research. The analysis, however, has all but been limited to the United States. Moreover, we notice that during the Great Recession volatility in all three countries has returned to levels that had not been observed in the decades before. Evidence on the question whether this implies the end of the Great Moderation is still inconclusive, and the causes of the increased volatility have only been studied for the United States. Consequently, we pose the following three research questions:

1. Did or does Sweden experience a Great Moderation?
2. Did the Great Recession in the United States, the United Kingdom, and Sweden mark the end of the Great Moderation in these countries?
3. What are the causes of the – at least in the short term – increased volatility?

Section 3 focuses on the analysis of the first and second question, whereas Section 4 concentrates on the third research question.

3 Structural Breaks in Volatility

In this section we investigate whether the macroeconomic variables at hand have experienced statistically significant changes in volatility by conducting break testing analysis. We find structural breaks in many of the macroeconomic variables during the 1980s and 1990s, indicating that the economies of the United States, the United Kingdom, and Sweden entered periods of lower volatility. Whereas this is a well-known fact for the U.S. and has previously been noted for the U.K., we are the first to explicitly show that the Great Moderation also took place in Sweden. Our results further suggest that the respective economies remain in a state of low volatility during the Great Recession. Across all three countries, the increased volatility during the Great Recession was not persistent enough to represent structural breaks in the volatility of GDP and its components. Only some breaks in macrofinancial variables hint at a state of higher volatility in the financial sector.

To conduct structural break analysis and detect lasting changes in the volatility of a variable, we need a framework which (i) accounts for the possibility of multiple breaks and (ii) enables us to investigate the origin of the possible breaks. One framework that meets those requirements is the sequential procedure for the detection of multiple structural breaks at an unknown date by Bai (1997) and Bai and Perron (1998, 2003a). We apply this sequential procedure to different features of the variable to assess both the occurrence and the origin of possible breaks.[1] First, we check for the presence of breaks in the unconditional variance of the variable. Then we examine if found changes in the unconditional variance are due to changes in the conditional mean (propagation), the conditional variance (impulses), or both. This distinction is crucial to explain the origin of a structural break.

In the following, we describe the application of the sequential procedure by Bai (1997) and Bai and Perron (1998, 2003a) in more detail. In Section 3.1, we outline the methodology used to estimate unknown break dates and assess their significance. In Section 3.2, we apply this procedure to our purposes, namely the detection of breaks in the unconditional variance, conditional mean and conditional variance. For this purpose, we use the example series of U.S.

[1] The analysis is carried out in MATLAB Version 8.3. All code and programs are available upon request from the authors. Some functions were obtained from Pierre Perron, whose generosity is gratefully acknowledged.

GDP from 1960:Q1 to 2014:Q2 to make the framework more comprehensible. Section Section 3.3 presents the results for all three countries.

3.1 Multiple Break Testing – Sequential Procedure

As mentioned in the previous section, there is a consensus about a break in macroeconomic volatility in the United States. When looking at the other two countries, however, the evidence for the Great Moderation is not as clear cut. We do not know if and when there are structural breaks in these time series. Moreover, we want to know whether there was a structural break in volatility at the beginning of the financial crisis and the subsequent recessions. Therefore we use the sequential estimation procedure of multiple breaks developed by Bai (1997) and Bai and Perron (1998, 2003a) to test for such breaks. This estimation of multiple unknown break dates essentially consists of two parts. We first need to find break date candidates in the data sample, which we then evaluate for their significance by using statistical tests designed for that particular purpose.

In a first step, we split the data sample at each possible break date, estimate a regression model by ordinary least squares and store the sum of squared residuals. In doing so, we are able to detect possible break dates, as the sum of squared residuals can have a local minimum near each break date (Bai, 1997). The global minimum - the break date which minimizes the sum of squared residuals (SSR) over the full sample – serves as the first break date candidate. Potential other local minima can be seen as indicators of subsequent break dates, if the first break date estimate is significant. Let us assume this situation proves to be the case. Then the sequential procedure splits the series in two at the first break date, creating two new *partitions*. If another significant break is found in at least one of the two created partitions, also referred to as *regimes* in the literature, another iteration starts until we cannot find any more significant breaks.

More specifically, we consider a multiple linear regression model with m breaks (and $m+1$ regimes):

$$y_t = \boldsymbol{x}_t' \boldsymbol{\beta}_j + \varepsilon_t \qquad (t = T_{j-1}+1, \dots, T_j), \tag{3.1}$$

for $j = 1, \dots, m+1$, using the convention $T_0 = 0$ and $T_{m+1} = T$. y_t is the observed dependent variable, $\boldsymbol{x_t}$ is the vector of length $q+1$ of the constant and q covariates, with $\boldsymbol{\beta}_j$ capturing the corresponding vectors of coefficients; ε_t is the error term. Since all coefficients $\boldsymbol{\beta}_j$ are subject to change, equation (3.1) is also called a pure structural change model.[2]

Based on the least-square principle, we then minimize the sum of squared residuals

$$\sum_{j=1}^{m+1} \sum_{t=T_{j-1}+1}^{T_j} [y_t - \boldsymbol{x}_t' \boldsymbol{\beta}_j]^2,$$

for each j-partition $(T_{j-1}, \dots, T_j)$, denoted by $\{T_j\}$. The resulting estimates of the coefficients are denoted by $\hat{\boldsymbol{\beta}}(\{T_j\})$. If we substitute those estimates $\hat{\boldsymbol{\beta}}(\{T_j\})$ in the objective function (3.1), we obtain the residuals of the model. Those can be used to calculate the sum of squared residuals $S_T(T_1, \dots, T_m)$. Minimizing over all partitions $\{T_1\} \dots, \{T_{m+1}\}$, we find the break date estimates $\widehat{T_1}, \dots, \widehat{T_m}$:

$$(\widehat{T_1}, \dots, \widehat{T_m}) = \underset{(T_1, \dots, T_m)}{\operatorname{argmin}} \; S_T(T_1, ..., T_m),$$

such that $T_j - T_{j-1} \geq h$, where h is the minimal permissible partition length. It is crucial to set an upper limit on the number of possible breaks m, since another break would always yield a better fit to the minimization problem. With increasing m, we would obtain more and more break date estimates without any knowledge about their statistical significance. Hence, a formal significance test is required to set a limit to the number of possible breaks.

For this purpose, Perron (2006) suggests a combination of two tests, a version of a double maximum ($Dmax$) test and the $F(l+1|l)$-test. The former is used to determine whether any structural break is present or not, whereas the latter is used to determine the number of breaks by sequentially testing l versus $l+1$ breaks. Perron (2006) highlights the usefulness of this procedure, especially in the case where multiple structural changes are difficult to detect: Consider a data-generating process with $m = 2$ breaks and the first and the third of the corresponding regimes being the same. If we would only conduct a $F(l+1|l)$-test, we would start with a $F(0|1)$-test which would most likely not reject the null of $l = 0$ breaks because of its low power against multiple reversing changes. Yet, there are actually two breaks in the data-generating process. Noting the importance of evaluating the outcome of the $Dmax$-test before turning to the $F(l+1|l)$-test, we adopt the approach by Perron (2006), which is detailed in the following.

[2] On the contrary, partial structural change models allow for the possibility that some coefficients are not subject to shifts. Since the lagged values of the independent variable are the only explanatory variables in our case, we can restrict our model to equation (3.1).

3.1.1 The *Dmax*-test

The double maximum test or *Dmax*-test evaluates the null hypothesis of no structural break against an unknown number of breaks given some upper bound M:

$$Dmax(M,q) = \max_{1 \leq m \leq M} a_m \quad \sup F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_m; q) \tag{3.2}$$

with some fixed weights $\{a_1, \ldots, a_M\}$. As Bai and Perron (1998) note, there is no guideline about the choice of the weights, but one can interpret the weight a_m as a prior on the likelihood of observing m breaks. In our analysis we will use the most common case, which assigns the value 1 to all weights $\{a_1, \ldots, a_M\}$. Equation (3.2) is called a double maximum test, as it is defined by the maximum of another supremum test, a *supF* type test of no structural break ($m = 0$) versus the alternative hypothesis of $m = k$ breaks. Bai and Perron (2006) define the finite sample version of the *supF*-statistic as:

$$\sup F_T(k;q) = F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_k; q) = \frac{1}{T}\left(\frac{T-(k+1)q}{kq}\right) \hat{\boldsymbol{\beta}}\boldsymbol{R'}\left(\boldsymbol{R}\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}})\boldsymbol{R'}\right)^{-1} \boldsymbol{R}\hat{\boldsymbol{\beta}}.$$

The *supF*-statistic evaluates the hypothesis $\boldsymbol{\beta}_1 = \ldots = \boldsymbol{\beta}_{k+1}$ against the alternative $\boldsymbol{\beta}_j \neq \boldsymbol{\beta}_{j+1}$ for some j given the partition $\{\widehat{T}_j\}, \ldots, \{\widehat{T}_{k+1}\}$. $\hat{\lambda}_j$ is defined by $\hat{\lambda}_j = \widehat{T}_j/T$ with $j = 1, \ldots, k$. $\boldsymbol{R}$ is a conventional matrix such that $(\boldsymbol{R\beta})' = (\boldsymbol{\beta}'_1 - \boldsymbol{\beta}'_2, \ldots, \boldsymbol{\beta}'_k - \boldsymbol{\beta}'_{k+1})$ and $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}})$ an estimate of the limiting variance covariance matrix of $\hat{\boldsymbol{\beta}}$ which can take different forms dependent on the assumptions made with respect to the distribution of the data and the error across partitions. When applying the procedure, we restrict ourselves to the two specifications in the construction of $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}})$ relevant for our purposes, which are detailed in Bai and Perron (2006).

The first case implies different distribution of the data across partitions, no serial correlation in the errors and different variances of the errors across partitions. The estimator of the variance covariance matrix becomes

$$\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}) = diag\left(\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_1), \ldots, \hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_{m+1})\right)$$

$$\text{with} \quad \hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_j) = \hat{\sigma}_j^2 \left[\frac{\sum_{t=\hat{T}_{i-1}+1}^{\hat{T}_i} \boldsymbol{x}_t \boldsymbol{x}_t}{\Delta\widehat{T}_j}\right]^{-1} \quad \text{and} \quad \hat{\sigma}_j^2 = \frac{\sum_{t=\hat{T}_{i-1}+1}^{\hat{T}_i} \hat{\varepsilon}_t^2}{\Delta\widehat{T}_j}. \tag{3.3}$$

Note that $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_j)$ is simply the OLS estimate of the variance covariance for the partition $\{\widehat{T}_j\}$, with $\hat{\sigma}_j^2$ as the estimate of the homoscedastic variance of ε.

The second case differs from the first case with respect to the correlation in the errors. While we stick with different distributions of the data and different variances of the errors across segments, we now explicitly allow for serial correlation in the error terms. Unlike the specification in (3.3), we now have to apply a heteroscedasticity and autocorrelation consistent (HAC) estimator of $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_j)$ that is slightly more involved.[3] Distinguishing between the two specifications becomes important when applying the procedure to our analysis, as it will be shown in Section 3.2.

Conducting asymptotic analysis, we also need to impose some restrictions on the break date candidates: Each break date has to be asymptotically distinct and bounded from the boundaries of the sample. For some arbitrarily small trimming parameter ϵ, defined by the minimal permissible lag length t over the sample size T, it must hold that $\Lambda_\epsilon = \{(\lambda_1, \ldots, \lambda_k); |\lambda_{i+1} - \lambda_i| \geq \epsilon, \lambda_1 \geq \epsilon, \lambda_k \leq 1 - \epsilon\}$.[4] Since the asymptotic distribution and the critical values for the *supF*-test and thus the *Dmax*-test are sensitive to the choice of ϵ, we choose this value in line with Bai and Perron (2003b) and dependent on the length of each time series. For time series that are available since at least 1980, we set $\epsilon = \frac{h}{T} = 0.1$, where h is the minimal permissible partition length. For time series with later availability, we set $\epsilon = \frac{h}{T} = 0.15$.

After having calculated the *supF*-statistic for $m = 1, \ldots, M$ breaks, we take the maximum value, our *Dmax(M,q)*-statistic, and compare it to the critical value table computed by Bai and Perron (2003c). If we are able to reject the null hypothesis, we found statistical evidence for the existence of one or several breaks. To specify the exact number of breaks, however, we need to apply the $F(l+1|l)$-test.

3.1.2 The $F(l+1|l)$-test

The $F(l+1|l)$-test proposed by Bai and Perron (1998) tests the null hypothesis of l breaks against the alternative that an additional break exists. Assuming we have rejected the null of the *Dmax*-test, we know that there is at least $l = 1$ break; but there may be $l + 1 = 2$ or even more breaks. The $F(l+1|l)$-test provides one way to answer this question by testing each $l+1$ segment for the presence of an additional break. In other words, we conduct $(l+1)$ tests with the null hypothesis of no structural change against the alternative of a single change, one for each partition $\{\widehat{T}_j\}, \ldots, \{\widehat{T}_{l+1}\}$ with $j = 1, \ldots, l$.

[3] The details for both specifications of the variance covariance matrix $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_j)$ can be found in Appendix C.

[4] See Bai and Perron (1998) for a comprehensive theory overview on the consistency and limiting distributions of break dates.

If the allowance of an additional break leads to a significant reduction of the *overall* minimum value of the sum of squared residuals compared to the the sum of squared residuals from the model with l breaks, we reject the null hypothesis and conclude in the favor of a model with $(l+1)$ breaks. In mathematical terms:

$$F(l+1|l) = \left\{ S_T(\widehat{T}_1, \ldots, \widehat{T}_l) - \min_{1 \leq q \leq l+1} \inf_{\tau \in \Lambda_{j,\epsilon}} S_T(\widehat{T}_1, \ldots, \widehat{T}_{j-1}, \tau, \widehat{T}_j, \ldots, \widehat{T}_l) \right\} / \hat{\sigma^2},$$

where

$$\Lambda_{j,\epsilon} = \left\{ \tau; \widehat{T}_{j-1} + (\widehat{T}_j - \widehat{T}_{j-1})\epsilon \leq \tau \leq \widehat{T}_j - (\widehat{T}_j - \widehat{T}_{j-1})\epsilon \right\}.$$

$\hat{\sigma}^2$ is a consistent estimate of σ^2 under the null hypothesis.[5] We use the critical values calculated by Bai and Perron (1998) and explicitly reported in Bai and Perron (2003c) to evaluate the significance.

3.1.3 Repartitioning

The sequential procedure outlined above has one weakness. As Bai (1997) shows, the limiting distributions of the estimates obtained by the sequential procedure are not the same as those obtained by the simultaneous procedure.[6] The simultaneous procedure of estimating break dates has a limiting distribution which only depends on the parameters of the adjacent regimes and therefore yields unbiased estimates. In the sequential case, the limiting distribution of the sequential procedure depends on the parameters in all regimes of the sample resulting in biased estimates of the break date.

To remedy this problem of the sequential procedure, we use the *repartition* approach introduced by Bai (1997). This fine-tuning measure translates to re-estimating each break date conditional on the adjacent break dates. For instance, let us assume we have found some initial estimates of break dates, denoted by $\widehat{T}_1^a, \ldots, \widehat{T}_m^a$. In repartitioning the sample, we obtain the second round estimate for the j^{th} break by estimating a model with $m = 1$ breaks between the observations

[5] The asymptotic distribution of the test does not require $\hat{\sigma}^2$ to be consistent under the alternative hypothesis, although better power can be achieved if $\hat{\sigma}^2$ is consistent under the alternative. See Bai and Perron (1998) for a detailed treatment.

[6] The simultaneous procedure is another way to find and test for break dates without the weakness of having biased limiting distributions. Yet, we choose the sequential procedure as it is more comprehensible and easier to implement. For a detailed treatment of the simultaneous procedure, the interested scholar may be referred to Bai and Perron (2003a).

starting at date $\widehat{T}^a_{i-1}+1$ and ending at date $\widehat{T}^a_{i+1}$. Bai (1997) finds that these second round estimates have the same limiting distributions as those obtained by the simultaneous procedure.

3.2 Testing for Breaks in Volatility

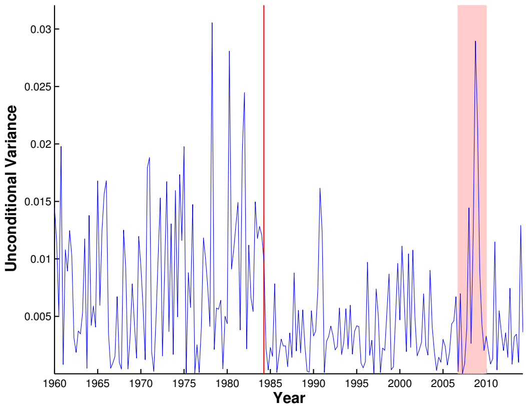
In this section we detail the application of the sequential procedure to our analysis. Our goal is to assess the occurrence and origin of structural breaks in the data described in section 2.3.1. For this purpose, we have to apply the sequential procedure to different transformations of our data. In a first step, we assess whether the series experienced a structural break in the unconditional variance. Yet, such break testing does not reveal the underlying dynamics of the change in volatility. The changes in the variance can be due to changes in the conditional mean, changes in the conditional variance, or both. These two nonexclusive sources give a hint to the origin of structural breaks: Changes in the conditional mean are captured by a change in the autoregressive coefficients and stand for a change in the propagation mechanism, a term describing the persistence of shocks to the variable at hand. On the other hand, changes in the conditional variance are due to changes in the innovation variance can be interpreted as unforecastable disturbances or impulses to the variable. Consequently, we need to test for structural breaks in the conditional mean and variance if we want to answer the question of the origin of a break. In the following, the application of the sequential procedure is illustrated by using the example series of U.S. GDP from 1960:1 to 2014:2, already transformed to logged first differences as described in Section 2.3.1.

