Università Politecnica delle Marche
Facoltà di Economia e Commercio "Giorgio Fuà"
Ph.D. in Economics, XXXIV cycle

A medium-run macroeconomic analysis of real and financial cycles

Supervisor:

Prof. Riccardo Lucchetti

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Dr. Federico Giri

Ph.D. Dissertation of:

Michele Andreani

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Piazzale Martelli, 8 – 60121 Ancona (AN), Italy

A tutta la mia famiglia.
A Fede, Jack, Claudia e Giulia.
A Pi, Bincio, Arfonso, Edoardo, Carolina, Giulia.
A San Michele, al mare e a chi vi ho scoperto.
Alla musica, in tutte le sue forme.
Al nuoto, e alla mia squadra.
All'invidia di ieri, ispirazione di oggi.

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Chapter 1.

A literature review for medium-term financial cycles

Definitions, characteristics and linkages with the real economy

Abstract

The aim of this chapter is to enlist the main contributions of macroeconomic and econometric literature related to a set of research fields, consisting of macroeconomic fluctuations and their impact on the economy, especially concentrating on their influence in the medium-run. The recent developments of economic literature regarding these themes suggest treating them as a "unique" macroeconometric field. Many definitions and peculiarities of the phenomenon are analysed here, especially when it is used to investigate backlashes in real economy, dynamics of credit/mortgaging sectors and the overall influence of house prices.

Introduction

During the last decades, economic research regarding macroeconomic cycles and aggregate economics fluctuations has largely increased, mainly concentrating on their distribution and evolution over time. Starting from the traditional business cycle literature, it helped to understand the cyclical behavior of aggregate real economy and to provide a technical procedure to isolate the *cyclical* component of a macroeconomic time series. The main set of empirical tools proposed by Burns and Mitchell (1947), ultimately expanded by Bry and Boschan (1971), allowed for business cycle's measurement and evaluation, making it possible to repeat the analysis for several countries and periods; even in more recent times, these seminal contributions are still recalled to explain recessionary and recovery phases of the economy, allocating *peaks* (the maximum point of an expansion) and *troughs* (the minimum point in a recession) to define the *cycles* in time (Harding and Pagan, 2002).[1] The isolation of turning points is still considered the main way to detect *reverting* phases into the economy, although typically examining variables in log-levels. This allows to detect the behavior of the so-called "business cycle,"[2] which is assumed to exhibit a coherent dynamic of expansion and contraction, and it is postulated to be the deviation from a deterministic growth trend in the long-run (Canova, 1998).

Even if a series presents several points in which the tendency is reversed, spectral analysis has been introduced to examine whether these fluctuations are dominant or not.[3] Part of this chapter will be devoted to an exhaustive review of spectral methodologies, which have been determinant in developing economic fluctuations theory.[4] This directly involves filtering procedures.

Although methodologies used to measure cyclical fluctuations are solid and well recognized in empirical research, most of the developments rely on the *cause* of these variations. The discussion is still open and allows for further improvements. According to real business cycle modeling theory, "cycles can arise through the reactions of optimizing agents to real disturbances, such as random changes in technology or productivity" (Stadler, 1994). These disturbances have been treated as main source for output and real aggregate variables' cyclical behaviour, along with the stochastic variation of total factor productivity (TFP). Several Real Business Cycles models tried to match their properties with real data (U.S. series have been mostly used in literature, as a main world economic benchmark). This supported the fact that business cycles could only be affected by real disturbances, i.e. there were just a

[1] The presence of these "repeated fluctuations around the long-term path of economic aggregate variables" has been suggested by Lucas (1977), among many others.

[2] Which can be safely assumed to be the logarithm of real GDP, as stated by Harding and Pagan (2005); of course, several other benchmark variables have been proposed, but this still tends to be the fundamental choice.

[3] Kulish and Pagan (2021).

[4] See section 1.4.1.

few categories of economic "causes" that could momentarily change the cyclical path of economic activity. Again, it is important to remember that these fluctuations must be considered as *transitory*, beside the typical economic growth framework of the long-run.

Since both classical and modern business cycle methodologies took place in empirical macroeconomic analysis, the focus has been directed to the different sources and causes for economic turmoils, recoveries, and periods of limited growth. As it has been demonstrated by Christiano et al. (1999), monetary aggregates do produce effects on real economic variables, meaning that the previous assumption of stochastic technology shocks must be revised; this allowed for the presence of a wide category of economic shock sources, which must include the presence of money, nominal rigidities, and monetary policy implications. The origin of these economic turmoils still remains a permanent question of research, whose most important evidences have been collected and explained within this chapter.

