The Great Moderation and the Financial Cycle

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Abstract

We show that the defining features of the Great Moderation were a shift from output volatility to medium-term fluctuations and a shift in the origin of those fluctuations from the real to the financial sector. We discover a Granger-causal relationship by which financial cycles attenuate short-term business cycle fluctuations while they amplify longer-term fluctuations at the same time. As a result, financial shocks systematically drive medium-term output fluctuations whereas real shocks drive short-term output fluctuations. We use these results to argue that the Great Moderation and Great Recession both result from the same economic forces. On the theoretical front, we show that long-run risk is a critical ingredient of DSGE models with financial sectors that seek to replicate these shifts. Finally, we used this DSGE model to refine "good luck" and "good policy" hypothesis of the Great Moderation.

JEL Classifications: E00, E32, E44, E50

Keywords: Great Moderation, *Business Cycle*, *Financial Cycle*, *Frequency-Domain*

1. Introduction

After 25 years of relatively mild business cycle fluctuations in the U.S., the so-called "Great Moderation", the Great Financial Crisis (GFC) caused tremendous turmoil and drew the U.S. economy into the Great Recession of 2009. In the business cycle literature, the Great Moderation (see among others Stock and Watson (2002), Gali and Monacelli (2005) and Giannone et al. (2008)) was one of the most studied phenomena until the Great Recession diverted researchers' attention (see among many others Christiano et al. (2014), Mian and Sufi (2010), Aiyar (2012)). However, the relationship between the two has been largely neglected. This paper argues that the Great Moderation and Great Recession are essentially one phenomenon – two sides of the same coin – and that the financial cycle is the force that forged it.

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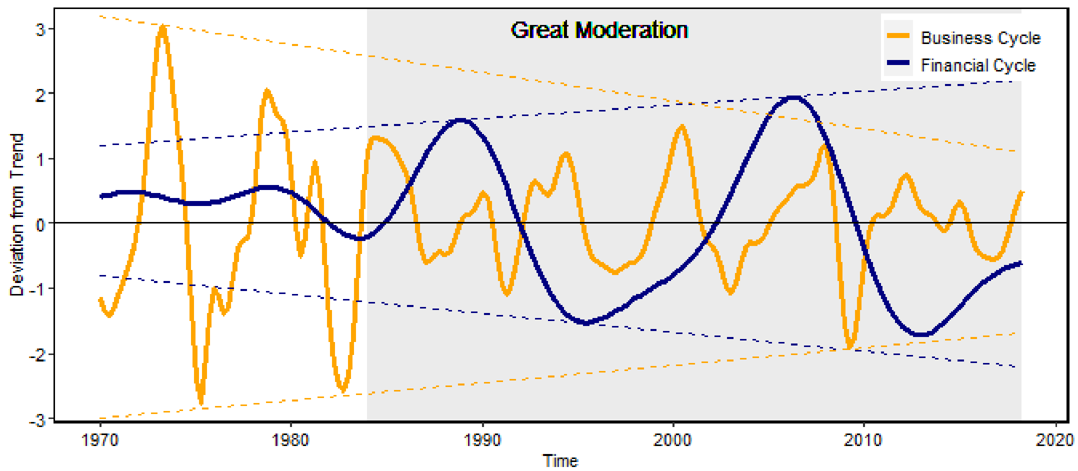
Figure 1: Business Cycle (GDP) and Financial Cycle (Indicator) in the United States



This figure shows the evolution of the U.S. business cycle and financial cycle between 1970 and 2018. The business cycle is calculated as the fluctuations between 5 and 32 quarter of GDP around its trend. The financial cycle is an indicator routinely calculated by the Bank for International Settlements as the average of the cyclical components of total credit volume, credit gap and house prices. The cyclical components are extracted with a bandpass filter with bounds of 32 and 120 quarters.

This approach is motivated by the observation in Figure 1. This figure shows that the financial cycle – represented by credit-volume-to-GDP (the so-called "credit gap") and house prices - witnessed large gains in its amplitude precisely at the same time at which the business cycle began its *moderation*. An *increase* of financial market volatility thus occurred long before the housing market bubble that eventually led to the GFC even began to build up. We find a single Granger-causal empirical relationship between the credit gap and output that rationalizes this observation. This relationship is such that credit can attenuate short-term output fluctuations *and* amplify medium-term output fluctuations. This led to two "shifts" that give the Great Moderation a new narrative: a shift of output volatility toward longer-term fluctuations and a shift in the source of medium-term volatility from the real (non-financial) to the financial sector. These shifts are both independent of the Great Recession.

This paper makes two contributions: The first contribution is the empirical characterization of the relationship between the business cycle and the financial cycle over the last five decades. Herefore, we use spectral analysis to decompose business cycle fluctuations into volatilities of different periodicities. Then, we estimate vector-autoregressive models (VARs) that describe the relationship between output and financial variables. In this context, we show how to use frequency-domain techniques to evaluate the properties of the VAR models and obtain novel results. Specifically, we characterize Granger-causal relationships between the financial cycle variables credit gap and house prices, and output (GDP). Finally, we identify structural shocks from the estimated VAR models to assess which shocks drive fluctuations of different periodicities. With this approach, we find that the volatility of the post-1984 economy moved mainly outside the classic business cycle range of cycles of 5-32 quarters (Burns and Mitchell (1946)) onto medium-term fluctuations between 32 and 120 quarters. While this led to a reduction in short-term volatility, medium-term volatility increased. This shift came with a shift in the origin of output volatility from the real (non-financial) sector to the financial sector: we show that shocks to financial variables increase greatly in importance but systematically drive mainly medium-term output volatility in the Great Moderation economy. Meanwhile real shocks (such as TFP shocks) continue to drive the majority of short-term output volatility.

Jointly, these shifts imply that the defining feature of the Great Moderation was a finance-driven shift in the origin of output volatility and in the distribution of output volatility across fluctuations of different lengths. These changes of the Great Moderation are linked by a Granger-causal relationship between between credit gap and output, which is not uniform across fluctuations of different lengths. Short-period reductions in output lead to short-period expansions of the credit gap. At the same time, medium-period expansions (contractions) in credit gap lead to medium-period expansions (contractions) of output. In other words, short-period credit gap movements attenuate short-period output movements, while medium-term credit gap movements amplify medium-term output movements. The short-term fluctuations for which we find the attenuation forces of credit are precisely the same on which we find that a moderation of output volatility occurred. At the same time, the fluctuations in which financial shocks manifest themselves as volatility are those on which the amplification forces and the resulting increases in output volatility are found.

We show that the attenuation-amplification property of the relationship between credit gap and output is not an artefact of the Great Moderation or the Great Recession period, but can be found in multiple periods of the U.S. economy after World War II. We argue that by this relationship, the Great Moderation and the Great Recession are the consequences of the attenuation and amplification forces, respectively. Therefore, they are inextricably linked.

The second contribution is the construction of a model that can replicate the most important frequency-domain features of the data. We show that a combination of modelling elements is required for this: a collateral constraint on an entrepreneur as in Iacoviello (2005) that gives rise to a financial accelerator, a leverage constraint on the financial intermediary as in Gertler and Karadi (2011) and the presence of long-run risk borrowed from Bansal and Yaron (2004) on the cost of entrepreneurial investments and on the lending ability of the financial intermediary. The collateral and leverage constraints generate the necessary interaction between the financial sector and the real sector. The long-run risk generates the necessary persistence to explain the medium-term fluctuation and ensures that shocks to the investment cost systematically feed into medium-term output volatility. In the absence of any of those three elements, the model's moments do not come close to those of the data. This extends to many standard off-the-shelf models from the literature, which consistently fail to reproduce the non-uniformity of the effects of financial and non-financial shocks on fluctuations of different lengths. In a similar spirit as emphasized by Gourio (2013), the right set of financial frictions is required to amplify the effects of the risk-structure of shocks to replicate the properties of the data.

The long-run risk is the theoretical counterpart in the argument that the Great Moderation and the Great Recession are two sides of the same coin. The presence of this risk has effects on prices in phases of moderate volatility but its main effect is only observed in relatively rare, but consequential events. We then use the parameter estimates of the model to refine the "good luck" hypothesis of the Great Moderation by showing that only the standard deviation of non-persistent (short-run) shocks occurred, while very persistent (long-run) shocks witnessed increases in their standard deviations. Additionally, we isolate the changes of monetary policy that occurred during the Great Moderation. We show that while monetary policy in the Great Moderation reduced short-term output volatility, it contributed to the systematic way that financial shocks cause medium-run output volatility - therefore came at the expense of more medium-run volatility. In other words, we can use the model to refine the "good policy" hypothesis of the Great Moderation as well.

In the course of this paper, there are several instances where the frequency-domain approach is required in order to discover new insights on the economics of business cycle and financial cycle. It reveals the non-uniformity of the empirical relationship between credit gap and output. Additionally, it leads to the finding that financial shocks systematically drive medium-term volatility. This adds a new property that economic models should be able to replicate.

The remainder of this paper is structured as follows: In section 2 we discuss the relation of my paper to the existing literature. Section 3 presents the empirical case. Section 4 introduces the model and discusses its estimation. Section 5 analyses the performance of the model on the frequency-domain properties of the time series. Section 6 concludes.

2. Related Literature

The paper is related to the literature in three ways: First, it is connected to the literature that characterizes the empirical properties of (domestic) financial cycles and their relationship with business cycles (see for instance Borio and White (2004), Borio et al. (2018), Claessens et al. (2011), Strohsal et al. (2015), Schularick and Taylor (2012), Jordà et al. (2011), Jordà et al. (2016), Jordà et al. (2017), Drehmann et al. (2012) or Adarov (2018)). Especially noteworthy is the work by Jordà et al. (2011) who provide very long-run data on financial cycles. The main results of this literature that 1) the financial cycle is significantly longer than the business cycle, 2) business cycle recessions that coincide with financial cycle downturns are larger and longer than those who do not and 3) the financial cycle is aligned with medium-term business cycle fluctuations are reflected in the findings of this paper. The prevalent approach of the literature has usually been to isolate fluctuations of a certain periodicity-range with a band-pass filter and calculate the average effect over the periodicity window (see for instance Drehmann et al. (2012) and Pancrazi (2015)). The former use this technique to find strongly positive correlation of medium-term output fluctuations and the (BIS) financial cycle indicator[2]. We advance this result by showing that the relationships between credit gap, house prices and output are non-uniform across different periodicities. In fact, the frequency-domain

2 This indicator is computed as the cyclical components between 32 and 120 quarters of total credit volume, credit gap and house prices; which are then averaged.

approach of this paper allows us to calculate a profile of correlations associated with different periodicities and give a Granger-causal interpretation to them. The combination of the two yields in a more detailed characterization of the empirical forces compared to the literature. In the case of credit gap and output, this yields a negative dynamic correlation on short periodicities in which output is Granger-causal and a positive dynamic correlation in which credit gap is Granger-causal on medium periodicities.

It has been recognized that credit booms sow the seeds of credit crunches (Minsky (1986), Kindleberger and Aliber (2011), Schularick and Taylor (2012), Aikman et al. (2014)). Therefore, the relationship between financial variables and output has been used to explain the Great Recession (Gorton and Ordoñez (2016), Bean (2010), Jordà et al. (2013)) or the failure to predict it (Gadea Rivas et al. (2014)) and it has been shown that the pair of credit and asset prices is one of the most powerful early warning indicator of a recession (Aldasoro et al. (2018)). However, this analysis is usually focused on the build-up of credit that occurred during the 2000s - not on the entire Great Moderation. This paper shows that the relationship between credit and output that underlies drives credit booms and busts, phases of moderation and phases of high volatility, already existed long before the Great Recession and even before the Great Moderation. Instead, the relationship has intensified: Granger-causality from financial to non-financial sector has become more significant and financial shocks cause more output volatility.

Second, these findings allows us to contribute to the literature on the Great Moderation with a novel view that complements the existing ones. Ever since Stock and Watson (2002) coined the term "Great Moderation", the academic debate largely evolved around the question of whether "good luck" or "good policy" were responsible for the Great Moderation. The good luck hypothesis, put forward among others by Stock and Watson (2003) and Ahmed et al. (2004) suggest that merely the size of shocks had decreased during the Great Moderation. The good policy hypothesis (see Bernanke (2004)[3]), Boivin and Giannoni (2006), and Benati and Surico (2009) accredits the perceived reduction in output volatility to the more aggressive reaction to inflation of monetary policy and better forward guidance under Volcker and Greenspan, compared to the pre-Volcker era. Without formalizing their ideas in a model, Drehmann et al. (2012) warn that monetary policy that does not take into account credit growth could dampen short-term volatility at the expense of more medium-term volatility which implicitly questions how "good" the revised monetary policy actually was. Bilbiie and Straub (2013) and Carvalho and Gabaix (2013) have pointed to increased asset market participation and the overall expansion of the U.S. financial sector as causes for the Great Moderation. The results of this paper do not stand in contrast to these positions, but we argue that none of these explanations is at the core of the changes that occurred during the Great Moderation. "Good luck", "good policy" or structural changes are competing narratives on the initial cause of the upswing in the credit gap at the beginning of the Great Moderation. We remain largely agnostic regarding what caused the upswing in credit gap. Instead we emphasize that the increased amplitude over the duration of the cycle lead to the Great Moderation. In this regard, we sharpen the finding of an increased contribution of the

3 https://www.federalreserve.gov/boarddocs/speeches/2004/20040220/ (accessed 19/09/2021)

financial sector to output volatility in the Great Moderation(Carvalho and Gabaix (2013), Khieu (2018)), by showing that financial shocks systematically feed into medium-term volatility. Consequently, we concur with Pancrazi (2015) and Crowley and Hallett (2015)[4] that the Great Moderation was a very heterogeneous phenomenon. The term "Great Moderation" is therefore misleading.

Thirdly, this paper is related to the theoretical literature that studies financial frictions and amplification mechanisms in relation to recessions. In the business cycle literature, the contributions of Bernanke et al. (1999), Kiyotaki and Moore (1997), Iacoviello (2005) and Gertler and Karadi (2011) stand out and are the basis for the theoretical model presented in section 4 of this paper.

Borio (2014) summarizes the theoretical insights into the relation between the financial cycle and business cycle and emphasizes the importance of studying the micro-level linkages between real and financial sector.

Herein, Rajan (2006) was among the first to suggest that increased access to finance may make the world riskier. He argues that while the expansion of the financial sector has made the world better off overall, financial intermediaries may "accentuate real fluctuations, they can also leave themselves exposed to certain small probability risks that their own collective behaviour makes more likely". In other words, when financial intermediaries grant credit, they can alleviate the real sector of some of its idosyncratic risk. Increased access to credit enables firms to smooth out some short-term financing constraints, which leads to a reduction in short-term volatility. However, these risks are pooled on banks' balance sheets where they pile up until either the loan is paid back or the risks materialize. The pooling of idiosyncratic risks creates systemic risk in the banking sector. When too many risks materialize at the same time (which is more likely, the higher the credit volume is), banks tighten credit constraints for firms; which has adverse effects on real economic activity. When enough risks materialize to push the banks to their own financing constraint, this can result in market freezes (such as in 2008) and banks become the super-spreaders in an financial crisis contagion - which leads to higher overall (medium-term) volatility. These ideas are taken up and formalized by Brunnermeier and Sannikov (2014)'s paradox of volatility and paradox of prudence. The former shows that in a model with lower exogenous volatility, intermediaries may be induced to increase leverage, which results in higher endogenous volatility. The latter describes how the individually rational deleveraging of financial intermediaries when financial turmoil is on the horizon can collectively drive the entire financial sector into a crisis. Gourio (2013) argues along similiar lines that lower perceived disaster risk can make the economy more fragile as agents lever up.

3. Empirical Case

This section first introduces the data and explains the methodological approach. Then, we show the shift of output volatility towards longer-term fluctuations that defines the Great Moderation. Further, we

4 They show that the rolling-window variances only of certain short-frequency wavelets experience decreases in their rolling window variance, whereas fluctuations between 64-128 quarters have seen an increase in the variance.

document the intensifying relationship of attenuation and amplification between credit gap and output, by characterizing co-movement and Granger-causality between these variables in the course of the Great Moderation. Finally, we move to a structural interpretation that shows how shocks on financial markets systematically cause medium-term output volatility in the Great Moderation economy.

3.1. Data

To study the interactions of real and financial markets we focus on GDP as the most common measure of aggregate activity, while credit volume and asset prices measure financial activity[5]. To gauge credit supply to demand, we use the “credit gap”, defined by the BIS as total credit to the private non-financial sector, divided by GDP. The role of asset prices in the description of financial market activity is that of a determinant of collateral value. As described by Borio (2014), the pair of credit gap and asset prices is the smallest set of variables that can describe the medium-term cycles that arise from the “self-enforcing interactions of perception of value and financing constraints” that constitute the financial cycle. Hence, we obtain indicators of stock prices and house prices. We do not have data on the composition of collateral by asset type and its evolution throughout time, but there is anecdotal evidence that the share of mortgage-backed lending has increased over time. As described by Drehmann et al. (2012) the lower short-term volatility of house prices relative to stock prices also makes houses a more suitable asset to pose as collateral. Additionally, Aldasoro et al. (2018) show that house prices are a better predictor of future recessions than stock prices. Hence, we use house prices as the main asset price and use stock prices only for a robustness check[6]. To these three variables, we add the Fed Funds rate - as it stands right at the intersection of the real and the financial economy. In another robustness check, we also extend the analysis to include the inflation rate which underwent a moderation of its own in the so-called “Volcker-disinflation” in the 1980s. The data are obtained from the Federal Reserve Economic Database (FRED) and the database of the Bank for International Settlements (BIS).

The data are available at quarterly frequency for the period 1970Q1-2018Q2, where the house price index constrains the sample to start in 1970. All time series with the exception of the policy rate and inflation rate are in real terms and are transformed into log-levels. We filter out the long-term trends using a one-sided band-pass filter to stationarize the time series (which is required for frequency-domain analysis). Importantly, the filter only removes the long-term trend but neither alters the frequency components of the data, nor uses future observations to extract the trend. This filter has a flat transfer function except at frequency zero. Hence it does not artificially accentuate some frequencies at the expense of others. To ensure that the results are not driven by the choice of filter, we run a robustness check in which the data is detrended with

5 The BIS computes an financial cycle indicator which is made up of the cyclical components between 32 and 120 quarters of total credit volume, credit gap and house prices. We use the same information in our three main variables. However, we study fluctuations of all frequencies (above seasonal ones).

6 As a further robustness check we compute the first principal component of detrended house prices and stock prices as an indicator of asset prices.

a one-sided HP-filter[7]. All variables are standardized.

To test the robustness further, we build the analogue data set for the UK with data from the FRED, BIS and the Office for National Statistics (ONS). In addition, we use the data set of Jordà et al. (2011) to cover the longest possible period. This data set covers the relevant variables for the U.S. from 1891 to 2016 but it is only available at yearly frequency (and therefore has even fewer data points than the main data set).

In addition to the full time series, we study multiple different sub-periods in the course of the analysis. In accordance with the literature (Stock and Watson (2003), Galí and Gambetti (2009)), we choose the first quarter of 1984 as the beginning of the Great Moderation. The period 1970Q1-1983Q4 is hence called pre-Great Moderation (and sometimes abbreviated pre-GM). The choice of end date is trickier: The standard narrative is that the Great Moderation was ended by the Great Recession[8]. This is not a consensus though: Gadea Rivas et al. (2014) and Clark et al. (2009) argue that the low volatility persists. In the context of a Markov-switching model, Grazzini and Massaro (2021) claim that the Great Moderation was only interrupted by the Great Recession and that the past decade could be characterized as a "Great Moderation (again)". Here, we will label the entire period between 1984Q1 and 2018Q2 as the "Great Moderation economy" (abbreviated GM) and call the period between 1984Q1 and 2007Q1 "narrow Great Moderation" (narrow GM). In contrast to Grazzini and Massaro (2021), the Great Recession is interpreted as a materialization of medium-term volatility rather than as two regime-switches. This choice is justified by the finding that short-term volatility has given way to more medium-term volatility. Additionally, in the study of financial markets, a cutoff in 2008 seems flawed as it would separate the Great Financial Crisis from the build-up of credit gap and house prices which led to it[9] (Gorton and Ordoñez (2016)).

3.2. Methodology

In this section we introduce the empirical methodology, which is based on vector autoregressive (VAR) models. In contrast to the majority of the literature, we will find it is useful to analyze the time series and the estimated VAR-processes in the frequency-domain. Herefore, we make use of the duality between time- and frequency-domain. It is important to stress that this does not change the properties of the time series or VAR-models - it is merely a different lens through which the properties are viewed.

Rather than evaluating the effects of shocks at a certain horizon, the frequency-domain approach decom-

7 The HP-filter does not have a flat transfer function as the band-pass filter. Hence, it accentuates the fluctuations of some frequencies at the expense of others in the detrending process. Therefore, the results obtained with the band-pass filter are of superior quality.

8 Bean (2009) argues this because of the increased volatility that came with the Great Recession. Taylor (2011)'s argument that the Great Moderation has ended is that policy rules deviated from the supposedly "good" policy rules of the Great Moderation era. Ng et al. (2012) find that the Great Moderation period is not enough to forecast the Great Recession. Therefore, they argue that there has been a structural break.

9 Additionally, there are two technical issues with defining 2008 as the end of the Great Moderation: 1) the Great Recession was such and extreme event that the choice of putting it into either a "Great Moderation Sample" (1984-2008) or a "post-Great Moderation Sample" (2009-2018) may sway results by construction. 2) Splitting the data at or near the peak of one time series may lead to instationarity of the resulting sub-series.

poses the time series into cycles of frequency $\omega \in (0, \pi)$ and studies the effects at each frequency. For illustrative purposes, we use the inverse of frequencies - "periodicities.". Denote periodicities $\tilde{\omega} = 1/\omega$. Fluctuations of frequency π correspond to a cycle that lasts only two periods (periodicity=2) while fluctuations of frequency 0 correspond to infinitely long-lasting cycles. For purposes of this paper, we are only interested in fluctuations between 5 and 120 quarters per cycle, which we categorize as follows: we refer to fluctuations between 5 and 16 quarters per cycle as "shorter business cycle periodicities", fluctuations between 16 and 32 quarters as "longer business cycle periodicities". This classification is borrowed from Pancrazi (2015)[10]. Following Drehmann et al. (2012), we refer to fluctuations between 32 and 120 quarters as "financial cycle periodicities". Seasonal fluctuations (below five quarters) are not of interest for purposes of this paper and neither are cycles longer than 120 quarters.

There are two reasons why the frequency-domain approach is advantageous in the study of the interactions between business cycle and financial cycle. The first reason is conceptual: The economic nature of the objects of study is inherently cyclical. The interaction of (collateral) asset prices and financing constraints gives rise to amplification effects in both directions that drive large booms an ensuing busts. Similarly, the business cycle is by definition the fluctuation of output around its trend or balance growth path[11]. By decomposing time series into cycles of different periodicities, the frequency-domain approach acknowledges the cyclical nature of the objects of study.

The second reason is more technical: The frequency-domain approach is especially suitable when a time series is an aggregate of multiple sub-series and we can give an interpretation to disaggregated frequency components. This is the case for output, which we know is the sum over all sectors of the economy[12]. It cannot be taken as given that the financial cycle interacts with all sectoral components of aggregate output in the same way, hence it should also not be assumed that it interacts equally with all periodicity components.

Misconceptions may arise when the periodicity-structure of time series is not properly taken into account: when two time series consist of multiple sub-series each, it is possible that the aggregate series have a zero correlation, even when the sub-series they are made up of are highly correlated. Recognizing the relation between two such series may require an intuition on how series can be correlated at a sub-aggregate level in order to specify relevant econometric models. After the estimation, frequency-domain tools can show how the time series interact at different frequencies.

Further, it is possible that a time series and its structural shocks only (Granger-) cause a certain periodicity-

10 Note: Pancrazi (2015) original definitions use the terms "higher business cycle frequencies" and "lower business cycle frequencies" instead of "shorter" and "longer" business cycle periodicites as he works with frequencies rather than periodicities.

11 This argument is supported by the fact that Schmitt-Grohé and Uribe (2021) show that a simple financial accelerator can in theory give rise to deterministic limit cycles. Similarly, Beaudry et al. (2016) and Gomes and Sprott (2017) explore limit cycle approaches to the business cycle, driven by demand complementarities or sentiment cycles, respectively.

12 For example, tourism, agriculture and construction industry display a lot of fluctuations on seasonal frequencies, whereas industrial processes tend to exhibit longer cycles. Although these sectors are not orthogonal, the disaggregation of the business cycle can provide new insights.

component of the fluctuations of another time series. In case of Granger-causality between time series, it is important to recognize which components of the time series we can forecast[13]. If such a component is related to a periodicity-range, frequency-domain Granger-tests can detect it, whereas time-domain Granger-test only calculate an average statistic over all frequencies. In case of structural shocks, the frequency-domain approach shows which types of fluctuations are caused by each shock.

On top of that, when we compare the interactions between two cycles, the amplitudes, differences in cycle length and phase interactions are of key interest. It is possible that a time series is at a short-cycle trough at the same time at which it is at a medium-cycle peak. The cycle with the larger amplitude then disguises the effects that play out on the smaller cycle.

The approach of the literature in response to this has often been to use a band-pass filter to isolate fluctuations of a specific frequency range to then study each component. In theory, the frequency-domain measure can be pieced together if this approach is performed on many different frequency ranges (Croux et al. (2001)). In practice, the application of frequency-domain methods to a VAR without selective filtering is a more wholistic and analyzes the effects at a much more disaggregated level. It allows us to calculate effects for each frequency rather than averages over a certain frequency-band as is done when components of the cycle are isolated with a band-pass filter.

In practice, we proceed as follows: We estimate VAR models and identify the orthogonal innovations. Then, we calculate the *dynamic correlation* implied by the VAR-model. Introduced by Croux et al. (2001), dynamic correlation is a measure of how the phases of two cycles interact. A negative dynamic correlation implies that the upswing of periodicity-$\tilde{\omega}$ cycle of variable x is associated with the downturn in periodicity-$\tilde{\omega}$ cycle of variable y. Conversely, a positive dynamic correlation implies that periodicity-$\tilde{\omega}$ components of x and y move through booms and busts together. The coefficient describes the direction of movements of one variable relative to the other, but cannot be interpreted as a directed coefficient in itself. To interpret the dynamic correlations as economic forces, we need to pair it with the second tool: A periodicity-specific measure of (Granger)-causality, following Breitung and Candelon (2006). This tests for each periodicity whether the whole time series x contains information that can be used to forecast periodicity-$\tilde{\omega}$ component of time series y (but not necessarily y's fluctuations of different frequencies).

The combination of Granger-test and dynamic correlation provide a directed measure of the strength and sign of the relationship between x and y at each periodicity $\tilde{\omega}$, which we can use to describe the economic forces that drive the interactions between business cycle and financial cycle variables.

Finally, we can conduct a structural decomposition by error. Via the Choleski-decomposition[14] we can identify the orthogonal innovations of the VAR-models. We impose 6 identification assumption: 1-3) The

13 Examples for such frequency-specific Granger-causal relationships are easy to find: The tourism sector is often affected by the weather (both in origin and destination of the tourist), which goes through seasons each year. Hence, temperature can be a powerful predictor of economic activity in the tourism sector but it only affects the seasonal frequencies. Temperature data does not help to predict economic activity on a multiyear horizon but it will help predict in which season tourists are coming.

14 Under the notation of Lütkepohl (2013), this is the "B-model".

Table 1: Baseline VAR key statistics

Sample		full	pre-GM	narrow GM	GM
		1970Q1-2018Q2	1907Q1-1983Q4	1984Q1-2007Q1	1984Q1-2018Q2
number of lags		10	4	4	10
portmanteau p-values		0.07913	1	0.9936	0.0821
	Credit Gap to House Prices	0.1497	0.0103	0.3764	0.1366
	House Prices to Credit Gap	0.0001	0.0576	0.1084	0.0016
Granger-causality	Credit Gap to Output	0.2061	0.9541	0.3911	0.1369
p-values	Output to Credit Gap	6.37e-07	0.1479	0.0221	0.0056
	House Prices to Output	0.0021	0.7649	0.0141	0.0967
	Output to House Prices	0.4874	8.44e-08	0.8487	0.1451

This table summarizes the key statistics of the baseline VAR model estimated on four different subsamples. The table lists the number of lags, the p-values of the Portmanteau-tests on serial correlation, and Granger-causality tests of the variable pairs listed in the first column.

orthogonal shocks to the Fed Funds rate do not affect any other variable contemporaneously. 4-5) The orthogonal shocks to house prices do not affect neither output, nor the Fed Funds rate contemporaneously. 6). The orthogonal shocks to credit gap do not affect output contemporaneously[15][16]. Next, we can recalculate the spectra, dynamic correlations and Granger-tests to assess which shocks are responsible for the effects at each periodicity that the SVAR gives rise to when all shocks except for one are shut down. The resulting spectra show how the volatility that the structural shocks cause spreads out over fluctuations of different periodicities. Such an error decomposition is standard procedure in the calculation of the forecast error variance decompositions (FEVD), which we can also represent in the frequency domain. The interpretation of the latter is almost exactly the same of as for a time-domain FEVD, except that it shows the forecast error variance at each frequency rather than for different horizons. Both dynamic correlation and FEVD are particularly helpful to visualize medium-term effects that are often hard to see in IRFs (that quickly converge to zero) and time-domain FEVD (that are often constant beyond a certain horizon). A detailed mathematical description of the frequency-domain methods is relegated to Appendix 11.

We choose as the baseline model the four-variable model of credit gap, house prices, output and the FED funds rate. The number of lags is chosen according to Akaike's information criterion subject to the Portmanteau test not rejecting its null hypothesis at 95% confidence. Table 1 summarizes key statistics of the baseline VAR models of the analysis. We also run bivariate VARs between credit gap, house prices and output to confirm the findings in a simplistic setting that help us to understand the effects between variable

15 The identification assumptions are the same as in the model in Section 4.

16 Multiple identification yield the same qualitative results. One alternative is to assume that 1-3) credit shocks do not affect any other variable contemporaneously, 4-5) house prices shocks affect neither output nor the Fed Funds rate contemporaneously and 6) Output does not affect the FED funds rate contemporaneously.

pairs in isolation[17]. In addition, we estimate a five-variable VAR model that adds the inflation rate to the variables of the baseline model.