Let $y^\mu_t = \left| y_t - \frac{\sum_{t=1}^T y_t}{T} \right|$, the absolute value of the demeaned of the series y_t, be the measure of the unconditional variance. Testing for a structural break in this case, the constant term becomes the only regressor included in $\boldsymbol{x}_t$ and equation (3.1) translates into:

$$y^\mu_t = x'_t\beta_j + \varepsilon_t = \beta_{0,j} + \varepsilon_t \qquad (t = T_{j-1}+1, \ldots, T_j).$$

Note that our measure of unconditional variance is not only likely to have heteroscedastic errors, but also exhibits autocorrelation. To estimate the break dates consistently, we therefore have to use the HAC estimator of the coefficient's variance covariance matrix $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_j)$. When conducting the sequential procedure on our example series, we find one break in 1984:Q2 at the 5% significance level. The break actually implies a significant moderation in volatility which can be seen in Figure 3.1. On the other hand, the red-shaded spike during the financial crisis does not cause a significant enough increase in volatility for the series to break.

Figure 3.1: Unconditional Variance of U.S. GDP

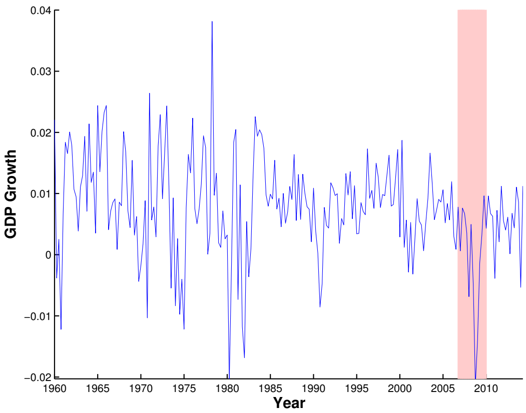


Taking the analysis one step further, we now look at the conditional mean of the series. In this case, the sequential procedure – again using the HAC robust estimate of $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_j)$ – is applied to the series y_t where the regressor $\boldsymbol{x}_t$ consists of the constant and p lagged values of y_t:

$$y_t = \boldsymbol{x}_t'\boldsymbol{\beta}_j + \varepsilon_t = \beta_{0,j} + \sum_{i=1}^{p} \beta_{p,j} y_{t-p} + \varepsilon_t, \qquad (t = T_{j-1}+1, \ldots, T_j). \tag{3.4}$$

Although visual inspection of Figure 3.2 suggests a moderate decrease in volatility of the autoregressive coefficients from the mid-1980s on, we do not find significant evidence for a structural break in the conditional mean when applying the $Dmax$-test and $F(l+1|l)$-tests. Again, the short-term volatility decrease during the financial crisis (shaded in red in Figure 3.2) is not persistent enough to cause the conditional mean to break. Once we have established whether there

Figure 3.2: Testing for Breaks in the Conditional Mean of U.S. GDP

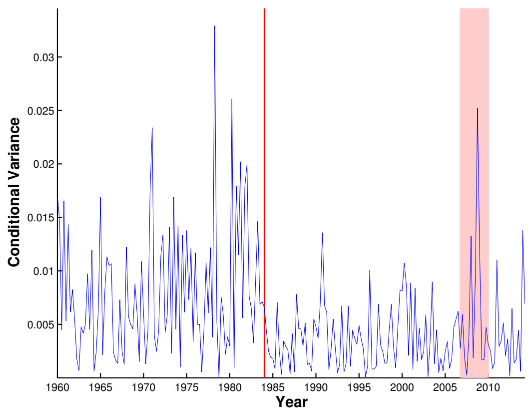


is a structural break in the conditional mean, we are able to test for breaks in the conditional variance. Let $\widehat{T}^{cm} = \{\widehat{T}_i^{cm}, \widehat{T}_{i+1}^{cm}, \ldots, \widehat{T}_k^{cm}\}$ be the k estimated break dates of the conditional mean in equation (3.4). Estimating equation (3.4) *with* the previously obtained breaks $\widehat{T}^{cm}$, we can derive the OLS residuals $\hat{\varepsilon}_t(\widehat{T}^{cm})$. As in Stock and Watson (2003), we use the absolute value of the OLS residuals $\left|\hat{\varepsilon}_t(\widehat{T}^{cm})\right|$ as a measure of the the conditional variance. If there is no break in the conditional mean, $\widehat{T}^{cm} = \{\emptyset\}$ and the conditional variance $\left|\hat{\varepsilon}_t(\widehat{T}^{cm})\right|$ is given by the OLS residuals of regression (3.4). Under the assumption of no structural break, we should find $\left|\hat{\varepsilon}_t(\widehat{T}^{cm})\right|$ to be constant. Hence, the sequential procedure for the conditional variance only uses a constant in the regressor $\boldsymbol{x}_t$ to test for a break:

$$\left|\hat{\varepsilon}_t(\widehat{T}^{cm})\right| = x_t'\beta_j + \eta_t = \beta_{0,j} + \eta_t, \qquad (t = T_{j-1} + 1, \ldots, T_j),$$

where η_t is the error term of the OLS regression. Since the OLS residuals have been estimated sequentially for each regime, we follow Stock and Watson (2003) and assume homoscedastic errors in the construction of $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\beta}}_j)$ for the sequential procedure. Applying the *Dmax*-test and $F(l+1|l)$-tests to the conditional variance, we find a significant break in 1984:Q1. The large decrease in volatility around this break date in Figure 3.3 supports the statistical finding.

Figure 3.3: Conditional Variance of U.S. GDP



Summarizing, the testing of structural breaks in the unconditional variance, conditional mean and conditional variance can be conducted by applying the following algorithm:

- Calculate the absolute value of the demeaned series y_t^{μ}
- Detect breaks in the unconditional variance by applying the sequential procedure to y_t^{μ}
- Create a regressor with p lagged values of y_t, with p being determined by SBC

- Detect breaks in the conditional mean by applying the sequential procedure to the series y_t, including the additional regressors
- Calculate the conditional variance $\left|\hat{\varepsilon}_t(\widehat{T}^{cm})\right|$, which is given by the absolute value of the OLS residuals in the step above
- Detect breaks in the conditional variance by applying the sequential procedure to the series $\left|\hat{\varepsilon}_t(\widehat{T}^{cm})\right|$

In our break testing analysis, we allow for a maximum of $M = 4$ breaks. This appears to be sufficient considering the length of data. The fact that we find no more than three breaks in any series justifies this setting.

3.3 Results

United States As outlined in Section 3.2, there are two main findings considering the structural breaks of U.S. GDP. First, the most noted variable in our analysis experienced a break both in the unconditional and conditional variance in 1984:Q1, significant at the 1% level. This decline in output volatility constitutes a finding consistent with the analysis of Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Stock and Watson (2003) and Sensier and van Dijk (2004), who date the break in a similar time span. Second and more importantly, no break could be detected during the Great Recession. The sequential procedure – based on the *Dmax*- and $F(l+1|l)$-test – finds no structural break in the unconditional variance, conditional mean and conditional variance in this time span. Apparently, the increase in volatility was too short to constitute a significant break. This finding is visually supported by the Figures 3.1, 3.2 and 3.3 and consistent with the results found by Chen (2011) and Gadea et al. (2013). Even the evidence of significantly increased output volatility brought forward by Clark (2009), Canarella et al. (2010) can be aligned with our results since it is based on data reaching only until 2009:Q2 and 2007:Q2, respectively.

The break dates for GDP and all other U.S. macroeconomic variables are summarized in Table 3.1. For each variable, structural breaks in the unconditional variance, conditional mean and conditional variance are reported along with their respective significance level and a 70% confidence interval. Every variable except the financial stress index and the oil price breaks at least once in the conditional variance, often coinciding with a break in the unconditional

Table 3.1: Structural Breaks in U.S. Macroeconomic Time Series

	Unconditional Variance		**Conditional Mean**		**Conditional Variance**	
Series	Date	Confidence Interval	Date	Confidence Interval	Date	Confidence Interval
GDP	1984:1***	[1980:2,1986:1]	–	–	1984:1***	[1981:2,1985:3]
CONS	1983:4**	[1974:3,1987:4]	–	–	1992:1***	[1988:1,1994:1]
INVST	1984:1***	[1977:1,1987:2]	–	–	1984:1***	[1978:3,1986:3]
GOV	1967:1***	[1964:4,1968:2]	–	–	1967:2**	[1965:1,1968;4]
	–	–	–	–	2001:4*	[1992:1,2006:1]
EXP	1973:2***	[1970:3,1974:2]	1972:3**	[1970:3,1973:3]	1978:4***	[1975:2,1980:3]
IMP	1985:4***	[1978:2,1989:1]	–	–	1985:4***	[1978:3,1989:1]
PICORE	1970:3***	[1969:1,1971:3]	1976:3***	[1973:3,1977:4]	1970:3**	[1969:2,1971:4]
	1986:2***	[1984:2,1987:2]	–	–	1986:3***	[1985:2,1987:3]
	–	–	–	–	1995:3**	[1971:1,2011:3]
HPI	1982:4***	[1981:4,1983:4]	–	–	1982:4***	[1981:3,1983:4]
	2008:1***	[2006:4,2008:4]	–	–	2003:3***	[2001:3,2004:3]
UR	–	–	–	–	1983:4**	[1968:4,1990:2]
TWEXR	1981:1***	[1979:4,1982:1]	–	–	1980:2**	[1978:4,1981:2]
	1988:4***	[1987:2,1989:4]	–	–	1989:2**	[1987:1,1990:3]
CBR	1970:2***	[1968:4,1971:3]	1975:2*	[1975:1,1975:4]	1967:4***	[1967:1,1968:4]
	1982:4***	[1981:2,1983:4]	1980:4***	[1980:4,1981:1]	1984:4***	[1983:2,1985:4]
	–	–	–	–	2008:4***	[2002:3,2011:3]
TB3M	1966:4***	[1963:4,1968:4]	1980:4***	[1979:3,1981:3]	1970:1***	[1968:2,1971:3]
	1979:3***	[1978:3,1980:3]	–	–	1984:4***	[1983:1,1986:1]
	1985:1***	[1984:3,1985:3]	–	–	2008:4***	[1998:1,2013:3]
TED	–	–	–	–	1992:4**	[1986:3,1999:3]
	–	–	–	–	2007:2**	[1993:2,2010:4]
FSI	–	–	2009:1***	[2006:3,2010:2]	–	–
OIL	–	–	1991:3*	[1989:3,1992:3]	–	–

Notes: The 70% confidence intervals are constructed following Bai and Perron (2003a).
*, **, *** Significant at the 10%, 5%, and 1% level, respectively

variance around the same date. By contrast, breaks in the conditional mean are less common. This generalized evidence suggests that the changes in volatility are associated with impulses to the variable (changes in the conditional variance) rather than the propagation mechanism (changes in the conditional mean).

When we turn to the dating of the breaks, we find many series to break in the 1980s, with most of the breaks significant at the 1% level. Again, the result is in agreement with the broad consensus of the Great Moderation to begin in the mid-1980s in the United States. Without further investigating break dates found even earlier, we focus on the breaks which have occurred over the last 15 years. Not a single GDP component experienced a structural break – the only exception is government expenditure with a break in conditional variance in 2001:Q4, but only at the 10% significance level. The variables capturing different interest rates, however, give a different picture. The federal funds rate, 3-month treasury bill rate and the TED spread all experience a break in the conditional variance during the Great Recession. The financial stress index also experiences a break in 2009:Q1, albeit in the conditional mean, indicating that not

Table 3.2: Structural Breaks in U.K. Macroeconomic Time Series

	Unconditional Variance		**Conditional Mean**		**Conditional Variance**	
Series	Date	Confidence Interval	Date	Confidence Interval	Date	Confidence Interval
GDP	1981:1***	[1975:4,1983:3]	1980:1***	[1977:3,1981:2]	1988:3***	[1985:3,1990:1]
CONS	1992:2**	[1984:1,1996:1]	–	–	1981:1***	[1975:3,1983:3]
	–	–	–	–	1992:3*	[1976:3,1993:2]
INVST	–	–	–	–	–	–
GOV	–	–	–	–	–	–
EXP	–	–	–	–	1966:1***	[1960:1,1971:1]
IMP	1983:1**	[1974:4,1986:4]	–	–	1983:1***	[1974:4,1986:4]
PICORE	1975:4***	[1973:4,1977:1]	1976:1***	[1975:3,1976:4]	1981:3***	[1980:1,1982:4]
	2001:3***	[1995:2,2004:2]	1980:3***	[1979:3,1981:2]	1995:4***	[1992:4,1997:3]
HPI	–	–	–	–	2009:3**	[2001:2,2013:1]
UR	–	–	–	–	2005:3**	[2002:1,2007:2]
TWEXR	1987:2***	[1984:1,1988:4]	–	–	1987:2**	[1984:3,1988:3]
CBR	1980:1**	[1978:1,1981:2]	1988:3*	[1978:1,1993:1]	1988:3***	[1987:3,1989:2]
	1993:1**	[1991:1,1994:1]	–	–	2009:3*	[1995:3,2014:2]
TB3M	1983:1*	[1980:2,1984:3]	–	–	1988:3***	[1987:2,1989:2]
	1993:1*	[1990:1,1994:3]	–	–	–	–
TED	–	–	–	–	2000:1***	[1991:2,2006:4]
	–	–	–	–	2007:2***	[2003:2,2009:1]
FSI	–	–	–	–	–	–
OIL	–	–	–	–	2010:2***	[2003:1,2013:3]

Notes: The 70% confidence intervals are constructed following Bai and Perron (2003a).
*, **, *** Significant at the 10%, 5%, and 1% level, respectively

only shocks but also the propagation of volatility in the financial sector could have changed. Another variable with significantly increased fluctuations is the house price index. We find a break in the conditional variance 2003:Q3 and a break in the unconditional variance in 2008:Q1.

United Kingdom So far, the evidence on the Great Moderation is – with the exception of van Dijk et al. (2002) – very much limited to the investigation of output and inflation volatility. Applying the sequential procedure to 15 macroeconomic variables, we do not only try to evaluate the question of the precise break date in output and inflation volatility, but want to give a broader picture updated to the most recent data.

As shown in Table 3.2, we find output volatility to break in both the unconditional variance and conditional mean in the early 1980s. The conditional variance, however, breaks in the late 1980s. Those break date estimates are approximately similar to the results of Benati (2004), Stock and Watson (2005), Fang et al. (2008) and other scholars which pin down the breaks in the early 1980s and early 1990s depending on the type of break and estimation procedure. Our measure of inflation is a variable with highly varying volatility, leading to two breaks in all three possible types of breaks. Although a high number of breaks can also be found in Benati (2004), the break date estimates are different in timing.

In general, dating the Great Moderation for the macroeconomic variables at hand is not as straightforward as for the United States. Similar to the case of output volatility and the findings by van Dijk et al. (2002), we find many variables to break either in the early 1980s or in the late 1980s and early 1990s. As in the case of the U.S., the majority of variables experience a break in the conditional variance and only few breaks in the conditional mean.

Breaks during the financial crisis are rare, but exist. For instance, the TED spread experienced a break in the conditional variance in 2007:Q2. Further variables with a break in the conditional variance are the central bank lending rate (however only at the 10% significance level), the house price index and the real price of oil. Notably, also the unemployment rate breaks in its conditional variance, but the break is estimated to have taken place prior to the financial crisis.

Sweden To the best of our knowledge, Ćorić (2012) and Cecchetti et al. (2006) provide the only studies concerning volatility of Swedish macroeconomic variables. This evidence – gathered by dating the Great Moderation internationally for several countries – boils down to the analysis of output volatility as the single variable under investigation. Consequently, our break testing results constitute the first broader volatility analysis of Swedish macroeconomic variables.

Comparing the only variable possible, we determine a break in the conditional mean of GDP in 1990:Q1, which is slightly earlier than the estimates found by Ćorić (2012) and Cecchetti et al. (2006). Also, the break in the conditional variance in 1984:Q2 – identical with the timing of the break in unconditional variance – matches the break estimated by Cecchetti et al. (2006). We now take the analyis one step further and look at the GDP components. With the exception of investment, the standard deviations of the components in Table 2.1 show a clear negative trend from the 1970s to the 1990s. The break testing results in Table 3.3 substantiate these descriptive observations. Many of the mentioned variables break around the early 1980s which constitutes a first candidate for dating the Great Moderation. For instance, the unconditional and conditional variance for exports and imports as well as the unconditional variance and conditional mean for government expenditure all break within one year.

The period between 1992 and 1994 is another focal point of structural breaks. This time period builds the second candidate for the start of the Great Moderation and describes the time after the severe Swedish banking crisis from 1990 to 1992. We find breaks across all macroeconomic categories: consumption, the 3-month treasury bill, the exchange rate and the house price index break in the unconditional variance; the central bank rate, the unemployment rate, the TED

Table 3.3: Structural Breaks in Swedish Macroeconomic Time Series

	Unconditional Variance		**Conditional Mean**		**Conditional Variance**	
Series	Date	Confidence Interval	Date	Confidence Interval	Date	Confidence Interval
GDP	1984:2***	[1978:4,1986:4]	1990:1**	[1986:2,1991:4]	1984:2***	[1981:2,1985:4]
CONS	1966:1**	[1960:2,1970:1]	1974:2***	[1971:2,1975:4]	1993:1***	[1987:1,1995:2]
	1993:1**	[1980:4,1998:2]	–	–	–	–
INVST	–	–	–	–	1967:2***	[1962:2,1969:3]
GOV	1981:4***	[1969:2,1987:3]	1970:1**	[1969:4,1970:4]	1969:4***	[1968:2,1971:1]
	2000:4*	[1986:2,2007:1]	1981:1**	[1979:4,1981:4]	1998:3**	[1996:1,1999:4]
EXP	1980:4***	[1976:2,1982:4]	–	–	1981:1**	[1972:3,1984:4]
IMP	1969:4**	[1967:4,1971:1]	1977:1**	[1973:3,1978:4]	1969:4***	[1968:2,1970:4]
	1980:4***	[1979:4,1981:3]	–	–	1980:4***	[1979:4,1981:3]
PICORE	1999:4*	[1991:3,2003:3]	–	–	–	–
HPI	1993:2*	[1988:2,1995:3]	1991:4***	[1991:3,1992:3]	–	–
	–	–	1996:3***	[1995:3,1997:2]	–	–
UR	1990:3*	[1983:2,1995:3]	1993:2**	[1989:4,1995:1]	2009:3**	[1999:2,2014:1]
TWEXR	1992:3**	[1987:3,1994:4]	–	–	1992:3***	[1987:2,1995:1]
CBR	1974:1*	[1963:4,1978:3]	1993:1*	[1984:4,1996:3]	1974:1*	[1968:2,1977:1]
	–	–	–	–	2003:2*	[1996:4,2006:1]
TB3M	1993:3***	[1991:3,1994:3]	–	–	1993:3***	[1991:2,1995:1]
	–	–	–	–	2009:2*	[1983:2,2014:2]
TED	–	–	1993:2**	[1989:3,1995:1]	1994:4*	[1991:4,1996:3]
	–	–	–	–	2007:2***	[2004:4,2008:3]
FSI	–	–	–	–	2007:2**	[2000:4,2010:2]
OIL	–	–	–	–	2010:2***	[2003:2,2013:2]

Notes: The 70% confidence intervals are constructed following Bai and Perron (2003a).
*, **, *** Significant at the 10%, 5%, and 1% level, respectively

spread and the house price index break in the conditional mean; consumption, the 3-month treasury bill rate, the exchange rate and the TED spread in the conditional variance.