Then, the aim here is to collect a set of information and results to establish the presence of cycles in financial sectors. Motivation has been guided by the presence of severe economic events and financial instability during last decades, trying to revisit the entire procedures used to anticipate financial crises and recessions. What will emerge is the direct connection between the length of these cycles and financial crisis episodes, also according to multi-countries analysis and many data sources from financial sectors. This is what mostly contributed to the origin of *financial cycle* research; next sections will update the body of research with last improvements.

1.1. Financial cycle: definition and stylized facts

What do we know about the financial cycle? Modern economic research did not provide a unique answer, trying to assess many definitions for this phenomenon. What we are experiencing is an increasing interest in the discipline, which has concretised into a consistent body of literature, providing this field with both theoretical and empirical results. To summarise these research efforts, one should first list some similarities with the definition of the business cycle, comparing them with the peculiarities of financial aspects. Once the framework is established, then it would be suitable to list some stylised facts about financial aggregates and their main dynamics. However, there's no doubt that the interest in financial cycle modelling has recently increased, reflecting its inclusion into business cycle's framework as a non-negligible source of economic fluctuations. This is consistent with the propagation and transmission of shocks arising from financial sectors, whose effects can substantially vary from normal times to more severe financial distresses; once a set-up for capturing financial imbalances is arranged and implemented in macroeconomic modelling, it can be used for guiding macro-prudential policy (Grinderslev et al., 2017).

Financial markets have experienced critical phases during the last two decades. These incorporated house price bubbles and equity market booms, asset price increases, and protracted credit booms. First developments in defining the main properties of credit dynamics, along with their main repercussions in financial crises, have been pioneered by Kindleberger and Manias (1978) and Minsky et al. (1986). These can be considered as a first brick put to explain critical phases for financial aggregates, providing a new field for modern macro-financial theories. Financial accelerator theory and the implementation of credit cycles (Bernanke et al., 1999, Kiyotaki and Moore, 1997) established the first transmission mechanisms between real and financial sides of the economy, including frictions and dynamics between lenders and borrowers into a quantitative framework, as first attempts to stylise representative agents' behaviour. More recent work implemented financial inefficiency into a financial-accelerator New Keynesian model, to underline the efficiency of contractual relations between borrowers and lenders

(Nolan and Thoenissen, 2009). Corrado and Schuler (2018) consider financial innovation as a key factor in determining financial bubbles, as a rapid build-up of credit conditions, possibly leading to cycle reverting, serious financial distress and prolonged economic disruption.

The main reason why this led to a more comprehensive inclusion of a "cycle" for financial volumes can be found into the fact that former researchers only analysed few aspects of a wider picture. This is simplified recognising that some concentrated on financial booms, while others put their interest on financial disruptions, excluding the possibility of analyzing a *full-length* cycle with both expansionary and contractionary phases. During the last decade, a common opinion was still considering those past research paradigms, although not proceeding the same direction: financial factors have been marginally *forgotten*, as if they would not contribute to business cycle's dynamics (Woodford, 2011; Borio, 2014; Borio, 2017).

The anatomy of these financial imbalances cannot be excluded from their natural real-side counterpart, especially due to their feedbacks in real economic sectors. These characteristics will be covered later in section 1.1.1. What will immediately follow is a list of empirical results, which added meaning and comprehension to these propositions, i.e. characterising main stylised facts and peculiar aspects.

Respecting chronology, the first attempt to define the financial cycle is found in Claessens et al. (2011), where the first cross-country analysis has been implemented to answer few critical questions: (*i*) what financial cycles are, (*ii*) how they behave within and across countries and (*iii*) what their main empirical properties are. These first empirical regularities have been confirmed and expanded during the last years, producing first the stylised facts for the *financial cycle*.