3.3. Results:

This subsection describes the results from the exercises outlined in the previous subsection. To keep the exposition simple and concise, we show only the results of the baseline VAR model of credit gap, house prices, output and interest rate in the main body of the text. The full results of the bivariate analysis and the inclusion of inflation can be found in the Appendix A.

We first show that volatility has shifted to more medium-term fluctuations in the course of the Great Moderation. Then, we show existence of the Granger-causal relationship between the credit gap and output and discuss the differences between the estimates on the pre-GM and GM sub-periods. The empirical characterization of the Great Moderation and its connection to the financial cycle is then pieced together from the results of the different exercises.

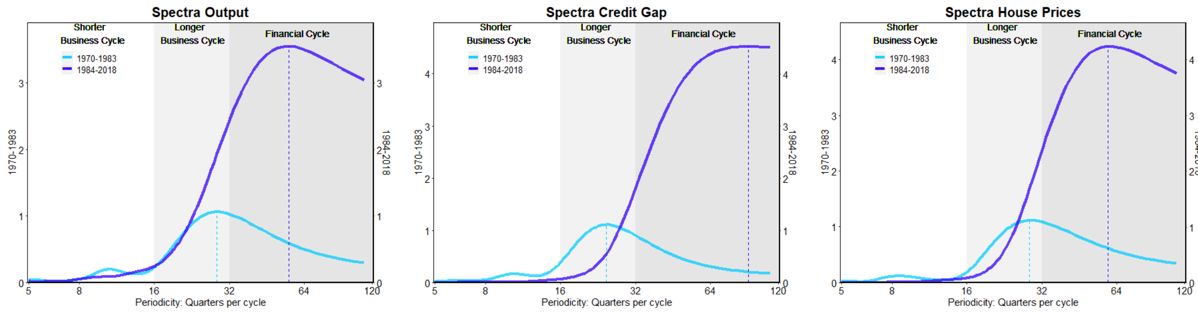
The first important observation stems from the analysis of the spectra prior to and during the Great Moderation. Figure 2 shows the spectra of output, credit gap and house prices that were estimated on the pre-Great Moderation (1970Q1-1983Q4) and Great Moderation sample (1984Q1-2018Q2). Output volatility has shifted dramatically towards longer periodicities. While the spectrum of the pre-Moderation sample features two peaks (near 10 and near 28 quarters per cycle) the Great Moderation spectrum has only one peak near 60 quarters. Volatility decreased on most shorter-business cycle periodicities during the Great Moderation but it increased on most longer-business cycle periodicities and on all financial cycle periodicities. In fact, the Great Moderation spectrum exceeds the pre-Moderation spectrum on all periodicities greater than 24 quarters per cycle. These effects are also found when the narrower definition of the Great Moderation (1984Q1-2007Q1) is applied as is shown in Figure 16. in the Appendix. The spectra of credit gap and house prices have also moved towards longer periodicities: their peaks moved from longer-business cycle to financial cycle periodicities and their volatility on shorter business cycle periodicities disappeared almost entirely. Compared to output, the changes in the spectra of credit gap and house prices are even larger. Volatility of output has increased 4-fold on whereas volatility of credit gap and house prices has increased 6-fold and 20-fold, respectively. The shifts towards longer periodicities are also larger in the financial cycle variables, especially for credit gap.

This means that both business cycle and financial cycle have increased substantially in length - short-term fluctuations of these variables have all given way to longer-term fluctuations. The increase in output volatility on financial cycle periodicities implies that the characterization of the business cycle post-1984 as a “moderation”.

The first piece of evidence that substantiates the importance of the financial cycle to the changes of the

17 In the bi-variate case, one assumption is sufficient to identify the structural shocks. In this particular case, the results of all three bivariate VARs are qualitatively robust to the choice of identifying assumption. In other words, the reduced form VARs are almost identified. The unrestricted entries of the B-matrix are close to zero.

Figure 2: Spectra pre-GM and GM: Output, Credit Gap and House Prices



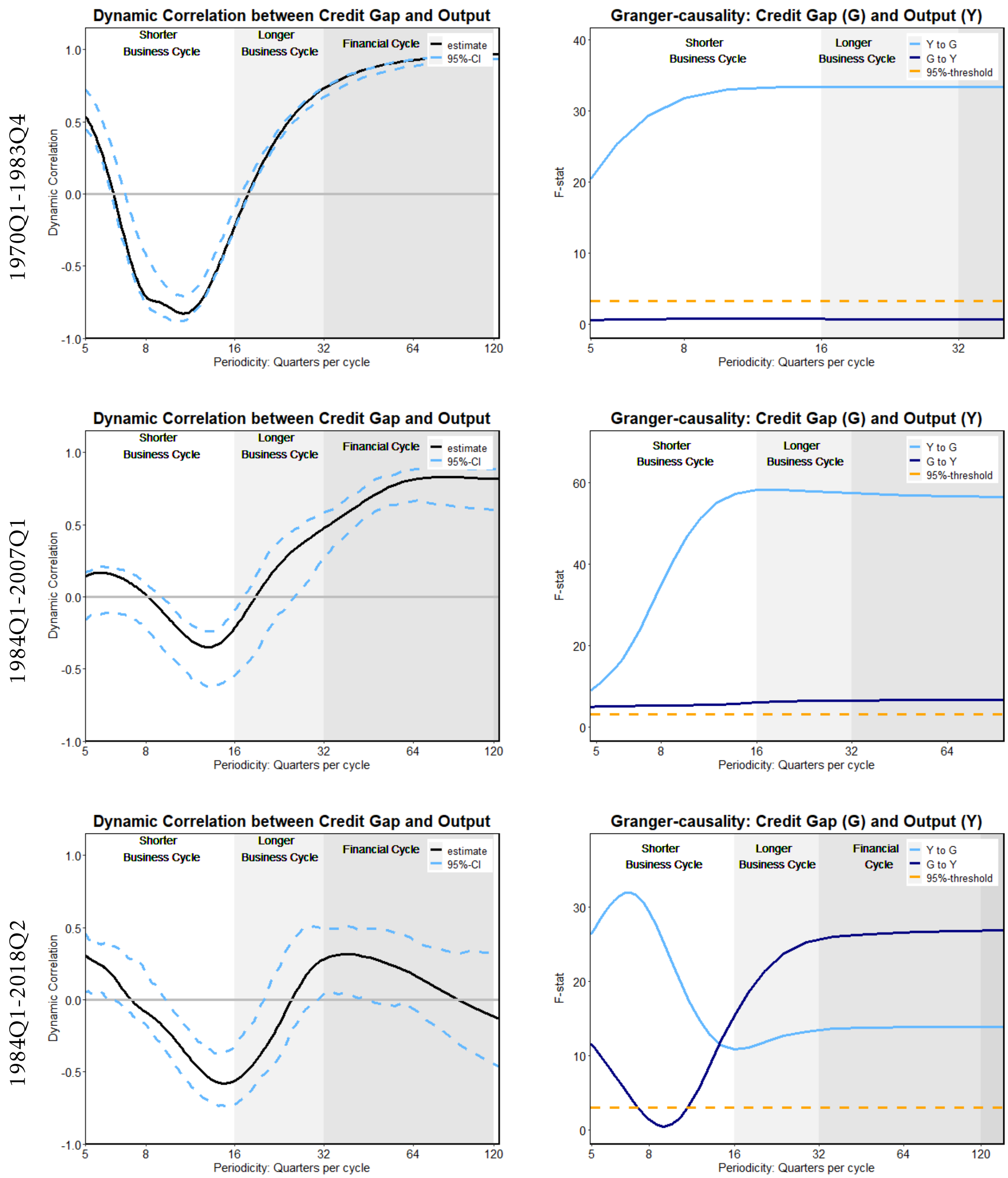
This figure shows the spectra of output (left panel), credit gap (middle panel) and house prices (right panel) estimated on the time series of the pre-GM (light blue) and the GM (dark blue) sample. The left axis measures the variance of the pre-GM spectrum. The right axis measures the variance scales the variance of the GM spectrum. The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. The spectra are normalized such that for each variable, the higher peak has a maximum of one.

Great Moderation comes from the dynamic correlations in combination with the Granger-causality statistics implied by the baseline VAR-models. Consequently, they are plotted together in Figure 3, in the left and right column, respectively. In the dynamic correlation plots, the dashed lines represent 95-% confidence bounds that are calculated from bootstrapping the coefficients of the VAR-model. The top row shows the estimates from the pre-GM sample, the middle row the estimates from the narrow-GM sample and the bottom row the estimates of the GM sample. By construction, dynamic correlation is between minus one and one.

We notice the following: The dynamic relationship between credit gap and output is negative on most shorter business cycle periodicities. It transitions into positive territory on longer business cycle periodicities and is positive on all financial cycle periodicities. While the magnitude of the dynamic correlation coefficients decreases in absolute terms from pre-GM to GM sample, the periodicity ranges on which it is positive and negative remain largely the same in all three samples. Importantly, the periodicity range on which the dynamic correlation coefficient is negative matches the range on which the output spectrum shows decreases in volatility closely. Conversely, the periodicity range on which output gained volatility during the Great Moderation corresponds to the positive dynamic correlation coefficient of credit gap and output.

We pair the dynamic correlations with the results of the Granger-causality tests in the right column. The solid lines show the F-statistics of the tests for Granger-causality at each periodicity. The dashed line is the 95% confidence threshold for these tests. The frequency at which the test-statistic reaches its maximum describes the fluctuations of y which are predicted most powerfully by x. If the Granger-test is not significant on a certain frequency range, this confirms that the economic forces are only relevant in a periodicity range around the peak of the test-statistic. This range must be interpreted with caution: the test-statistics are a continuous function $F(\tilde{\omega})$. Hence, even when there is only a causal effect on one specific periodicity,

Figure 3: Dynamic Correlation and Granger Causality between Credit Gap and Output



This Figure shows the dynamic correlations (left column) and the F-statistics of the Granger-causality test (right column). These measures are calculated on data from 1970Q1-1983Q4 (top row), 1984Q1-2007Q1 (middle row) and 1984Q1-2018Q2 (bottom row). The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. Dynamic correlation is measured on a y-axis from -1 to 1. The y-axis of the Granger-causality test measures the F-statistic. The solid lines show the F-statistic at each periodicity, where the legend shows the cause variable of each test. The dashed line is the 95% threshold of the Granger-test.

the test will still reject the null hypothesis of Granger-non-causality on the neighboring periodicities.

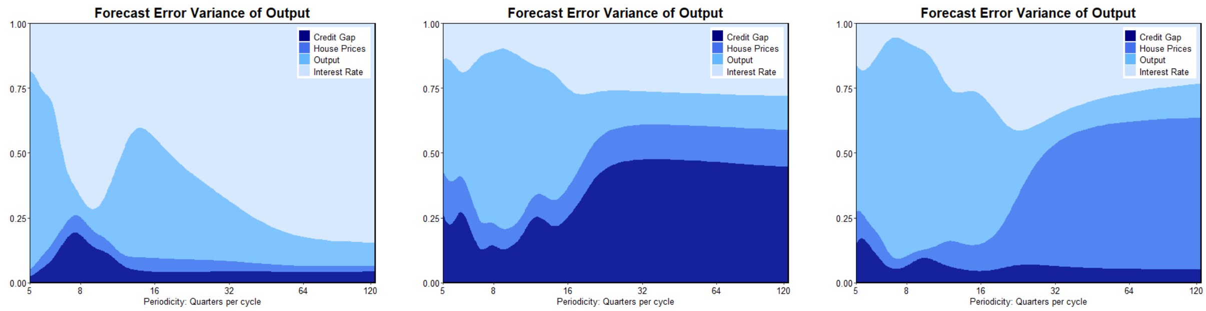
We see the following: prior to the Great Moderation output Granger-caused the credit gap and the significance of this relationship was monotonically increasing towards longer periodicities . At this time the reverse was not true. During the Great Moderation, both variables Granger-cause each other. In the narrow-GM sample, the significance of the Granger-causality of credit increase monotonically towards longer periodicities. On the other hand, the F-statistics when output is the cause variable reach their peak already on shorter business cycle periodicities and decline thereafter. In the GM sample, we see that credit gap and output Granger-cause each other at fundamentally different periodicities. The peak of Granger-causality of output on credit gap is located near 8 quarters and thereby within the shorter business cycle periodicities. For longer-period fluctuations of the credit gap, output exerts less Granger-causal influence, as the test statistic of the Breitung-Candelon tests decreases substantially, yet stays well above the significance threshold. In contrast, the credit gap's Granger-causality on output is insignificant for a range of shorter business cycle periodicities. It then increases for longer-period fluctuations and attains its maximum on financial cycle periodicities.

The combination of dynamic correlation and Granger-causality statistics point to the following relationship between credit gap and output: A short-period downturn in output (Granger-) predicts a short-period upswing of credit gap. In turn, the upswing in credit gap predicts an attenuation of the downturn in output. However, as we move through longer business cycle- and financial cycle periodicities, the effects change: A medium-period credit boom predicts an output boom but when credit gap falls into a medium-period trough, we expect that it draws output with it as well. In other words, credit movements amplify medium-term movements of output.

Figures 11 - 13 in the Appendix show the results for bivariate models between credit gap, house prices and output. Their results can be confirm our findings: The relationship between credit gap and output has the same properties as in the baseline VAR model: Output Granger-cause the credit gap on short fluctuations but on financial cycle periodicities the direction of Granger-causality is reversed. The dynamic correlation between house prices and output is low (near zero) on for fluctuations between 5 and 12 quarters. It then increases and is strongly positive for fluctuations between 16 and 120 quarters. The relationship is bidirectionally Granger-causal both prior to and during the Great Moderation. The Granger-causality of house prices on output is more significant in the GM sample than in the pre-GM sample, whereas the reverse is true for the Granger-causality of output on house prices. The dynamic correlation between credit gap and house prices is near zero on short periodicities and significantly positive on longer periodicities. The periodicities on which it is significantly positive have become substantially longer in the course of the Great Moderation.

The second piece of evidence shows the changes in the relationship between financial cycle and business cycle that caused the shifts in the spectrum that we observed earlier. This is derived from the results of the FEVD of the baseline VAR model, which shows two things: Firstly, prior to the Great Moderation, neither of the financial cycle variable played a major role. In fact, most of the forecast error in the pre-GM

Figure 4: FEVD for the pre-GM (left), narrow GM (middle) and GM (right) sample.



This figure shows the frequency-domain FEVD of output derived from the baseline VAR-model. The left panel was estimated on data from 1970Q1-1983Q4. The panel in the middle was estimated on data from 1984Q1-2007Q1. The right panel was estimated on data from 1984Q1-2018Q2. The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. The y-axis shows the contribution of each shock to the overall forecast error variance.

sample is driven by monetary shocks. However, in the Great Moderation sample, we see that structural shocks to the credit gap and house prices have gained significantly in importance relative to output shocks during the Great Moderation. Both financial shocks have in common that they exert most of their influence on medium-period output fluctuations, while short-period output fluctuations are largely driven by real shocks (structural innovations to output). Depending on whether the narrow or wide definition of the Great Moderation is applied, the forecast error share is attributed either to credit shocks or house price shocks. The periodicities on which the forecast error share of either financial shock increases the most - fluctuations between 16 and 20 quarters - is very close to the periodicity where the dynamic correlation between credit gap and output transitions from negative to positive. The same thing can be seen when we analyze the spectra that these VAR models imply when all shocks but one are shut down (Figure 15 in the Appendix). Financial shocks systematically lead to lower volatility on short periodicities but to more volatility on medium-term periodicities than output shocks. This property developed during the Great Moderation.

3.4. Robustness

We check the robustness of these results along four dimensions. First, we show that the main properties of dynamic correlation and FEVD also hold in the bivariate VAR-models as well as when inflation is added to the baseline specification. The qualitative properties of the dynamic correlation and FEVD described above also hold in the VAR-model that includes inflation. Dynamic Correlation is negative on shorter business cycle periodicities and positive on longer business cycle periodicities. The effects are Granger-causal and importantly, the Granger-causal effect from output to credit gap is more clearly significant on shorter periodicities. Dynamic correlation between house prices and output is close to zero on shorter business cycle periodicities but significantly positive on financial cycle periodicities. The significance of Granger-causality from house prices to output rises towards longer periodicities. If anything, the Granger-causality from output to house prices is more strongly significant on shorter business cycle periodicities. The forecast error variance decompositions show roughly the same pattern. Orthogonal innovations of output are the dominant driver of only shorter business cycle periodicities but have little effect on longer periodicities in the samples that include the Great Moderation. In contrast, the innovations to the financial variables lead to forecast error mostly on long periodicities, especially the innovations to the credit gap. The variance attributed to monetary shocks comes in between and attain their maximum forecast error variance share at around 20 quarters per cycle. Inflation behaves similarly to the financial variables, driving very little forecast error at short periodicities and a lot on long periodicities.

Secondly, we show that the dynamic correlation pattern is not driven by any particular period in the data. Specifically, we assess the robustness in the following sub-samples: The post-war economy (1946-1983), the Bretton-Woods era (1944-1976), the narrowly defined Great Moderation (1983-2007)[18] and the longest possible pre-GM sample available in the JST data (1893-1983). The plots of dynamic correlation, Granger-causality and forecast error variance decomposition can be seen in the Appendix (Figures 16 and 17). The results hold without qualifications when the narrow definition of the Great Moderation is applied. They also hold in the Bretton-Woods and post-war sub-sample with some qualifications: The dynamic correlation between credit gap and output is negative for short-term fluctuations (<4 years) before becoming positive on medium term fluctuations - however, it turns negative again for periodicities beyond 7 years[19]. The effects between house prices are Granger-causally driven by output on short periodicities and driven by house prices on long-periodicities, each time with a positive coefficient. The FEVD of the Bretton-Woods era tells a different story than the GM one. The financial cycle has next to no relevance as a driver of volatility. Additionally, monetary shocks drive most short-term volatility and output is the main driver of medium-term fluctuations. The results cannot be found in the very long-run pre-GM sample.

Thirdly, I run the same analysis on UK data from the FRED, BIS and Office of National Statistics (ONS). The results of this robustness check can be seen in Appendix 18. Overall, they point in the same direction - although less significantly as in the U.S.: In the UK data, the financial cycle is characterized by a medium-term dynamic correlation between credit gap and house prices. Dynamic correlation between credit gap and output is negative on some shorter-business cycle periodicities and positive on longer periodicities. The FEVDs show that financial shocks systematically drive mainly medium-term fluctuations and the largest increase in the share attributed to financial shocks is also located near cycles of 16 quarters. The greatest disparity between the U.S. and the UK is the Granger-causal power of house prices on output, which is non-existent in the UK[20]. Finally, I confirm that the results are not driven by the choice of filter. I obtain similar results when using a one-sided HP-filter to remove the trend (see Appendix 19).

18 The selection of a cutoff in 2008 is not possible - by then the boom in house prices was so large that it is impossible to estimate a stationary model on such a sub-sample.

19 House prices were used as a collateral value to a much smaller extend prior to the 1980s. We can find results that show very similar patterns to those of the latter samples by using a weighted average of stock prices and house prices for this era.

20 A likely source of the differences is the lower usage of mortgages as collateral in the UK.

3.5. An accurate picture of the Great Moderation

The results shown above propose a novel interpretation of the Great Moderation and the forces that led to it. An accurate characterization must primarily point to a transfer of volatility from short-term fluctuations to medium-term fluctuations and a shift in the source of those fluctuations from real to financial sector. At medium periodicities, the U.S. economy witnessed increases in volatility which are especially pronounced for the credit gap and house prices (where volatility has increased 6-fold and 20-fold, respectively. This transfer of volatility to longer-term fluctuations parallels the findings of increased persistence of the literature (Giannone et al. (2008), Pancrazi (2015)). The structural error decomposition has shown that in this periodicity range, output fluctuations are primarily driven by financial shocks. Hence, we must infer that the origin of output volatility has gravitated to the financial sector.

These shifts are not driven by the Great Recession of 2008 (see Figure 14 in the Appendix). Hence, even when the narrow definition of the Great Moderation is applied, it was not as moderate as its name suggests. The volatility between 1984 and 2007 was merely a prelude to the dramatic downturn that came with the Great Recession. While there may be multiple reasons for the increases in persistence of output volatility, it fits into the picture of a finance-driven Great Moderation that the financial cycle itself, i.e. the dynamic interaction of credit gap and house prices has shifted to longer periodicities in the course of the Great Moderation. This is shown in Figure 10. We see that the range in which this dynamic correlation is strongly positive shifted significantly towards medium-term, "financial cycle" periodicities. This shift across periodicities in the dynamic correlation of credit gap and house prices is far greater than the shifts in the dynamic correlations between credit gap and output or house prices and output. Instead, the most significant changes to the latter relationships that came with the Great Moderation concern the development or strengthening of Granger-causality on output; and the diminution of the reverse effect. Rather, the fact that the qualitative properties of the dynamic correlations regarding attenuation and amplification were already present before the Great Moderation suggests the presence of a structural link between credit and output which is not a product of any mechanism that the literature has used explained the Great Moderation. The story of the Great Moderation must hence be about the intensification of the previously existing links between real and financial sector of the economy and the stronger attenuation and amplification forces that resulted from it. This intensification of the existing volatility transmission mechanisms coupled with the increased persistence of the financial cycle then leads to the heterogeneous phenomenon that we witnessed over the past 35 years: Episodes of moderation with low short-term volatility and finance-driven phases in which medium-term output volatility surfaces in the form of great recessions.

These findings sideline the academic debate on whether "good luck" or "good policy" drove the Great Moderation. Our analysis nevertheless allows us to comment on the positions of this debate. The first main comment is that there was indeed "good luck". An analysis of the structural innovations (figure 23 in the Appendix) shows that a reduction in the error variance did occur in the 1980s and affected both real and financial variables. However, we also see that the error variance did not remain low until the Great Recession. Instead it rose sharply in the 1990s and early 2000s - which points again towards the result that the Great Recession was part of a medium-term fluctuation and not of a sudden increase in short-term volatility. With regard to "good policy", we notice that the contribution of monetary shocks to the forecast error of output has decreased substantially in the course of the Great Moderation. However, it is hard to call the effects of either shocks or policy "good" while we argue that overall volatility has increased on medium-term periodicities.

4. Model

This section shows that while off-the-shelf models with financial frictions largely fail to replicate the frequency-domain statistics, a model with long-run risk and the right set of financial frictions can go a long way towards doing so. Herefore, we examine 6 models from the literature[21] on the dynamic correlations and FEVD they imply. Additionally, we build and estimate a model that nests the financial sectors of Iacoviello (2005) (abbreviated "IAC" in the following) and Gertler and Karadi (2011) (abbreviated "GK") and the combination of the two in a New Keynesian economy. These financial sectors are characterized by a collateral constraint on entrepreneurial borrowing and a leverage constraint on financial intermediaries, respectively. Throughout the rest of this paper, we refer the model with both collateral and leverage constraint as the "IGK model".

As a first pass on the data, we show that Bayesian-estimated forms of the three submodels all fail to replicate the empirical frequency-domain statistics. The key shortcoming of all submodels is that in contrast to the data, financial shocks never feed systematically into medium-term fluctuations. To reconcile model and data, we show in a second step that the inclusion of long-run risk elements in spirit of Bansal and Yaron (2004) has the ability to mitigate this shortcoming. The resulting submodel with both frictions can be calibrated to fit the data well.

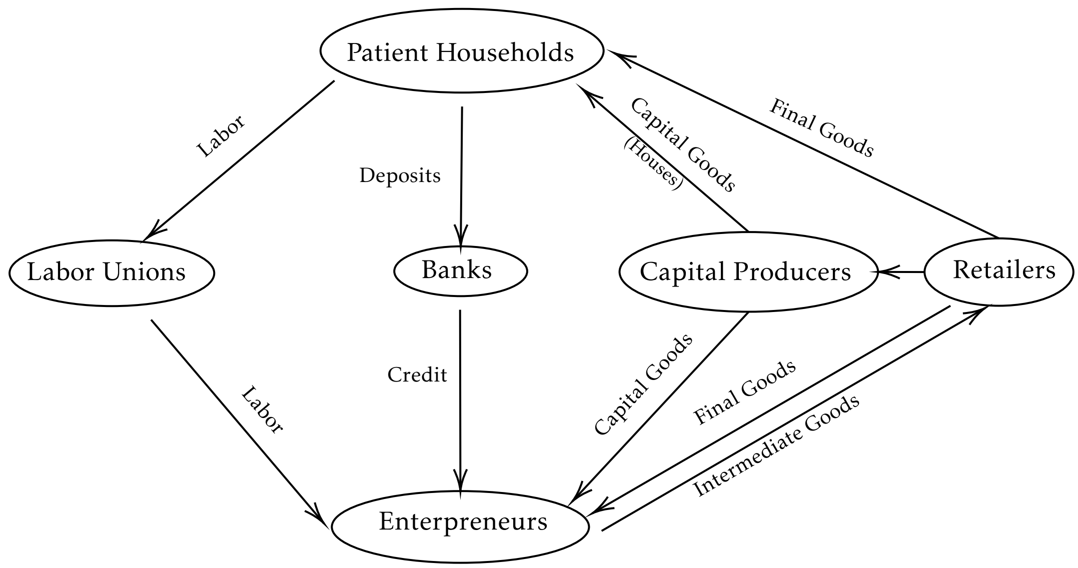
Notation and the majority of the model's setup follows Villa (2016)[22]. The basic framework is a New Keynesian economy which is enriched with elements found to be of quantitative importance by Smets and Wouters (2003). We further set up the model in spirit of Christiano et al. (2005) in order to maintain a close mapping between model and the identifying restrictions of the structural VARs. Figure 5 summarizes the general structure of the model economy:

There is a mass 1 of identical patient households indexed by i. Households maximize their utility through choice of consumption C_t, housing K_{t+1}, deposits D_t in a financial intermediary and labor supply L_t. Their utility from consumption depends on external habit and capital depreciates at rate δ. Each household owns

21 The six models are: Iacoviello (2005), Kannan et al. (2012), Gambacorta and Signoretti (2014), Stracca (2013) and Villa (2016) which contains two estimated models with the frictions of Bernanke et al. (1999) and Gertler and Karadi (2011).

22 Villa (2016) builds a similar model in which the costly state-verification framework gives rise to the BGG financial accelerator.

Figure 5: Model Economy: Agents and Flows of Goods



This picture shows the model economy. The optimizing agents of the model are encircled. The arrows designate flows of goods and services between agents.

a bank and receives its bank's profits. Their maximization problem is:

$$
maxE_t \sum_{t=0}^{\infty} \beta^t \Big\{ log(C_{it} - hC_{t-1}) - \frac{L_{it}^{1+\phi_l}}{1+\phi_l} + \nu log(K_{it+1}) \\
- \mu_{it}[C_{it} + Q_t(K_{it+1} - (1-\delta)K_{it} + D_{it+1} - R_{t-1}D_{it} - W_t^H L_{it} - \Pi_t + T_t - TR_t] \Big\}
$$

Houses are bought and sold but cannot be rented. Households are subjected to government taxation T_t and transfers TR_t. Labor is supplied to labor unions, which differentiate it, aggregate it and sell the labor aggregate to entrepreneurs. There is a mass 1 of identical entrepreneurs indexed by j in the economy. As in Iacoviello (2005), entrepreneurs only consume non-durable goods and use the capital goods to produce new intermediate goods. Entrepreneurs choose non-durable consumption C_t^F, labor demand L_t and capital utilization U_t. Increased capital utilization results in higher output and comes at higher costs of maintenance of the capital stock. To maintain its capital, the firm needs to purchase additional final goods. Entrepreneurs' production technology is:

$$
Y_{t+1} = A_t (U_t K_{t+1}^F)^{\alpha} L_t^{1-\alpha} - \Theta
$$

where Θ is a fixed cost and A_t is an AR(1) process for TFP. To finance themselves, entrepreneurs can borrow B_{t+1}^F from a financial intermediary through one-period loans at interest rate R_t^L. As in Iacoviello (2005), a framework of costly state-verification introduces a financial friction into the economy. Originally introduced by Townsend (1979), this friction micro-founds the requirement for entrepreneurs to pose collateral for the loans they obtain from the financial intermediary[23]. We assume that the cost of state verification amounts to a share ζ of the value of assets that the banks can recover. Hence, when banks can only keep $1-\zeta$ of the entrepreneurs assets in case the latter does not repay, they can ensure themselves of full repayment by only lending up to $(1-\zeta)$ of the entrepreneur's collateral. Credit given to the entrepreneur B^F times the lending rate R^L must be smaller than the loan-to-value ration $(1-\zeta)$ times the collateral value QK^F This leads to a financial accelerator: If collateral value increases (exogenously), more credit can be obtained, used for more purchases of houses which can again be used for collateral. On the flipside, the entrepreneurs may be forced into a liquidation spiral if house prices decrease.