On the other hand, the evidence for breaks during the Great Recession is scarce. While we cannot observe any break in the conditional mean, we do find breaks in the conditional variance of the real oil price and various macrofinancial variables. The 3-month treasury bill, the TED spread and the financial stress index all break and hint once more at the increased volatility in the financial sector. Surprisingly, we also detect a break in the conditional variance of the unemployment rate suggesting a decrease in volatility (the standard deviations in Table 2.1 decrease from the 2000s to 2010s). The general picture, however, remains unchanged. Similar to the U.S. and the U.K., neither GDP itself nor one of its components experiences a break in variability during the Great Recession. Moreover, none of variables with a break in the conditional variance undergo a break in the unconditional variance, in contrast to similar breaks during the Great Moderation period.

4 Sources of Increased Volatility

The results in Section 3 have provided first evidence that the Great Moderation has not ended with the beginning of the Great Recession, since we find almost no structural breaks in the macroeconomic series considered. Yet, the descriptive statistics in Section 2 have shown that macroeconomic volatility was clearly elevated during this period. This section sheds some light on the sources of the rise in fluctuations. Section 4.1 justifies and outlines the general methods used for analysis. In Section 4.2, we calculate instantaneous standard deviations for each variable, which indicate that the increase in volatility was transitory. The macroeconomic model in Section 4.3 shows that much of the increase in volatility was caused by shocks to the financial system.

4.1 Methodology

The time-varying parameter autoregression used to calculate instantaneous standard deviations is a univariate specification of the time-varying parameter vector autoregression (TVP-VAR) used to estimate the macroeconomic model. Even if we do not find structural breaks in the autoregressive parameters or volatility of most of the variables during the Great Recession, there is possibly some time variation in the underlying structure of the economy. On the one hand, the coefficients describing the instantaneous and lagged effects of one variable on another could have changed over time. Using a TVP-VAR allows us to capture this time variation in a flexible and robust manner (Nakajima, 2011). On the other hand, the magnitude of shocks to a variable could also have varied. Hence, we must allow for time variation in the variance covariance matrix of the innovations to model the causes of volatility during the Great Recession in a meaningful way.

Therefore, we choose the TVP-VAR specification with stochastic volatility pioneered by Primiceri (2005). In the following paragraphs, we outline the general model and the method used to obtain the forecast error variance decomposition for the macroeconomic model. Exact specifications and priors used in the Bayesian estimation of the models are discussed separately for the univariate and the multivariate case in the respective sections.

4.1.1 The Time-Varying VAR Model

We start by considering the following VAR model with n variables and p lags:

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1,t}\mathbf{y}_{t-1} + \cdots + \mathbf{B}_{p,t}\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{4.1}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of observed variables, $\mathbf{c}_t$ is an $n \times 1$ vector of time-varying intercepts, $\mathbf{B}_{1,t}, \ldots, \mathbf{B}_{p,t}$ are $n \times n$ matrices of time-varying coefficients, and $\mathbf{u}_t$ are heteroscedastic unobservable shocks with the corresponding variance covariance matrix $\mathbf{\Omega}_t$. Following Primiceri (2005), the triangular reduction of $\mathbf{\Omega}_t$ is then defined by

$$\mathbf{A}_t\mathbf{\Omega}_t\mathbf{A}_t' = \mathbf{\Sigma}_t\mathbf{\Sigma}_t', \tag{4.2}$$

where $\mathbf{A}_t$ is given by the lower triangular matrix

$$\mathbf{A}_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn-1,t} & 1 \end{bmatrix},$$

and $\mathbf{\Sigma}_t$ is the diagonal matrix

$$\mathbf{\Sigma}_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}.$$

Given the triangular reduction (4.2), the model in (4.1) can also be written as

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1,t}\mathbf{y}_{t-1} + \cdots + \mathbf{B}_{p,t}\mathbf{y}_{t-p} + \mathbf{A}_t^{-1}\mathbf{\Sigma}_t\boldsymbol{\varepsilon}_t, \tag{4.3}$$

where the error term $\boldsymbol{\varepsilon}_t$ is assumed to be distributed as $N(\mathbf{0}, \mathbf{I}_n)$. Stacking all the coefficients on the right-hand side in a vector $\mathbf{b}_t$ and defining $\mathbf{X}_t' = \mathbf{I}_n \otimes [1, \mathbf{y}_{t-1}', \ldots, \mathbf{y}_{t-p}']$, where $\otimes$ denotes the Kronecker product, we obtain

$$\mathbf{y}_t = \mathbf{X}_t'\mathbf{b}_t + \mathbf{A}_t^{-1}\mathbf{\Sigma}_t\boldsymbol{\varepsilon}_t. \tag{4.4}$$

As Nakajima (2011) notes, there are various ways to model the process for the time-varying parameters. As in Primiceri (2005), we choose to model the elements of the vector $\mathbf{b}_t$ and the free elements of the matrix $\mathbf{A}_t$ as random walks, while the standard deviations evolve as geometric random walks. Let $\boldsymbol{\alpha}_t$ be a stacked vector of the lower-triangular elements in $\mathbf{A}_t$, and let $\boldsymbol{\sigma}_t$ be the vector of the diagonal elements of $\boldsymbol{\Sigma}_t$. Then the dynamics of the model can be described as follows:

$$\mathbf{b}_t = \mathbf{b}_{t-1} + \boldsymbol{\nu}_t \tag{4.5}$$

$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{\zeta}_t \tag{4.6}$$

$$\log \boldsymbol{\sigma}_t = \log \boldsymbol{\sigma}_{t-1} + \boldsymbol{\eta}_t \tag{4.7}$$

The innovations $\boldsymbol{\varepsilon}_t, \boldsymbol{\nu}_t, \boldsymbol{\zeta}_t, \boldsymbol{\eta}_t$ of the model are assumed to be jointly normally distributed. Following Primiceri (2005), we make the following assumption about the variance covariance matrix:

$$Var\left(\begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \boldsymbol{\nu}_t \\ \boldsymbol{\zeta}_t \\ \boldsymbol{\eta}_t \end{bmatrix}\right) = \begin{bmatrix} \mathbf{I}_n & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{Q} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{S} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{W} \end{bmatrix} \quad \forall t,$$

where $\mathbf{I}_n$ is an n-dimensional identity matrix, and $\mathbf{Q}$, $\mathbf{S}$, and $\mathbf{W}$ are positive definite matrices.

4.1.2 Estimation Procedure

We use Bayesian methods to estimate the model in Equation 4.4.[1] These methods are particularly efficient in dealing with the high dimensionality of the parameter space and the nonlinearities of the model (Koop and Korobilis, 2009). In particular, we follow Primiceri (2005) and others in employing the Gibbs sampler, a variant of Markov Chain Monte Carlo (MCMC) algorithms. The Gibbs sampler repeatedly draws from conditional distributions in order to obtain joint and marginal distributions of the posteriors. The details of the algorithm used in our study may be found in Del Negro and Primiceri (2013), who correct the algorithm originally proposed by Primiceri (2005). The priors and other estimation specifications differ between

[1]The analysis is carried out in MATLAB Version 8.3. All code and programs are available upon request from the authors. Parts of the code were obtained from Gary Koop and Dimitris Korobilis, whose generosity is gratefully acknowledged.

the calculation of instantaneous standard deviations and the macroeconomic model and are described in the respective sections.

4.1.3 Forecast Error Variance Decomposition

The macroeconomic model outlined above is used to derive a forecast error variance decomposition at each point of time. This time-varying decomposition enables us to disentangle the sources of volatility in the model which can stem from different shocks in different time periods. Such analysis is not possible in a time-invariant model in which the decomposition would be constant over time.

To obtain the decomposition in each period t, we need to rewrite the reduced form VAR(p) process in (4.1) into its VAR(1) form. This gives us the following model:

$$\mathbf{z}_t = \boldsymbol{\kappa}_t + \boldsymbol{\Psi}_t \mathbf{z}_{t-1} + \boldsymbol{\chi}_t, \tag{4.8}$$

where

$$\boldsymbol{\Psi}_t = \begin{bmatrix} \mathbf{B}_{1,t} & \mathbf{B}_{2,t} & \cdots & \mathbf{B}_{p-1,t} & \mathbf{B}_{p,t} \\ \mathbf{I}_n & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_n & & \mathbf{0} & \mathbf{0} \\ \vdots & & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_n & \mathbf{0} \end{bmatrix},$$

$$\mathbf{z}_t = \begin{bmatrix} \mathbf{y}_t \\ \mathbf{y}_{t-1} \\ \vdots \\ \mathbf{y}_{t-p+1} \end{bmatrix}, \quad \boldsymbol{\kappa}_t = \begin{bmatrix} \mathbf{c}_t \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}, \quad \boldsymbol{\chi}_t = \begin{bmatrix} \mathbf{u}_t \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}.$$

Following Lütkepohl (2005) and discarding the constant term, we can rewrite the VAR(1) representation into a moving-average process of the form

$$\mathbf{y}_t = \sum_{i=0}^{\infty} \boldsymbol{\Theta}_{t,i} \mathbf{w}_{t-i},$$

where the elements of $\mathbf{w}_t$ are uncorrelated and each have unit variance. This representation is obtained by decomposing $\boldsymbol{\Omega}_t$ as $\boldsymbol{\Omega}_t = \boldsymbol{\Xi}_t \boldsymbol{\Xi}_t'$. In our specific case, this decomposition can be directly obtained from (4.2) and is equal to the lower triangular given by $\mathbf{\Xi}_t = \mathbf{A}_t^{-1}\mathbf{\Sigma}_t$. $\mathbf{\Theta}_{i,t}$ is then given by $\mathbf{\Theta}_{i,t} = \mathbf{\Phi}_{i,t}\mathbf{\Xi}_t$, where $\mathbf{\Phi}_{i,t} = \mathbf{J}\mathbf{\Psi}_t^i\mathbf{J}'$ with $\mathbf{J}$ defined as the $(n \times np)$ matrix $\mathbf{J} = [\mathbf{I}_n, \mathbf{0}, \cdots, \mathbf{0}]$. $\mathbf{w}_t$ is thus defined by $\mathbf{w}_t = \mathbf{\Xi}_t^{-1}\mathbf{u}_t$.

The forecast error variance of the h-step ahead forecast of the j-th component of $\mathbf{y}_t$ accounted for by w_{kt} innovations in period t can then be calculated as

$$\omega_{jk,h,t} = \sum_{i=0}^{h-1}(\mathbf{e}_j'\mathbf{\Theta}_{i,t}\mathbf{e}_k)^2, \tag{4.9}$$

where $\mathbf{e}_j$ is the j-th column of an n-dimensional identity matrix $\mathbf{I}_n$. The overall h-step forecast error variance of variable j can easily be calculated by summing these variance contributions over k:

$$\mathrm{MSE}(y_{j,t}(h)) = \sum_{k=1}^{n}\sum_{i=0}^{h-1}(\mathbf{e}_j'\mathbf{\Theta}_{i,t}\mathbf{e}_k)^2. \tag{4.10}$$

Relative variance contributions are then obtained by dividing the two values in (4.9) and (4.10). Similar to Clark (2009), we perform the forecast error variance decomposition in each period t for each saved draw in our sample. The estimates are based on 50-step ahead decompositions, a horizon at which the forecast error variances converge to the unconditional variances of $\mathbf{y}_t$ (Hamilton, 1994). The reported values are calculated as posterior medians.

4.2 Instantaneous Standard Deviations

The descriptive statistics in Section 2.3 only enable us to examine volatility for different periods of time, which are somewhat arbitrarily chosen. The model employed in this section enables us to compute so called instantaneous standard deviations for each quarter. At each point of time, the instantaneous standard deviation of a variable is what the standard deviation would be for all future periods, assuming that the variance of shocks and the coefficients on the lags remain unchanged (Clark, 2009). Analyzing these instantaneous standard deviations makes it possible to obtain a better understanding of the development of volatility of each variable and can provide some idea of the proximate causes of increased variability during the Great Recession. To save space, we only present selected graphs in this section – the full set of graphs may be found in Appendix D.

Overall, the results in this section are in line with our findings in Section 2 and Section 3. We find increases of volatility in many of the series, but volatility returns to Great Moderation levels within a short time frame. This supports the evidence that there have been only few structural breaks, but rather a short-term rise in variability.

4.2.1 Estimation Procedure and Prior Selection

In order to obtain the instantaneous standard deviations, we follow Clark (2009) in estimating a time-varying parameter process of the following form:

$$y_t = \mathbf{x}_t'\mathbf{b}_t + \sigma_t\varepsilon_t \tag{4.11}$$

where y_t is the variable of interest, $\mathbf{x}_t$ is a vector of the right-hand-side variables (the constant and the lags of y_t), $\mathbf{b}_t$ is a stacked vector of coefficients, σ_t is the instantaneous standard deviation, and ε_t is an independent shock. As such, the model is a univariate simplification of the multivariate model in (4.4), and the dynamics of the time-varying parameters $\mathbf{b}_t$ and σ_t follow the processes in (4.5). The estimation of the model in (4.11) is performed over the entire period for which data is available for the respective variable. The prior distributions of $\mathbf{b}_t$ and $\log\sigma_t$ are (multivariate) normal and uninformative. The prior distribution of $\mathbf{b}_t$ has a zero vector as mean and a block diagonal variance covariance matrix with diagonal elements equal to one and off-diagonal elements equal to zero. The prior distribution of $\log\sigma_t$ has a mean of one and a standard deviation of four. In the choice of priors for the hyperparameters we follow Clark (2009). The prior for variance of the shocks on the AR coefficients $\boldsymbol{\nu_t}$ follows an inverse Wishart distribution with a scale matrix of $1 \cdot 10^{-5}$ and 10 degrees of freedom. The prior for the variance of the shock to $\log\sigma_t$ follows an inverse Wishart distribution with a scale matrix of 0.002 and 5 degrees of freedom.[2] The reported results are posterior medians from a sample of 10,000 draws, obtained by saving every fifth draw from 50,000 replications after a burn-in period of 10,000 draws. The number of lags for each variable is selected using the Schwarz Bayesian Information Criterion, where we allow for a maximum of 8 lags.

[2]The results remain qualitatively unchanged when trying alternative prior specifications as proposed in Clark (2009).

4.2.2 Results

United States Evaluating the instantaneous standard deviations for the United States in Figure 4.1 and Figure D.1, we first notice that the Great Moderation is clearly visible in almost all variables we consider. For GDP, investment, and imports there is distinct drop in volatility in the mid 1980s, while for consumption, government expenditure, and inflation the decrease in variability rather appears to represent a trend. For the interest rates, we also observe a declining trend since the 1970s, interrupted by a period of high volatility in the early 1980s. Overall, the visual evidence confirms the breaks in volatility found in Section 3.

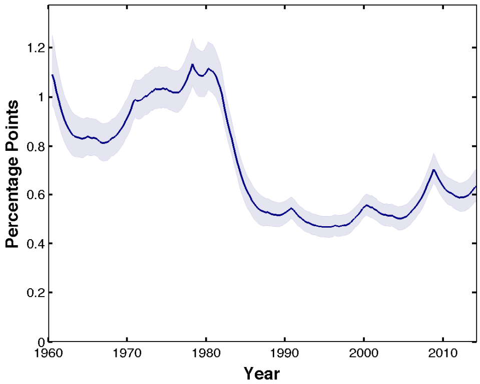
During the Great Recession, we observe volatility spikes in many of the series. Yet, the variability for most series remains below the levels observed before the beginning of the Great Moderation in the mid 1980s. Volatility has markedly increased for GDP, investment, and the trade components. The volatility of consumption, government expenditure, exchange rates, and PCE inflation has been affected only slightly or not at all. The strongest increases in variability, however, took place in measures related to financial distress, namely the financial stress index and the TED spread, as well as the real oil price. It is important to note that for almost all series the volatility returns to pre-recession levels. Only the house price index remains somewhat more volatile. This confirms our finding that this is the only series exhibiting a break in the unconditional variance during the Great Recession.

United Kingdom Inspecting the results for the United Kingdom in Figure 4.2 and Figure D.2, we again find clear indication of the Great Moderation. The reduction in volatility took place with a similar timing as in the United States but is focused on different time series. We observe a large drop in volatility of GDP, consumption, and exports in the early 1980s. Similarly, the variability of PCE inflation and interest rates has strongly and consistently decreased until 2000. In contrast, the fluctuations in investment, the house price index, and unemployment have hardly changed over the decades. Again, the visual evidence is aligned with our break testing results in the previous section.