Then, a fundamental definition is provided. The financial cycle reflects the cyclical behaviour of single (or multiple) variables in financial markets such as credit, private debt, asset and house

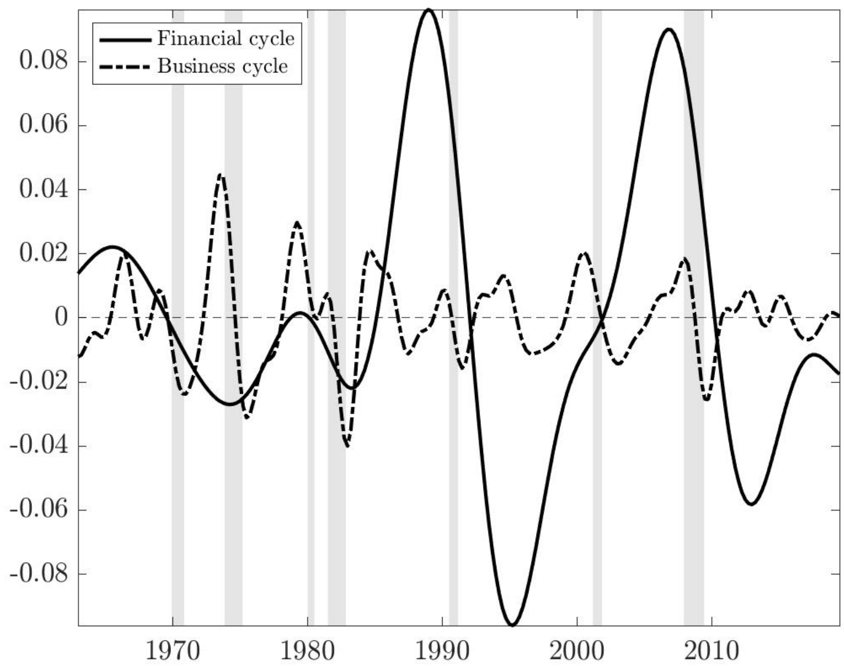

Figure 1.1.: Financial and business cycles in the United States. Grey shaded areas depict NBER recession dates. *Source:* Drehmann et al. (2012), author's replication

prices. Hypotheses about a single global cycle have been proposed, but it is clear that multiple cycles are present in the economy worldwide. These cycles exhibit fluctuations whose periodicity extends to the medium-run interval, and tend to be related to business cycle phases. Economic depressions are likely to coincide with contractionary phases in the financial cycle; this is also valid for credit expansions and periods of economic growth, although their relationship still needs to be figured out. Main empirical characteristics are described in following sections, especially where the "relationship" with the business cycle is explained (section 1.1.1) and where a variety of financial variables is analysed (section 1.2).

Even if financial cycles can be differentiated according to their durations, amplitudes, frequency bands, financial markets' conditions and so on, these exhibit some empirical regularities. The most outstanding feature of financial cycles is that their duration is considerably longer, and their amplitudes are larger than those of the classical business cycle. According to Drehmann et al. (2012), financial cycles have a longer duration, lasting from 10 to 20 years; these prolonged periodicities tend to be justified by the increasing financial instability of the early '00s, which later triggered the Great Financial Crisis, in 2008. Another crucial link is found in whether the economy is more or less liberalized: the more it is, the longer are financial cycles (Claessens et al., 2011; Agnello et al., 2019).

Moreover, when the financial cycle reaches its peak, it is closely associated with financial disruptions. Figure 1.1 depicts these findings, firstly obtained through empirical analysis:[5] swings in the financial cycle are also more pronounced than those in the business cycle. Focusing on average contractionary phases, those of financial aggregates tend to last more than business cycles'; real economy recessions are more severe when these do coincide with financial contractions, even if the financial crunch is not driven by banking crises (which has been usually considered as the main factor in triggering financial recessionary phases).

These preliminary results are somewhat different once we turn to cross-country studies, as this may reflect profound differences between financial markets and interactions. Again, this is still valid once different financial variables are used: different financial variables exhibit different cycles, whose common factor is their prolonged frequency; these fundamental characterisations have been confirmed with studies by Claessens et al. (2011), Drehmann et al. (2012), Borio (2014), Stremmel (2015), Rünstler et al. (2018), Adarov (2018) and Strohsal et al. (2019), along with many others.

[5] This figure has been replicated according to instructions provided by the authors in their original article, see Drehmann et al. (2012) and Borio (2014).

1.1.1. Financial and business cycles

In most cases, anytime a definition for the financial cycle is given, the association with the business cycle is habitual; this is valid for both recent and pioneering literature, where the former examined the "financial novelty" with well-established instruments[6] and the latter contributed to determine the first empirical regularities of financial impacts in real activities.