Entrepreneurs discount the future at factor $\gamma\beta$, where $\gamma < 1$ shrinks their discount factor below the one of the patient households and ensures that entrepreneurs will always be borrowing constraint. Accordingly, the problem of the entrepreneur is:

$$
\begin{aligned}
maxE_t \sum_{t=0}^{\infty} (\gamma\beta)^t \Bigg\{ & \frac{(C^F_{jt} - h^F C^F_{t-1})^{1-\phi_f}}{1-\phi_f} \\
& + \mu^F_{jt}[\Phi_t Y_{jt} + B^F_{jt+1} - C^F_{jt} - W_t L_t - \Psi(U_{jt})K^F_{jt} - Q_t(K^F_{jt+1} - (1-\delta)K^F_{jt}) - R^L_{t-1} B^F_{jt}] \\
& + \mu^C_t E_t[(1-\zeta_t)Q_{t+1}K^F_{jt+1}(1-\delta) - R^L_t B^F_{jt+1}] \Bigg\}
\end{aligned}
$$

The modeling of the financial intermediaries (banks) follows Gertler and Karadi (2011). In this framework, the managers of financial intermediaries (banks) can divert a fraction of the assets that they manage back to their household. They will do so whenever their continuation value of stealing (and then being prohibited from managing the bank in future periods) is greater than their continuation value from not stealing. The incentive constraint that resolves this moral hazard problem restricts the bank's ability to lever up - it must accumulate net worth to use alongside deposits in order to lend to entrepreneurs: As a consequence, the bank may not be able to raise enough to deposits to satisfy the entrepreneurs' demand for credit at a lending rate which equals the deposit rate. Hence, the lending rate in the GK-framework will exceed the deposit rate whenever the leverage constraint is binding. Banks die in each period with probability $1-\theta$. In this case, they return their entire net worth to their household, who consumes it and starts a new bank. This setup leads to the objective:

$$
\begin{aligned}
\Upsilon_t &= maxE_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \beta^{i+1} \Lambda_{t,t+i+1} N_{t+i+1} \\
\Upsilon_t &= maxE_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \beta^{i+1} \Lambda_{t,t+i+1} (R^L_{t+i} B^F_{t+1+i} - R_{t+i} D_{t+1+i} - R_{t+i} N_{t+i})
\end{aligned}
$$

23 Alternatively, the costly state-verification can be used to justify an external finance premium as in Bernanke et al. (1999)

Gertler and Karadi (2011) show that this implies the leverage constraint:

$$B_{t+1}^{F} \leq \frac{H_t}{\lambda_t - V_t} = lev_t N_t$$

where H_t and V_t stand for the banks value of increasing assets and increasing net worth, respectively. lev_t represents the leverage ratio (assets/net worth) and N_t is the bank's net worth. The inability of the bank to obtain sufficient funds to equalize the marginal return to capital of the entrepreneur with the households intertemporal margin drives a wedge between deposit and lending rate - such that the firm earns positive profits.

When both frictions are active at the same time, they interact as follows: At the steady-state, the values of ζ and λ determine which constraint is binding. For very low values of λ, the leverage constraint will be non-binding the equilibrium lending rate will be $R^L = R = \frac{1}{\beta}$. A λ increases, the leverage constraint tightens and eventually starts binding. The binding leverage constraint leads to a shortage in credit supply, which leads to an increase in the lending rate. This continues as long as $R^L \leq \frac{1}{\gamma\beta}$. If λ increases further the collateral constraint stops binding and only the leverage constraint binds. The leverage constraint has made credit so expensive that entrepreneurs will no longer borrow up to their collateral constraint. Accordingly, the equilibrium level of debt and the lending rate should satisfy:

$$\begin{aligned} B_{t+1}^{F} &= min\left\{\frac{(1-\zeta_t)(1-\delta)Q_t K_{t+1}^{F}}{R_t^L}, \frac{(1-\zeta)Q_{t+1}K_{t+1}^{F}}{R_t EP^{-1}(EP_t)}, lev_t N_t\right\} \\ R_t^L &= max\{R_t, R_t EP_t\} \end{aligned}$$

The combinations that are possible are most conveniently written in two complementary slackness conditions, that capture the economics described above:

$$\begin{aligned} 0 &= \mu_t^C (B_{t+1}^F R_t^L - (1-\zeta_t)(1-\delta)Q_{t+1}K_{t+1}^F) \\ 0 &= (EP_t - 1)(B_{t+1}^F - lev_t N_t) \end{aligned}$$

We can distinguish the following cases: When only the Iacoviello friction is active, $\mu_t^C > 0$ so we can divide by it and obtain the collateral constraint. Since the leverage constraint will not be binding, the second equation delivers $EP_t = 0$. When both Iacoviello and GK-friction are active, the first equation gives the collateral constraint and the second one the leverage constraint. In this case the parameters ζ and λ control the strengths of the frictions and we can analyze their interaction throughout their support. Suppose that in steady state for a particular parameterization only the collateral constraint binds. When the fraction λ that managers can divert is increased at one point the leverage constraint will bind as well. As λ is increased further both constraints continue to bind and the interest rate increases as a consequence of the GK-friction. But as soon as the interest rate increases enough to offset the impatience of entrepreneurs completely, the collateral constraint will cease to bind in steady state. For all higher values of λ, only the leverage constraint binds.

The financial frictions ζ and λ are also used to introduce financial supply shocks into the model. That is, ζ

and λ follow AR(1) processes with persistences ρ_ζ, ρ_λ and standard errors $\epsilon_\zeta, \epsilon_\lambda$. This generates an "active" financial accelerator that is not solely a propagator, but also a source of shocks[24]. Retailers differentiate intermediate goods and aggregate them into a final good. Final goods are sold to the patient household for consumption, to entrepreneurs for consumption and maintenance of the capital stock; and to capital producers as a production input. Retailers adjust their prices according to a Calvo scheme with parameter σ_p the probability that they cannot adjust their price in a given period. In this case, the prices of firms that cannot re-optimize are indexed to inflation. Thus, the retailers maximize

$$maxE_t \sum_{s=0}^{\infty} \frac{\mu_{t+s}}{\mu_t} (\beta\sigma_p)^s Y_{t+s}(f) \left[\frac{P_t^r(f)}{P_{t+s}} \left(\frac{P_{t+s-1}}{P_{t-1}} \right)^{\sigma_{pi}} - \frac{\Phi_{t+s}}{P_{t+s}} \right]$$

The optimal mark-up that retailers choose is subject to an AR(1) mark-up shock ϵ_t^p. Capital producers purchase some of the final goods and transform them into houses (capital goods) and sell them to households and entrepreneurs. The problem of capital producers is:

$$maxE_t \sum_{t=0}^{\infty} \beta^t \Pi_t + \mu_t^K \left[\Pi_t - (Q_t^n - P_t) I_t + x_t I_t \left(1 - F\left(\frac{I_t}{I_{t-1}} \right) \right) \right]$$

where x_t is a stochastic process which includes an investment cost shock.
The central bank sets its policy rate according to the Taylor rule

$$ln\left(\frac{R_t^n}{R_t}\right) = \rho_i ln\left(\frac{R_{t-1}^n}{R^n}\right) + (1-\rho_i)\left[\rho_\pi ln\left(\frac{\Pi_t}{\Pi_{t-1}}\right) + \rho_y ln\left(\frac{Y_t}{Y_t^p}\right)\right] + \rho_{\Delta_y} ln\left(\frac{Y_t/Y_{t-1}}{Y_t^p/Y_{t-1}^p}\right) + \epsilon_t^r$$

at the end of each period. ϵ_t^r is a monetary shock.
Market clearing on final goods market and capital market is given by:

$$Y_t = C_t + C_t^F + I_t + \Psi(U_t)K_t^F + G_t$$
$$I_t = K_{t+1} - (1-\delta)K_t + K_{t+1}^F - (1-\delta)K_t^F$$

Final goods that are produced in this economy are split between private, entrepreneurial and government consumption of non-durables, investment into durables and maintenance of the current capital stock at the chosen utilization rate. On the market for durable capital, total investment is given by the changes in the durables stocks of patient household and entrepreneurs. Labor markets and credit markets clear.
In this form, we have a model that is very close to work-horse models of the literature. However, we show in Appendix 10.2 that Bayesian-estimated forms of this model are unable to replicate the main periodicity-domain statistics of the data. Specifically, we document this failure for the dynamic correlations for the pairs credit gap and output, house prices and output, and credit gap and house prices and for the FEVD of output. Two discrepancies between model and data arise consistently: firstly, no matter which financial friction is used, the model generates a dynamic correlation between credit gap and house prices that is positive on short periodicities and decreases towards longer periodicities. In other words, the models

24 This responds to the criticisms of Schularick and Taylor (2012), Borio (2008) and Hume and Sentance (2009)

Timing within a period

- Enter with debt and capital stocks - Observe technology, capital quality and mark-up shocks.	- Firm chooses labor demand and utilization rate. - Final goods is produced and final goods market clears.	- Investment shocks and financial supply shocks are realized. - Capital is produced and capital and debt markets operate.	- Central Bank observes output gap and inflation and chooses its policy rate.

This figure shows the sequence of events that happen in every period in the model.

contain a financial cycle that is a short-term phenomenon. This stands in contrast to the data where this interaction, the financial cycle, was shown to be a medium-term phenomenon, described by a dynamic correlation that only only turned significantly positive on medium-term periodicities. Secondly, all submodels generate forecast error shares that are relatively flat across periodicities. Hence, the property of the data that TFP shocks drive short-term fluctuations while financial shocks drive medium-term fluctuations is not contained in the model.

The dynamic correlations between credit gap and output and between house prices and output also show large departures from their data counterparts, albeit in less consistent ways. The key ingredient that these models are missing is long-run risk. Long-run risk mechanically leads to a shift of spectral density towards longer periodicities. With the goal of ensuring that financial shocks drive medium-term volatility, we augment the stochastic process of λ_t and x_t by long-run risk components in the spirit of Bansal and Yaron (2004):

$$
\begin{aligned}
x_t &= e_t^x + s_t^{LR} \\
s_t^{LR_x} &= \rho_x s_{t-1} + e_t^{LR_x} \\
\lambda_t &= e_t^\lambda + s_t^{LR_\lambda} \\
s_t^{LR_\lambda} &= \rho_\lambda s_{t-1} + e_t^{LR_\lambda}
\end{aligned}
$$

Hence, the composite process features both short-run and long-run risk. To maintain a close mapping between empirical and model-based analysis, we impose timing assumptions on the model in spirit of Christiano et al. (2005) as shown in the timeline below:

This allows for the derivation of six short-run restrictions that can be used to identify a four-variable SVAR of the credit gap, asset prices, output and the policy rate: The central bank moves last in each period. Hence, the monetary shock cannot affect any other variable contemporaneously. Credit and capital markets operate after goods markets have already closed. Output was produced with the capital installed yesterday and labor input and utilization rate were chosen to optimize the production plan. Hence, neither financial shocks cannot affect output contemporaneously[25]. In summary, this gives us the following restrictions:

1. The monetary shock ϵ_r cannot affect any other variable contemporaneously. This is achieved by making the central bank the last mover in each period. This provides three restrictions.
2. The investment price shock ϵ_x cannot affect output contemporaneously (because output is created with last period's installed capital). As the investment price shock does not have an immediate effect on output, it does not have any immediate effect on the policy rate either - as this is set according to a purely backward-looking Taylor rule that only follows output gap and inflation. This adds two restrictions.
3. The credit supply shock cannot affect output contemporaneously as it is realized after the production in period t has taken place. It also has no contemporaneous effect on the policy rate for the same reason mentioned for the capital quality shock.

4.1. Calibration

We fix the parameters of the households, entrepreneurs, unions, retailers and financial frictions that are related to steady state values. As can be seen in Table 2 we set these parameters equal to values estimated in Villa (2016) or used Bernanke et al. (1999), Iacoviello (2005) and Gertler and Karadi (2011). The capital share in the production function of 0.33, the discount factor of 0.99 when periods represent quarters and a depreciation rate of 0.025 are used throughout the literature and require no further discussion. Entrepreneurial impatience relative to households (=0.9898) and survival probability (=0.972) are taken from Iacoviello (2005) and Gertler and Karadi (2011), respectively. The inverse Frisch elasticity of 1.81 is near the higher end of the range that the literature has found. The weight of houses in the household's utility function and curvature of entrepreneurs utility are almost the same as those used in Iacoviello. While the habit parameter for households is standard, most models that follow Iacoviello abstract from entrepreneurial habit. As the agent in the economy that engages in risky ventures, entrepreneurial income is more likely to be volatile - hence we assume a low value of the habit parameter. The elasticities of substitution for both goods and labor varieties equal 6, which implies steady-state mark-ups of 20%. Steady-state utilization costs are set to 5% of output. We also fix the values of the Calvo parameters of goods prices and wages and indexation to past prices, which we simply set the values of Smets and Wouters (2003). In accordance with Iacoviello (2005), the cost of state-verification is set to 0.11 (Bernanke et al. (1999) use 0.12). The fraction of divertable funds is equal to 0.38 as in GK. Next, we modify the parameters which govern the financial frictions to obtain the three sub-models that the model nests: Under the benchmark parameterization from Table 2 only the collateral constraint is binding (Iacoviello model). However, when the fraction of divertable funds is increased to 0.52 (which is the posterior mode Villa (2016) obtains), both

25 In the bivariate models of credit gap and output, and house prices and output, the results of the SVAR are robust to the choice of identification assumption. That is, the unrestricted element of the B-matrix is almost zero - so that the VAR is almost identified on its own. This finding supports the choice of the identification assumption that neither financial shock affects output contemporaneously.

leverage and collateral constraint bind in steady state. The collateral constraint can be de-activated by setting $\zeta = \infty$.

The remaining parameters are calibrated to fit the model to the data. Herein, we use simulated method of moments to target the empirical dynamic correlations for the variable pairs credit gap and output, credit gap and house prices, and house prices and output. Additionally, we target the FEVD estimated by the four-variable VAR of credit gap, house prices output and the policy rate. Herefore, we pick the policy parameters of the Taylor rule, persistences and standard errors of the shocks to minimize the distance between model and data moments. Given that the empirical targets consist of one moment for each frequency, the model is overidentified. Since section 3 focused mainly on the dynamic correlation between credit gap and output, we penalize deviations from this dynamic correlation more heavily than deviations from the other dynamic correlations. Dynamic correlations and FEVD enter the loss function with equal weights. Deviations of model moments from data moments are penalized uniformly for all periodicities. For further details on the calibration exercise, we refer the reader to Appendix 10.1. We calibrate each sub-model separately for pre-GM and GM period. For expositional reasons, we only discuss the calibration of the best-performing submodel here: the framework that combines collateral and leverage constraint. The calibrated parameters of this submodel are shown in Table 4. We make three observations in Table 4: Firstly, central bank policy responds more to inflation and output gap in the Great Moderation period than prior to the Great Moderation, but the importance of interest rate smoothing has decreased. Secondly, the persistences of the financial shock, adjustment cost shock and monetary shock have remained on the same order of magnitude. However, the persistence of TFP shocks has increased from 0.364 to 0.9701. The persistence of mark-up shocks has decreased from 0.4478 to 0.1153. Thirdly, there are also important changes in the standard errors of the shocks. The standard error of the short-run investment cost shock has increased 5-fold and the standard error of the long-run risk shock has increased even 7-fold. Meanwhile, the standard errors of the financial shock, TFP, monetary and mark-up shock have fallen.

Figure 6 shows the spectra of the model-generated data. We can see that both GK and IAC model perform poorly. The models generate too much long-term volatility for both samples. While the IAC model at least produces more short-term volatility in the calibration to pre-GM data, the spectra implied by the GK-model do not have any of the qualitative properties of the empirical spectra. The IGK model replicates the feature that short-term volatility has decreased relative to medium-term volatility in the GM sample. However, it does not replicate the overall shift towards longer periodicities. The peak of the spectrum of the IGK model calibrated to fit the pre-GM moments is already on financial cycle periodicities.

Figure 7 shows how the model-implied dynamic correlations between credit gap and output and the FEVD of output compare to their data counterparts.

First and foremost, the model with both collateral constraint and leverage constraint (IGK model) is by far the best-fit to the data. It vastly outperforms the models with only one financial friction especially regarding the FEVD, but also on the dynamic correlation between credit gap and output.

In both pre-GM and GM sample, the IGK model replicates the qualitative properties of the frequency-

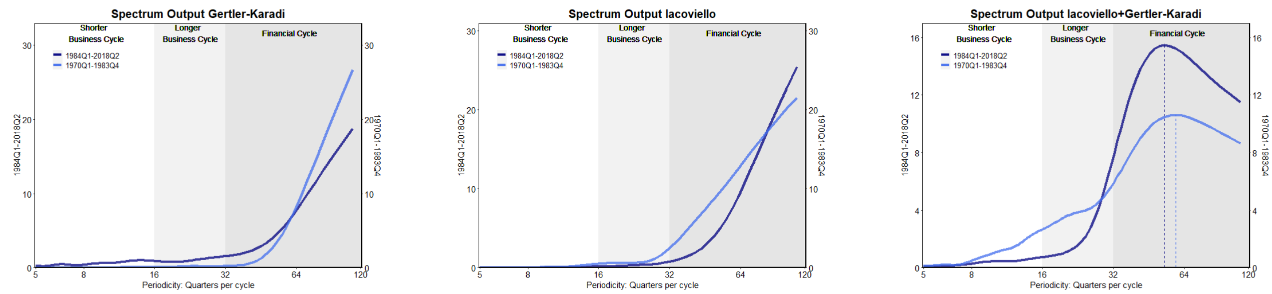
Table 2: Parametrization

Parameter	Description	Value	Source
α	capital production elasticity	0.33	Iacoviello (2005)
β	discount factor	0.99	Villa (2016)
γ	entrepreneurial impatience	0.9898	Iacoviello (2005)
θ	survival probability banks	0.972	GK (2011)
δ	depreciation rate	0.025	Bernanke-Gertler-Gilchrist (1999)
ϕ_l	inverse Frish elasticity	1.81	Villa (2016)
ν	weight of durables in utility	0.03	Iacoviello (2005)
ϕ_f	curvature utility entrepreneurs	0.99	~Iacoviello (2005)
h	habit households	0.8	GK (2011)
h^F	habit entrepreneurs	0.1	-
ϵ_p	elasticity of substitution goods	6	Villa (2016)
ϵ_w	elasticity of substitution labor	6	Villa (2016)
σ_w	Calvo parameter labor unions	0.7370	Smets-Wouters (2003)
σ_{wi}	wage indexation	0.7630	Smets-Wouters (2003)
σ_p	Calvo parameter retailers	0.9080	Smets-Wouters (2003)
σ_{pi}	wage indexation	0.4690	Smets-Wouters (2003)
ψ_0	steady-state utilization expenditure	0.05	-
ψ_1	marginal utilization expenditure	0.0351	Villa (2016)
ψ_2	curvature utilization expenditure	0.850	Villa (2016)
ξ	adjustment costs	4.500	Villa (2016)
χ	scale of transfer to new banks	0.002	GK (2011)
$\bar{\zeta}$	cost of state-verification banks	0.11	Iacoviello (2005)
$\bar{\lambda}$	share of divertable funds banks	0.38	GK (2011)
G	government consumption	0.2	Bernanke-Gertler-Gilchrist (1999)

This benchmark calibration yields a binding collateral constraint and a non-binding leverage constraint when collateralization is required by the lender (Iacoviello model). When $\bar{\zeta} = 0.52$, both collateral and leverage constraint are binding (Iacoviello-Gertler-Karadi model. Without collateralization, the leverage constraint binds (Gertler-Karadi case).

Figure 6: Spectra of model-generated data

GK Model | IAC Model | IGK Model



This figure shows the spectra of the calibrated models. he x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes show the variance and the respective periodicity.

domain statistics of the data. The dynamic correlation between credit gap and output is negative on short-periodicities and positive on medium periodicities. In the GM sample the model-implied dynamic correlation closely tracks the empirical one. In the pre-GM sample, the model-implied dynamic correlation is flatter than the empirical estimate and only turns positive on financial cycle periodicities rather than on longer business cycle periodicities. The model-implied FEVD also replicates most qualitative and even quantitative properties of the empirical FEVD: In the pre-GM sample it replicates the large forecast error share of monetary shocks that still increases on longer periodicities. It largely replicates the forecast error share of TFP shocks that decrease in importance on longer periodicities. It also acknowledges the minor role that financial shocks played prior to the Great Moderation. In the GM sample, the model exhibits the feature that short-term fluctuations are mainly driven by TFP shocks, where as medium-term fluctuations are driven by financial, especially asset price shocks (investment cost shocks in the model). It matches the forecast error share and the periodicities that investment cost shocks feed into closely. The most obvious shortcoming of the model is that it somewhat underestimates the role that monetary shocks played in the GM, especially on longer-business cycle and financial cycle periodicities.

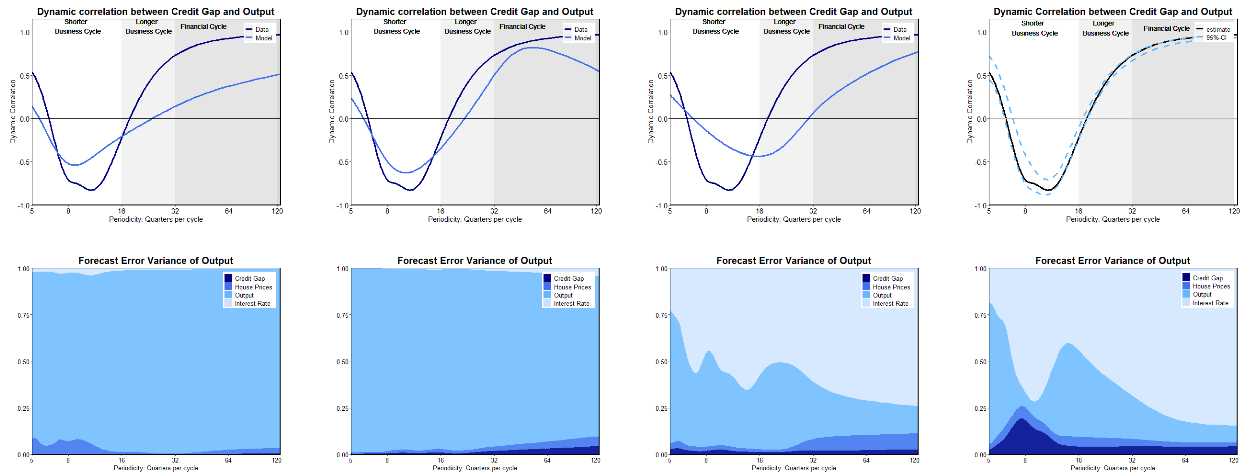
The GK and IAC model do not come close to the performance of the IGK model. The IAC model replicates the qualitative properties of the dynamic correlations between credit gap and output but falls short quantitatively. The qualitative features of the IAC-model-implied dynamic correlations depart from the empirical ones on every dimension. Importantly, the qualitative properties of the pre-GM and GM sample are largely the same. In the GK model, the dynamic correlation of the GM-sample is negative on almost all periodicities. Its FEVD does not have the targeted feature that financial shocks mainly feed into medium-term periodicities.

Despite all successes, the IGK submodel still falls short on other the targeted moments. The dynamic correlations that it produces between house prices and credit gap, and house prices and output, are positive on short periodicities and decrease (sometimes become negative) on longer periodicities (Figure 25). As dis-

Figure 7: Dynamic correlation and FEVD: Model versus Data

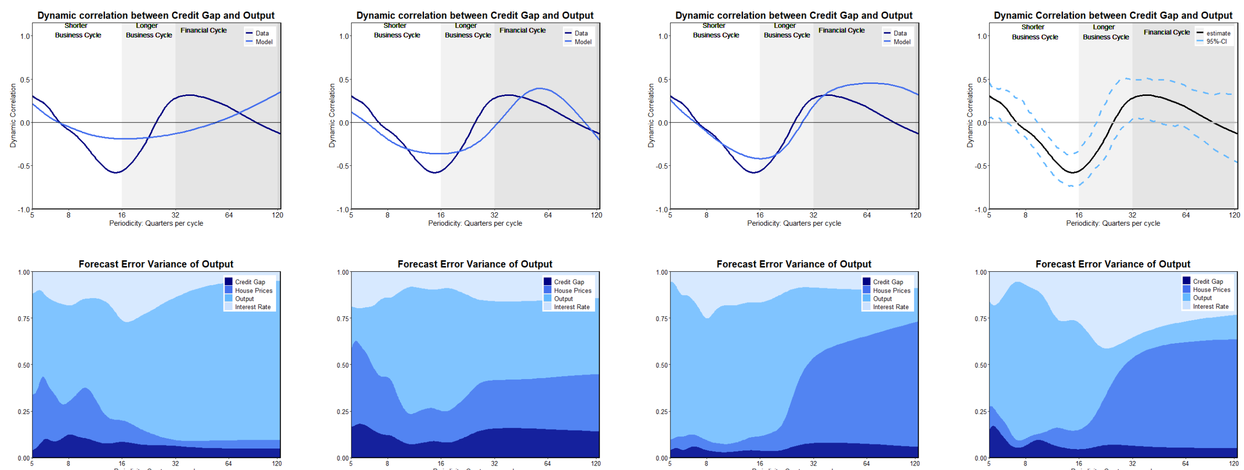
1970Q1-1983Q4

GK Model | IAC Model | IGK Model | Data



1984Q1-2018Q2

GK Model | IAC Model | IGK Model | Data



This figure shows how the model-implied dynamic correlations and FEVD compare to their data counterparts of the baseline VAR-model. The top two rows show the results when the model is calibrated to fit the moments from the estimates on data between 1970Q1-1983Q4. The bottom two rows the results when the model is calibrated to fit the moments from the estimates on data between 1984Q1-2018Q2. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the dynamic correlation on a scale from -1 to 1. The y-axes of the FEVD plots measure the contribution of the orthogonal shock to variable listed in the legend to the overall forecast error variance.

cussed previously, in the data the opposite is the case - these dynamic correlations should increase towards longer periodicities. This disparity between model and data is shared by all submodels[26]. The difficulty

26 This may not be surprising, since these dynamic correlations were weighted less heavily in the calibration.

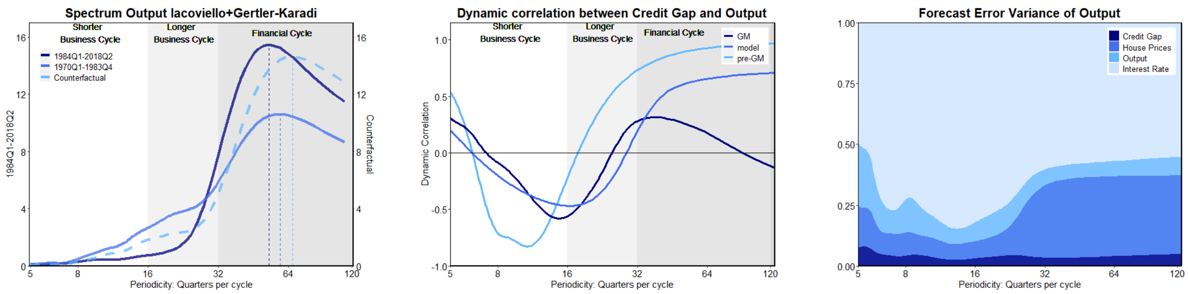
of any model from the literature of producing a dynamic correlation between credit gap and house prices that increases towards longer periodicities indicates that this problem may be systematic. The construction of a model that contains a medium-term financial cycle is thus a task that still requires more attention in future research.

5. Discussion

The estimated parameters shed light on the changes that define the Great Moderation. Firstly, the largest changes are the increases in the standard errors of the investment cost shocks. These changes directly affect house prices in the model, which are responsible for the largest part of medium-term volatility. The long-run risk shock has gained in variance even more than the short-run component. The financial supply shock has seen reductions in the standard errors of both its short-run and its long-run component; and the short-run component has decreased relative to the long-run component. Hence, the calibrated parameters suggest that a key feature of the Great Moderation was an increase in long-run risk relative to short-run risk. Hence, we can argue that that the “good luck hypothesis” can be refined with respect to the medium-run: There was indeed “good luck” but only concerning the short-run risk, but through the financial sector, there was no good luck in the mdeium run. A short-run reduction of risk can also be detected in the standard deviation of the TFP shock size in the GM sample - points towards ”good luck” as a relevant contributing factor to the Great Moderation. The small changes to persistence and standard error of the mark-up shocks indicate that the model assigns at most a minor role to inflation as a driver of the Great Moderation.

Secondly, the fact that only the combined Iacoviello+Gertler-Karadi financial sectors in combination are able to replicate the frequency-domain properties of the data emphasizes the importance of modeling both collateral and leverage constraint and offers further insights into the mechanics by which shocks feed into fluctuations of different periodicities. In the pure Iacoviello framework, the interest rate is purely determined by the difference between the discount factors of patient household and lender. Hence, if a shock hits the collateral constraint, it transmits immediately to the entrepreneurial capital holdings and thereby affects production. In combination with the Gertler-Karadi friction, the lending rate increases in response to a negative shock on the banks’ maximum leverage and thereby can absorb the immediate effect of the shock. Paired with the long-run risk persistence of the shock to the credit supply technology of the banks, this can then feed into much longer-term fluctuations than shocks that hit the collateral constraint directly. Despite the success of the long-run risk augmented model in replicating those key features of the data, long-run risk remains a mechanical way of increasing the persistence of volatility in the model. This relates to the well-known issue that RBC models only generate persistence when it is explicitly built into the model. A model that contains an accurate financial cycle in the form of a purely medium-term interaction between credit gap and house prices that can endogenously generate the frequency-domain statistics would enhance our understanding of the relationship between real and financial sector more than the notion of long-run risk.

Figure 8: Monetary Policy Counterfactual



This Figure shows summary statistics of the monetary policy counterfactual. This is calculated by using the pre-GM estimates of the model and substituting out the Taylor Rule coefficients by the GM-estimated values. The left subfigure shows the resulting spectra of pre-GM model, GM model and counterfactual. Equivalently, the middle subfigure shows the corresponding dynamic correlations. The right subfigure shows the FEVD of the counterfactual.

We can use the model to run "counterfactuals" to isolate the effects that result from the changes in the Taylor Rule, the persistences of the shocks and the shock sizes. We calculate these by re-running the model calibrated to pre-GM (GM) data while replacing the relevant values by those estimated from GM (pre-GM) data. The results are shown in Figures 28 and 29 and yield interesting insights: In the pre-GM model economy with the GM Taylor Rule there is lower short-term output volatility but more medium-term output volatility compared, as can bee seen in Figure 8. Additionally, the investment shock already drives systematically medium-term fluctuations. In contrast, the contribution of financial shocks to the output forecast error is small and relatively flat in a hypothetical GM-economy with the calibrated pre-GM Taylor Rule. This suggests that monetary policy may have contributed to the effects of financial markets on medium-term volatility[27]. Hence, we can argue that the "good policy" hypothesis of the Great Moderation can also be refined with respect to the medium-run implications of monetary policy.