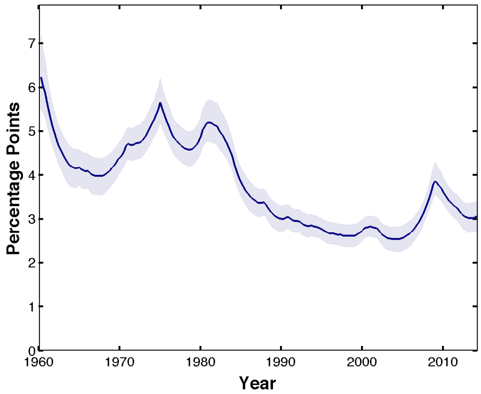
We observe increased volatility for some series during the Great Recession. For instance, the volatility of GDP, consumption, and imports has gone up considerably. The fluctuations of exports even exceeded the levels observed in the 1970s and already started to increase in the late 1990s. In contrast, the variability of investment growth, inflation, the house price index, and unemployment has remained virtually unchanged. As in the United States, the strongest

Figure 4.1: Instantaneous Standard Deviations of Selected U.S. Macroeconomic Time Series

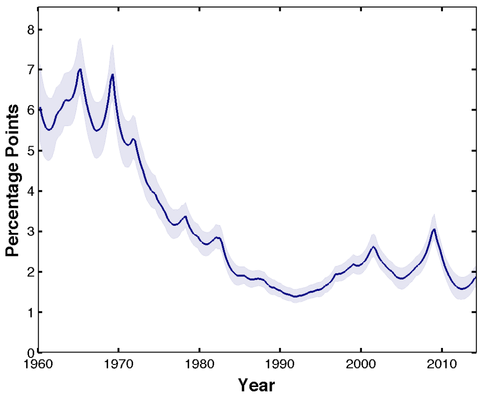
(a) GDP



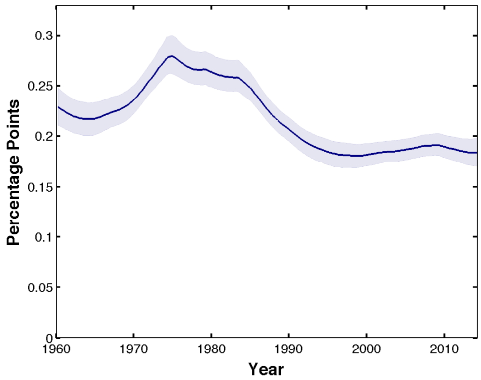
(b) Investment



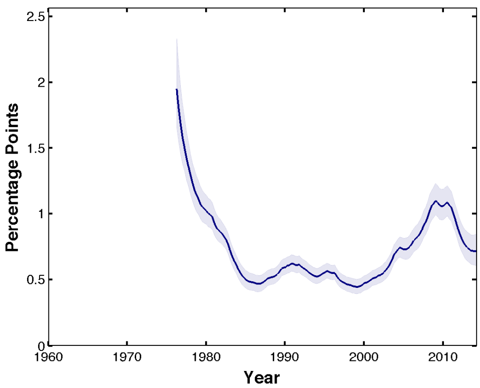
(c) Exports



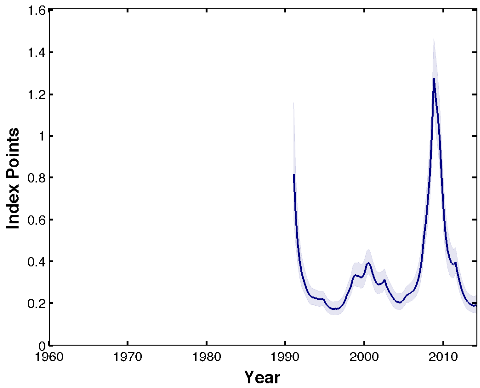
(d) Inflation



(e) House Price Index



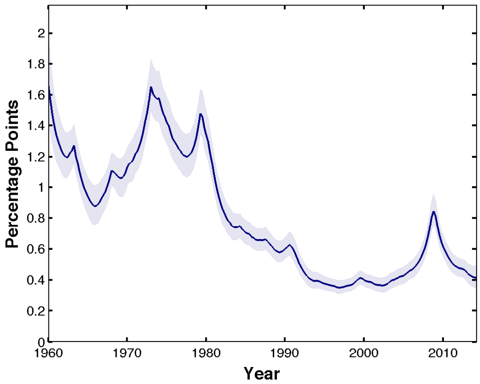
(f) Financial Stress Index



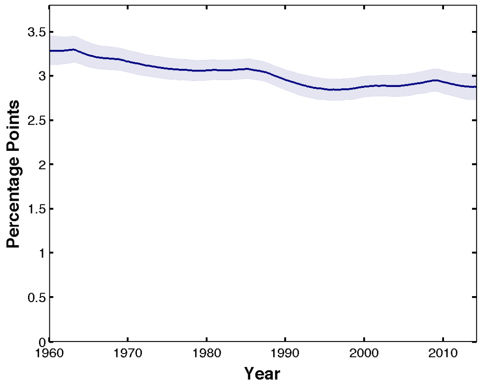
Note: The shaded area indicates a 70% confidence interval. Full set of series in Figure D.1.

Figure 4.2: Instantaneous Standard Deviations of Selected U.K. Macroeconomic Time Series

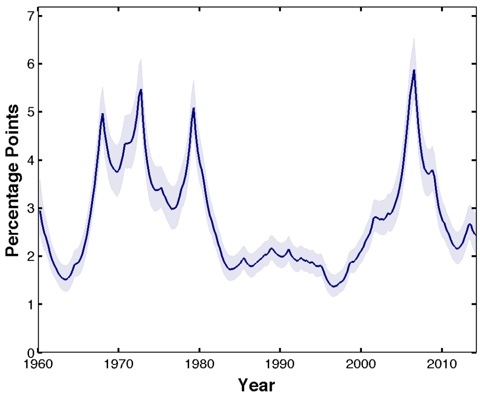
(a) GDP



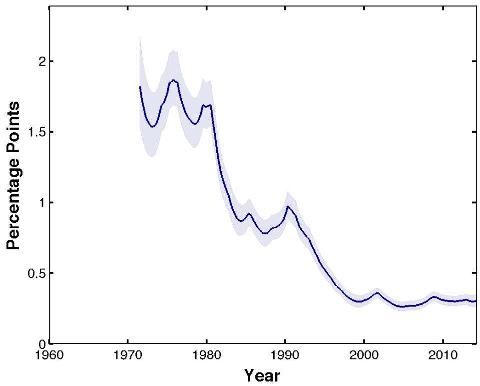
(b) Investment



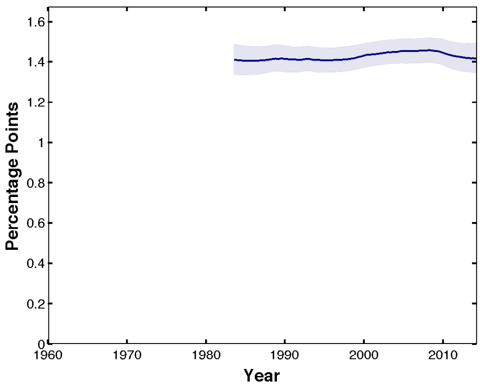
(c) Exports



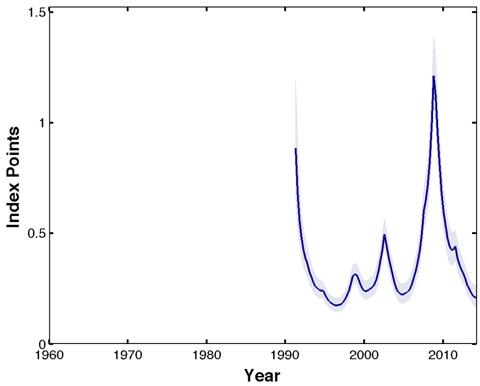
(d) Inflation



(e) House Price Index



(f) Financial Stress Index



Note: The shaded area indicates a 70% confidence interval. Full set of series in Figure D.2.

increases in fluctuations took place in the TED spread, the financial stress index, and the real price of oil. Also, the volatility of each series returned to pre-recession levels fairly quickly, confirming our finding of no breaks in unconditional variance.

Sweden In Figure 4.3 and Figure D.3, we find clear evidence of the existence of the Great Moderation in Sweden. Since the early 1980s the volatility of GDP has clearly decreased, only slightly interrupted by the financial crisis in the early 1990s. Similarly, the fluctuations of inflation have decreased since the 1970s, but were markedly higher during the early 1990s. The volatility of consumption and exports has shown a long and steady decline beginning in the mid-1960s, while investment and unemployment variability has stayed level. Overall, these results are in line with the breaks found in Section 3.

During the Great Recession, we again observe increased volatility in some series, but fluctuations have not returned to pre-moderation levels. Higher variability is especially visible in GDP, imports, inflation, the house price index, and exchange rates. Volatility of consumption, investment, and unemployment has practically not changed. As in the United States and the United Kingdom, the TED spread and the financial stress index exhibit increased variation, but not to the same extent. Again, all series stabilized quickly after the recession and macroeconomic volatility returned to its previous levels – in line with the results in Section 3.

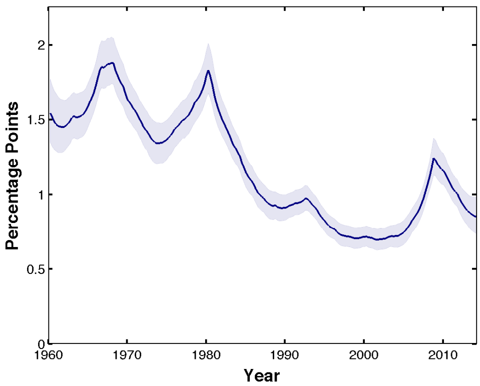
4.3 Macroeconomic Model

In this section, we introduce a small macroeconomic model to decompose the variance each variable has experienced over the last 20 years. More precisely, we estimate a TVP-VAR model including five variables reflecting a simplified version of the U.S., U.K., and Swedish economies. After a detailed description of the model specification, we turn to our estimation procedure and the prior selection and then present the results for each country.

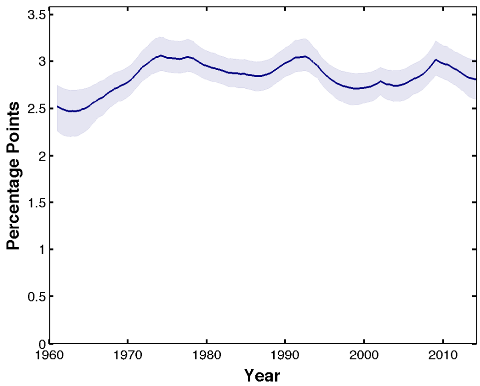
The finding of short-term increased volatility in all three countries is further substantiated. Yet, there is a considerable difference in the magnitude of the increases, which are substantial for the United States and the United Kingdom, but milder in the case of Sweden. The largest share of increased volatility can be attributed to shocks in the financial system, while other shocks only play a minor role. Again, the effects are more pronounced in the two Anglo-Saxon countries.

Figure 4.3: Instantaneous Standard Deviations of Selected Swedish Macroeconomic Time Series

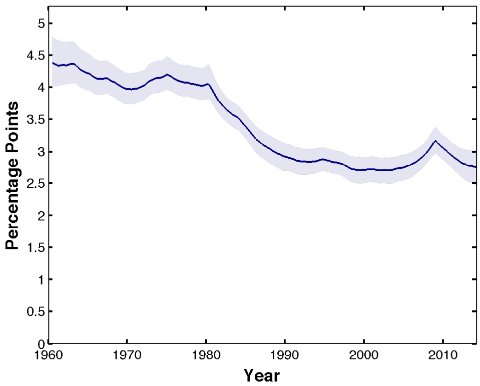
(a) GDP



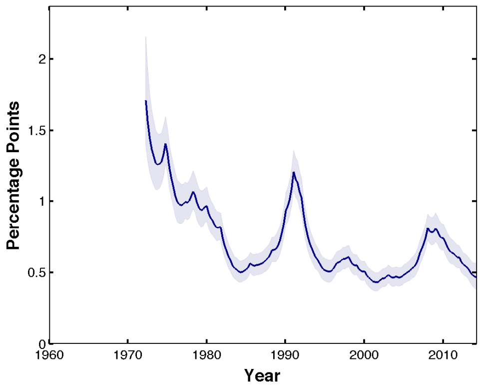
(b) Investment



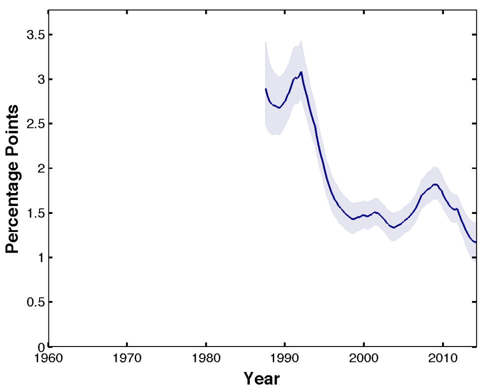
(c) Exports



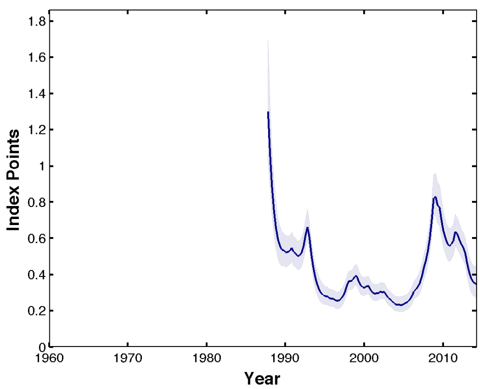
(d) Inflation



(e) House Price Index



(f) Financial Stress Index



Note: The shaded area indicates a 70% confidence interval. Full set of series in Figure D.3.

4.3.1 Model Specification

The method chosen in this study to model the relationship between variables is inherently limited in the number of variables that can reasonably be included (Koop and Potter, 2011; Stock and Watson, 2012). Therefore we restrict our analysis to five variables. To ensure comparability of results, we employ the same model for all three countries.

First of all, the Great Moderation primarily refers to the reduced variability of real GDP and inflation. To analyze the volatility of these series, they must be included in our model. Moreover, we include three variables that – based on the evidence presented in previous sections and the literature – appear most relevant in explaining the volatility observed during the Great Recession. A natural starting point for causes of the end of the Great Moderation could be the causes of the Great Moderation itself. Yet, it is unlikely that good practices have turned into bad practices or that good policy has turned into bad policy (Canarella et al., 2010; Clark, 2009). Our findings in the previous sections also indicate that the Great Moderation has not been reversed, but rather interrupted by short-term shocks. In a sense, the Great Recession may have been the result of "bad luck". Thus, we focus on different shocks that may have caused this increase in volatility.

For both the United States and the United Kingdom, we find the largest increases in variability in measures of financial stress. Similarly, the literature suggests that financial stress played an important role in causing the Great Recession in the U.S. and we include the financial stress index as a third variable (Arellano and Kehoe, 2012; Christiano et al., 2014). Besides, Clark (2009) and Stock and Watson (2012) attribute some of the drop in output to oil price shocks. Since real oil prices also showed considerably increased volatility during the Great Recession in all three countries, we include these in our model. Finally, we note that house price volatility was clearly elevated in both the U.S. and Sweden and may have played some role in the recession. Consequently, we include the house price index as the fifth variable.

As noted, the identification of our system is based on a Cholesky decomposition and the ordering of variables in our model may affect results. To establish a sensible ordering, we rely on economic reasoning and previous empirical findings. Since we want to estimate the effect of the other variables on output and inflation volatility, we order GDP and inflation in the last two places. Blanchard and Simon (2001) suggest that inflation volatility may affect variability of output growth. Therefore, we order GDP after inflation. Oil prices are generally thought of as exogenous shocks, which are not affected by other variables. Also, Stock and Watson (2012) suggest that the Great Recession was to some extent caused by an initial oil price shock. Following this reasoning we order real oil prices first. The ordering of the house price index and the financial stress index can then be based on historical evidence. Bean (2010) and others note that the financial crisis in the United States started after the subprime-mortgage crisis. Therefore we order the house price index before the financial stress index. Even though this argument is only based on U.S. evidence, we employ the same ordering for the other two countries.

In summary, the TVP-VAR model takes the form outlined in Section 4.1 with $n = 5$ variables. The variables are the real oil price, the house price index, the financial stress index, inflation, and the gross domestic product, named in the sequence of their ordering. All data are normalized over the estimation period.[3] In line with previous literature, we set the number of lags included in the TVP-VAR to $p = 2$ (Benati, 2008; Primiceri, 2005).

4.3.2 Estimation Procedure and Prior Selection

The estimation sample of our TVP-VAR spans 78 quarters and reaches from 1995:Q1 to 2014:Q2. Similar to Clark (2009), we choose informative and normally distributed priors for $\mathbf{b}_0$, $\mathbf{A}_0$, and $\log \boldsymbol{\sigma}_0$. Parameter values for these priors are obtained from a time invariant VAR model that is estimated over a so called training sample prior to the estimation sample. Due to data availability limitations, we do not have access to the full 40 quarters prior to the beginning of the estimation sample. Since we consider a minimal length of the training sample more important than a strict separation of training and estimation sample, we let the data sample for estimating the priors (*prior sample*) overlap to ensure a VAR estimation based on at least 40 observations.[4] Hence, for the United States the prior sample reaches from 1991:Q1 to 2000:Q4, for the United Kingdom from 1991:Q4 to 2001:Q3 and for Sweden from 1988:Q2 to 1998:Q1. In line with Clark (2009), Gerba and Hauzenberger (2013) and others we use the point estimates of the coefficients ($\hat{\mathbf{b}}_{OLS}$) and the $\mathbf{A}$ matrix ($\hat{\mathbf{A}}_{OLS}$) as the prior mean and four times the respective variance for the prior variance. For the mean of the distribution of $\log \boldsymbol{\sigma}_0$ we choose the logarithm of the OLS point estimate and assume the variance covariance matrix to be the identity matrix.

[3] OIL, FSI, and GDP are transformed as described in Section 2.3.1. To ensure efficiency of the MCMC sampler, we do not difference HPI and PICORE. Robustness checks show that this change is innocuous.

[4] Evidence on the data used for the calculation of informative priors is mixed. While most scholars – among them Clark (2009) and Primiceri (2005) – only use data prior to estimation sample, Gerba and Hauzenberger (2013) base their priors on time invariant VAR estimates of the complete estimation sample.