Years before the financial cycle research field became popular, the presence of financial structures into the economy was considered irrelevant; the role of banks and financial intermediation was minor, albeit a new perspective in determining real and financial fluctuations was taking place, also thanks to new methodological studies which contributed leaving *traditional literature* in favor of a *new* branch of modern research.

The related literature from the early '30s to the last half of the '80s, which includes seminal articles as Friedman and Schwartz (1963), Fama (1980), Hamilton (1987) and others, has been reviewed and summarized by Gertler (1988), who gave the general conclusion that a connection between these two main sectors must occour. Unfortunately, the results provided by a high percentage of those early works are mainly qualitative and theoretical; this underlined the need for future research to concentrate on methodology and quantitative developments, although this was the first step towards a unified framework for the future. It also emerges that this kind of analysis has not received much attention before the financial crisis of 2008, but once it occurred, then, financial turmoils have been included as possible candidates to explain business cycle fluctuations.

One of the aspirations for financial cycle literature is to capture the core features of the link between the business cycle and financial crises (Borio, 2014). The existence of such interaction mechanism behind financial-real cycles has been postulated by many re-

[6]Which will be described in detail in section 1.4.

searchers during the last two decades (Avouyi-Dovi and Matheron, 2003; Nolan and Thoenissen, 2009; Chen et al., 2012; Rünstler et al., 2018; Fehrle, 2019; Stockhammer et al., 2019 and others). This resulted, again, in a multitude of methodologies involved in answering similar questions, postulating the non-exclusive nature of both cycles: the complete comprehension of business cycles' phenomena cannot be performed without dissecting and examining financial dynamics, i.e. not considering the financial cycle. A pioneering approach by Avouyi-Dovi and Matheron (2003) tried to tie stock market indices, real activity, and interest rates over the business cycle, concluding that *in the longer term* these seem to share some common determinants; this established one of the first attempts to jointly analyze cyclical components from different economic frameworks, inducing several future research developments.

These, then, allowed to explore cycles in many sectors. Igan et al. (2011) consider a *paramount* macroeconomic linkage, formed by housing, credit, and real activity in a multi-country analysis; results underline heterogeneity between countries, with the United States leading economic activities worldwide, also determining that house prices lead credit and real GDP in the long-run. Nolan and Thoenissen (2009) examined the efficiency of financial sectors into a *financial-augmented* model à la Bernanke et al. (1999), including a shock into a financial accelerator mechanism; results support the presence of strong linkages between post-war business cycles and financial sectors, finding that these are strongly related to prolonged recessions and account for a large portion of real GDP variance. A similar set of results has been provided by the bank-augmented DSGE model by Iacoviello (2015), whose bank-induced recession mechanism produces defaults in the economy by contracting the supply of loans due to deleveraging and credit freezing. Compared to other financial DSGE models, the effects on consumption, borrowing, and lending are quite more severe, *financially* determining real GDP contractions. It is proven that, according to the model's structural analysis, financial shocks account for about two-thirds of output decline during the Great Recession. These improvements directly involved *macroeconometric* modeling, to properly identify and implement financial shocks in models. However, even if these financial conditions have been already carried on in some pioneering models such as Kiyotaki and Moore (1997), Bernanke et al. (1999) and Smets and Wouters (2007), these seem to fail in catching the transmission mechanisms between cycles, especially when this concerns acute boom and bust dynamics. The main features of these critics are found in Pagan and Robinson (2014) and Beaudry et al. (2020), which suggests considering a *more persistent* specification for shocks specifically driving the business cycle. Berger et al. (2020) developed a medium-sized Bayesian VAR model to assess the impact of financial markets on the U.S. business cycle, documenting the presence of sharp declines in output motivated by the presence of a financial cycle. Moreover, they also describe how these financial conditions were less predominant during the early '00s, as the role of financial factors tends to be larger since then.[7]

Empirical knowledge about financial and real sectors' interconnections has further expanded during the years, mainly thanks to large cross-country studies; this allowed to enlarge datasets and possible transmission mechanisms between cycles and sectors. Results from the work of Claessens et al. (2012) emphasised that duration and amplitude of recessions and recoveries are often shaped by linkages between business and financial cycles, especially when economies deal with financial disruptions. A role for credit and mortgages is established in both recessions and recoveries: when the former is provoked by financial instabilities, then it tends to be quite acute and severe, while the latter are stronger if they coexist with growth in credit and house prices.

[7]Berger et al. (2020).