At the same time, the change in Taylor Rule does not affect the dynamic correlations between credit gap, house prices and output much. The analogue experiments can be run to test the effects of changes to the shocks persistences and standard deviations. When we reset the persistences to the values of the other period, we also adjust the shock sizes to ensure that the overall variance of the stochastic process remains constant. The details of this exercise are in 10.3[28]. Their results imply that changes to the persistences greatly amplified the contribution of the financial shocks to the forecast error of output. On top of that, they show that the qualitative properties of financial shocks feeding systematically into medium-term volatility vanishes easily when any of the coefficients are replaced by their counterparts from the other sub-period. This re-emphasizes the fact that only a combination of multiple model ingredients has the ability

27 This confirms the suspicion of Drehmann et al. (2012) that monetary policy can reduce short-period volatility at the expense of more long-term volatility.

28 10.4 also contains a further sensitivity analysis of the model and its properties in the GM economy.

to replicate the features of the Great Moderation and its relationship with the financial cycle.

6. Conclusion

In this paper we have shown that the narrative of the Great Moderation as a pure reduction of volatility does not hold when financial cycle data is included in the analysis. Instead, we saw that the defining features of the Great Moderation were a shift of volatility to longer periodicities and a shift in the source of volatility to the financial sector. The latter shows up in the data as a systematic manifestation of financial shocks into medium-term output fluctuation. On top of that, we showed that a frequency-domain analysis reveals previously undiscovered properties of the interaction of the business cycle with financial cycle variables. In point of fact, we documented a Granger-causal mechanism between credit gap and output that features attenuation forces on short periodicities but amplification forces on medium periodicities. This mechanism is not linked to a specific period and also appears in UK data. Hence, we argued that it should be thought of as structural. We use this evidence to argue that Great Moderation and Great Recession are intrinsically tied together. The former was a consequence of the short-term attenuation forces whereas the latter was an inevitable result of the amplification forces.

These features are only improperly replicated by off-the-shelf quantitative DSGE models. The elements Smets and Wouters (2003) found to be important to throw sand in the wheels of the model and generate the persistent fluctuations we observe in the data, and the financial frictions of Iacoviello (2005) and Gertler and Karadi (2011) do not distinguish accurately between the different period fluctuations that shocks emerging in different sectors of the economy feed into. This led to a disparity between the dynamic correlations of key variable pairs between model and data. We showed that a long-run risk structure enhances the models flexibility in this respect. The interaction of long-run investment cost risk with collateral and leverage constraint gets very close to replicating a) the dynamic correlation between credit gap and output that is negative on short periodicities and positive on long periodicities and b) shocks on the relative price of capital goods that feed mainly into medium-term volatility while leaving short-term volatility relatively unaffected.

We used the estimated parameters of the model to show that the "good luck" hypothesis of the Great Moderation is only true with respect to short-run risk. Meanwhile, long-run risk has increased. We also used a monetary policy counterfactual of the model to argue that the "good policy" hypothesis of the Great Moderation can be refined with respect to the longer-run effects. While the changes in monetary policy during the Great Moderation led to lower short-term output fluctuations, this came at the expense of higher medium-term volatility.

More research is needed to fully understand the mechanisms that led to the Great Moderation and Great Recession. On the empirical side this concerns the initial developments that triggered the intensification of the relationship between real and financial sector. Additionally, a causal identification of the resulting effects of financial intermediaries and the growth of the financial sector on short- and medium-term output volatility would greatly enhance our understanding of the linkages that ultimately led to the Great

Financial Crisis and Great Recession. On the theoretical front the main shortcoming is that the model does not represent the financial cycle, the interaction between credit gap and house prices accurately. Additionally, at this point it is not clear whether other existing models are able to replicate the frequency-domain properties outlined above. Fruitful avenues for future revenues open up: A model that can capture both attenuation and amplification of finance to the real economy, containing a financial cycle that captures the medium-term self-enforcing interactions of credit and house prices and accurately replicate the periodicity-structure of output volatility would go a long way towards a deeper understanding of the relationship between finance and the real economy. An accurate understanding of whether an economic situation is truly a fundamental moderation or merely a low-volatility phase of a longer and larger cycle could help predict and prevent great finance-related recessions of the future.

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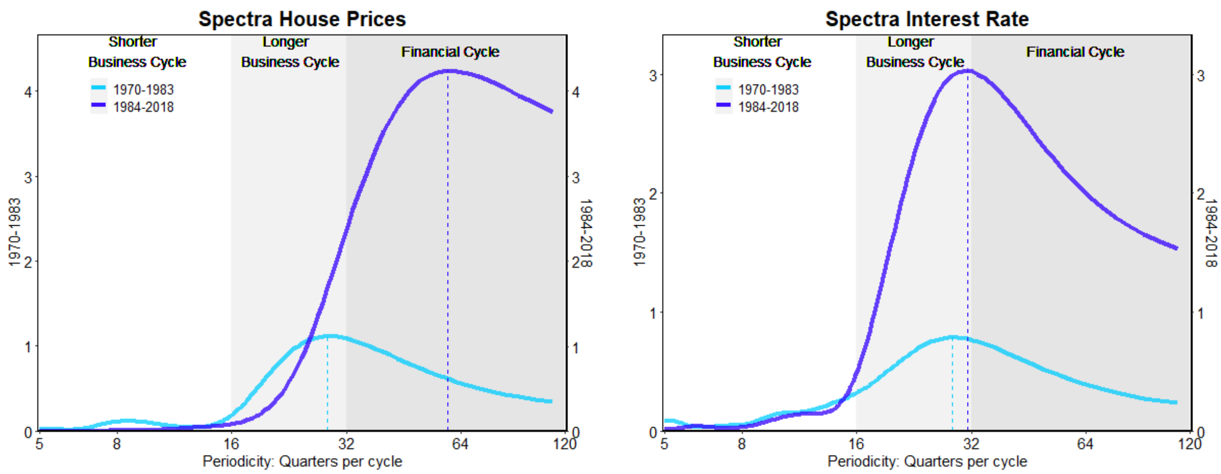
7. Robustness Checks and Extras for Empirical Case

7.1. *Spectra House Prices and Interest Rates*

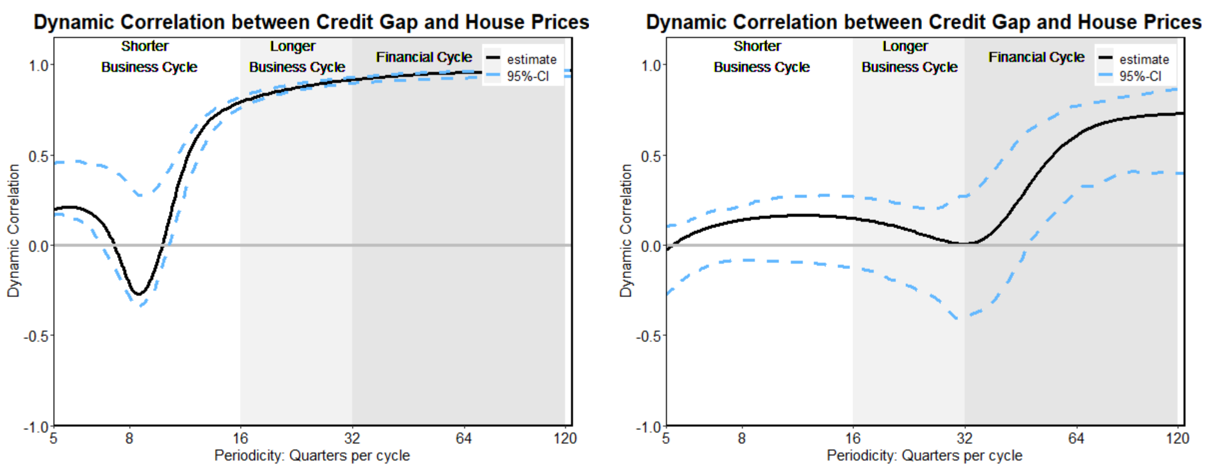
Figure 9: Spectra House Prices and Interest Rate



This figure shows the spectra of house prices (left panel) and the FED funds rate (right panel) estimated on the time series from 1970Q1-1983Q4 (light blue) and the GM from 1984Q1-2018Q2 (dark blue) sample. The left axis measures the variance of the pre-GM spectrum. The right axis measures the variance scales the variance of the GM spectrum. The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated.

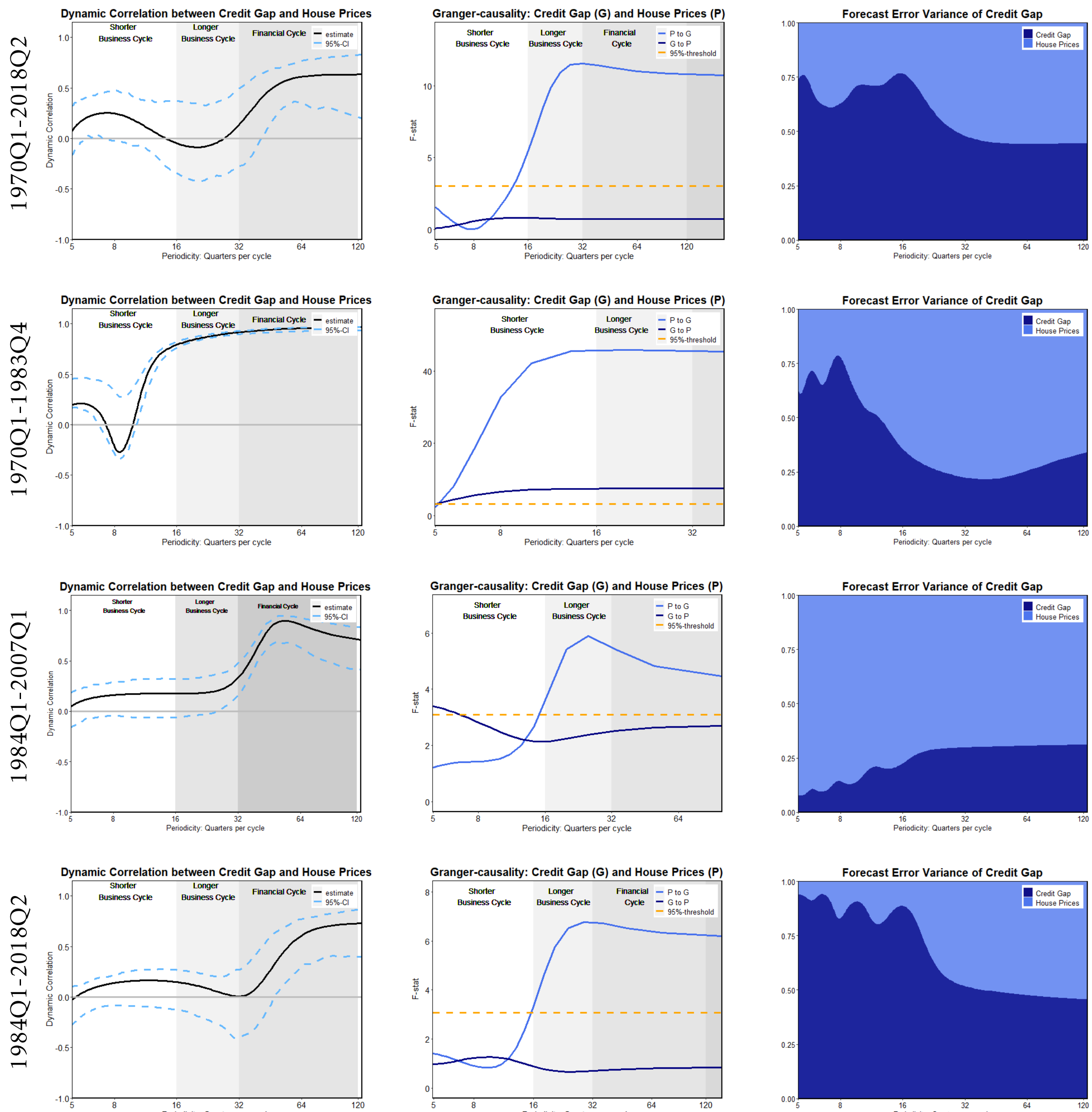
7.2. *Result from bivariate VAR models (1), (2) and (3)*

Figure 10: Financial Cycle Interaction pre-GM (left) and GM (right)



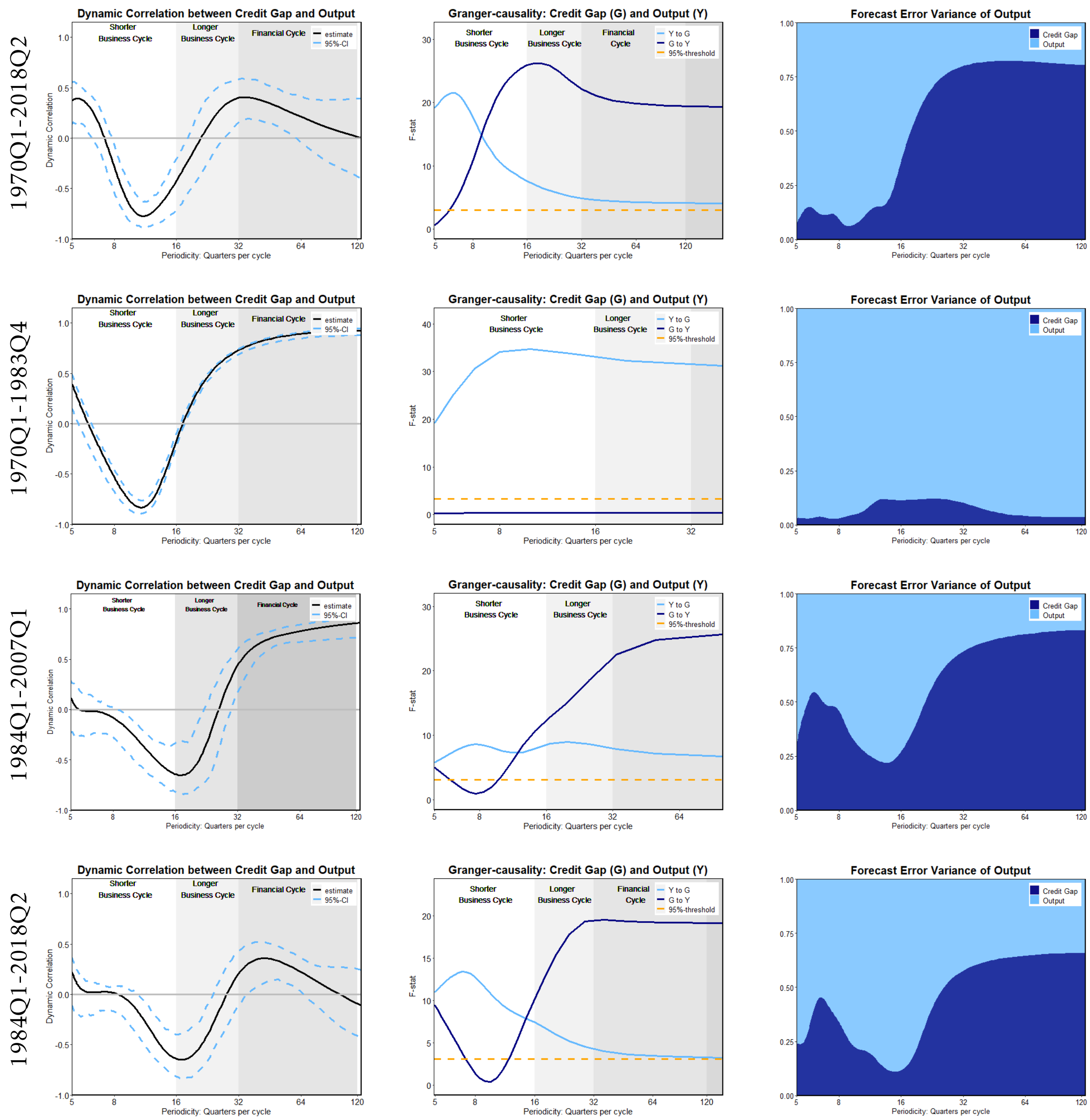
This figure shows the dynamic correlations derived from the bivariate VAR-model (2). The left panel was estimated on data from 1970Q1-1983Q4. The right figure was estimated on data from 1984Q1-2018Q2. The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. The y-axis measures the dynamic correlation on a scale from -1 to 1.

Figure 11: Dynamic Correlation, Granger-Causality and FEVD between Credit and House Prices



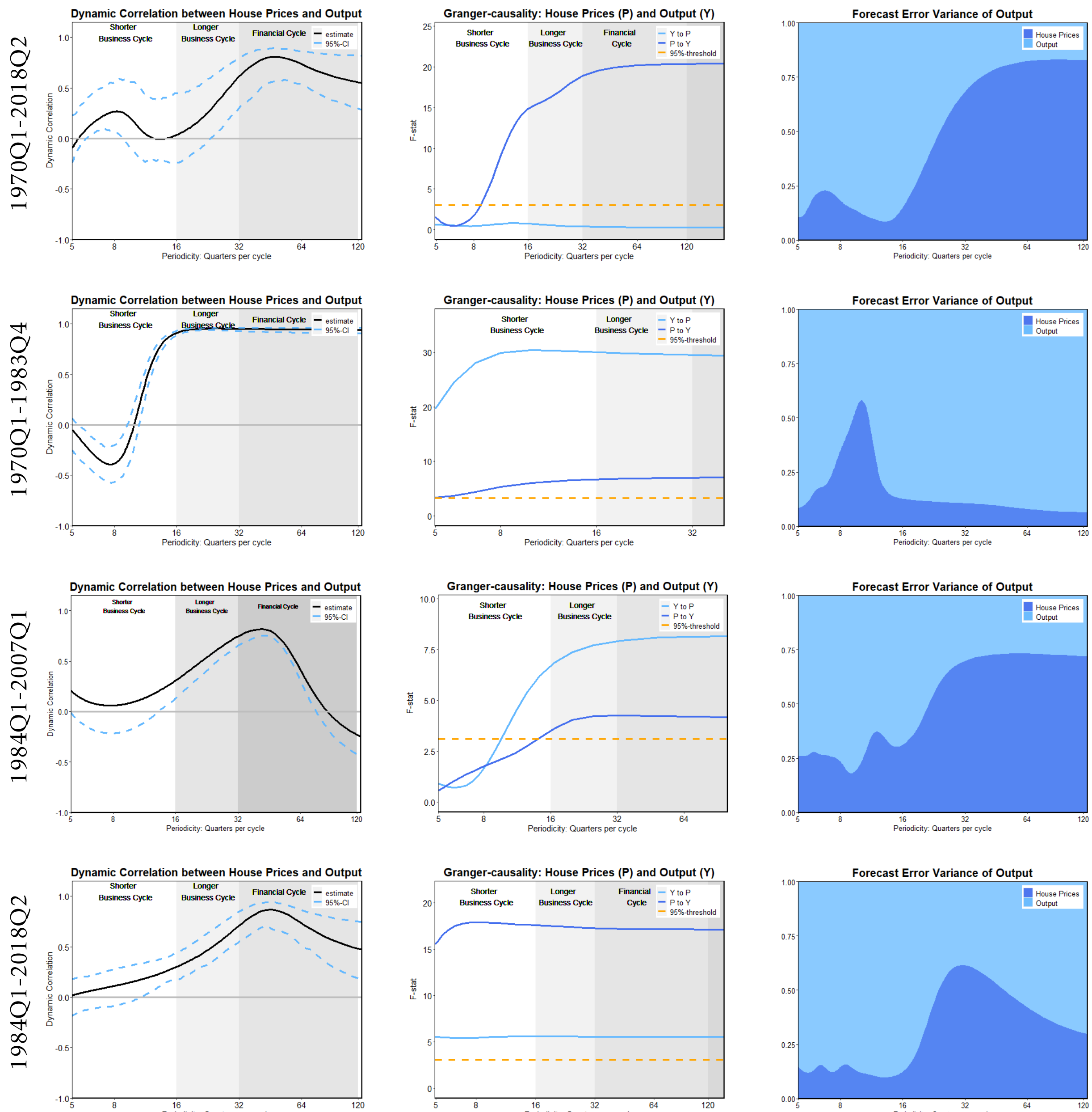
This Figure shows the dynamic correlations (left column), the F-statistics of the Granger-causality test (middle column) and FEVD (right column) of the bivariate VAR model of credit gap and house prices. These measures are calculated on data from 1970Q1-2018Q2 (first row), 1970Q1-1983Q4 (second row), 1984Q1-2007Q1 (third row) and 1984Q1-2018Q2 (fourth row). The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. Dynamic correlation is measured on a y-axis from -1 to 1. The y-axis of the Granger-causality test measures the F-statistic. The solid lines show the F-statistic at each periodicity, where the legend shows the cause variable of each test. The dashed line is the 95% threshold of the Granger-test. The y-axes of the FEVD measure the contribution of orthogonal shocks to the variables listed in the legend to the overall forecast error.

Figure 12: Dynamic Correlation, Granger-Causality and FEVD between Credit Gap and Output



This Figure shows the dynamic correlations (left column), the F-statistics of the Granger-causality test (middle column) and FEVD (right column) of the bivariate VAR-model of credit gap and output. These measures are calculated on data from 1970Q1-2018Q2 (first row), 1970Q1-1983Q4 (second row), 1984Q1-2007Q1 (third row) and 1984Q1-2018Q2 (fourth row). The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. Dynamic correlation is measured on a y-axis from -1 to 1. The y-axis of the Granger-causality test measures the F-statistic. The solid lines show the F-statistic at each periodicity, where the legend shows the cause variable of each test. The dashed line is the 95% threshold of the Granger-test. The y-axes of the FEVD measure the contribution of orthogonal shocks to the variables listed in the legend to the overall forecast error.

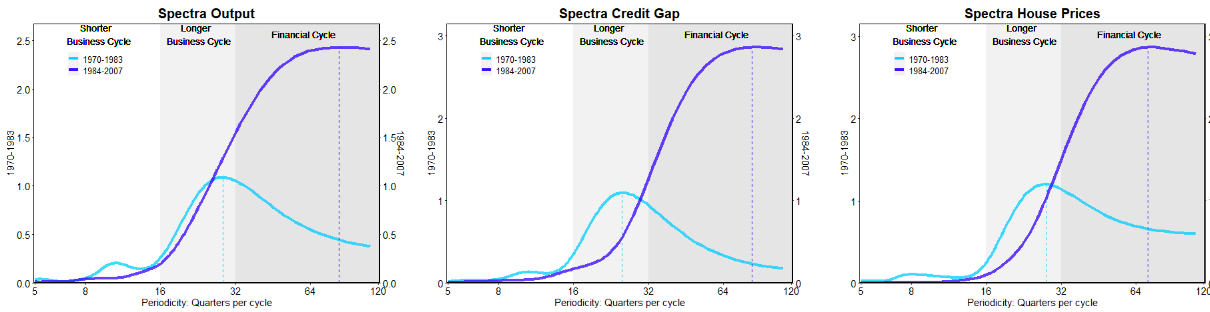
Figure 13: Dynamic Correlation, Granger-Causality and FEVD between House Prices and Output



This Figure shows the dynamic correlations (left column), the F-statistics of the Granger-causality test (middle column) and FEVD (right column) of the VAR-model (3). These measures are calculated on data from 1970Q1-2018Q2 (first row), 1970Q1-1983Q4 (second row), 1984Q1-2007Q1 (third row) and 1984Q1-2018Q2 (fourth row). The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. Dynamic correlation is measured on a y-axis from -1 to 1. The y-axis of the Granger-causality test measures the F-statistic. The solid lines show the F-statistic at each periodicity, where the legend shows the cause variable of each test. The dashed line is the 95% threshold of the Granger-test. The y-axes of the FEVD measure the contribution of orthogonal shocks to the variables listed in the legend to the overall forecast error.

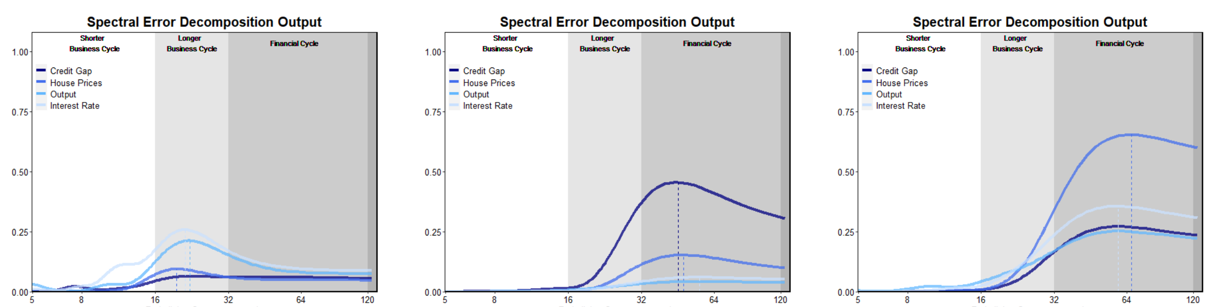
7.3. Robustness checks with VAR models (4) and (5)

Figure 14: Spectra Credit Gap and Output 1984-2007



This figure shows the spectra of output (left panel) and credit gap (right panel) estimated on the time series from 1970Q1-1983Q4 (light blue) and the narrowly-defined GM from 1984Q1-2007Q1 (dark blue) sample. The left axis measures the variance of the pre-GM spectrum. The right axis measures the variance scales the variance of the GM spectrum. The x-axes are the periodicities i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated.

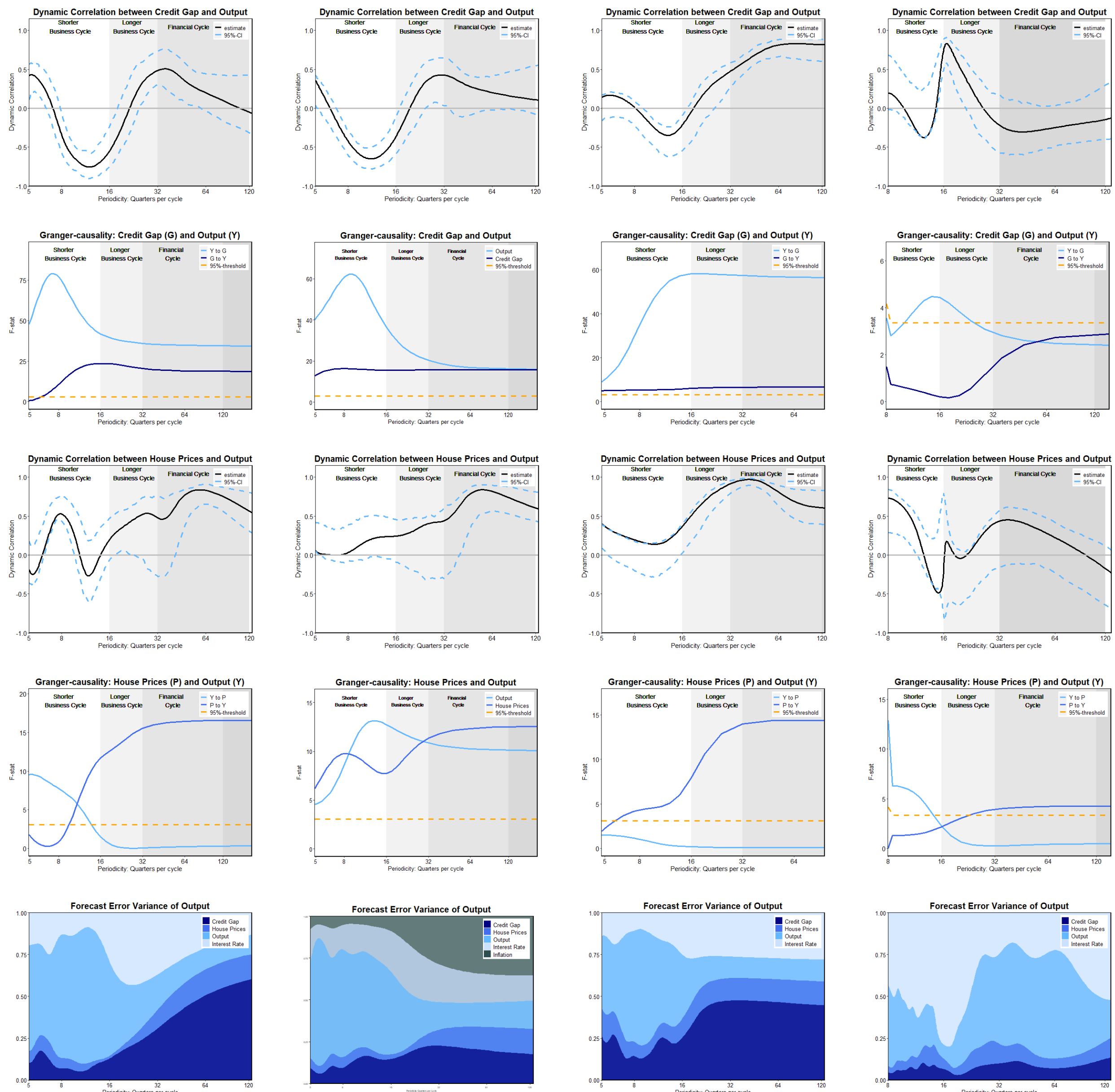
Figure 15: Spectra for the pre-GM (left), narrow GM (middle) and GM (right) sample.



This figure shows the spectra of output derived from the baseline VAR-model. The left panel was estimated on data from 1970Q1-1983Q4. The panel in the middle was estimated on data from 1984Q1-2007Q1. The right panel was estimated on data from 1984Q1-2018Q2. The x-axis is the periodicity, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. The y-axis shows the resulting volatility when only one type of structural shock is active.