For the hyperparameters $\mathbf{Q}$, $\mathbf{S}$, and $\mathbf{W}$, we choose priors which have become more or less standard in the literature on TVP-VAR models. These hyperparameters are assumed to follow an inverse Wishart distribution. As in Primiceri (2005), we additionally make the assumption that $\mathbf{S}$ is block diagonal, which implies that the coefficients of the contemporaneous relations among variables evolve independently in each equation. In line with the literature, we choose the scale matrix of the distribution of $\mathbf{Q}$ to be 0.0001 times the dimension of $\hat{\mathbf{b}}_{OLS}$ plus one times the OLS point estimate of the variance of $\hat{\mathbf{b}}_{OLS}$. For the scale matrix of the distribution of $\mathbf{S}$ we choose 0.001 times the respective block's dimension plus one times the OLS point estimate of the variance of $\hat{\mathbf{A}}_{OLS}$ for the corresponding block. For the scale matrix of the distribution of $\mathbf{W}$, we choose 0.001 times the dimension of $\hat{\boldsymbol{\sigma}}_{OLS}$ plus one times an n-dimensional identity matrix. To have a proper prior, the degrees of freedom for each inverse Wishart distribution must exceed the dimension of the respective hyperparameter by at least one. We choose exactly these values for the degrees of freedom, thus putting as little weight as possible on these priors and making them diffuse and uninformative (Gerba and Hauzenberger, 2013). The choice of priors can be summarized as follows:

$$
\begin{aligned}
\mathbf{b}_0 &\sim N(\hat{\mathbf{b}}_{OLS}, 4 \cdot V(\hat{\mathbf{b}}_{OLS})),\\
\mathbf{A}_0 &\sim N(\hat{\mathbf{A}}_{OLS}, 4 \cdot V(\hat{\mathbf{A}}_{OLS})),\\
\log \boldsymbol{\sigma}_0 &\sim N(\log \hat{\boldsymbol{\sigma}}_{OLS}, \mathbf{I}_n),\\
\mathbf{Q} &\sim IW(0.0001 \cdot (dim(\hat{\mathbf{b}}_{OLS}) + 1) \cdot V(\hat{\mathbf{b}}_{OLS}), dim(\hat{\mathbf{b}}_{OLS}) + 1),\\
\mathbf{S}_i &\sim IW(0.001 \cdot (i+1) \cdot V(\hat{\mathbf{A}}_{i,OLS}), i+1), \quad i = 1, \ldots, n-1,\\
\mathbf{W} &\sim IW(0.001 \cdot (dim(\hat{\boldsymbol{\sigma}}_{OLS}) + 1) \cdot \mathbf{I}_n, dim(\hat{\boldsymbol{\sigma}}_{OLS}) + 1).
\end{aligned}
$$

Assuming that the matrix $\mathbf{A}$ is a lower triangular implies that the identification of the system is based on a recursive, or Cholesky, ordering. Consequently, the ordering of variables in the vector $\mathbf{y}_t$ affects the results. If we order oil prices first, for instance, a shock to oil prices can have an immediate effect to GDP growth, but GDP growth can only affect oil prices after one period.

The reported values are calculated as posterior medians, based on a sample of 5,000 draws. This sample is obtained by first generating 10,000 burn-in draws and then saving every fifth draw from the next 25,000 draws. Burn-in draws are used to ensure convergence to the true distributions. Following Clark (2009), we only use every fifth draw after the burn-in period to reduce autocorrelation in the sample. As Cogley and Sargent (2005), we exclude explosive autoregressive roots from the estimation.[5]

4.3.3 Results

United States Figure 4.4 illustrates the modeled U.S. estimates of the instantaneous variance of each variable, broken down into the estimated contribution of each source of shock. The total height of the shaded contours depicts the variable's variance over the estimation sample. The contribution from each shock is depicted by the differently colored contours, with wider contours implying larger contributions.

As expected, we observe volatility increases for all five variables during the financial crisis. The sharp decreases shortly after substantiate our finding of no structural breaks in the respective series. The variances of the real oil price, inflation and the financial stress index return to pre-crisis levels, whereas those of the house price index and GDP remain somewhat higher than before the crisis.

Considering the separated shocks contributing to volatility, we notice that the shocks of the respective variable are responsible for the bulk of the variance, leaving only a minor role to the shocks caused by other variables. Yet, during the financial crisis we find a large increase of the financial stress index as a variance contributor for all variables. Apparently, the increased volatility in the financial sector led to increased insecurity in the whole economy captured by the variables' higher volatility. Another striking finding is the persistently increasing role of housing price shocks when considering the variance process of the house price index. The process of the light grey shaded area in panel (b) of Figure 4.4 implies that shocks in the housing price index continuously increased until 2011 and have remained in a high state afterwards. Comparing the beginning and the end of the estimation sample, we see that the doubled volatility in housing prices is solely caused by those shocks.

For a more detailed analysis regarding the change in total variance and variance contributions, we back the visual evidence with figures reported in Table 4.1. The first two columns of Table 4.1 report the change in the average instantaneous variance of each variable between the period of the estimation sample which can be classified as the Great Moderation era (1995:Q1 - 2006:Q4) and the period of the financial crisis (2007:Q1 - 2009:Q4). The remaining columns report

[5] We adopt the strategy of Cogley and Sargent (2005) and use a algorithm developed by Carter and Kohn (1994) to draw an entire vector of states and then discard this entire vector if we find the vector to be explosive.

Figure 4.4: Variances and Variance Contributions from the TVP-VAR Model for the U.S.

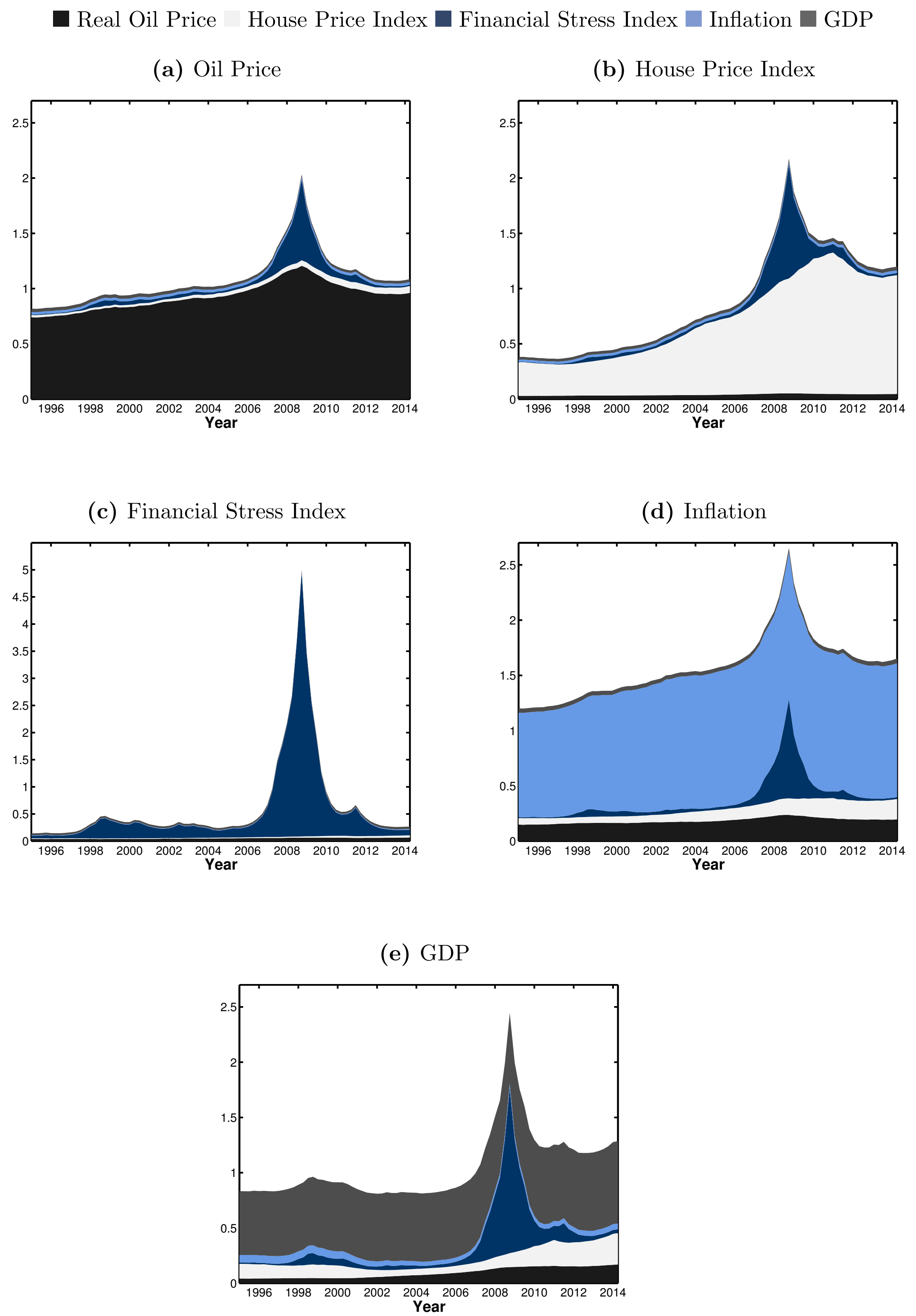


Table 4.1: Changes in Total Variance and Variance Contributions

Country Variable	**Change in Total Fitted Variance** Total	in %	**Change in Variance Contribution** OIL	HPI	FSI	PICORE	GDP
United States							
OIL	0.58	60.93	0.28	0.02	0.29	0.00	-0.01
HPI	1.01	183.73	0.02	0.56	0.43	0.00	0.00
FSI	2.02	694.89	0.02	0.01	1.99	0.00	0.00
PICORE	0.69	48.93	0.06	0.07	0.35	0.22	0.00
GDP	0.72	84.48	0.08	0.02	0.59	-0.02	0.05
United Kingdom							
OIL	0.44	42.75	0.14	0.03	0.28	-0.02	0.01
HPI	0.60	59.45	0.03	0.20	0.37	-0.01	0.00
FSI	2.60	831.18	0.01	0.00	2.59	0.00	0.00
PICORE	0.08	5.36	0.02	0.02	0.30	-0.28	0.02
GDP	0.69	81.87	0.03	0.07	0.46	-0.01	0.14
Sweden							
OIL	0.13	11.86	0.10	0.00	0.02	0.01	0.00
HPI	0.13	9.63	0.05	-0.03	0.05	0.07	0.00
FSI	0.42	44.03	0.04	0.00	0.36	0.01	0.01
PICORE	0.35	32.28	0.01	-0.01	0.04	0.31	0.00
GDP	0.33	28.35	0.05	0.00	0.10	0.05	0.12

Note: Changes are calculated by subtracting the respective average of the Great Moderation period (1995:Q1 - 2006:Q4) from the average of the Great Recession period (2007:Q1 - 2009:Q4), with positive numbers indicating rising variance. The first two columns report the change in the total variance of each variable. The remaining columns report the contribution in the change of variance accounted for by each shock in the model. All figures are computed from posterior medians of the described macroeconomic model.

the relative change in variance contribution accounted for by each shock in the model. These estimates indicate the relative importance of the shocks as variance contributors.

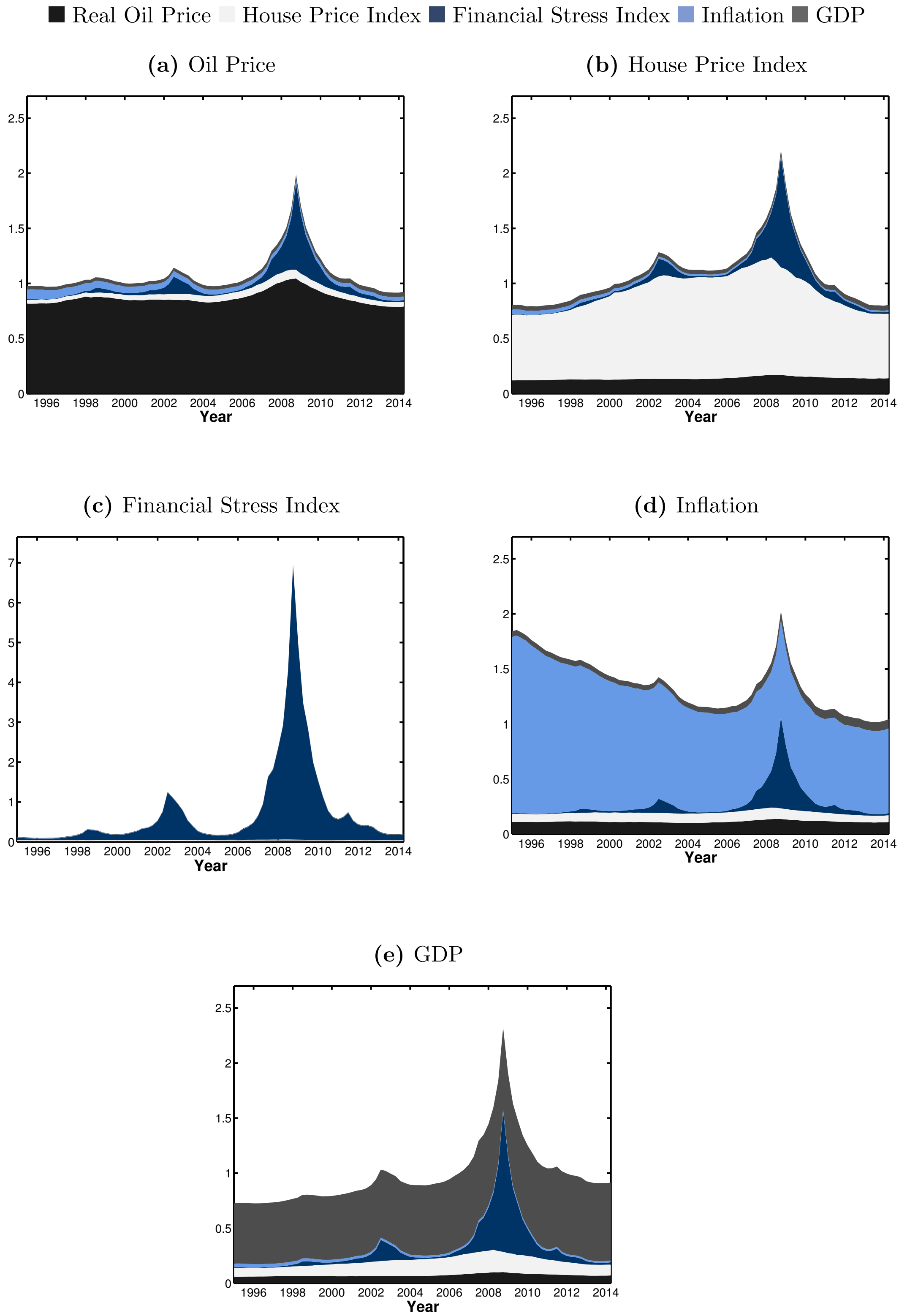
The magnitude of the changes in total variance, which can be seen best when looking at the percentages in the second column, is staggering. The 49% volatility increase in inflation is the lowest compared with the ones for the real oil price (61%), GDP (84%), and the house price index (184%). The volatility spike of the financial stress index in Figure 4.4 even amounts to an increase of 695%. Searching for the contributors responsible for those sharp increases, we find the financial stress index to play a major role. Using the prominent example of GDP growth, the doubling in volatility is mainly caused by shocks in the financial sector (82%). Shocks in the oil price (11%), house price index (3%), and GDP itself (7%) only add little to the increased volatility, the contribution of inflation shocks is in fact negative (-3%). The finding of financial shocks as the main contributor for the increased volatility qualitatively holds for the real oil price, inflation, and housing prices. The only difference stems from the individual shock of the variable, which take a higher share of the increased volatility than in case of output volatility. The increased volatility in the financial stress index is almost completely explained by shocks to the variable itself.

United Kingdom The results from the macroeconomic model for the U.K. are illustrated in Figure 4.5. The instantaneous variance process shows a similar pattern as the U.S. variance process – especially the same volatility spike during the financial crisis stands out. Yet, we observe some interesting differences. The U.K. lived through a short period of increased volatility around 2003, indicated by a small spike in the variance of all five variables. Notably, we see a moderation in the volatility of inflation over the whole estimation sample, interrupted only by the short-term increase during the financial crisis. Also, the variance process in housing prices is quite distinct from the one in the United States. Housing prices in the U.K. enter a period of higher volatility around 2002, spike during the financial crisis and then return to values observed in the first five years of the estimation sample. The observation of higher volatility already starting in 2002 also explains the difference in house price index volatility increases between the U.K (59%) and the U.S. (184%). Considering the variance contributors, the contribution of housing price shocks in the U.S. continued to increase after 2009 and remained in a high state (see the light-grey shaded area in panel (b) of Figure 4.4). This is not the case in the United Kingdom, where the contribution of housing price shocks decreases since 2008 and remains low afterwards.

The figures in Table 4.1 support the visual evidence. Although slightly different in magnitude, the large increase in total variance is qualitatively similar to the one in the United States. The variance in the real oil price increases by 43%. Even higher increases are noted in the variance of housing prices (59%), GDP (82%) and the financial stress index (+831%). Judging from panel (d) of Figure 4.5, however, the observation that inflation volatility only appears to increase by a small amount can be considered a statistical artifact. Inflation volatility has been steadily decreasing since the beginning of our estimation sample, the increase compared to the period directly before the recession is considerable. As for the United States, we find that the bulk of the volatility increase in most variables comes from financial stress. Oil price and housing price shocks only play a minor role in the increased variability during the Great Recession.

Sweden Figure 4.6 depicts the results for the macroeconomic model when using Swedish data. We find increases in the estimated variances of each variable, just as in the case of the United States and the United Kingdom. Yet, the effects are extremely attenuated: the magnitude of volatility change is considerably smaller than in the other two countries. As a matter of fact, the change is barely visible in the case of the house price index and only to a certain extent in the case of the real oil price and inflation. The financial stress index experiences

Figure 4.5: Variances and Variance Contributions from the TVP-VAR Model for the U.K.