1.2. What variables to include in the financial cycle?

Although some evidence of the importance of the financial cycle has been already provided, the interest is to focus on each variable which may be a proper candidate in summarizing it. As argued by Drehmann et al. (2012) and Borio (2014), a proper description of the financial cycle can be mostly summarized in terms of credit and property prices.[8] More recent literature suggests focusing on the behavior of credit[9] and house prices, albeit several other combinations have been introduced and sustained by economic research. Bezemer and Zhang (2014) is a proper example of a thorough analysis of mortgages and property prices, empirically detected as the main determinants of the financial cycle, monitoring their "boom-bust" empirical properties. A quarterly database built by Comunale (2015) measures financial cycles for 41 countries,[10] mainly focusing on the predictive ability of mortgages and property prices; again, the role for equity prices is reduced, as this exhibit *shorter* periodicities in their cycles.[11]

To assess the differences between G-7 countries' financial cycles, Schüler et al. (2020) provided two synthetic measures, namely narrow and broader measures, where the former simply includes credit and house prices, and the latter adds equity and bond prices; both performances are important in predicting financial crises, being much more precise than the usual credit-to-GDP ratio for real-time policy interventions. They also stressed that these policy mandates should take into account the different lengths and amplitude of cycles between countries, also considering their different level of synchronization with their pertinent business cycle. Given these

[8] This definition is justified by the presence of consistent co-movements between the two aggregates, especially at low frequencies.
[9] Namely, bank loans, and real estate loans.
[10] Including European Union members as in 2014, and 13 (non-EU) OECD countries, see Comunale (2015).
[11] As previously found by Claessens et al. (2011).

differences, countries with developed financial sectors are very sensitive to the conditions and behavior of credit lending and property prices.[12]

A detailed analysis of these variables is provided below, mainly focusing on credit and house prices; this is done by collecting the main results of a multitude of works, whose analyzes of both credit and property prices are quite relevant for this review.

1.2.1. The role of credit

Given the first stylized facts about the financial cycle, we can consider its specific segments according to a more precise analysis of involved variables. A broad category of macroeconomics considers credit as the heart of modern economics; therefore, the extension to financial cycle research seems to be immediate and natural, especially for an adequate policy design. The association with both cyclical nature and triggering of financial crises is consistent too; as pointed out by Aikman et al. (2014), credit cycles are easily identifiable, as they present many distinctions with the business cycles in frequency and amplitude, exhibiting a significant *medium-term* component.[13]

The choice of key credit variables is crucial, as each one is typically assumed to represent a single fragment of the entire credit market. To specify a credit market cycle, Adarov (2018) include activity in the banking sector and overall monetary conditions, mainly combining private credit volumes, short-run and long-run interest rates, monetary aggregates, and financial deposits. Aikman et al. (2014) use a large dataset built up by Schularick and Taylor (2012), including data on bank loans and bank assets, together with GDP and money aggregates. Figure 1.2, panels a) and b), show cyclical components of fluctuations in real loan growth and real GDP growth in the UK and US, extracted through Christiano

[12]These links will be discussed in further details in section 1.2.2.
[13]The *medium-term* discussion will be developed in section 1.3.