Figure 16: Robustness Checks Dynamic Correlation and FEVD

1970-2018 (Model 4) | 1970-2018 (Model 5) | 1983-2007 (Model 4) | 1944-1976 (Model 4)

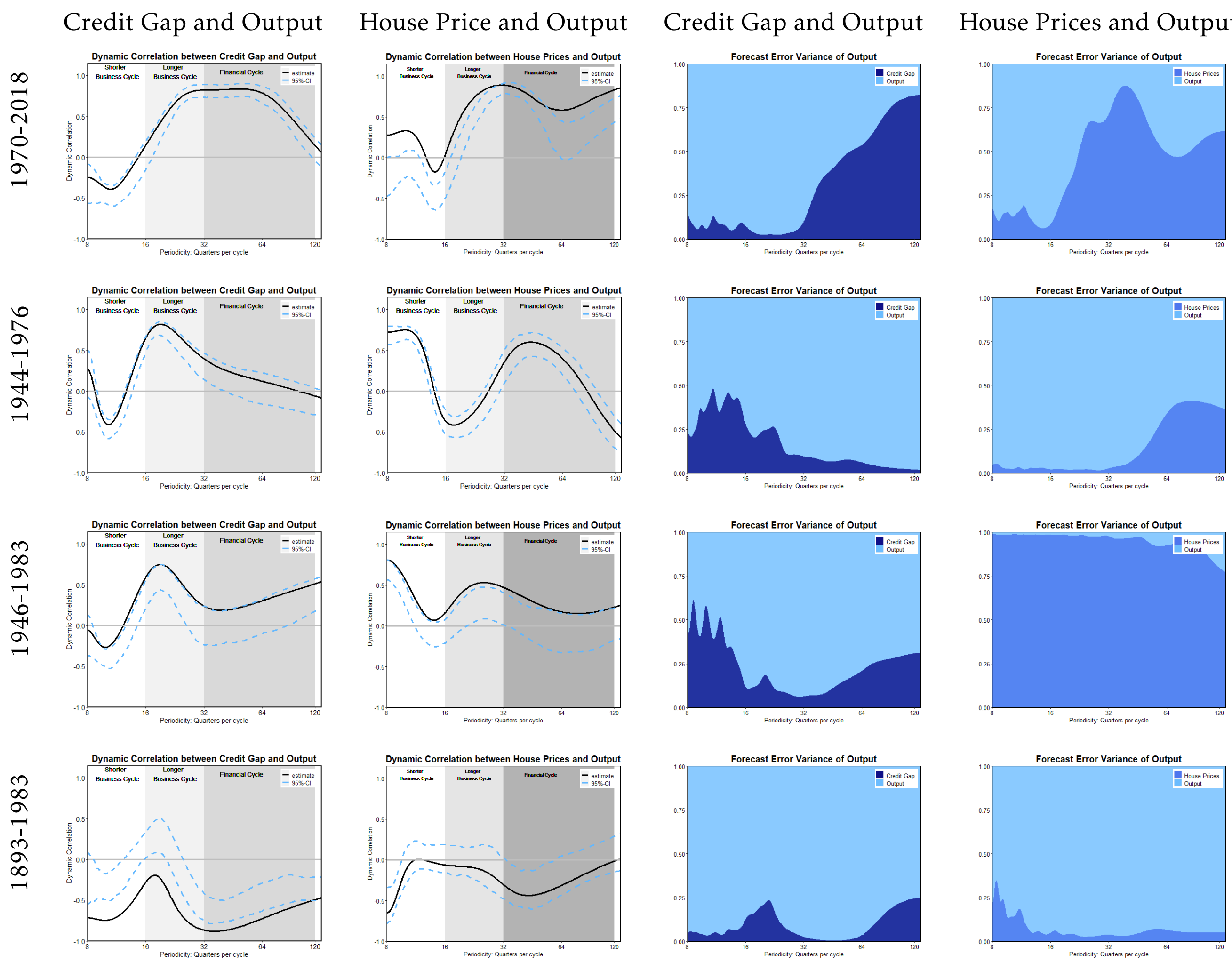


This Figure shows the dynamic correlations (1st and 3rd row), the F-statistics of the Granger-causality test (2nd and 4th row) and FEVD (bottom row) of the VAR-models (4) and (5).

7.4. JST data robustness

The fact that the statistics look very different for the very early sample is not surprising, and in line with Schularick and Taylor (2012) categorization of "two eras of finance capitalism". The first one up to 1939

Figure 17: Dynamic Correlation, Granger-Causality and FEVD, Bivariate VARs, JST data

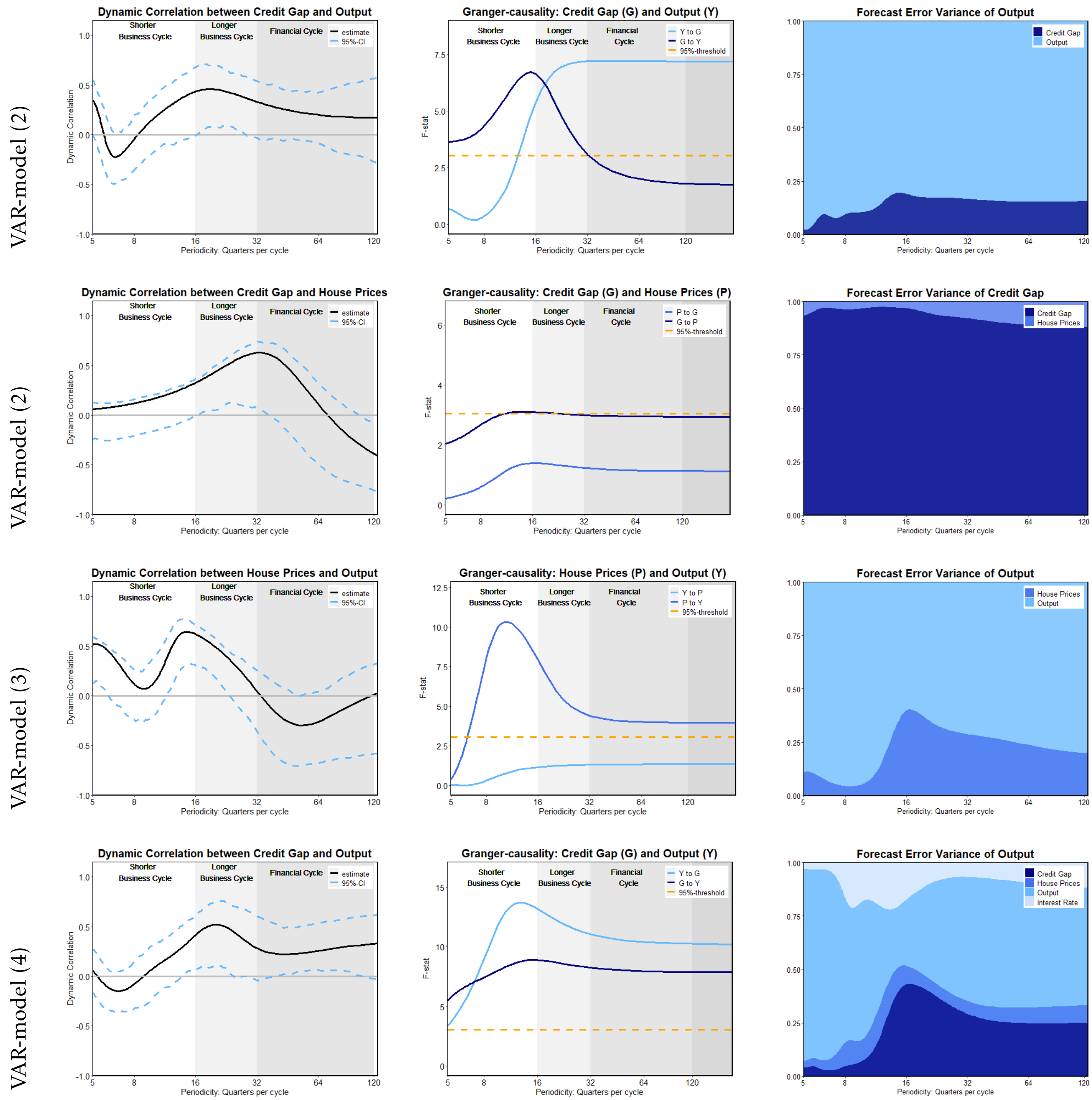


This Figure shows the dynamic correlations (left columns), and FEVDs (right columns) of the VAR-model (1) and (3). These measures are calculated on data of the time period stated on the left. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. Dynamic correlation is measured on a y-axes from -1 to 1. The y-axes of the FEVD measure the contribution of orthogonal shocks to the variables listed in the legend to the overall forecast error.

and the second one post 1945 (or 1944, the start of Bretton-Woods). Noticeably, the dynamic correlation curves of credit gap and output are very similar to those estimated from the main data - with the exception of dataset that begins in 1893. The dynamic correlation curves between house prices and output do not show a qualitatively similar pattern in the pre-Great Moderation samples. While I do not investigate this more closely, I remark that the use of houses as collateral surged only later - so that houses assumed a fundamentally new role in the financial cycle.

7.5. UK robustness checks

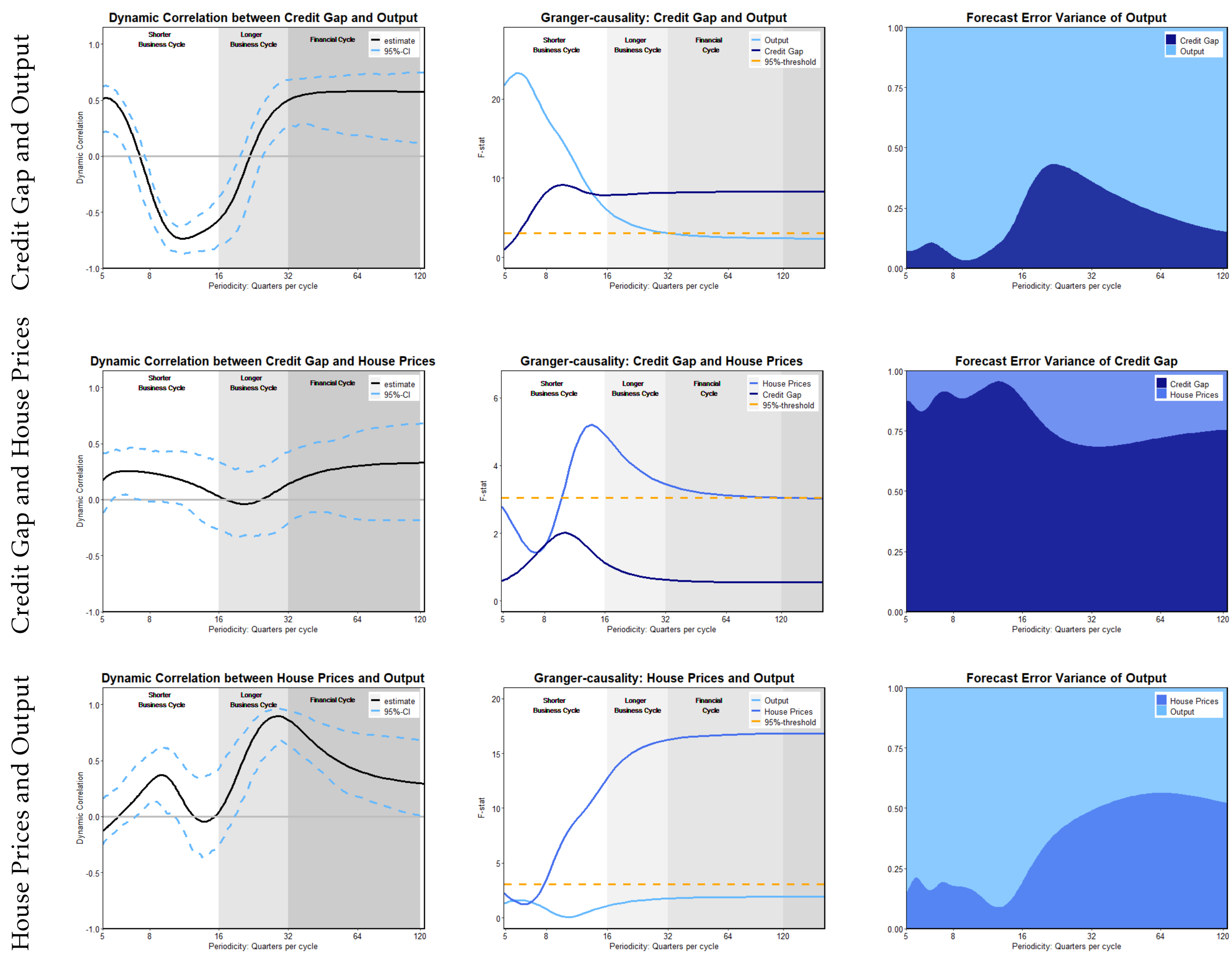
Figure 18: UK: Dynamic Correlation, Granger-Causality and FEVD



This Figure shows the dynamic correlations (left column), the F-statistics of the Granger-causality test (middle column) and FEVD (right column) of the VAR-model (1-4). These measures are calculated on UK data from 1970Q1-2018Q2 (top row), 1970Q1-1983Q4 (middle row) and 1984Q1-2018Q2 (bottom row). The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. Dynamic correlation is measured on a y-axis from -1 to 1. The y-axis of the Granger-causality test measures the F-statistic. The y-axes of the FEVD measure the contribution of orthogonal shocks to the variables listed in the legend to the overall forecast error.

7.6. *HP-filter Robustness check*

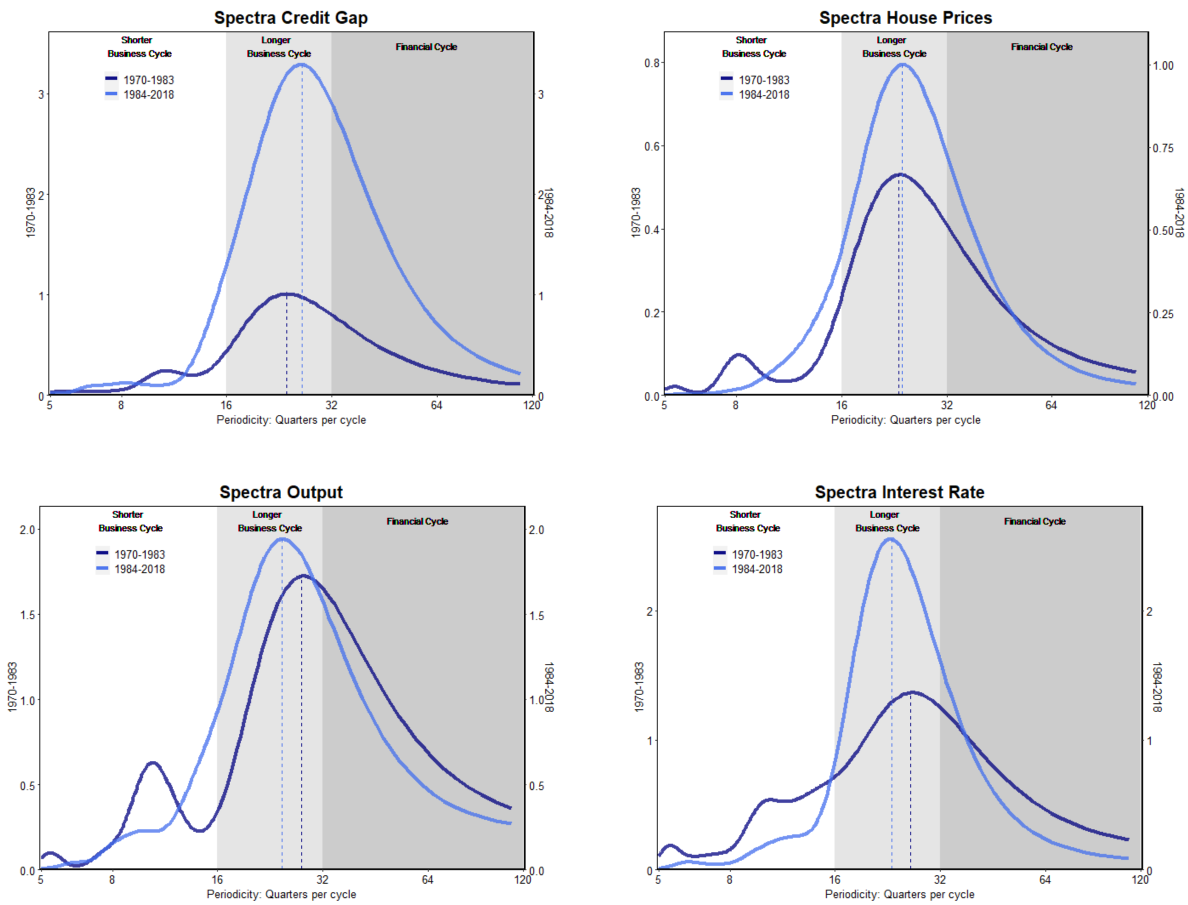
Figure 19: HP Filter: Dynamic Correlation, Granger-Causality and FEVD between House Prices and Output



This Figure shows the dynamic correlations (left column), the F-statistics of the Granger-causality test (middle column) and FEVD (right column) of the VAR-model (3). 1984Q1-2007Q1 (bottom row) for VAR-models (1-3). The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measure is calculated. Dynamic correlation is measured on a y-axis from -1 to 1. The y-axis of the Granger-causality test measures the F-statistic. The solid lines show the F-statistic at each periodicity, where the legend shows the cause variable of each test. The dashed line is the 95% threshold of the Granger-test. The y-axes of the FEVD measure the contribution of orthogonal shocks to the variables listed in the legend to the overall forecast error.

7.7. *Deliberate false filtering*

Figure 20: Selective Filtering: Spectra pre- and during Great Moderation

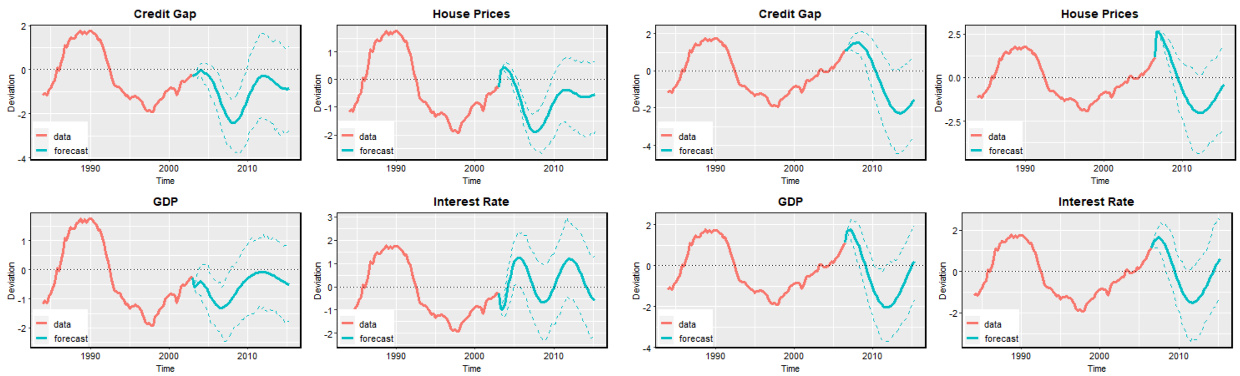


This figure shows the spectra of the main variables of this analysis filtered between 5 and 32 quarters. This illustrates that error that is generated when a frequency-specific filter is applied. All variables have the majority of their volatility below 32 quarters by construction in both subsamples. We can see the "heterogenous Great Moderation" in the reduction of output volatility on periodicities up to 16 quarters but not between 16 and 32 quarters as Pancrazi (2015) has shown. However, we are missing the shift to longer periodicities entirely. The better option is to analyse data in the frequency-domain when it is economically reasonable to focus the analysis on cycles. As stationarity is a prerequisite of the frequency-domain analysis, the trend should be removed either through a one-sided filter or by differencing (in the absence of cointegration).

7.8. Forecasting the Great Recession

Here, I document the following exercise: I estimate a four-variable VAR model (credit gap, house prices, output, interest rate) on data up to 2003Q1 (left) and 2007Q1 (right). I then forecast the evolution from there onwards until 2010. From the standpoint of 2003Q1 there is no evidence of a great recession on the horizon. The model predicts downturns in credit gap and house prices and output, but especially the forecast predicts at worst a mild recession. This changes drastically when looking at the forecast of 2007Q1: Here, the model predicts drastic declines in all variables, especially for house prices and output. This is exactly what happened with the Great Financial Crisis. Borio et al. (2018) find that the financial cycle indicator outperforms the term spread as a predictor of recessions. The predictability of the Great Recession in this model should hence not be surprising.

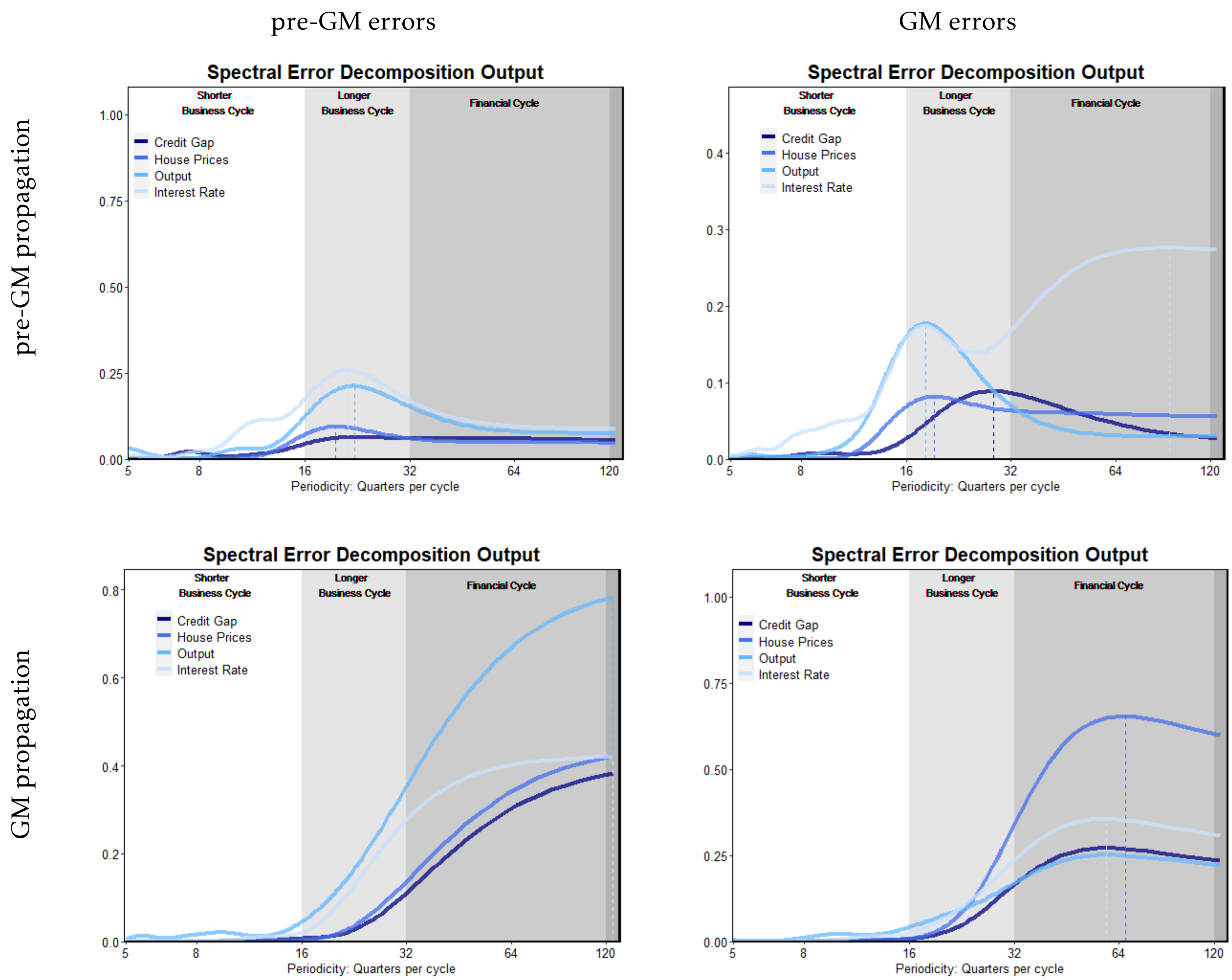
Figure 21: Great Recession Forecast



This figure shows the evolution of the four variables of VAR-model (4), credit gap, house prices, output and interest rate up to 2003 (left panel) and 2007 (right panel). The green lines are the forecasts implied by the VAR model (4) with the 95% confidence intervals (dashed lines).

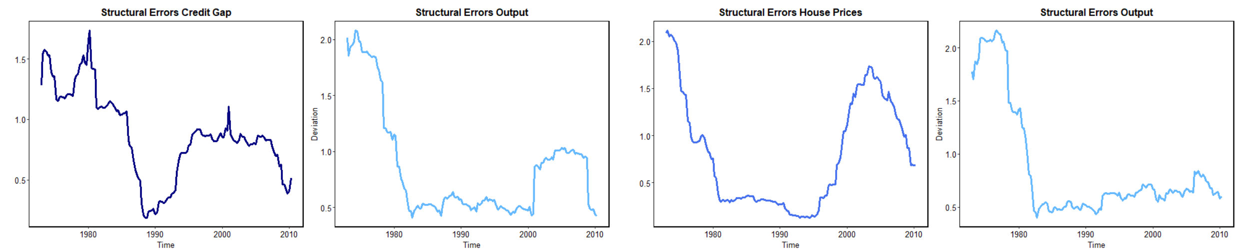
7.9. Good Luck and Good Policy

Figure 22: Counterfactuals holding the propagation or shock distribution constant



The empirical analysis of good policy is based on comparing the error decomposition of the spectrum of output (top-left, bottom-right) to counterfactual scenarios (bottom-left,top-right). The counterfactual scenarios are calculated by simulating the spectral error decomposition using the VAR-coefficients of the pre-GM scenario with the orthogonal innovations from the GM estimation (top-right); and using the VAR-coefficients of the GM scenario with the innovations of the pre-GM estimation. This reveals the following: Without any change in propagation, the monetary policy shocks during the Great Moderation would have still led to much more volatility than prior to the Great Moderation. This is especially true on financial cycle periodicities. Hence the monetary shocks did not do any good. However, central bank policy may have had beneficial effects that affected propagation. Here we essentially see the same thing. Given the change in propagation that occurred, monetary policy shocks still lead to much higher volatility on financial cycle periodicities than in the pre-GM benchmark. However, on shorter business cycle volatility did decrease. Hence: We do not know if monetary policy caused or contributed to causing the changes in propagation that occurred during the Great Moderation. But if it did, the positive effects of reduced volatility has to be weighted against the higher volatility on financial cycle periodicities in a normative analysis to assess whether policy was ”good.

Figure 23: Rolling-Window Error Variance



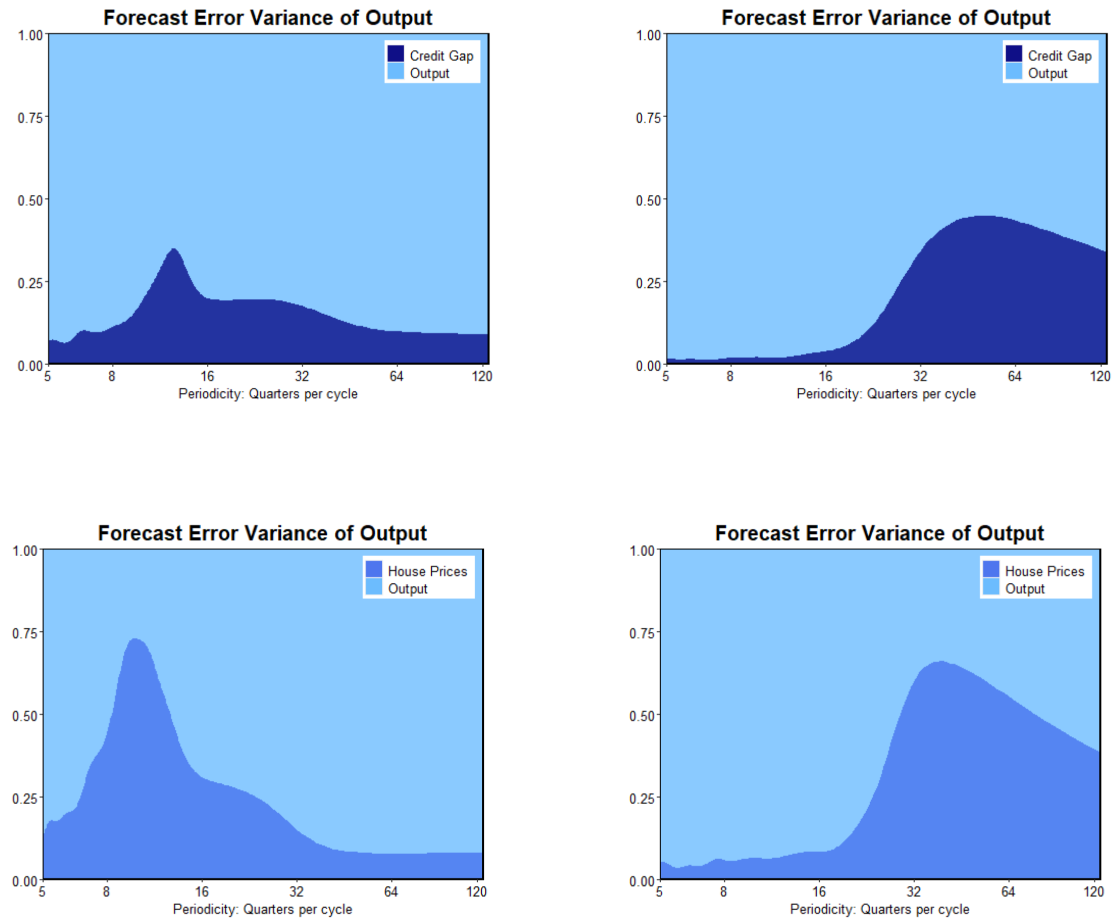
Model: Credit Gap and Output

Model: House Prices and Output

Each date labels the time-window that begins in this year, i.e. 1984 refers to the variance between 1984 and 1992. We can see that in the beginning of the 1980s, the error variance of all variables decrease significantly. However, after a short period of low volatility, the error variance of financial variables increase sharply long before the year 2007. While output volatility was still low, innovations to credit and house prices were already laying the groundwork for the Great Recession downturn (i.e. medium-term volatility of output). Additionally, we notice that in relative term,s the error variance of output has reduced with respect to the error variance of house prices. Hence, the Great Moderation spectra must be closer to the one driven only by house price errors than to the one created by only output errors.

7.10. Impulses versus propagation

Figure 24: Impulse versus propagation



The first row shows the bivariate analysis of credit gap and output, the second row the one of house prices and output. The first column shows the FEVD of the VARs estimated on the 1970-1983 sample, using the errors of the 1984-2018 sample. The second column shows the FEVD of the VARs estimated on the 1983-2018 sample, using the structural errors of the 1970-1983 sample. In both cases, the shift towards longer periodicities seems to be a result of changes in the propagation of the shocks. In case of credit gap and output, there may however be also a non-negligible effect of the shocks.