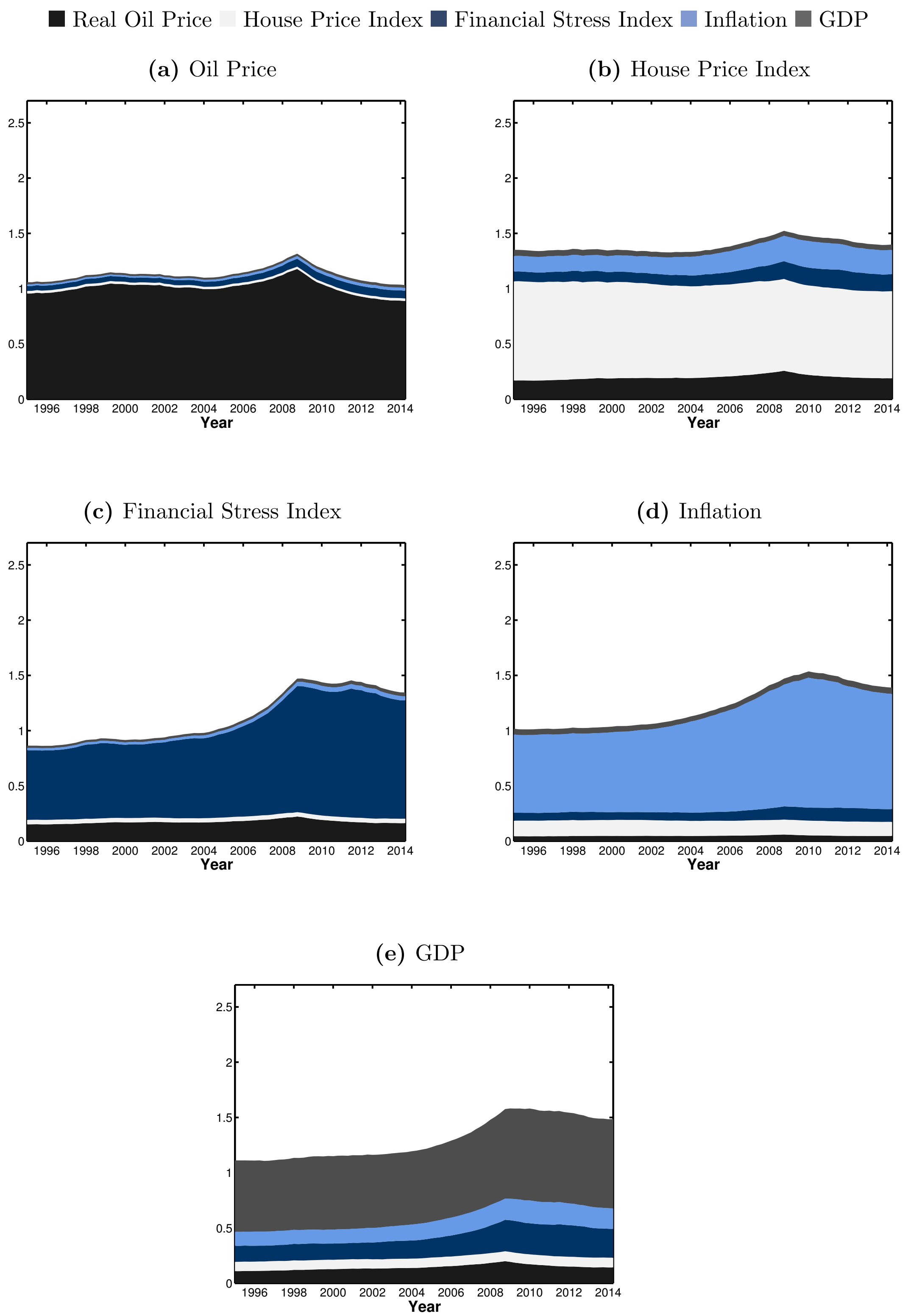
a moderate volatility increase, predominantly caused by its own shocks. In a similar manner, output volatility experienced a moderated increase. The contributions for this increase, however, are more equally distributed among the different shocks.

The contrast in the visual findings for Sweden is supported by the figures in Table 4.1. The mild changes in the real oil price, the house price index and inflation amount to volatility increases of 12%, 10%, and 32%, respectively. Whereas the changes are predominantly caused by shocks of the own variable in the case of oil and inflation, the marginal increase in house prices is caused by a combination of oil price, inflation and financial shocks. The variance of the financial stress index increased by 44% during the Great Recession, considerably less than the increases in the U.K. (831%) and in the U.S. (695%). Yet, the finding that the increased volatility in the financial stress index is predominantly caused by its own shocks also holds for Sweden. The increase in output volatility amounts to 28% and is significantly weaker compared to the increases of 85% in the United States and 82% in the United Kingdom. Decomposing the variance, we note that shocks of all variables (except the house price index) contribute to the moderate increase. About a third of the output volatility increase is explained by shocks to the financial stress index, a much lower portion than in the United States and the United Kingdom. This finding indicates that the transmission of shocks from the financial to the real sector is less pronounced than in the Anglo-Saxon countries. Also, financial stress plays only a very small role in explaining increased inflation fluctuations.

4.3.4 Robustness

The results described above are qualitatively robust to different orderings of the variables. Also, changing the time span of the prior sample and the length of the estimation window does not affect the results in any substantial way. Conducting convergence diagnostics of the MCMC sampler, we follow Primiceri (2005) and investigate the autocorrelation of the draws. Low autocorrelations suggest that the MCMC sampler mixes well and draws are almost independent, which implies a higher efficiency of the algorithm. Similar to Primiceri (2005), we plot the 20-th-order sample autocorrelation of the draws. As shown in Appendix E, we obtain satisfactory convergence results. With some exceptions the autocorrelations for the time-varying coefficients $\boldsymbol{b}_t$, the time-varying simultaneous relations $\boldsymbol{A}_t$ and the time-varying volatilities $\boldsymbol{\sigma}_t$ remain below 0.2.

Figure 4.6: Variances and Variance Contributions from the TVP-VAR Model for Sweden



5 Interpretation and Discussion

In this section, we discuss our findings obtained in Section 3 and Section 4. Comparing the results between the countries and in the context of the existing literature, the discussion is organized in line with the research question posed in Section 2. Some limitations of our empirical study are outlined in Section 5.4.

5.1 The Great Moderation in Sweden

Building on the evidence of the break testing analysis and the instantaneous standard deviations, we document a major decline in the volatility of many Swedish macroeconomic variables. The Figures 4.3 and D.3 show that many of the time series have experienced a decrease in volatility.

Considering the time prior to the Great Recession, the process of the instantaneous standard deviations of GDP, consumption, exports and imports shows a downward trend since the 1980s. The volatility of government expenditure also decreased in the early 1980s, but only to a smaller extent. It remained in this state until the end of the 1990s, where it dropped to a even lower state (an observation that is supported by the break dates reported in Table 3.3). Other variables, such as the volatility of inflation, the exchange rate, the 3-month treasury bill rate or the TED spread follow a decreasing pattern, where the state of low volatility is interrupted only during the Swedish banking crisis in the early 1990s.

It is precisely this banking crisis which severely hit the Swedish economy and makes it hard to date the beginning of a possible Great Moderation. We find two time periods which comprise many structural breaks and can therefore be seen as possible start dates of a Great Moderation era in Sweden. The first possible start date centers around the early 1980s, similar to the case of the United States. The volatility of GDP as well as both its trade components experience breaks in the conditional and unconditional variance during this time period. Additionally, government expenditure and imports break in the conditional mean. The years after the banking crisis in the early 1990s constitute the second candidate to pin down the start of the Great Moderation. Whereas many GDP components already experienced breaks in the 1980s, the volatility of the exchange rate, the house price index and financial market measures break in the years subsequent to the crisis. Yet, it should be noted that possible earlier volatility decreases of these variables or even breaks cannot be observed due to the data availability restrictions.

Moreover, the propagation mechanism seems to play a role for the breaks occurring in the early 1990s. The volatility of the housing price index, the central bank rate, the TED spread, the unemployment rate and even GDP experience a break in the conditional mean. This change in the autoregressive coefficients combined with the substantiated decrease in volatility supports the idea of a change in the stability of the Swedish economy. Nonetheless, the reduction of shocks is a prominent feature which can be seen in the numerous breaks in the conditional variance, many of them to be found in the longer time series and also prior to the banking crisis.

Investigating the panels of Figures 4.3 and D.3, we can also obtain some indications on the underlying causes of the decrease in output volatility. While we note only minor decreases in the volatility of investment and government expenditure for Sweden, the panels for the United States in Figure D.1 show a sharp volatility downturn across all GDP components. Thus, it is unlikely that those two components are responsible for the decrease in output volatility. What we do observe, however, is a pronounced co-movement of inflation and output volatility. This finding supports the view hold by Blanchard and Simon (2001) who attribute decreases in output volatility to policy-induced reductions in inflation volatility.

Our results may not finally answer the question whether there has been a long-time downward trend or a one-time decrease in volatility, but provide profound evidence of lower volatility throughout the Swedish economy over the last decades. The Great Moderation in Sweden might have already started during the 1980s, but was interrupted by the banking crisis in 1990 resulting in higher volatility in the short-term. Yet, our findings suggest that Sweden – just like other countries – entered a Great Moderation era, at the latest from 1994.

5.2 Signs for the Continuation of the Great Moderation

Based on the visual evidence in Section 4.2.2 and Appendix D, a continuation of the Great Moderation in the United States, the United Kingdom, and Sweden is very likely. The instantaneous standard deviations for most series spike during the Great Recession, but quickly return to pre-crisis levels. The turmoil in the financial system causes the volatility rise of the financial stress index to be the highest of all spikes. In contrast, the volatility in consumption, government expenditure, and unemployment rates remains low in all countries.

Interesting differences can be observed in the volatility of inflation. While the variance remains low in the U.S. and the U.K., we find a notable increase in inflation variability in Sweden. This may represent differences in the conduct of monetary policy during the financial crisis, the analysis of which is beyond the scope of this study. Furthermore, the volatility of housing prices differs substantially between countries. We observe an almost trending increase in the United States during the 2000s, whereas the volatility stayed level in the United Kingdom. In Sweden, we note a short-term increase during the Great Recession. Comparing these three processes, the volatility movement in U.S housing prices in recent years becomes visible. The general picture, however, remains unchanged. The volatility of most variables at hand returned to Great Moderation levels soon after the Great Recession.

This interpretation is supported by the results of our tests for structural breaks. Judging from the break dates reported in the Tables 3.1, 3.2 and 3.3, a reversal of the Great Moderation caused by the aftermaths of the financial crisis is highly unlikely. Only few breaks occurred during the Great Recession, most of them in the conditional variance of financial variables. This finding points at the large shocks in the financial system during those years and is consistent with the variance decomposition results reported in Section 4.3.3. The fact that no structural changes in the conditional mean can be found (with the exception of the U.S. financial stress index), can be interpreted as another strong sign for the continuation of the Great Moderation: the propagation mechanism did not experience significant breaks, implying that the persistence of shocks to the variables for the most part has not changed significantly. This interpretation also connects to the suspected causes of the Great Moderation discussed in Section 2.2. It appears unlikely that the structural changes in policy and practices – which probably explain some of the decrease in volatility during the Great Moderation – have suddenly reverted. The Great Moderation may only have been reverted to the extent to which it was actually explained by good luck.

As such, our evidence for the United States is in line with the earlier findings of Chen (2011) and Gadea et al. (2013), but covers a much wider set of variables and more recent data. Our findings for the United Kingdom contradict the preliminary evidence of Canarella et al. (2010) that the Great Moderation has ended in 2007. As Chen (2011), we find that output volatility returned to a low-volatility state, but extend evidence to a wider dataset. The evidence for Sweden is completely novel and can thus not be compared to other findings.

5.3 Financial Stress as a Source of Volatility

For the United States, our empirical results indicate that a large portion of volatility in GDP can be explained by financial stress, with shocks to oil prices playing only a secondary role. This evidence is largely in line with the findings of Clark (2009) and Stock and Watson (2012). In this respect, the findings for the United Kingdom look very similar; GDP volatility also increases by approximately 80% during the Great Recession. As suggested by Hills et al. (2010), the financial system can be identified as the main source of the crisis and volatility. The role of oil price shocks in the United Kingdom is even lower than in the United States. Inflation volatility increases in both countries are also a result of financial stress.

Interestingly, the overall variance in our model is much lower for Sweden. The impact of shocks to the financial stress index on output and inflation volatility appears to be attenuated when compared to the other two countries. This finding is clearly in line with the argument of Benati (2012), who reasons that Sweden has been more affected through trade channels rather than issues in its own financial systems. The high shares of exports and imports relative to GDP substantiate the argument of trade as a possible transmission channel in the case of the Swedish economy. Benati (2012) also notes that Sweden has revamped its financial system following the banking crisis in the early 1990s. This could have made it more resilient and reduced transmission of financial shocks to the real economy. Further research on the Great Recession in Sweden may therefore focus on the trade channel and its importance for volatility in the Swedish economy.

5.4 Limitations

Several aspects have to be taken into account when interpreting our results. As outlined by Koop and Potter (2011), the dimensionality of the TVP-VAR model must be limited to ensure not only efficiency, but power. Due to the high number of estimated parameters in a TVP-VAR model, we therefore have to restrict the number of variables. The five variables included in our model capture a fair portion of the economy, but cannot mimic the complete system. To do so, alternatives such as the dynamic factor model (DFM) employed by Stock and Watson (2012) are required. While a DFM is able to include a huge number of variables, the re-identification of shocks again relies an strong assumptions about the respective factors.

Related to this limitation, the variables included are not able to capture particular shocks as sensitively as desired. For instance, the house price index is limited in capturing movements in the subprime mortgage market, a variable indicating an even higher volatility than the aggregated house price index. Due to reasons of data availability, we restrict our estimation to the named variables ensuring comparability across the countries to the greatest possible extent.

The variance decomposition enables us to capture the share of each other variable contributing to the increased variance. Yet, we cannot tell where the variation of contributions comes from. Due to the time-varying nature of the model, they can be caused by shocks in the coefficients $\boldsymbol{b}_t$, simultaneous relations $\boldsymbol{A}_t$ or volatilities $\boldsymbol{\sigma}_t$. Hence, the major role of the increased volatility in the financial sector could be due to larger propagation effects ($\boldsymbol{b}_t$), changed simultaneous effects between the financial stress index volatility and inflation and output volatility ($\boldsymbol{A}_t$) or larger volatility shocks in the financial system itself ($\boldsymbol{\sigma}_t$), with the other relations remaining more or less constant.

6 Conclusion

During the Great Recession, the United States, the United Kingdom, and Sweden experienced levels of macroeconomic volatility that had not been observed in the decades before, a time period commonly referred to as the Great Moderation. This led observers to ask whether the beginning of the Great Recession has marked the end of the Great Moderation (Bean, 2010; Canarella et al., 2010; Clark, 2009). While there has been some evidence on this question for the United States, research for the United Kingdom and Sweden has been very limited so far. Moreover, the Great Moderation has previously not been explicitly documented for Sweden. Therefore, this study sets out to provide some further insights on macroeconomic volatility during the Great Moderation and the Great Recession in all three countries. For this purpose, we employ a series of econometric methods, including tests of structural breaks developed by Bai (1997) and a TVP-VAR with stochastic volatility pioneered by Primiceri (2005).

The contribution to literature of our study is threefold: First, we find clear evidence of the existence of a Great Moderation in Sweden that is connected to reduced levels of macroeconomic volatility since the 1980s, interrupted by the banking crisis in the early 1990s. Decreased fluctuations are especially observed for output, consumption, and inflation. Second, we show that the Great Moderation appears to be still intact. The Great Recession represented only a short-term increase in volatility, which quickly returned to its moderated levels. Third, the increased volatility in the late 2000s can largely be attributed to shocks in the financial system, rather than structural changes in the economy. We further note that the impact of financial stress on the macroeconomy in Sweden has been lower than in the United States and the United Kingdom.

Our findings regarding the causes of increased volatility must be interpreted in light of the macroeconomic model used and its inherent limitations. Due to the high number of estimated parameters, the dimensionality of the TVP-VAR must be limited to ensure power. We can therefore not include all variables of interest, noticing that especially trade variables may be interesting to include in future research. Moreover, the macroeconomic perspective we take on the issue enables us to identify the proximate causes of volatility, but not the underlying dynamics of the (financial) shocks observed.

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A Data – Characteristics, Transformation and Pre-Testing

A.1 Original Data Used in the Analysis

Table A.1 reports the original data used in the analysis as well as some main features. The first two columns specify the used abbreviation for the variable and the variable itself. The following five columns report data characteristics. In particular, Column 3 (*Spec.*) indicates whether the variable is nominal (n) or real (r). Only the crude oil price had to be transformed to real values by using the respective GDP deflator of the country. Column 4 specifies the data frequency (*Freq.*), where q stands for quarterly, m for monthly and d for daily reported data. If the data was not already reported quarterly, we transformed the variable accordingly by taking the average of the measuring unit within one quarter. In the fifth column (*SA*), we indicate whether the variable is seasonally adjusted (sa) or not (nsa) – we used seasonally adjusted data when avaibable. The sixth column (*Availability*) reports the first quarter for which data is available. The last column (*Source*) describes the data source. For the U.S, all data is obtained from the Federal Reserve Economic Data (FRED) database, provided by the Federal Reserve of St.Louis. For the other two countries, we rely on several sources. Data on GDP and its decomposing variables as well as inflation[1] is obtained from the OECD Stat Extracts database. The unemployment rates stem from the Eurostat database. Interest rates and the trade-weighted exchange rate index were retrieved from the databases of the respective central banks, the Bank of England (BOE) and the Riksbank. For other cases where no data could be found, we calculate the variables ourselves (see Appendix B).

[1]Inflation is measured by the change in the price index of core personal consumption expenditure (PCE), which includes all expenditures, except expenditures for food and energy. Thus, the original data source required is the core PCE.

Table A.1: Original Data Used in the Analysis

Country Abbr.	Variable	Spec.	Freq.	SA	Availability	Source
United States						
GDP	Gross Domestic Product	r	q	sa	1947:Q1	FRED
CONS	(Private) Consumption	r	q	sa	1947:Q1	FRED
INVST	Investment	r	q	sa	1947:Q1	FRED
GOV	Government Expenditure	r	q	sa	1947:Q1	FRED
EXP	Exports of Goods and Services	r	q	sa	1947:Q1	FRED
IMP	Imports of Goods and Services	r	q	sa	1947:Q1	FRED
PICORE	Inflation	n	m	sa	1959:Q1	FRED
HPI	All-Transactions House Price Index	n	q	nsa	1975:Q1	FRED
UR	Unemployment Rate	n	m	sa	1948:Q1	FRED
TWEXR	Trade-Weighted Exchange Rate Index	n	m	nsa	1973:Q1	FRED
CBR	Base Rate (Federal Fund Rate)	n	m	nsa	1954:Q3	FRED
TB3M	3-month Treasury Bill	n	m	nsa	1934:Q1	FRED
TED	Interest Rate Spread (TED)	n	d	nsa	1986:Q1	FRED
FSI	Kansas City Financial Stress Index	n	m	nsa	1990:Q2	FRED
OIL	Crude Oil Price - West Texas Intermediate	r*	m	nsa	1986:Q1	FRED
United Kingdom						
GDP	Gross Domestic Product	r	q	sa	1955:Q1	OECD
CONS	(Private) Consumption	r	q	sa	1955:Q1	OECD
INVST	Investment	r	q	sa	1955:Q1	OECD
GOV	Government Expenditure	r	q	sa	1955:Q1	OECD
EXP	Exports of Goods and Services	r	q	sa	1955:Q1	OECD
IMP	Imports of Goods and Services	r	q	sa	1955:Q1	OECD
PICORE	Inflation	n	q	nsa	1970:Q1	OECD
HPI	Halifax House Price Index	n	q	sa	1983:Q1	BOS
UR	Unemployment Rate	n	m	sa	1983:Q1	Eurostat
TWEXR	Trade-Weighted Exchange Rate Index	n	q	nsa	1980:Q2	BOE
CBR	Base Rate (Bank Rate)	n	q	nsa	1975:Q2	BOE
TB3M	3-month Treasury Bill	n	q	nsa	1975:Q2	BOE
TED	Interest Rate Spread (LIBOR - TB3M)	n	q	nsa	1991:Q1	own calc.
FSI	Financial Stress Index	n	q	nsa	1991:Q1	own calc.
OIL	Crude Oil Price - Brent-Europe	r*	m	nsa	1987:Q3	FRED
Sweden						
GDP	Gross Domestic Product	r	q	sa	1960:Q1	OECD
CONS	(Private) Consumption	r	q	sa	1960:Q1	OECD
INVST	Investment	r	q	sa	1960:Q1	OECD
GOV	Government Expenditure	r	q	sa	1960:Q1	OECD
EXP	Exports of Goods and Services	r	q	sa	1960:Q1	OECD
IMP	Imports of Goods and Services	r	q	sa	1960:Q1	OECD
PICORE	Inflation	n	q	nsa	1970:Q1	OECD
HPI	Real Estate Price Index for One- and Two-dwelling Buildings for Permanent Living	n	q	nsa	1986:Q1	SBC
UR	Unemployment Rate	n	m	sa	1983:Q1	Eurostat
TWEXR	Trade-Weighted Exchange Rate Index	n	q	nsa	1981:Q4	Riksbank
CBR	Base Rate (Repo Rate)	n	q	nsa	1955:Q1	OECD
TB3M	3-month Treasury Bill	n	q	nsa	1983:Q1	Riksbank
TED	Interest Rate Spread (STIBOR - TB3M)	n	q	nsa	1987:Q1	own calc.
FSI	Financial Stress Index	n	q	nsa	1987:Q1	own calc.
OIL	Crude Oil Price - Brent-Europe	r*	m	nsa	1987:Q3	FRED

Notes: BOS is the abbreviation for Bank of Scotland, SBC stands for Statistika Centralbyrån. All other explanatory notes are given in Section A.1. * indicates that oil prices were transformed to real variables using the respective GDP deflator of the country.

Table A.2: Data Transformation and Pre-Testing

Variable	Transformation Code	United States		United Kingdom		Sweden	
		Lags	ADF test	Lags	ADF test	Lags	ADF test
GDP	2	2	0.00	1*	0.00	1*	0.00
CONS	2	3	0.00	3	0.00	1	0.00
INVST	2	1	0.00	0	0.00	3	0.00
GOV	2	4	0.01	1	0.00	3	0.00
EXP	2	1	0.00	1	0.00	1	0.00
IMP	2	0	0.00	0	0.00	1	0.00
PICORE	3	1	0.00	4	0.00	7	0.00
HPI	3	3	0.00	0	0.00	4	0.00
UR	1	1	0.00	1	0.02	1	0.00
TWEXR	1	1	0.00	1	0.00	1	0.00
CBR	1	7	0.00	1	0.00	1	0.00
TB3M	1	7	0.00	1	0.00	0	0.00
TED	1	1	0.00	0	0.00	2*	0.00
FSI	1	2	0.00	0	0.00	2*	0.00
OIL	2	5	0.00	5	0.00	5	0.00

Notes: * indicates that lags were added because of remaining serial correlation attested by the Ljung-Box test. The p-values of the ADF test are rounded to two decimals.

A.2 Data Transformation and Pre-Testing

Depending on the nature of the variable Y_t, we transformed the data by:

- First Differences: $Y_t - Y_{t-1}$
  (Transformation Code: 1)

- The first difference of the logarithm: $\log(Y_t/Y_{t-1})$
  (Transformation Code: 2)

- The first difference of the logarithm: $\log(Y_t/Y_{t-1}) - \log(Y_{t-1}/Y_{t-2})$
  (Transformation Code: 3)

A detailed overview of the transformation used for the respective variable can be found in the first column of Table A.2. The remaining columns report the p lags included in the univariate analysis as well as the p-value of the ADF test (given by Equation 2.1) for each variable in each country. The p-values suggest a rejection of a unit root process at the 1% significance level for all time series, ensuring a robust estimation and inference.

B Financial Stress Indices for the United Kingdom and Sweden

The financial stress indices for the United Kingdom and Sweden are constructed based on the method of Fordd Sandahl et al. (2011), who construct a stress index for Sweden from 1997 to 2011. The authors include broad measures of financial stress in three different financial markets: the credit market, the equity market, and the foreign exchange market. Since appropriate data for the foreign exchange market is not available for the entire period of our analysis, we exclude this measure from the financial stress index.

For Sweden we construct a monthly index from 1987:M1 to 2014:M6, for the United Kingdom from 1991:M1 to 2014:M6. In our choice of stress indicators in each market we closely follow Fordd Sandahl et al. (2011), but make some adjustments for data availability. Table B.1 shows the data we used and some descriptive statistics.

As a measure of stress in the equity markets, we use the volatility in the stock market. While Fordd Sandahl et al. (2011) use option-implied volatility, we employ historical volatility of the respective country's main stock index. This measure is not necessarily representative of the firms' capital cost at time of measurement, but a very high correlation for the period where both measures are available makes us confident that historical volatility serves as a good proxy. Historical volatility is calculated as the monthly standard deviation of daily returns.

Table B.1: Data Used in the Construction of Financial Stress Indices

	Source	Mean	Std. dev.
United Kingdom			
FTSE100: Volatility of daily returns	Yahoo Finance	0.010	0.005
3-month interbank rate	Bank of England	4.76	2.84
3-month rate Treasury bills	Bank of England	4.37	2.77
Barclays Sterling Aggregate 100 - yield	Thomson Reuters	5.70	2.08
5-year rate Government bonds	Thomson Reuters	5.02	2.43
Sweden			
OMXS30: Volatility of daily returns	NASDAQ OMX	0.013	0.007
3-month interbank rate	The Riksbank	5.52	4.05
3-month rate Treasury bills	The Riksbank	5.20	4.08
Stadshypoteket's 5-year mortgage bond rate	The Riksbank	6.62	3.64
5-year rate Government bonds	The Riksbank	5.94	3.65

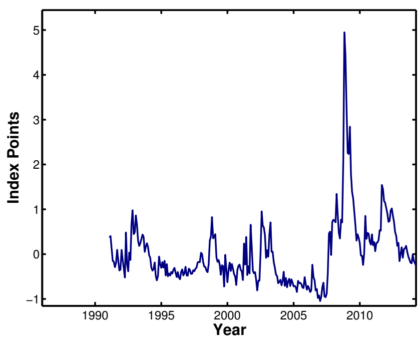
Note: Means and standard deviations are calculated for the respective index period.

To measure stress in the credit markets we use two different indicators: one for short-term money market and one for the long-term bond market. The 3-month TED spread, which is defined as the difference between the interest on a 3-month interbank loan and the interest rate on a treasury bill of the same maturity, is employed to represent stress in the money market. To measure stress in the bond market, we use the interest differential between a relatively secure private bond and and a 5-year government bond. Due to data availability, we choose somewhat different measures for private bonds for the United Kingdom and Sweden. For the United Kingdom we use the yield-to-redemption of the Barclays Sterling Aggregate 100 Index. For Sweden we use the interest rate for Stadshypoteket's mortgage bond CAISSE, which is also chosen as a representative measure by the Riksbank. The interest differentials for each market are calculated on a monthly basis.

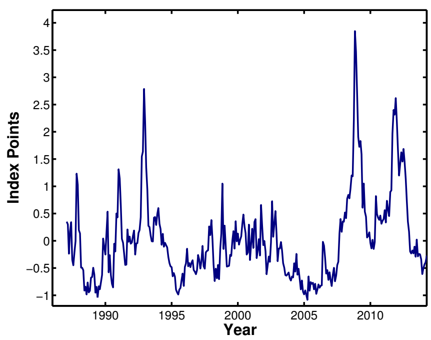
To calculate one combined index from all three measures, each measure is first standardized over the entire period for which the index is constructed. In particular, we subtract the overall mean from each monthly value and then divide by the respective measure's standard deviation. Finally, all three measures are averaged to obtain the financial stress index. The indices for both countries are shown in Figure B.1.

Figure B.1: Financial Stress Indices

(a) UK



(b) Sweden



C Appropriate Specifications of the Variance Covariance Matrix $V(\hat{\beta})$

Consider the multiple linear regression model

$$y_t = \boldsymbol{x}_t^{'}\boldsymbol{\beta} + \varepsilon_t,$$

where y_t is the observed dependent variable, $\boldsymbol{x_t}$ is the $(q+1 \times 1)$ vector of the constant and q covariates with $\boldsymbol{\beta}$ capturing the corresponding vectors of coefficients; ε is the error term. For OLS models, the estimated coefficients are determined by $\hat{\boldsymbol{\beta}} = (\boldsymbol{x}^{'}\boldsymbol{x})^{-1}\boldsymbol{x}^{'}\boldsymbol{y}$ and the variance covariance matrix is defined as:

$$\begin{aligned} \boldsymbol{V}(\hat{\boldsymbol{\beta}}) &= \left(\boldsymbol{x}^{'}\boldsymbol{x}\right)^{-1} \boldsymbol{x}^{'}\Omega\boldsymbol{x} \left(\boldsymbol{x}^{'}\boldsymbol{x}\right)^{-1} \\ &= \left(\frac{1}{n}\boldsymbol{x}^{'}\boldsymbol{x}\right)^{-1} \frac{1}{n}\Phi \left(\frac{1}{n}\boldsymbol{x}^{'}\boldsymbol{x}\right)^{-1}, \end{aligned} \tag{C.1}$$

where $\boldsymbol{\Phi} = \frac{1}{n}\boldsymbol{x}^{'}\boldsymbol{\Omega}\boldsymbol{x}$ is the variance covariance matrix of the estimating functions $v(\boldsymbol{\beta}) = \boldsymbol{x}_t(y_t - \boldsymbol{x}_t^{'}\boldsymbol{\beta})$. Since a consistent estimate of $\boldsymbol{V}(\hat{\boldsymbol{\beta}})$ is essential for inference of the model, we have to consider the following case differentiation, dependent on the assumption on the error term.

In our first case, independent and homoscedastic errors with variance σ^2 are assumed, which yields $\boldsymbol{\Omega} = \sigma^2\boldsymbol{I}_T$, with $\boldsymbol{I}_T$ being the T-dimensional identity matrix, and thus $\boldsymbol{V}(\hat{\boldsymbol{\beta}}) = \sigma^2(\boldsymbol{x}^{'}\boldsymbol{x})^{-1}$. Plugging in the OLS estimator $\hat{\sigma}^2 = \frac{\sum_{t=1}^{T}\hat{\varepsilon_t}^2}{T}$, the variance covariance matrix $\boldsymbol{V}(\hat{\boldsymbol{\beta}})$ can be consistently estimated. Applying these results to the partition $\{\widehat{T}_j\}$, we obtain Equation 3.3.

Yet, when the independence and/or homoscedasticity assumption is violated, we face the problem that the estimator $\boldsymbol{V}(\hat{\boldsymbol{\beta}})$ is biased. In the second case, we therefore have to compute an estimate $\hat{\boldsymbol{\Omega}}$ which is consistent in the presence of heteroscedasiticy and autocorrelation. Since it is cumbersome to estimate $\boldsymbol{\Omega}$ directly if the form of heteroscedasticity and autocorrelation is unknown, it has become standard to estimate $\boldsymbol{\Phi}$ instead. Such an HAC estimator for $\boldsymbol{\Phi}$ takes the form:

$$\hat{\boldsymbol{\Phi}} = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{T}\boldsymbol{w}_{|t-k|}\hat{v}_t\hat{v}_k^{'}, \tag{C.2}$$

where $\boldsymbol{w} = (w_0, \ldots, w_{T-1})'$ is a vector of weights decreasing with lag $l = |t-k|$. The standard of decreasing weights stems from the assumption that the autocorrelations should decrease with lag l. By now, there are different suggestions for the exact form of the weight vector $\boldsymbol{w}$, which have become standard in the econometrics literature. We choose a data dependent method developed by Andrews (1991), the quadratic spectral kernel. The resulting weights are:

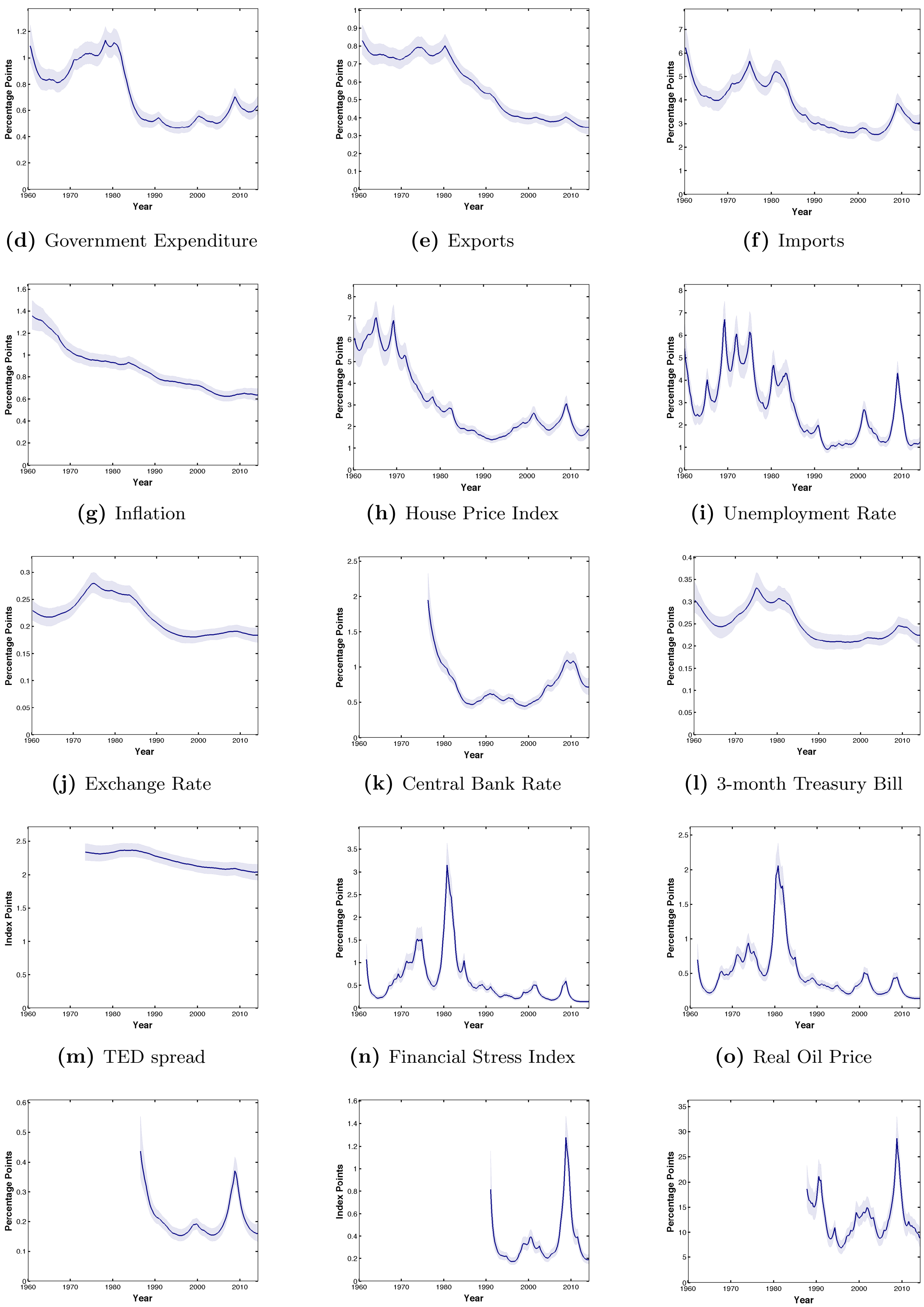
$$\boldsymbol{w}_l = \frac{3}{z^2}\left(\frac{\sin(z)}{z} - cos(z)\right),$$

where $z = \frac{6\pi}{5} \cdot \frac{l}{B}$. B is the so called bandwidth parameter, computed on the basis of an AR(1) approximation (Andrews, 1991). Plugging in the calculated values of $\boldsymbol{w}$ into Equation C.2, we obtain the HAC estimator $\hat{\boldsymbol{\Phi}}$, which in turn can be used to calculate an estimate of the variance covariance matrix $\boldsymbol{V}(\hat{\boldsymbol{\beta}})$ in Equation C.1. If heteroscedasticity and autocorrelation are assumed, such as in the cases of the unconditional variance and conditional mean, we use this HAC robust estimate of $\boldsymbol{V}(\hat{\boldsymbol{\beta}})$ for the respective partition $\{\widehat{T}_j\}$.