8. Detailed Description of the Model

The setup of the model closely builds on Villa (2016), modifying the framework only where necessary to incorporate all financial frictions. There is a mass one of identical patient households which consume two goods: A non-durable final good and a capital good - housing. Houses are bought and sold but cannot be rented. To pay for their expenses, households supply labor to labor unions, which differentiate it, aggregate it and sell the labor aggregate to entrepreneurs. Households deposit their savings with financial intermediaries (banks), which use these funds to give credit to entrepreneurs. Entrepreneurs combine labor and the capital good to produce intermediate goods which they sell to retailers. Retailers aggregate intermediate varieties into a final good. Final goods are sold to the patient household for consumption, to entrepreneurs for consumption and for maintenance of the capital stock; and to capital producer as a production input. Capital producers transform final goods into durable capital/houses and sell them to patient households and entrepreneurs. Additionally there is a central bank that chooses its policy rate according to a Taylor rule, and a government that levies taxes on the household and can purchase final goods.

8.1. Households' Problems

There is a mass 1 of identical patient households indexed by i. Households maximize their utility through choice of consumption C_t, housing K_{t+1}, deposits D_t in a financial intermediary and labor supply L_t. Their utility from consumption depends on external habit and capital depreciates at rate δ. Each household owns a bank and receives the its bank's profits. Household are subjected to government taxation and transfers. Their maximization problem is:

$$
\begin{aligned}
maxE_t \sum_{t=0}^{\infty} \beta^t \Bigg\{ & log(C_{it} - hC_{t-1}) - \frac{L_{it}^{1+\phi_l}}{1+\phi_l} + \nu log(K_{it+1}) \\
& - \mu_{it}[C_{it} + Q_t(K_{it+1} - (1-\delta)K_{it} + D_{it+1} - R_{t-1}D_{it} - W_t^H L_{it} - \Pi_t + T_t - TR_t] \Bigg\}
\end{aligned}
$$

Since all households are identical, the index i is suppressed in the following. The first order conditions of this problem are:

$$
\begin{aligned}
L_t^{\phi_l} &= \frac{W_t^H}{(C_t - hC_{t-1})} \\
(C_t - hC_{t-1})^{-1} &= \beta R_t E_t (C_{t+1} - hC_t)^{-1} \\
Q_t (C_t - hC_{t-1})^{-1} &= \beta \left(\nu K_t^{-1} + E_t \left[(C_{t+1} - hC_t)^{-1} (1-\delta) \right] \right)
\end{aligned}
$$

This yields standard Euler equation, consumption-labor margin, and investment equation.

8.2. Labor Unions' Problems

Households supply homogenous labor to monopolistic labor unions which differentiate it:

$$L_t = \left[\int_0^1 L_t(l)^{\frac{\epsilon_w - 1}{\epsilon_w}} dl \right]^{\frac{\epsilon_w}{\epsilon_w - 1}}$$

The unions' optimization problems are:

$$
\begin{aligned}
& min \int_0^1 W_t(l) L_t(l) dl \\
& st.\bar{L} \leq \left[\int_0^1 L_t(l)^{\frac{\epsilon_w - 1}{\epsilon_w}} dl \right]^{\frac{\epsilon_w}{\epsilon_w - 1}}
\end{aligned}
$$

The demand for labor of union l is given by:

$$L_t(l) = \left(\frac{W_t(l)}{W_t} \right)^{-\epsilon_w} L_t$$

This implies for wages:

$$W_t = \left[\int_0^1 W_t(l)^{1-\epsilon_w} dl \right]^{\frac{1}{1-\epsilon_w}}$$

Unions adjust wages according to a Calvo scheme with parameter σ_w. In a given period, the wages of firms that cannot re-optimize are indexed to inflation. The union maximizes

$$maxE_t \sum_{s=0}^{\infty} \frac{\mu_{t+s}}{\mu_t} (\beta\sigma_w)^s L_{t+s}(l) \left[\frac{W_t^r(l)}{P_{t+s}} \left(\frac{P_{t+s-1}}{P_{t-1}} \right)^{\sigma_{wi}} - \frac{W_{t+s}^H}{P_{t+s}} \right]$$

The first-order condition is:

$$E_t \sum_{s=0}^{\infty} \frac{\mu_{t+s}}{\mu_t} (\beta\sigma_w)^s L_{t+s}(l) \left[\frac{W_t^r(l)}{P_{t+s}} \left(\frac{P_{t+s-1}}{P_{t-1}} \right)^{\sigma_{wi}} - \frac{W_{t+s}^H}{P_{t+s}} \frac{\epsilon_w}{\epsilon_w - 1} u_t^w \right] = 0$$

where u_t^w is a mark-up shock that follows:

$$u_t^w = \rho_w u_{t-1}^w + \epsilon_t^w, \qquad \epsilon_t^w \sim N(0, \sigma_w^2)$$

8.3. Retailers' Problems

Monopolistic retailers purchase intermediate goods at marginal cost from entrepreneurs, differentiate the goods and sell a final good made from the different varieties: Retailers adjust according to a Calvo scheme with parameter σ_p. In a given period, the prices of firms that cannot re-optimize are indexed to inflation. The retailers maximize

$$maxE_t \sum_{s=0}^{\infty} \frac{\mu_{t+s}}{\mu_t} (\beta\sigma_p)^s Y_{t+s}(f) \left[\frac{P_t^r(f)}{P_{t+s}} \left(\frac{P_{t+s-1}}{P_{t-1}} \right)^{\sigma_{pi}} - \frac{\Phi_{t+s}}{P_{t+s}} \right]$$

The first-order condition is:

$$maxE_t \sum_{s=0}^{\infty} \frac{\mu_{1t+s}}{\mu_{1t}} (\beta\sigma_p)^s Y_{t+s}(f) \left[\frac{P_t^r(f)}{P_{t+s}} \left(\frac{P_{t+s-1}}{P_{t-1}} \right)^{\sigma_{pi}} - \frac{\Phi_{t+s}}{P_{t+s}} \frac{\epsilon}{\epsilon - 1} u_t^p \right] = 0$$

where u_t^w is a mark-up shock that follows:

$$u_t^p = \rho_p u_{t-1}^p + \epsilon_t^p, \qquad \epsilon_t^p \sim N(0, \sigma_p^2)$$

Final output is a composite of the differentiated intermediate goods $f \in (0,1)$:

$$Y_t = \left[\int_0^1 Y_t(f)^{\frac{\epsilon-1}{\epsilon}} df \right]^{\frac{\epsilon}{\epsilon-1}}$$

Final goods firms are competitive and their optimization problems are:

$$min \int_0^1 P_t(f) Y_t(f) df$$
$$st. \bar{Y} \leq \left[\int_0^1 Y_t(f)^{\frac{\epsilon-1}{\epsilon}} df \right]^{\frac{\epsilon}{\epsilon-1}}$$

The demand for the good of retailer f is given by:

$$Y_t(f) = \left(\frac{P_t(f)}{P_t} \right)^{-\epsilon} Y_t$$

This implies for prices:

$$P_t = \left[\int_0^1 P_t(f)^{1-\epsilon} df \right]^{\frac{1}{1-\epsilon}}$$

The equation describing the dynamics of aggregate price level is given by:

$$P_{t+1} = \left[(1-\sigma_p)(P^r_{t+1}(f))^{1-\epsilon} + \sigma_p (P_t \left(\frac{P_t}{P_{t-1}} \right)^{\sigma_{pi}})^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}}$$

8.4. Capital Producers

Capital producers purchase some of the final goods and transform them into (durable) capital goods. They sell them to the household which consume capital (interpreted as housing) and to entrepreneurs which use the capital to produce. The problem of capital producers is:

$$maxE_t \sum_{t=0}^{\infty} \beta^t \Pi_t + \mu^K_t \left[\Pi_t - (Q^n_t - P_t) I_t + x_t I_t \left(1 - F\left(\frac{I_t}{I_{t-1}} \right) \right) \right]$$

The first order condition is

$$(Q^n_t - P_t) \equiv Q_t = x_t \left[1 - F\left(\frac{I_t}{I_{t-1}} \right) - \frac{I_t}{I_{t-1}} F'\left(\frac{I_t}{I_{t-1}} \right) \right] + \beta E_t x_{t+1} \left(\frac{I_{t+1}}{I_t} \right)^2 F'\left(\frac{I_{t+1}}{I_t} \right)$$

8.5. Financial Intermediaries' Problems

Competitive financial intermediaries (banks) maximize the discounted sum of their future profits. Banks survive a period with probability θ. In case they die, they give their entire net worth back to their household, after which they are immediately reborn and given transfer N^n by their household.

Banks take deposits from patient households which are paid deposit rate R_t in exchange. Each bank uses those funds along with its own net worth to provide credit to entrepreneurs. Credit comes in the form of simple 1-period bonds and the lending rate is denoted R^L_t. Two frictions impact the choices of the banks: 1) Costly state-verification, 2) moral hazard of bankers, which may try to divert the banks' funds back to their household. The following shows how each financial friction constrains the financial intermediary's optimization.

Costly-state verification and repossession: The framework of costly state-verification goes back to Townsend (1979). It is assumed that if the debtor fails to repay the loan, the bank needs to pay a cost of ζ to find and repossess one unit of the borrower's assets. In this paper, I assume that this cost ζ is stochastic and evolves according to

$$\zeta_t = \zeta_{t-1}^{\rho_\zeta} \bar{\zeta}^{1-\rho_\zeta} e^{\epsilon^\zeta_t}$$

so that its average over time is $\bar{\zeta}$. This can be interpreted as a shock to the financial technology of the bank. Hence, the bank will ensure itself of repayment by forcing the entrepreneur to pose collateral for the debt, thereby imposing a quantity restriction on the debt incurrence of the entrepreneur. This is the approach of Iacoviello (2005) which gives rise to the financial accelerator as in Kiyotaki and Moore (1997). The collateral constraint is:

$$(1-\zeta_t) Q_{t+1} K^F_{jt+1} (1-\delta) \geq B^F_{jt+1}$$

When the entrepreneur does not repay, the bank can pay the repossession cost and will (in expectation) be able to cover its losses completely by selling the entrepreneur's leftover capital. Hence, the lending rate will equal the deposit rate in the Iacoviello economy.

Moral hazard: Finally, following Gertler and Karadi (2011), the manager of the bank has the option to divert a fraction λ of the bank's resources back to his household. As the cost of state verification, I assume that λ is stochastic. This gives rise to an incentive constraint in the form of a leverage constraint. This limits the ability of the bank to obtain deposits. This setup leads to the objective:

$$\Upsilon_t = maxE_t \sum_{i=0}^{\infty}(1-\theta)\theta^i \beta^{i+1}\Lambda_{t,t+i+1}N_{t+i+1}$$
$$\Upsilon_t = maxE_t \sum_{i=0}^{\infty}(1-\theta)\theta^i \beta^{i+1}\Lambda_{t,t+i+1}(R^L_{t+i}B^F_{t+1+i} - R_{t+i}D_{t+1+i} - R_{t+i}N_{t+i})$$

In this optimization, $\Lambda_{t,t+1} = \frac{\mu_{t+1}}{\mu_t}$ To ensure that the banker does not divert any funds, we require that the value of continuing to operate the bank is always greater than the value of stealing:

$$\Upsilon_t = \lambda_t D_{t+1}$$

As Gertler and Karadi (2011) show, this can be written as:

$$\Upsilon_t = V_t D_{t+1} + H_t N_t$$

with

$$V_t = E_t(1-\theta)\beta\Lambda_{t,t+1}(R^L_t - R_t) + \beta\theta\Lambda_{t,t+1}X_{t,t+1}V_{t+1}$$
$$H_t = E_t(1-\theta) + \beta\Lambda_{t,t+1}\theta Z_{t,t+1}H_{t+1}$$

where $X_{t,t+1} = B^F_{t+2}/B^F_{t+1}$ and $Z_{t,t+1} = N_{t+1}/N_t$. To ensure that the banker does not divert any resources, the bank then needs to fulfill the constraint

$$V_t B^F_{t+1} + H_t N_t \geq \lambda_t B^F_{t+1}$$
$$B^F_{t+1} \leq \frac{H_t}{(\lambda_t - V_t)} N_t = lev_t N_t$$

which places an upper bound on the leverage of the bank. This leverage constraint prevents banks from channeling enough funds from patient household to entrepreneurs to equilibrate households marginal value of saving and entrepreneurs' marginal value of credit. Hence, the bank can charge up $R^L > R$ without fearing that its profits are competed away. The lending rate R^L is given by the entrepreneurs marginal value of credit.

The net worth of banks evolves a follows:

$$N^{total}_t \equiv N_t = N^e_t + N^n_t = \theta\Big((R^L_t - R_t)lev_t + R_t\Big)N_t + \chi Q_t K^F_{t+1}$$

where $N^n_t = \chi B^F_{t+1}$ is the transfer that newborn banks receive from their household in order to start operations.

8.6. Entrepreneurs' Problems

There is a mass 1 of entrepreneurs indexed j in the economy. As in Iacoviello (2005) they only consume non-durable goods and use the capital goods to produce new intermediate goods. In this model the entrepreneurial problem is set up in such a way that if utility is linear consumption C_t^F, entrepreneurs can be reinterpreted as the intermediate firms' which profit Π_t which are returned to the patient households[29]. As in Christiano, Eichenbaum and Evans (2005), the entrepreneurs engage in a sequence of actions. Upon entering a period, entrepreneurs first observe their state variables K_t^F and B_t^F and technology, capital quality and mark-up shocks $\epsilon_a, \epsilon_k, \epsilon_w, \epsilon_p$. Given this information, they choose their labor demand and capital utilization. Increased capital utilization results in higher output and comes at higher costs of maintenance of the capital stock. To maintain its capital, the firm needs to purchase additional final goods[30]. The entrepreneurs' production, unions' and retailers' decisions as well as labor market and final goods market clearing occur simultaneously. Next, capital producers sell capital goods (housing) which they created from the final goods they bought. Entrepreneurs and households observe the financial and investment shocks $\epsilon_\zeta, \epsilon_\lambda$ and ϵ_x, respectively, and determine their capital demands and debt/savings decisions - markets for capital and credit clear. Finally, the central bank observes output gap and inflation and resets its policy rate.

Entrepreneurs' production technology is:

$$Y_{t+1} = A_t (U_t K_{t+1}^F)^\alpha L_t^{1-\alpha} - \Theta$$

Entrepreneurs also die in each period with probability θ. In this case entrepreneurs are immediately reborn. This effectively shrinks their discount factor and ensures that they will always be borrowing constraint. Accordingly, the problem of the entrepreneur is:

$$\begin{aligned} maxE_t \sum_{t=0}^{\infty} (\gamma\beta)^t \Bigg\{ & \frac{(C_{jt}^F - h^F C_{t-1}^F)^{1-\phi_f}}{1-\phi_f} \\ & + \mu_{jt}^F [\Phi_t Y_{jt} + B_{jt+1}^F - C_{jt}^F - W_t L_t - \Psi(U_{jt}) K_{jt}^F - Q_t (K_{jt+1}^F - (1-\delta) K_{jt}^F) - R_{t-1}^L B_{jt}^F] \\ & + \mu_t^C E_t [(1-\zeta_t) Q_{t+1} K_{jt+1}^F (1-\delta) - R_t^L B_{jt+1}^F] \Bigg\} \end{aligned}$$

29 In this case, the optimization problem can simply be written as:

$$\begin{aligned} maxE_t \sum_{t=0}^{\infty} (\theta\beta)^t \{ & \pi_{jt} \\ & + \mu_{jt}^F [\Phi_t Y_{jt} + B_{jt+1}^F - W_t L_t - \Psi(U_{jt}) K_{jt}^F - Q_t (K_{jt+1}^F - (1-\delta) K_{jt}^F) - R_{t-1} B_{jt}^F - \pi_{jt}^F] \\ & + \mu_t^C [(1-\zeta_t) Q_{t+1} K_{jt+1}^F (1-\delta) - R_t B_{jt+1}^F]\} \end{aligned}$$

Households are perfectly diversified across firms.

30 As an example, think of a machine (durable good) that can be utilized more only if more electricity (final good) is used. Alternatively, think of a Diesel engine that need oil changes more frequently if it is utilized more. The costs of maintenance are usually related to non-durable goods.

Given that entrepreneurs die, they will effectively discount the future at lower values than the patient household. Thus, they will always borrow funds from the bank. The lending rate depends on the financial frictions that are present in this economy. In case of the Gertler-Karadi friction, the bank can charge the marginal value of debt to the entrepreneur as the lending rate. Since credit markets operate after consumption of period t has taken place, all funds obtained in the credit market goes towards capital purchases. Hence, the marginal value of debt to the entrepreneur is equal to its marginal return to capital divided by the price of capital. The return to capital purchases today is the sum of the instantaneous benefit of loosening the collateral constraint and tomorrow's return to capital. In the Iacoviello case, the borrowing rate and deposit rate will be equal. The fact that entrepreneurs die out makes them discount the future more heavily which implies that the collateral constraint will always be binding.
The entrepreneurs' first order conditions are (again surpressing index j):

$$\begin{aligned}
\mu_t^F &= (C_t^F - h^F C_{t-1}^F)^{-\phi_f} \\
(C_t^F - h^F C_{t-1}^F)^{-\phi_f} - \mu_t^C R_t^L &= \gamma \beta R_t^L E_t[(C_{t+1}^F - h^F C_t^F)^{-\phi_f}] \\
W_t &= \Phi_t (1-\alpha) A_t \left(\frac{U_t K_t^F}{L_t}\right)^{\alpha} \\
\Psi(U_t) K_t^F &= \alpha \Phi_t A_t (K_t^F)^{\alpha} \left(\frac{L_t}{U_t}\right)^{1-\alpha} \\
Q_t (C_t^F - h^F C_{t-1}^F)^{-\phi_f} - \mu_t^C (1-\zeta_t)(1-\delta) E_t Q_{t+1} &= \beta \gamma E_t \Bigg\{ [(C_{t+1}^F - h^F C_t^F)^{-\phi_f}] \\
&\quad \left[\Phi_{t+1} \alpha A_{t+1} (U_{t+1})^{\alpha} \left(\frac{L_{t+1}}{K_{t+1}^F}\right)^{1-\alpha} + Q_{t+1}((1-\delta) - \Psi(U_{t+1}))\right] \Bigg\}
\end{aligned}$$

8.7. Central Bank

The central bank sets its policy rate according to the Taylor rule

$$ln\left(\frac{R_t^n}{R_t}\right) = \rho_i ln\left(\frac{R_{t-1}^n}{R^n}\right) + (1-\rho_i)\left[\rho_\pi ln\left(\frac{\Pi_t}{\Pi_{t-1}}\right) + \rho_y ln\left(\frac{Y_t}{Y_t^p}\right)\right] + \rho_{\Delta_y} ln\left(\frac{Y_t/Y_{t-1}}{Y_t^p/Y_{t-1}^p}\right) + \epsilon_t^r$$

and

$$R_{t+1} = E_t\left[\frac{R_t^n}{\Pi_{t+1}}\right]$$

I have to assume that the central bank chooses its policy after all other actions have taken place so that the there is no contemporaneous effect from the monetary policy innovation to asset prices.

8.8. Market Clearing Conditions

Market clearing on final goods market and capital market is given by:

$$\begin{aligned}
Y_t &= C_t + C_t^F + I_t + \Psi(U_t) K_t^F + G_t \\
I_t &= K_{t+1} - (1-\delta) K_t + K_{t+1}^F - (1-\delta) K_t^F
\end{aligned}$$

In words, the final goods that are produced in this economy are split between private, entrepreneurial and government consumption of non-durables, investment into durables and maintaining the current capital stock at the chosen utilization rate. On the market for durable capital, total investment is given by the changes in the durables stocks of patient household and entrepreneurs.

8.9. Government

The government's budget constraint is

$$T_t = G_t$$

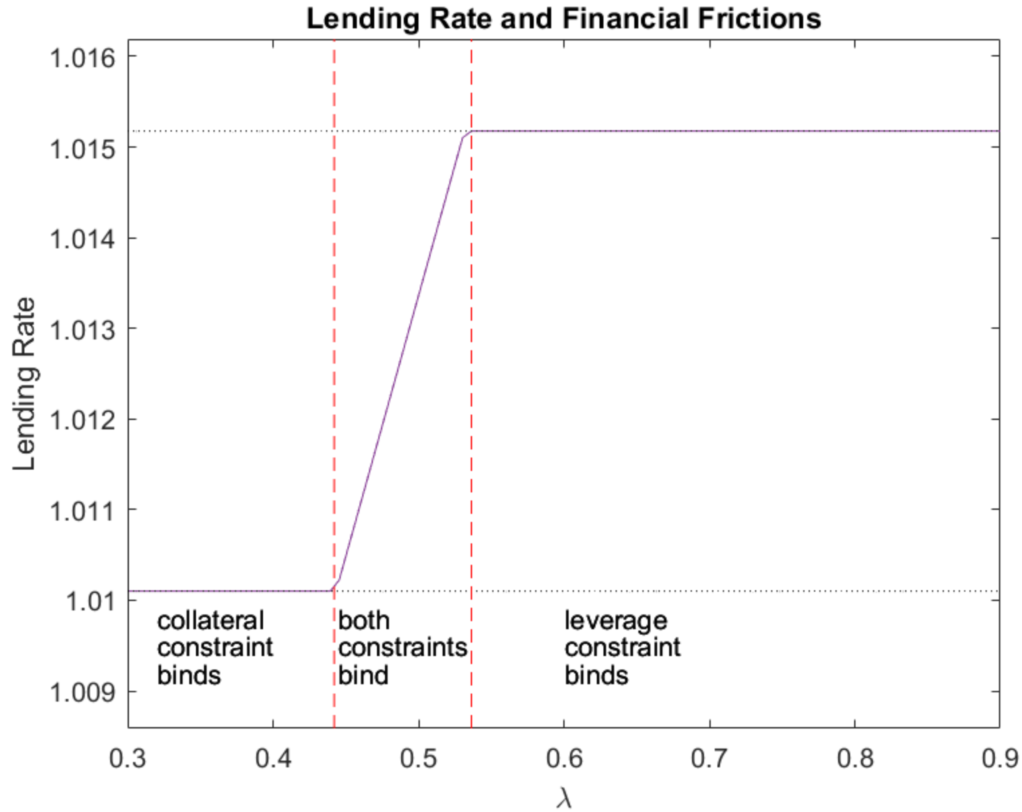
For maximum simplicity, I assume that government spending is an exogenous stochastic process (AR(1)) and taxes are lump-sum and levied on the patient household only. Government spending is either useless or simply rebated lump-sum to the patient household.

8.10. Steady State of the Model

There are 22 variables: $L, W, C, C^F, K, K^F, \Phi, Y, B^F, R, R^L, \mu^C, Q, V, H, Z, X, N, N^e, N^n, lev, EP$ and 22 equations.

$$
\begin{aligned}
L^{\phi_l} &= W^H((1-h)C)^{-1} \\
\frac{1}{\beta} &= R \\
Q((1-h)C)^{-1} &= \beta(\nu K^{-1} + (1-\delta)((1-h)C)^{-1}) \\
Q &= 1 \\
(1-\gamma\beta R^L)((1-h^F)C^F)^{-\phi_f} &= \mu^C R^L \\
Y &= A(UK^F)^\alpha L^{1-\alpha} \\
\frac{W}{\psi_1 K^F} &= \frac{1-\alpha}{\alpha}\frac{U}{L} \\
((1-h^F)C^F)^{-\phi_f}[1-\beta\gamma(\Phi\alpha\frac{Y}{K^F} + Q(1-\delta) - \psi_0)] &= \mu^C(1-\bar{\zeta})(1-\delta)Q \\
(1-\bar{\zeta})QK^F(1-\delta) &= R^L B^F \\
C^F + WL + \psi_0 K^F + Q\delta K^F + R^L B^F &= \Phi Y + B^F \\
Y &= C + C^F + \delta(K + K^F) + \psi_0 K^F + G \\
EP(.) &= \frac{R^L}{R} \\
\Phi &= \frac{\epsilon_p - 1}{\epsilon_p} \\
W^H &= \frac{\epsilon_w - 1}{\epsilon_w} W \\
V &= (1-\theta)\beta(R^L - R) + \beta\theta V \\
H &= (1-\theta) + \beta\theta H \\
Z &= 1 \\
X &= 1 \\
N^n &= \chi Q K^F \\
N^e &= \theta((R^L - R)lev + R)N \\
N &= N^e + N^n \\
lev &= \frac{H}{\bar{\lambda} - V} \\
0 &= \mu^C(R^L B^F - (1-\bar{\zeta})(1-\delta)QK^F) \\
0 &= (EP - 1)(B^F - levN)
\end{aligned}
$$

The steady-state has to be obtained as follows: For very low values of $\bar{\lambda}$, the leverage constraint will be non-binding and the steady-state is calculated with only the Iacoviello friction. This implies that $R^L = R = \frac{1}{\beta}$. As $\bar{\lambda}$ increases, the leverage constraint tightens and eventually starts binding. This leads to increases in the



steady-state lending rate so that $R^L > \frac{1}{\beta}$. This continues up to $\bar{\lambda} = \frac{1}{\gamma\beta}$, at which point the collateral constraint stops binding and the steady state can be computed purely from the Gertler-Karadi equations. The profile of the lending rate R^L evaluated throughout the parameter space of λ is shown in the figure below: This figure was created using $\gamma = 0.995$ and $\theta = 0.94$. The dotted lines represent $R = \frac{1}{\beta}$ and $R^L_{GK} = \frac{1}{\gamma\beta}$. The further γ decreases below 1, the wider will the area in which both constraints bind be, as this increases the spread between the minimum and maximum lending rate.

8.11. Log-linearized model

Table 3: Log-linearized Model Equations

(1) Household Euler Equation	$\frac{1+h}{1-h}\hat{C}_t = \frac{1}{1-h}\hat{C}_{t+1} + \frac{h}{1-h}\hat{C}_{t-1} - \hat{R}_t$
(2) Household Investment	$\hat{Q}_t - \frac{1}{1-h}\hat{C}_t + \frac{h}{1-h}\hat{C}_{t-1} = \frac{-\nu K^{-1}}{Q(C(1-h))^{-1}}\hat{K}_{t+1} + \beta(1-\delta)Q(\hat{Q}_{t+1} - \hat{C}_{t+1} + h\hat{C}_t)$
(3) Phillips Curve Wages	$\hat{W}_t = \frac{(1-\beta\sigma_w)(1-\sigma_w)}{1+\beta\sigma_w^2}\left[\phi_l\hat{L}_t - \frac{h}{1-h}\hat{C}_{t-1} + \frac{1}{1-h}\hat{C}_t\right] + \frac{1}{1+\beta\sigma_w^2}\hat{W}_{t-1} + \frac{\sigma_{wi}}{1+\beta\sigma_w^2}\hat{\pi}_{t-1} - \frac{(1+\beta\sigma_{wi})}{1+\beta\sigma_w^2}\hat{\pi}_t + \frac{\beta}{1+\beta\sigma_w^2}E_t\hat{W}_{t+1} + \frac{\beta}{1+\beta\sigma_w^2}E_t\hat{\pi}_{t+1}$
(4) Capital Producers' FOC	$\hat{I}_t = \frac{1}{\xi(1+\beta)}(\hat{Q}_t + \hat{x}_t + \beta\hat{x}_{t+1}) + \frac{1}{1+\beta}\hat{I}_{t-1} + \frac{\beta}{1+\beta}E_t[\hat{I}_{t+1}]$
(5) Entrepreneur Euler Equation	$\frac{-\phi_f}{1-h^F}\hat{C}_t^F + \frac{\phi_f h^F}{1-h^F}\hat{C}_{t+1}^F = \beta\gamma R^L\hat{R}_t^L - \beta\gamma R^L\frac{\phi_f}{1-h^F}\hat{C}_{t+1}^F + \beta\gamma R^L\frac{\phi_f h^F}{1-h^F}\hat{C}_t^F + \frac{\mu^C R^L}{((1-h^F)C^F)^{-\phi_f}}(\hat{\mu}_t^C + R_t^L)$
(6) Production Function	$\hat{Y}_t = \hat{A}_t + \alpha(\hat{K}_t^F + \hat{U}_t) + (1-\alpha)\hat{L}_t$
(7) Entrepreneurs' FOCs	$\hat{W}_t = \hat{K}_t^F + \hat{U}_t + \frac{\psi_2}{\psi_1}U\hat{U}_t - \hat{L}_t$
(8) Entrepreneurs' Investment Equation (Consumption and Collateral constraint)	$\frac{-\phi_f}{1-h^F}\hat{C}_t^F + \frac{\phi_f h^F}{1-h^F}\hat{C}_{t-1} + \hat{Q}_t = \beta\gamma\left(\frac{-\phi_f}{1-h^F}\hat{C}_{t+1}^F + \frac{\phi_f h^F}{1-h^F}\hat{C}_t^F\right)\left((1-\delta)Q - \psi_0 + \alpha\Phi\frac{Y}{K^F}\right)$ $+\beta\gamma\left[(1-\delta)Q(+\hat{Q}_{t+1}) - \psi_1 U\hat{U}_{t+1} + \alpha\Phi\frac{Y}{K^F}(\hat{\Phi}_{t+1} + \hat{Y}_{t+1} - \hat{K}_{t+1}^F)\right] + \frac{\mu^C(1-\delta)(1-\bar{\zeta})}{((1-h^F)C^F)^{-\phi_f}}[\hat{\mu}_t^C + \hat{Q}_{t+1}] - \frac{\mu^C(1-\delta)\bar{\zeta}}{((1-h^F)C^F)^{-\phi_f}Q}\hat{\zeta}_t$
(9) Entrepreneurs' Real Marginal Costs	$\hat{\Phi}_t = (1-\alpha)\hat{W}_t - \hat{A}_t - \alpha(\frac{\psi_2}{\psi_1}U\hat{U}_t)$
(10) Entrepreneurs' Budget Constraint	$C^F\hat{C}_t^F + \psi_1 K^F U\hat{U}_t + \psi_0 K^F\hat{K}_t^F) + WL(\hat{W}_t + \hat{L}_t) + QK^F(\delta\hat{Q}_t + \hat{K}_{t+1}^F - (1-\delta)(\hat{K}_t^F)) + R^L B^F(\hat{R}_{t-1}^L + \hat{B}_t^F) = \Phi Y(\hat{\Phi}_t + \hat{Y}_t) + B^F\hat{B}_{t+1}^F$
(11) Final Goods Market Clearing	$\hat{Y}_t = \frac{C}{Y}\hat{C}_t + \frac{C^F}{Y}\hat{C}_t^F + \frac{I}{Y}\hat{I}_t + \frac{G}{Y}\hat{u}_t^g + \psi_1\frac{K^F}{Y}\hat{U}_t$
(12) Capital Goods Market Clearing	$\hat{I}_t = \frac{K}{I}\hat{K}_{t+1} - \frac{(1-\delta)K}{I}\hat{K}_t + \frac{K^F}{I}\hat{K}_{t+1}^F - \frac{(1-\delta)K^F}{I}\hat{K}_t^F$
(13) Phillips Curve Prices	$\hat{\pi}_t = \frac{(1-\beta\sigma_p)(1-\sigma_p)}{\sigma_p(1+\beta\sigma_p\sigma_{pi})}\hat{\Phi}_t + \frac{\sigma_{pi}}{\sigma_p(1+\beta\sigma_p\sigma_{pi})}\hat{\pi}_{t-1} + \frac{\beta}{\sigma_p(1+\beta\sigma_p\sigma_{pi})}E_t\hat{\pi}_{t+1} + \epsilon_t^p$
(14) Central Bank's Taylor Rule	$\hat{R}_t^n = \rho_i\hat{R}_{t-1}^n + (1-\rho_i)[\rho_\pi\hat{\Pi}_t + \rho_y(\hat{Y}_t - \hat{Y}_t^p)] + \rho_{\Delta y}[\hat{Y}_t - \hat{Y}_t^p - (\hat{Y}_{t-1} - \hat{Y}_{t-1}^p)] + \epsilon_t^r$
(15) Fisher Equation	$\hat{R}_t^n = \hat{R}_{t+1} + E_t\hat{\Pi}_{t+1}$
(16) Banks' Lending Rate	$\hat{R}_t^L = \hat{R}_t + \hat{EP}_t$
(17) Banks' gain from expanding assets	$V\hat{V}_t = ((1-\theta)\beta\Lambda)\left((R^L - R)E_t[\hat{\Lambda}_{t,t+1}] + R^L E_t[\hat{R}_t^L] - R\hat{R}_t]\right) + \theta\beta VX\Lambda E_t[\hat{X}_{t,t+1} + \hat{V}_{t+1} + \hat{\Lambda}_{t,t+1}]$
(18) Banks' value from expanding net worth	$H\hat{H}_t = \theta\beta ZHE_t[\hat{\Lambda}_{t,t+1} + \hat{Z}_{t,t+1} + \hat{H}_{t+1}]$
(19) Gross growth rate in net worth	$\hat{Z}_{t,t+1} = \frac{1}{Z}[levR^L E_t[\hat{R}_t^L] + R(1-lev)\hat{R}_t + (R^L - R)lev\hat{lev}_t]$
(20) Gross growth rate in in assets	$\hat{X}_{t,t+1} = E_t\hat{lev}_{t+1} + \hat{Z}_{t,t+1} - \hat{lev}_t$
(21) Leverage	$\hat{lev}_t = \hat{H}_t + \frac{\lambda}{\lambda-V}\hat{\lambda}_t - \frac{V}{\lambda-V}\hat{V}_t$
(22) Net worth of existing banks	$\hat{N}_t^e = \hat{N}_{t-1} + \frac{1}{Z}[levR^L E_t[\hat{R}_t^L] + R(1-lev)\hat{R}_t + (R^L - R)lev\hat{lev}_t]$
(23) Net worth of new banks	$\hat{N}_t^n = \hat{Q}_t + \hat{K}_{t+1}^F$
(24) Total net worth of banks	$\hat{N}_t = \frac{N^e}{N}\hat{N}_t^e + \frac{N^n}{N}\hat{N}_t^n$
(25) Complementary Slackness condition 1	$0 = (B^F R^L - (1-\bar{\zeta})(1-\delta)QK^F)\hat{\mu}_t^C + B^F R^L(\hat{B}_{t+1}^F + \hat{R}_t^L) - (1-\bar{\zeta})(1-\delta)QK^F(\hat{Q}_{t+1} + \hat{K}_{t+1}^F) + (1-\delta)QK^F\hat{\zeta}_t$
(26) Complementary Slackness condition 2	$0 = (B^F - levN)EP\hat{EP}_t + (EP-1)(B^F\hat{B}_{t+1}^F - levN(\hat{lev}_t + \hat{N}_t))$
(IAC) Collateral Constraint	$-\frac{\zeta}{1-\zeta}\hat{\zeta}_t + \hat{Q}_{t+1} + \hat{K}_{t+1}^F = \hat{R}_t^L + \hat{B}_{t+1}^F$
(GK) Banks' incentive constraints	$\hat{B}_{t+1}^F = \hat{lev}_t + \hat{N}_t$

The redundant equation (left out by Walras Law) is the budget constraint of the patient households. The 26 variables are: $C, C^F, Y, I, K, K^F, U, W, L, \pi, \Phi, R, R^n, R^L, Q, X, V, Z, H, lev, N, N^e, N^n, B^F, \mu^C, EP$.

9. Implementation in Dynare

This section describes how the model, specifically the interaction of the financial sectors was implemented in dynare. The implementation is more or less standard, but there are a few noteworthy points:

- The steady states of the model are declared as parameters. Their values are calculated in a verbatim block, which automatically creates a matlab function, to which the calculation is outsourced. The code inside the verbatim block checks which framework is used, which constraints are binding and accordingly calculates the steady state values.
- At this point it is not possible to use a completely frictionless model. The steady state calculations are not set up for this. At least one of the frictions has to be active for the model to work. When deactivating the frictions, it is advisable to set them to a sufficiently small, but positive number. Economically, this is equivalent. A zero parameter may mess with the calculation of $\mathfrak{G}(\bar{e})$ even when this value is not needed.
- The model block contains the 26 equations of Table 1 that describe the sticky price economy, 24 equations of the flexible price economy (Fisher equation and Taylor rule do not have flexible-price-counterparts), two auxiliary equations for Λ_t and Λ_t^{flex}. The final equation defines the credit gap as $cred_t = \frac{B^F}{Y_t}$. This is in line with the empirical definition of "credit to the non-financial sector".
- Everything else is standard dynare procedure.

10. Calibration and Estimation

10.1. Calibration

We use simulated method of moments to target the empirical dynamic correlations and forecast error variance decomposition. We pick parameters to minimize the loss function:

$$
\begin{aligned}
Loss = \quad & 0.1 \sum_{\tilde{\omega}=5}^{120} \left(\rho^{model}_{Credit\ Gap,House\ Prices}(\tilde{\omega}) - \rho^{data}_{Credit\ Gap,House\ Prices}(\tilde{\omega}) \right)^2 \\
& + 0.8 \sum_{\tilde{\omega}=5}^{120} \left(\rho^{model}_{Credit\ Gap,Output}(\tilde{\omega}) - \rho^{data}_{House\ Prices,Output}(\tilde{\omega}) \right)^2 \\
& + 0.1 \sum_{\tilde{\omega}=5}^{120} \left(\rho^{model}_{House\ Prices,Output}(\tilde{\omega}) - \rho^{data}_{House\ Prices,Output}(\tilde{\omega}) \right)^2 \\
& + \sum_{i=1}^{4} \sum_{\tilde{\omega}=5}^{120} \left(forecast\ error\ share\ shock\ i^{model}(\tilde{\omega}) - forecast\ error\ share\ shock\ i^{data}(\tilde{\omega}) \right)^2
\end{aligned}
$$

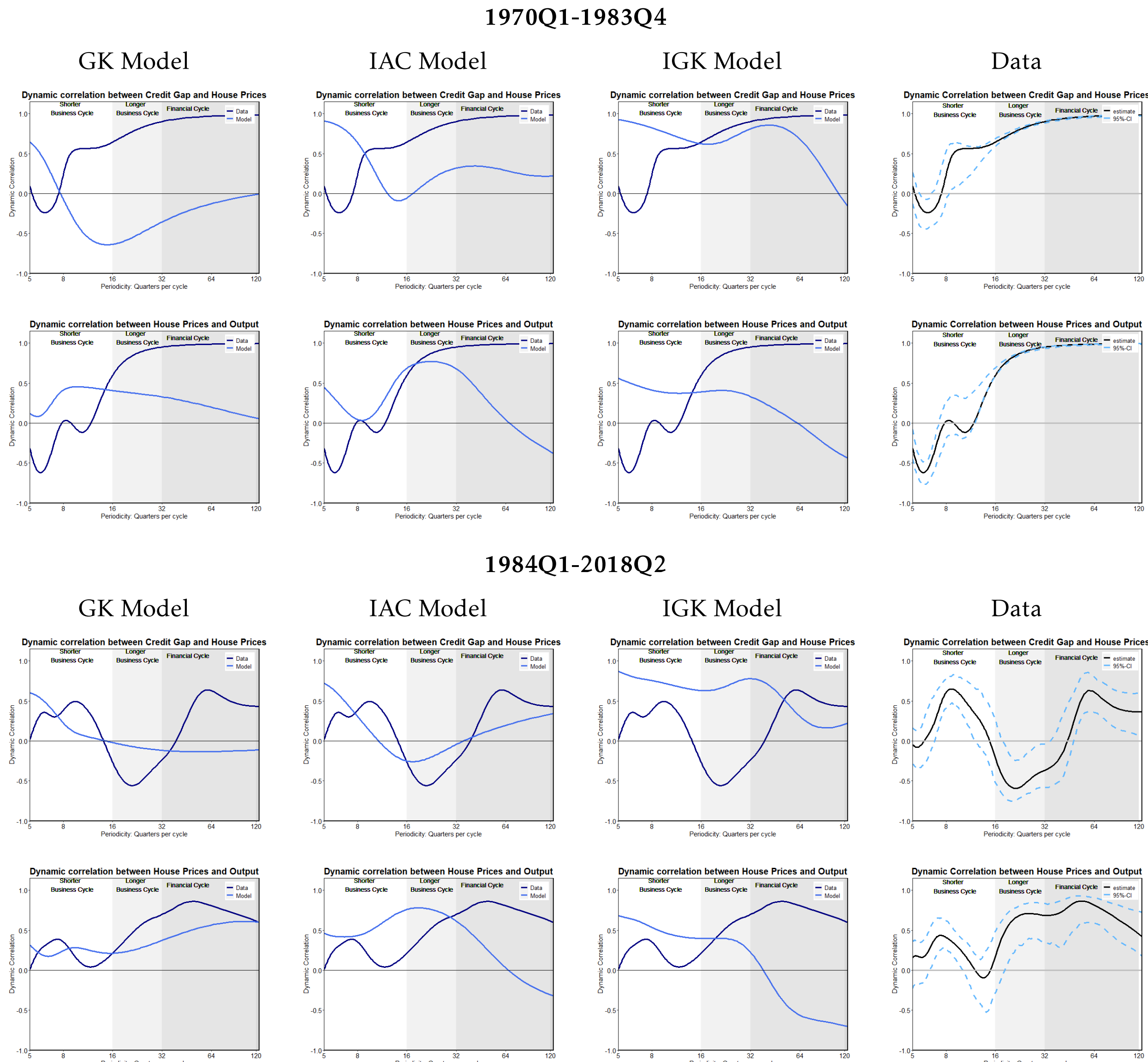
where $\tilde{\omega}$ is the periodicity, i.e. the inverse of frequency, measured in quarters per cycle: Mathmatically, $\tilde{\omega} = \frac{2\pi}{\omega}, \quad \omega \in (0, \pi)$. The minimization is implemented in Matlab with the function cmaes.m (Evolution Strategy with Covariance Matrix Adaptation (CMA-ES) for nonlinear function minimization). Table 4 shows the calibration results for all three submodels for the pre-GM and GM period.

Table 4: Calibrated Parameters

	Period	GK		IAC		IGK	
Parameter	Description	pre-GM	GM	pre-GM	GM	pre-GM	GM
ρ_π	Taylor Rule Inflation	2.8757	2.4203	1.0100	4.8540	1.8991	2.3028
ρ_i	Taylor Rule Interest Rate	0.8431	0.8152	0.9350	0.0856	0.9657	0.7812
ρ_y	Taylor Rule Output Gap	0.0058	0.0061	0.6698	0.4363	0.0722	0.1438
ρ_{dy}	Taylor Rule Output Gap Change	0.0874	0.1458	0.3429	0.2382	0.1651	0.2729
ρ_λ	persistence λ	0.2610	0.2765	0.5506	0.9534	0.928	0.8905
ρ_x	persistence adj.costs	0.6521	0.4899	0.9510	0.0802	0.8499	0.9652
ρ_a	persistence TFP	0.9513	0.9565	0.5153	0.9098	0.364	0.9701
ρ_r	persistence interest rate shock	0.6277	0.3401	0.0388	0.5000	0.675	0.6473
ρ_p	persistence mark-up shock	0.0158	0.4834	0.0100	0.0888	0.4478	0.1153
σ_λ	std.error short-run risk λ	0.3839	6.9835	7.5804	8.3061	1.9096	1.0323
σ_x	std. error short-run risk adj.costs	13.2173	6.2877	6.8723	11.1321	0.2715	1.2887
σ_a	std. error TFP	3.9376	8.1011	6.6513	1.8104	0.7892	0.0801
σ_r	std. error monetary shock	5.3708	2.6680	0.0100	7.1535	0.4438	0.373
σ_p	std. error mark-up shock	0.3419	1.2679	0.2182	0.7267	0.1717	0.1595
σ_λ^{LR}	std. error long-run risk	4.8006	4.8469	4.1614	5.0799	0.5323	0.3724
σ_x^{LR}	std. error long-run risk	3.3049	1.3036	1.6257	6.1017	0.0794	0.5543

This table shows the calibrated values for the three sub-models. GK stands for the model with only the leverage constraints (as in Gertler and Karadi (2011)). IAC stands for the model with only the collateral constraint (as in Iacoviello (2005)). IGK stands for the model with both frictions (Iacoviello (2005)+Gertler and Karadi (2011)). The pre-GM columns corresponds to the parameters of the model calibrated to match the frequency-domain statistics of the baseline VAR-model on data from 1970Q1-1983Q4. The GM columns correspond to the parameters of the model calibrated to match the frequency-domain statistics of the baseline VAR-model on data from 1984Q1-2018Q2.

Figure 25: Dynamic correlation: Model versus Data



10.2. Estimation

Each model contains five orthogonal structural shocks: a technology shock ϵ_a, a financial supply shock $\epsilon_f, f \in \{\zeta, \lambda\}$, an investment shock ϵ_x, a mark-up shock ϵ_p and monetary policy shock ϵ_r. The financial supply shock is modeled as a shock on the cost of state-verification whenever this friction is relevant. In the pure Gertler-Karadi model, in which the cost of state-verification is not relevant, the financial supply shock is modeled as a shock on the stealing technology of bank managers. All shocks follow AR(1) processes except for the monetary policy shock, which is identically independently distributed. To achieve full identification, I use the same five observables as in the empirical section: The credit gap, house prices, output, policy rate and inflation rate. The data stem from the FRED and BIS databases and cover the period from 1970Q1-2018Q2. However, I depart from the empirical exercises in two important ways: Firstly, in order to avoid issues related to the zero-lower bound after 2009, the Fed Funds rate is replaced by the shadow interest rate from Wu and Zhang (2019)[31]. Secondly, to stick as closely as possible to the prevalent estimation strategy of the literature, I estimate the model on the first differences of the credit gap, house prices and output rather than on filtered levels. I hence have 5 observational equations:

$$\Delta cred_t^{obs} = \hat{cred}_t - \hat{cred}_{t-1}$$
$$\Delta Q_t^{obs} = \hat{q}_t - \hat{q}_{t-1}$$
$$\Delta Y_t^{obs} = \hat{y}_t - \hat{y}_{t-1}$$
$$r_t^{obs} = \hat{R}_t^n - 1$$
$$\pi_t^{obs} = \hat{\pi}_t$$

The estimation is executed in dynare and follows standard dynare procedure. The results of the estimation can be found in Table 3. There are substantial differences in the posterior estimates of the different sub-models, especially between the submodels with collateralization versus those without collateralization. Firstly, the model with the GK financial sector attains the highest log-density, followed by the IAC-type model and the combined model. The models also differ substantially in how the estimation decides to match the persistence of the data. While GK model yields high persistences of the shock processes ρ and low values of ξ, the IAC and IAC+GK model yield the opposite. The models with collateral constraint also produce vastly greater standard errors of the shocks. Then, I use the estimated models to generate 200 artificial time series of 1000 periods each, from which I calculate the same frequency-domain statistics as on the actual data. To achieve maximum comparability between the four submodels, I use the same sequence of errors drawn from a standard normal distribution for each submodel - scaled by the estimated standard deviations of the shocks.

A subsequent analysis of the model generated data shows that no financial sector that the model nests replicates the quantitative and qualitative properties of the frequency-domain statistics even to a moderate extent. While the model-generated spectrum of the GM-sample shifts towards longer periodicities compared to the pre-GM spectrum, the periodicities at which this occurs are not the same as we observe in the data. All financial sectors also fail to replicate the dynamic correlation patterns of the data. In the model with a collateral constraint (Iacoviello framework) the dynamic correlation between credit gap and output is positive on all periodicities. When a leverage constraint is included (GK and IGK framework) the dynamic correlation is negative on a intermediate range of periodicities, but it is not the same as in the data. The dynamic correlation between credit gap and output is negative well into financial cycle periodicities. The dynamic correlation between house prices and output, and credit gap and house prices are also replicated inaccurately: In the data they are near to zero and highly positive on financial cycle periodicities, all models generate dynamic correlations that are decrease towards longer periodicities. This is especially

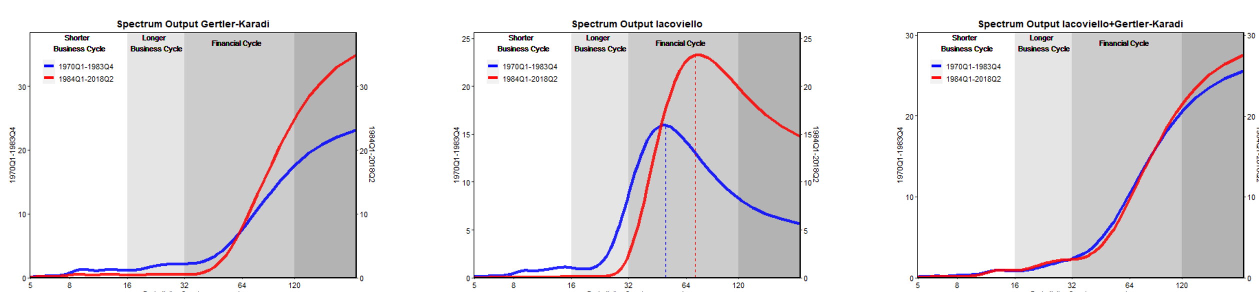
31 https://sites.google.com/view/jingcynthiawu/shadow-rates (04/06/2021)

Table 5: Estimation Results

Parameter	Description	Prior distribution			Posterior mode		
		1st moment	2nd moment	shape	GK	IAC	IAC+GK
ψ_2	utilization elasticity	0.85	0.1	normal	1.1656	0.1142	0.1748
ξ	adjustment costs	4.5	2.5	normal	0.1933	4.2520	4.3961
ρ_π	Taylor rule inflation	1.75	0.25	normal	1.5800	3.4799	3.2161
ρ_y	Taylor rule output gap	0.125	0.05	beta	0.0163	0.1545	0.0164
ρ_{dy}	Taylor rule change in output gap	0.0625	0.05	beta	0.1947	0.0123	0.0179
ρ_i	Taylor rule interest rate smoothing	0.80	0.1	beta	0.8526	0.6723	0.8387
ρ_z	persistence ζ	0.85	0.1	beta	-	0.8177	0.7881
ρ_l	persistence λ	0.85	0.1	beta	0.4297	-	-
ρ_x	persistence investment shock	0.85	0.1	beta	0.7926	0.1825	0.4379
ρ_a	persistence TFP	0.85	0.1	beta	0.8792	0.6796	0.7727
ρ_p	persistence mark-up shock	0.85	0.1	beta	0.7416	0.9398	0.5979
σ_ζ	standard error ζ	0.5	2	inv. gamma	-	32.6560	113.6227
σ_λ	standard error λ	0.5	2	inv. gamma	13.6287	-	-
σ_x	standard error investment shock	0.5	2	inv. gamma	2.2366	54.8954	41.8979
σ_a	standard error TFP	0.5	2	inv. gamma	0.9781	0.8681	2.8899
σ_r	standard error policy shock	0.5	2	inv. gamma	0.3328	1.2501	1.2440
σ_p	standard error mark-up shock	0.5	2	inv. gamma	0.0114	0.0180	0.1232
	log data density				-1687.3560	-1818.3554	-2090.3163

Figure 26: Spectra of model-generated data

GK | Iacoviello | Iacoviello+GK



This figure shows the spectra implied by the models, estimated on data from 1970Q1-1983Q4 and 1984Q1-2018Q2. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the variance at each periodicity.

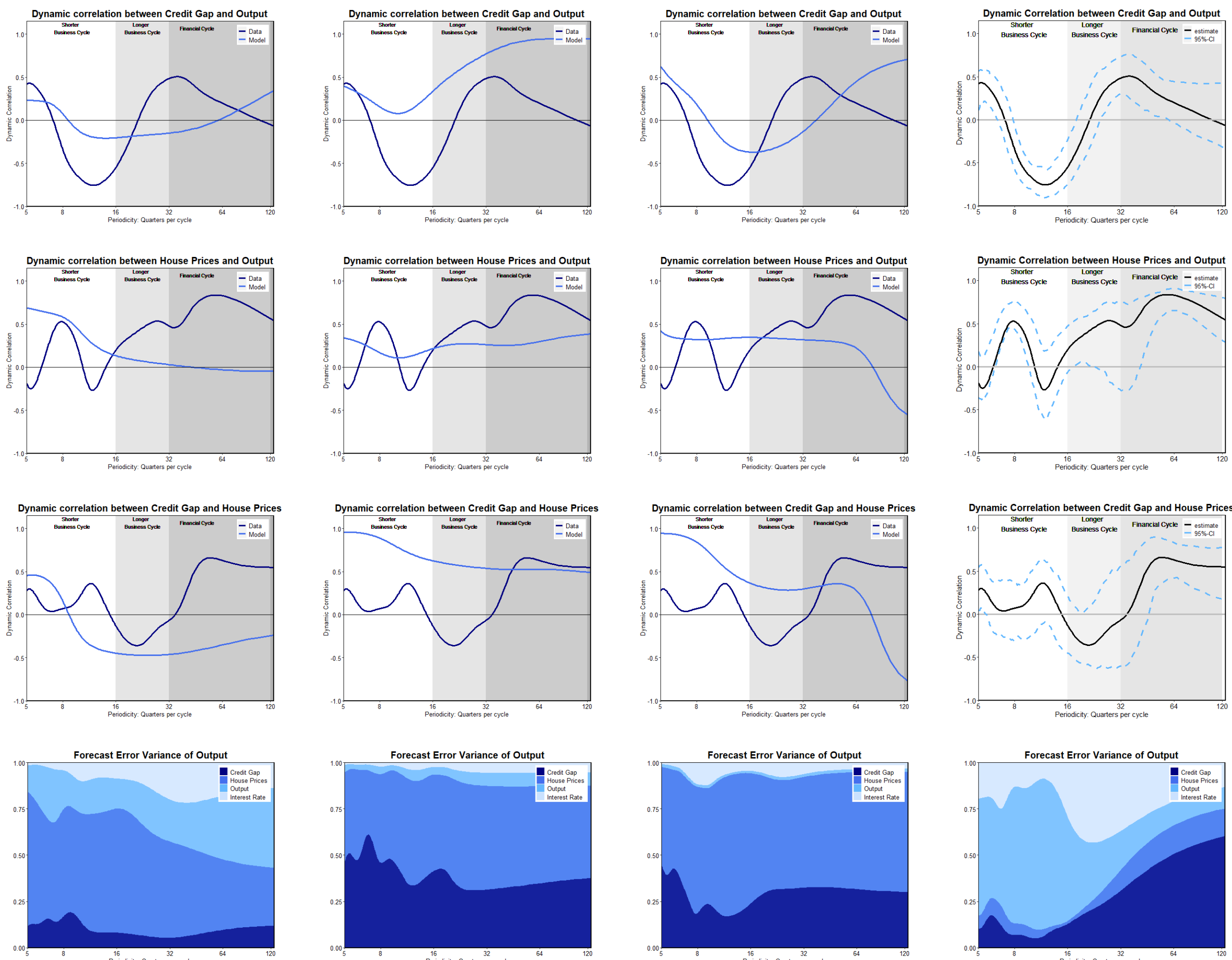
Table 6: Subsample Estimation Posteriors

Parameter	Description	1970Q1-1983Q4			1984Q1-2018Q2		
		GK	IAC	IGK	GK	IAC	IAC+GK
ψ_2	utilization elasticity	0.8526	0.1049	0.7892	1.0930	0.2266	0.1002
ξ	adjustment costs	0.1556	1.3132	2.2580	0.0699	9.8202	11.3330
ρ_π	Taylor rule inflation	2.2614	1.8688	2.7971	3.1149	3.2520	3.1160
ρ_y	Taylor rule output gap	0.0036	0.5302	0.0100	0.0163	0.0920	0.0015
ρ_{dy}	Taylor rule change in output gap	0.2760	0.0097	0.0188	0.1947	0.0149	0.0586
ρ_i	Taylor rule interest rate smoothing	0.5561	0.6028	0.7806	0.6223	0.7663	0.8560
ρ_z	persistence ζ	-	0.5878	0.7114	-	0.8776	0.2726
ρ_l	persistence λ	0.8085	-	-	0.7657	-	-
ρ_x	persistence investment shock	0.3946	0.1735	0.2634	0.9778	0.4385	0.5158
ρ_a	persistence TFP	0.6395	0.8135	0.7200	0.5106	0.9913	0.9582
ρ_p	persistence mark-up shock	0.2019	0.9685	0.5492	0.6119	0.8815	0.6809
σ_ζ	standard error ζ	-	34.3424	117.6259	-	29.4022	114.8479
σ_λ	standard error λ	8.3510	-	-	8.3619	-	-
σ_x	standard error investment shock	2.9313	53.1559	42.7528	1.0613	56.3684	44.8990
σ_a	standard error TFP	1.3877	0.9194	3.3110	1.1097	0.5436	1.5822
σ_r	standard error policy shock	1.1694	2.1870	2.0619	0.7920	0.5581	0.8068
σ_p	standard error mark-up shock	0.0097	0.0277	0.1959	0.0093	0.0239	0.2044
	log data density	-453.1186	-567.2295	-685.0693	-909.8452	-1067.1725	-1350.9275

The estimation follows a two-step process, in which first only the standard errors are estimated with the priors specified in the table above. The second step estimates all variables listed above and uses the posterior modes of the first step as priors.

Figure 27: Dynamic Correlation and FEVD: Benchmark Model

GK model | IAC model | IGK model | Data



This figure shows how the moments of the estimated models compare to their data counterparts. The models were estimated on data from 1970Q1-2018Q2. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the dynamic correlation on a scale from -1 to 1. The y-axes of the FEVD plots measure the contribution of the orthogonal shock to variable listed in the legend to the overall forecast error variance.

clear for the relationship between credit gap and house price, i.e. the financial cycle. Their dynamic interaction is medium-term in the data but is consistently produced as short-term in the model. In fact, we run robustness checks with 6 other off-the-shelf models with financial sectors from the literature which all err in the same way with regard to the financial cycle.