D Instantaneous Standard Deviations

Please see the next three pages for the full sets of graphs of instantaneous standard deviations for each country.

Figure D.1: Instantaneous Standard Deviations of U.S. Macroeconomic Time Series



(a) GDP (b) Consumption (c) Investment

(d) Government Expenditure (e) Exports (f) Imports

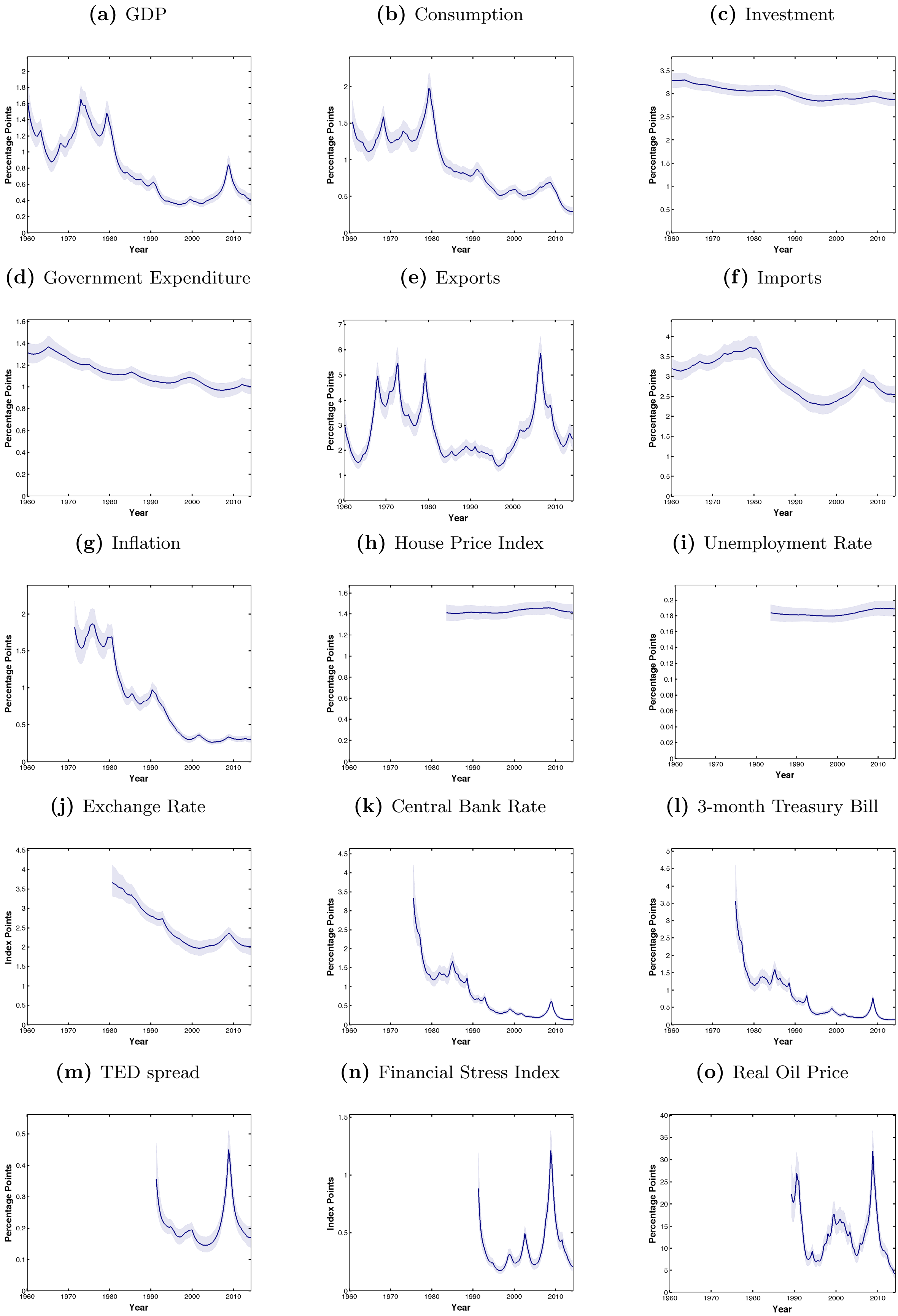
(g) Inflation (h) House Price Index (i) Unemployment Rate

(j) Exchange Rate (k) Central Bank Rate (l) 3-month Treasury Bill

(m) TED spread (n) Financial Stress Index (o) Real Oil Price

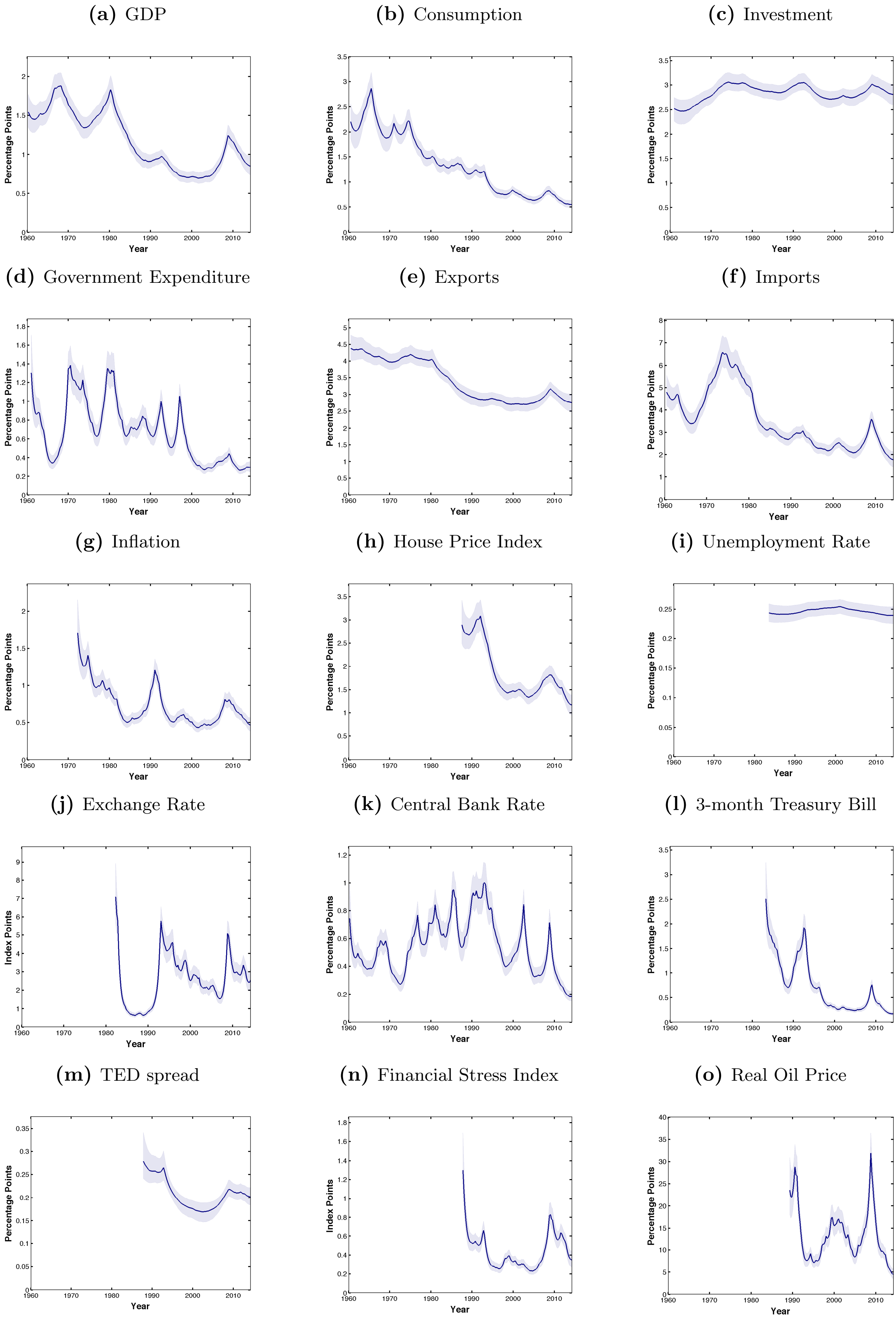
Note: The shaded area indicates a 70% confidence interval.

Figure D.2: Instantaneous Standard Deviations of
U.K. Macroeconomic Time Series



Note: The shaded area indicates a 70% confidence interval.

Figure D.3: Instantaneous Standard Deviations of Swedish Macroeconomic Time Series

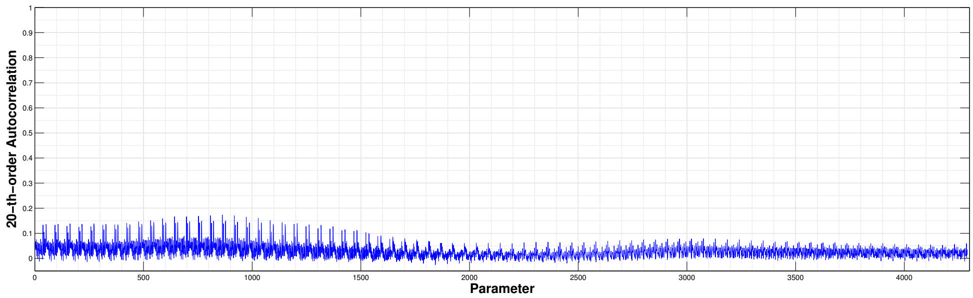


Note: The shaded area indicates a 70% confidence interval.

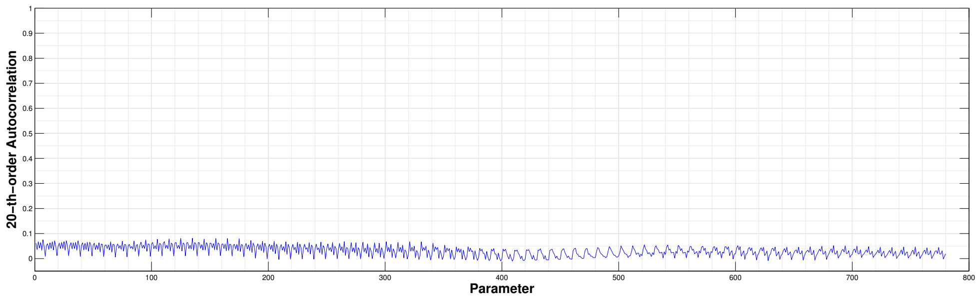
E Convergence Diagnostics of the MCMC Sampler

Figure E.1: 20-th-order Autocorrelation of the Draws – United States

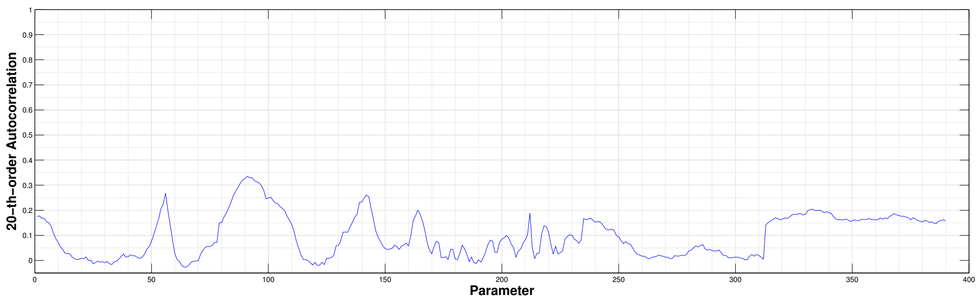
(a) Parameters of $\mathbf{b}$



(b) Parameters of $\mathbf{A}$



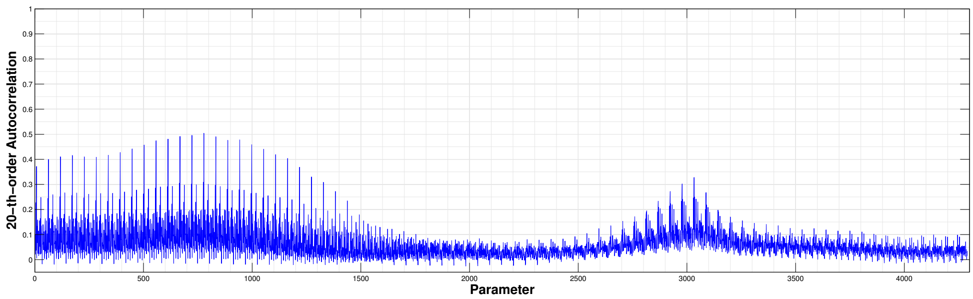
(c) Parameters of σ



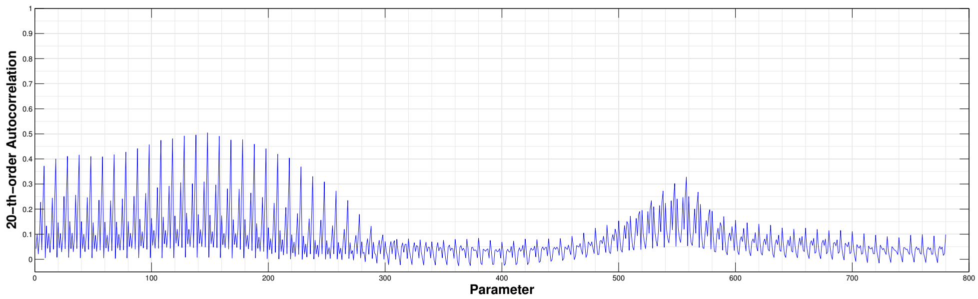
Note: The parameters on the x-asis are ordered as they appear in the respective matrix, one time period after another.

Figure E.2: 20-th-order Autocorrelation of the Draws – United Kingdom

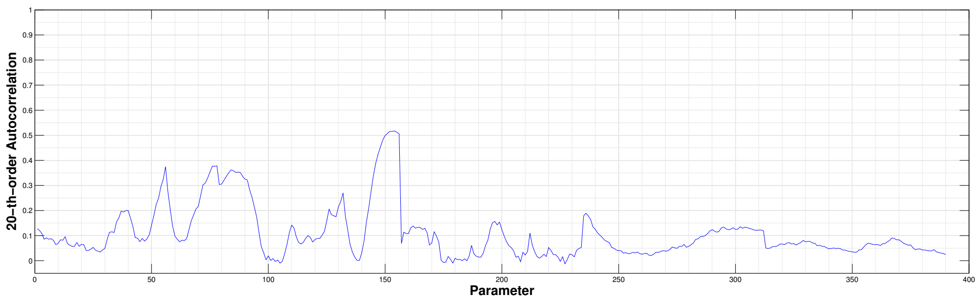
(a) Parameters of b_t



(b) Parameters of A_t



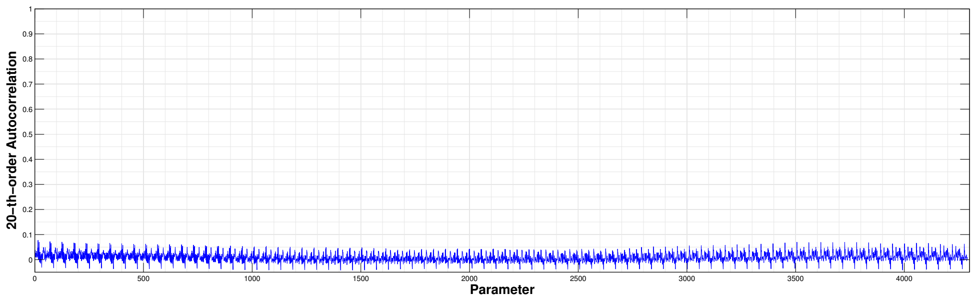
(c) Parameters of σ



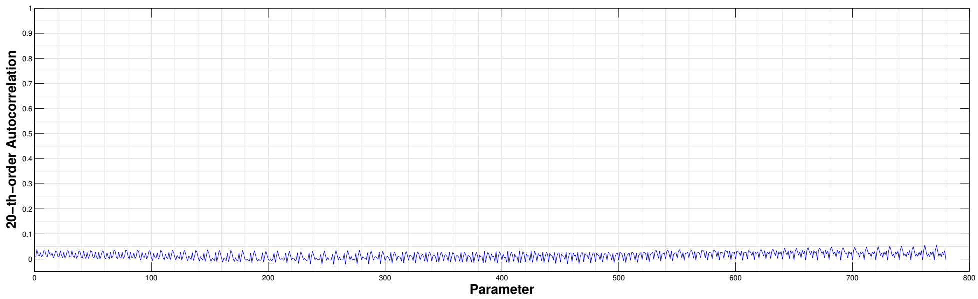
Note: The parameters on the x-asis are ordered as they appear in the respective matrix, one time period after another.

Figure E.3: 20-th-order Autocorrelation of the Draws – Sweden

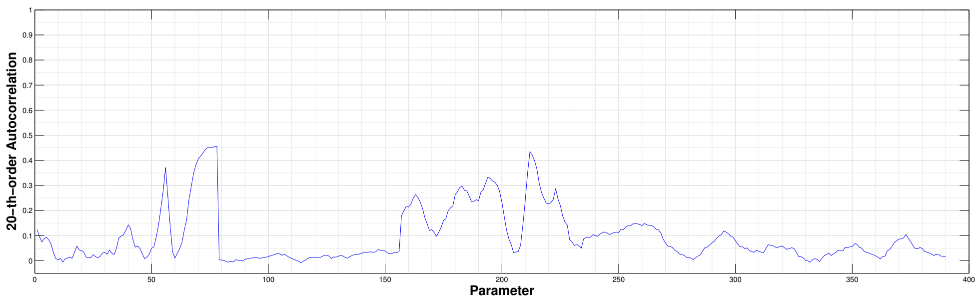
(a) Parameters of b_t



(b) Parameters of A_t



(c) Parameters of σ_t



Note: The parameters on the x-asis are ordered as they appear in the respective matrix, one time period after another.