10.3. Counterfactuals

In this subsection, we use the model to run six "counterfactual" exercises. For this, we take the IGK-model calibrated to the pre-GM period. We build three counterfactuals by changing 1) only the Taylor Rule coefficients, 2) only the persistences of the shocks and 3) only the standard errors of the shocks to the values of the model calibrated to the GM period. Equivalently, we build the analogue counterfactual with the GM-calibrated model as a benchmark and changing Taylor Rule, persistences and standard errors to their pre-GM values. It is important to note that when changing the persistences, we ensure that the overall volatility of the stochastic processes stays constant. For example, when variance the TFP AR(1) process in the pre-GM sample is:

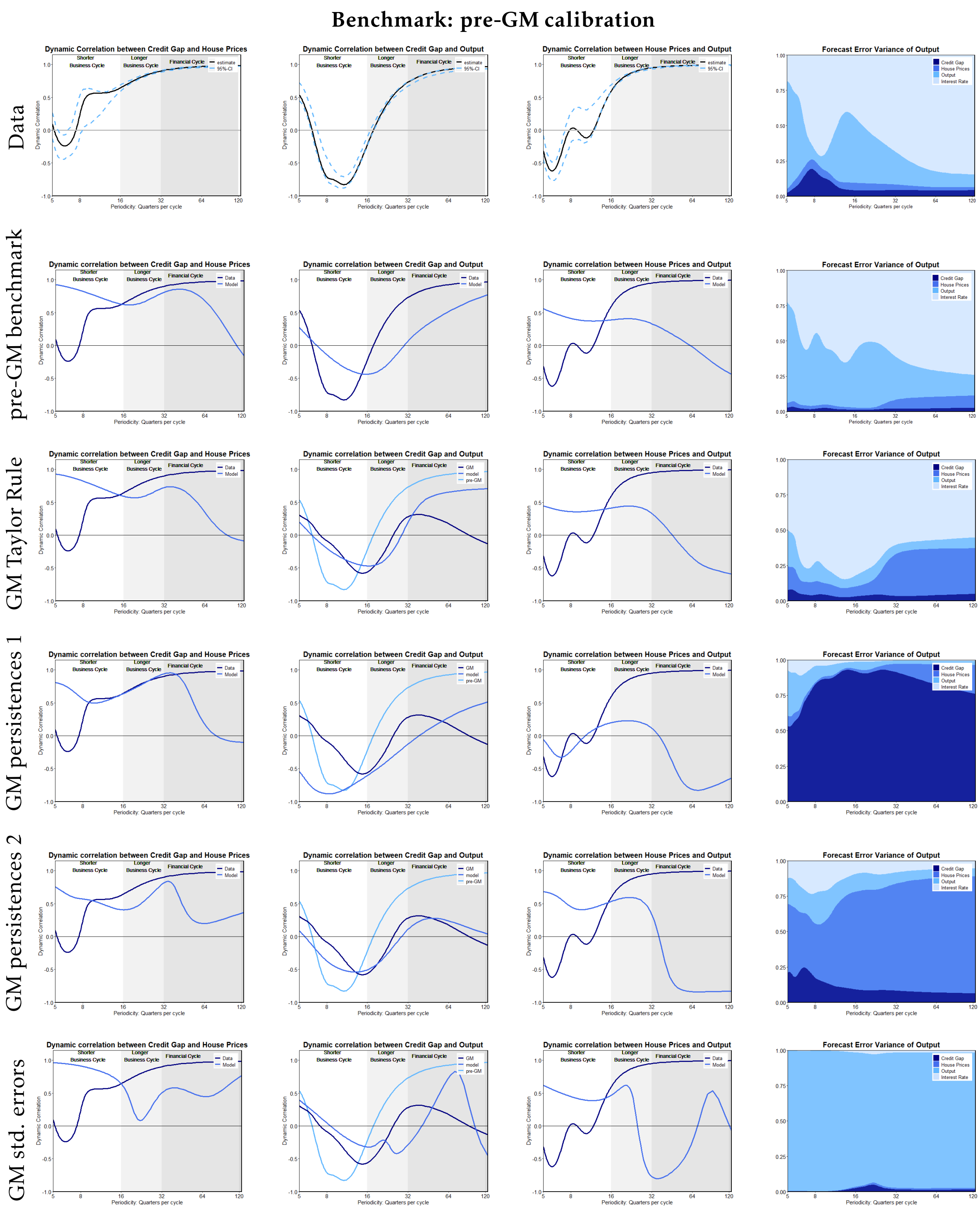
$$var(a_t)^{pre-GM} = \frac{\sigma_a^{pre-GM\,2}}{1-\rho_a^{pre-GM\,2}}$$

Then, when replacing ρ_a^{pre-GM} by ρ_a^{GM}, we also adjust σ_a^{pre-GM} to

$$\sigma_a^{pr\tilde{e}-GM} = \sqrt{var(a)^{pre-GM}(1-\rho_a^{GM\,2})}$$

The same holds for the monetary and mark-up shocks. The long-run risk processes of x and λ have two shocks each, hence, we need to run two counterfactuals each. Counterfactual 1 holds the standard error of the long-run shock constant and adjusts the short-run standard error to maintain the volatility. Counterfactual 2 holds the standard error of the short-run shock constant and adjusts the long-run standard error to maintain the level of volatility. Figures 28 and 29 show the results of this exercise.

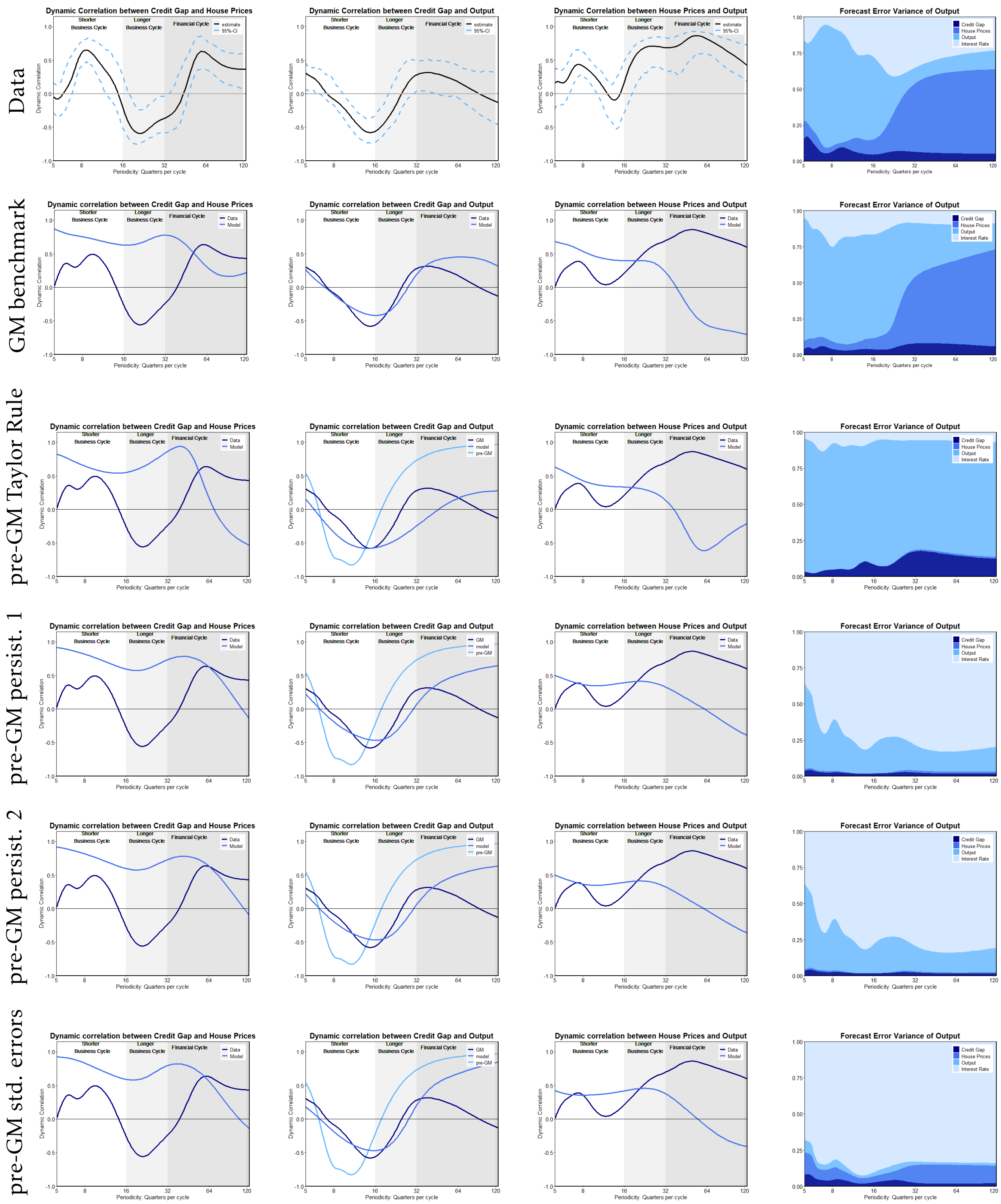
Figure 28: Dynamic correlation and FEVD: Counterfactuals



This figure shows how the model-implied dynamic correlations and FEVD compare to their data counterparts of the baseline VAR-model. The first row shows the data moments. The second row shows the moments of the model calibrated to fit the pre-GM data. The third row shows the model moments when only the Taylor Rule coefficients are replaced by those calibrated to GM data. The fourth row shows the model moments when the persistences of the GM calibration are used. The fifth row shows the model moments when the standard errors of the GM calibration are used. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the dynamic correlation on a scale from -1 to 1. The y-axes of the FEVD plots measure the contribution of the orthogonal shock to variable listed in the legend to the overall forecast error variance.

Figure 29: Dynamic correlation and FEVD: Counterfactuals

Benchmark: GM calibration

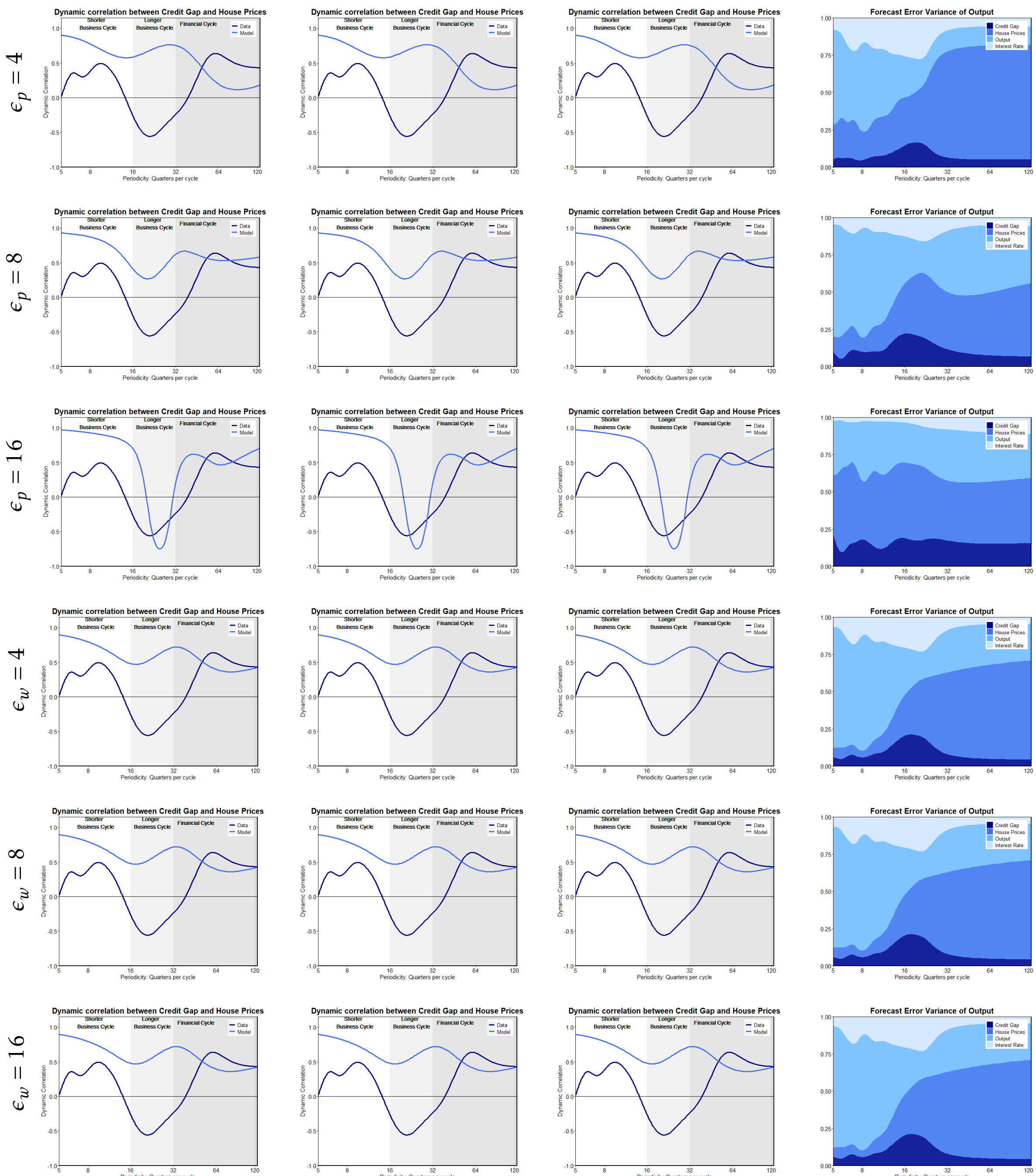


This figure shows how the model-implied dynamic correlations and FEVD compare to their data counterparts of the baseline VAR-model. The first row shows the data moments. The second row shows the moments of the model calibrated to fit the GM data. The third row shows the model moments when only the Taylor Rule coefficients are replaced by those calibrated to pre-GM data. The fourth row shows the model moments when the persistences of the pre-GM calibration are used. The fifth row shows the model moments when the standard errors of the pre-GM calibration are used. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the dynamic correlation on a scale from -1 to 1. The y-axes of the FEVD plots measure the contribution of the orthogonal shock to variable listed in the legend to the overall forecast error variance.

10.4. Sensitivity Analysis

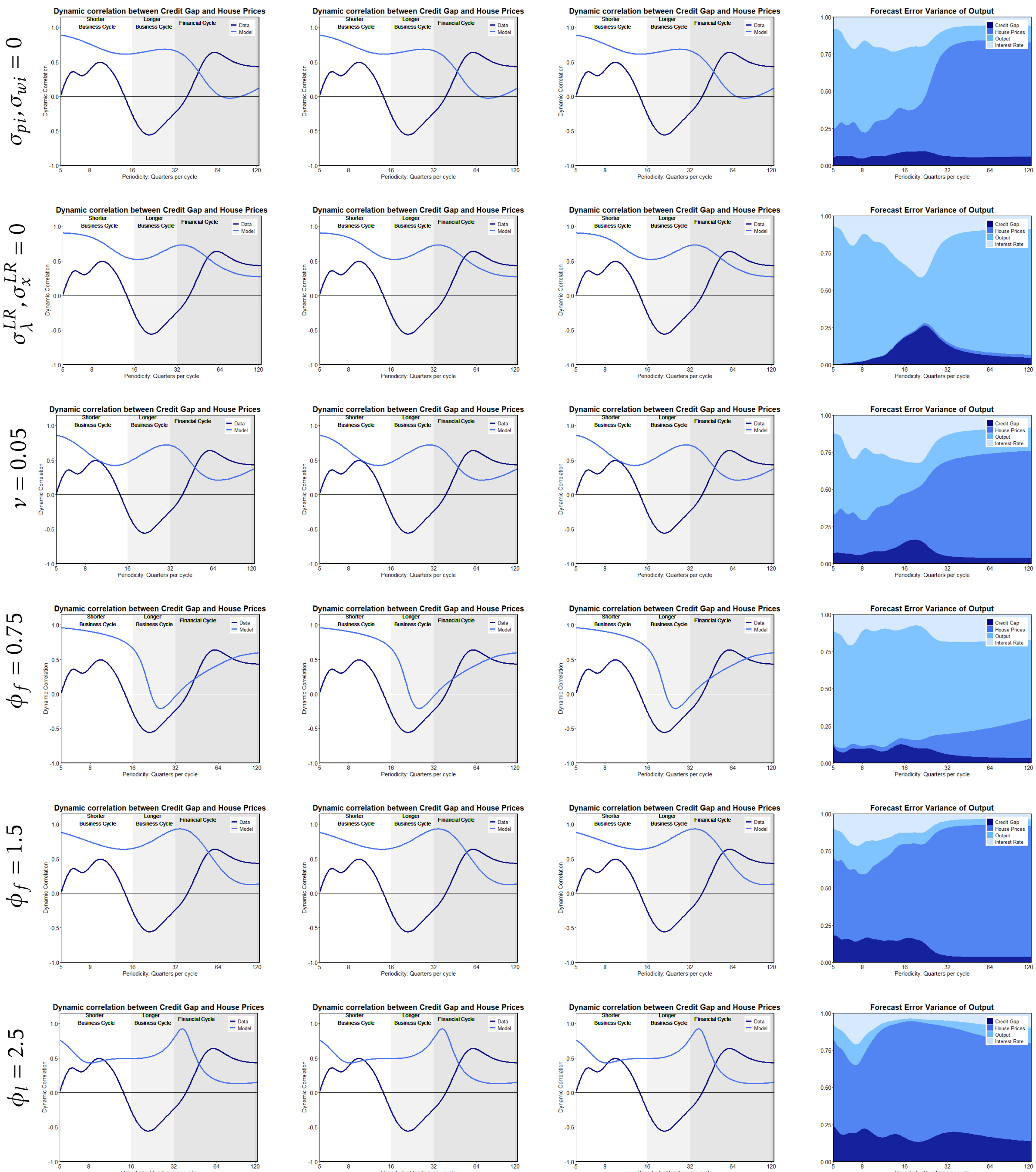
This section shows the results of a further sensitivity analysis on the parameters of the model. This includes both parameters that were fixed, as well as calibrated parameters.

Figure 30: Dynamic correlation and FEVD: Model Sensitivity



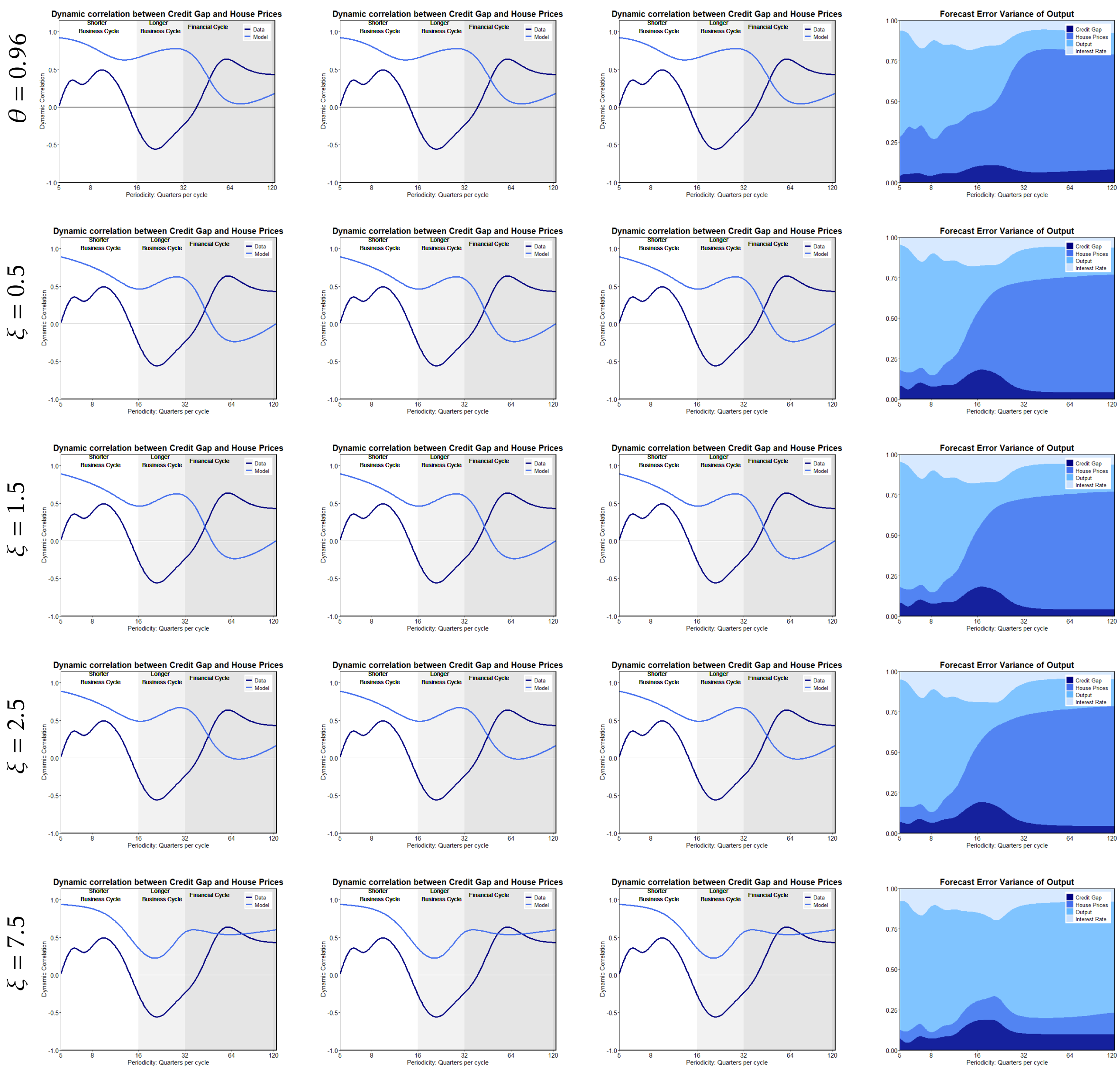
This figure shows the results of a sensitivity on the model parameters. The left column indicates the parameter change. The subfigures show the model moments. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the dynamic correlation on a scale from -1 to 1. The y-axes of the FEVD plots measure the contribution of the orthogonal shock to variable listed in the legend to the overall forecast error variance.

Figure 31: Dynamic correlation and FEVD: Model Sensitivity



This figure shows the results of a sensitivity on the model parameters. The left column indicates the parameter change. The subfigures show the model moments. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the dynamic correlation on a scale from -1 to 1. The y-axes of the FEVD plots measure the contribution of the orthogonal shock to variable listed in the legend to the overall forecast error variance.

Figure 32: Dynamic correlation and FEVD: Model Sensitivity



This figure shows the results of a sensitivity on the model parameters. The left column indicates the parameter change. The subfigures show the model moments. The x-axes are the periodicities, i.e. the number of quarters per cycle of the fluctuations for which the measures calculated. The y-axes measure the dynamic correlation on a scale from -1 to 1. The y-axes of the FEVD plots measure the contribution of the orthogonal shock to variable listed in the legend to the overall forecast error variance.

11. Frequency-domain tools:

Frequency-domain methods build on the Fourier-transform, which disaggregates time series into cycles of different frequencies $\omega \in (0, \pi)$. The most commonly used frequency-domain tool in economics is the spectrum, denoted S_{xx}, which measures how much variance is attributed to the cycles of each frequency. It is calculated as the Fourier-transform of the autocovariance function $\Gamma_{xx} = Cov(x_t, x_{t-j})$ $j \in (\underline{t}, \overline{t})$ of time series x_t (with $\underline{t} \leq t \leq \overline{t}$):

$$S_{xx} = \frac{1}{2\pi} \sum_{j=\underline{t}}^{\overline{t}} \Gamma_{xx}^{(j)} e^{-i\omega j}$$

In multivariate time series, the (complex) cross-spectrum between two variables x and y is denoted $S_{xy}(\omega)$ and describes the co-variance on each frequency - calculated as the Fourier-transform of the cross-covariance function Γ_{xy}.

Assume that the evolution of our variables can be described by a vector-autoregressive process of K variable of p lags each. Without loss of generality, define $X = (x, y, z_1, ... z_{K-2})$ the variables of the VAR. Each regression equation of the underlying VAR is of the form

$$x_t = c_k + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{j=1}^{p} \beta_j y_{t-j} + \sum_{k=1}^{K-2} \sum_{l=1}^{p} \gamma_{k,l} z_{k,t-l} + e_t$$

where c_k is the equation-k intercept and α_i, β_j and γ_k, l are the regression estimates. Transforming the VAR(p) into its VAR(1) form, denote M the companion matrix of the VAR, then

$$\tilde{X}_t = M \tilde{X}_{t-1} + \epsilon_t$$

From this state-space form of the VAR, the dynamic correlation P_{xy} is calculated as[32]:

$$P_{xy}(\omega) = (I - Me^{-i\omega})^{-1} \Sigma (I - Me^{i\omega})^{-1}$$

where I is a $K \times K$ identity matrix and Σ is the estimated covariance matrix of the VAR. The test for frequency-domain Granger-causality tests the hypothesis

$$H_0: \quad M_{y \to x}(\omega) = 0$$

that cause variable y does not Granger-cause effect variable x at frequency ω in a bivariate VAR model[33]. The corresponding test statistic from Geweke (1982) is

$$M_{y \to x}(\omega) = log \left[\frac{2\pi S_{xx}(\omega)}{|\Psi_{11}(e^{-i\omega})|^2} \right]$$

32 On time-series data, the dynamic correlation can be computed as: $\rho_{xy}(\omega) = \frac{real(S_{xy}(\omega))}{\sqrt{S_{xx}(\omega) S_{yy}(\omega)}}$ as shown by Croux et al. (2001)

33 For the multivariate models Breitung and Candelon (2006) show how to modify the test to condition on variables $z_1 ... z_{K-2}$, i.e. to test the hypothesis $M_{y \to x | (z_1, ..., z_{K-2})}(\omega) = 0$.

where $\Psi(L)\eta_t = \Phi(L)\epsilon_t$, $\Phi(L)$ is the lag polynomial and $\eta_t = G\epsilon_t$ where G is a lower-triangular matrix such that $E(\eta_t \eta_t) = I$ is an identity matrix. As shown by Breitung and Candelon (2006), this is equivalent to testing a pair of linear hypotheses $H_0 : R(\omega)\beta = 0$ where β is the vector of estimates and

$$R(\omega) = \begin{bmatrix} cos(\omega) & cos(2\omega) & ... & cos(p\omega) \\ sin(\omega) & sin(2\omega) & ... & sin(p\omega) \end{bmatrix}$$

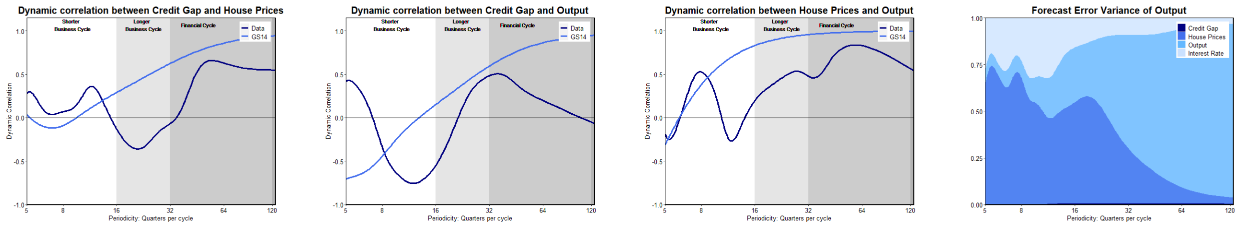
12. Models from the literature

Additionally, I check for the robustness of the findings by generating time series from models of 6 models from the literature (in their original form)[34]. The 6 models are: Iacoviello (2005),Villa (2016) (estimated BGG and GK models), Christiano et al. (2010) (financial factors), Gambacorta and Signoretti (2014) (leaning against the wind), Kannan et al. (2012) (house price booms) and Stracca (2013) (inside money). None of the models is able to accurately replicate the frequency-domain features of the data. All of the models have in common that they produce time series in which the credit gap and house prices have more short-term volatility than the output - which is clearly at odds with the data. Additionally, none of the models is really able to replicate the FEVD of the data. This strengthens the position that current models that are used to analyze the economy and on which policy decisions are made miss the the effects that the financial cycle has on the economy. As a result, endeavours should be undertaken to come up with models that can replicate the frequency-domain properties of the data.

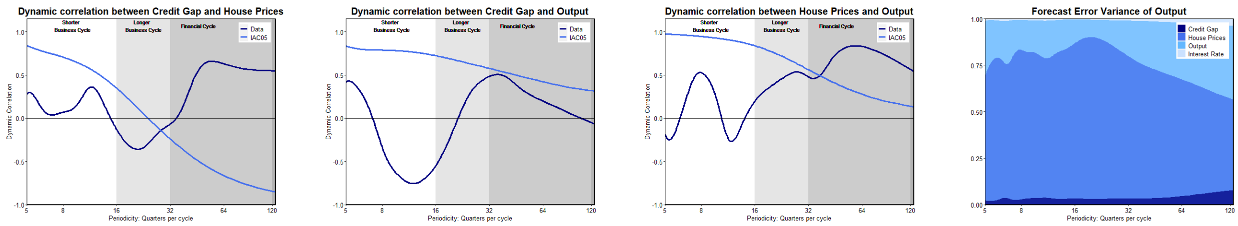
34 This is made possible by the Macro Modelbase from Wieland et al. (2012).

Figure 33: Statistics of Models from the literature

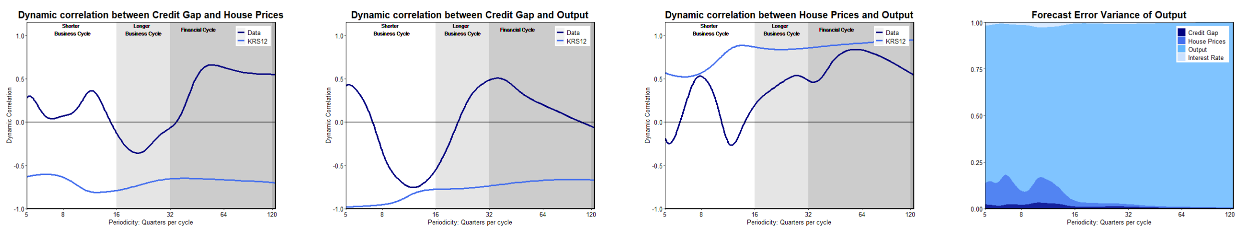
Gambacorta and Signoretti (2014)



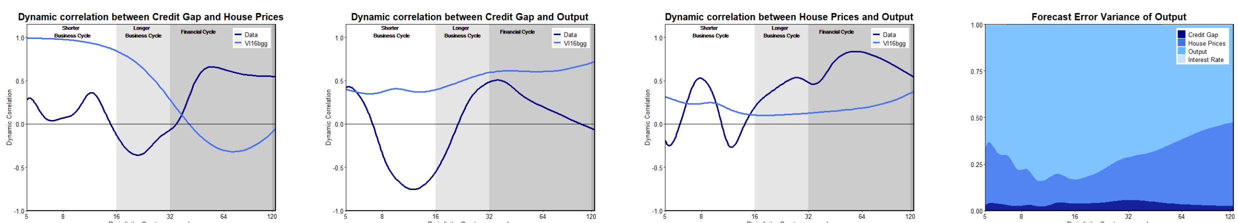
Iacoviello (2005)



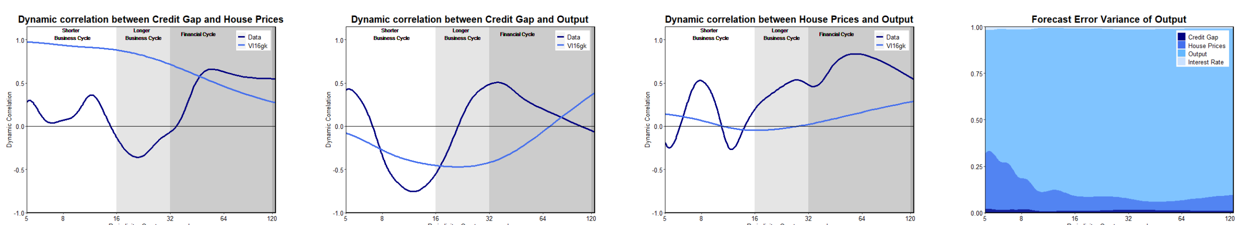
Kannan et al. (2012)



Villa (2016) (BGG-model)



Villa (2016) (GK-model)



Stracca (2013)