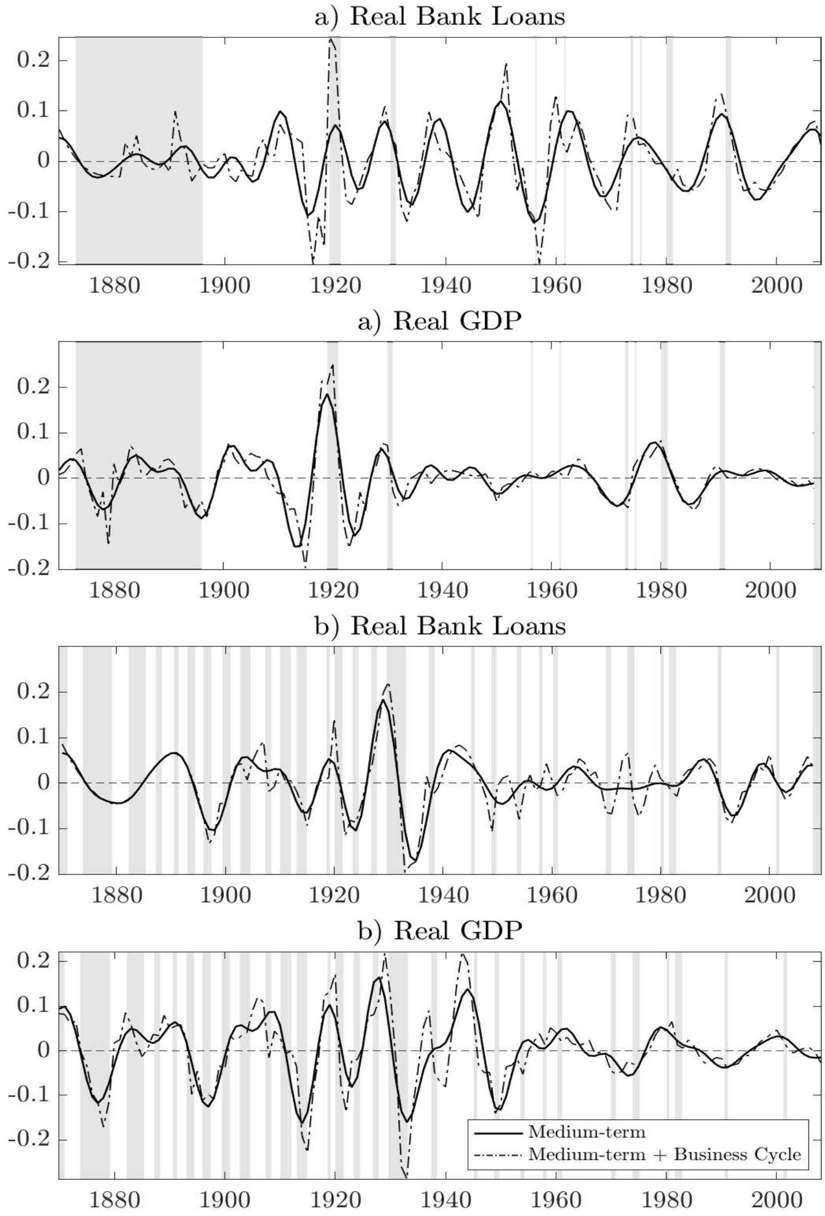

Figure 1.2.: Medium-term Cycle in Real GDP and Real Bank Loans, 1880-2008; a) UK, b) US. Grey shaded areas depict both UK and NBER recession dates. *Source:* Aikman et al. (2014), author's replication

and Fitzgerald (2003) optimal finite sample approximation to the band-pass filter.

1.2.2. The role of property prices

Economic literature frequently highlighted the importance of residential investments, mainly due to their boom-bust nature, which consequently leads to financial disruptions. It emerged that residential property prices are quite persistent and, just citing one peculiar feature, one should relate to both price and volume cycles, as suggested by Leamer (2007). The nature of the housing sector strictly depends on the number of building permissions, amount of houses sold and, of course, their price; these elements contribute shaping a very particular "cycle", whose declines are often larger than those in earlier periods (Claessens et al., 2012). Its repercussions into business cycle alternating phases has been evaluated by Leamer (2007), Igan et al. (2011), Chen et al. (2012), Jordà et al. (2015), Leamer (2015), Strohsal et al. (2019) and others.

A medium-sized structural model by Iacoviello (2015), then, considers the variation of value for real estates, chaining this decline to a great number of financial defaults, which consequently trigger credit rationing and financial crisis. Subsequent structural analysis confirms that the decline in value provokes a large amount of variance explained for the real business cycle, i.e. house prices do produce backlashes into real activity sectors.

1.3. The medium run

Once the importance of credit and property prices in shaping the financial cycle has been explained, the next piece of discussion deals with their effect in cycles chronology, especially in the medium run.

In recent years, the implementation of "medium-term" fluctuations or medium-term cycles contributed to macro-financial topics, curbing this field through detrending methods, structural analysis, and theoretical modelling. Although these results are significant and can be directly linked to real and financial dynamics, its earlier origin dealt with definitions of alternative equilibria and macroeconomic transmission channels.

Blanchard (1997) was the first one to consider the presence of an *intermediate timing* in macroeconomics, lying between business cycle and economic growth theories. Solow (2000) already imagined a valid macrodynamic "at every time scale," whose evolution from short to medium alignments might be driven by wage and price dynamic settings. These two seminal improvements contemplated the existence of such prolonged periodicities in macroeconomic and business scenarios, albeit not directly prompting empirical evidence even in later fields of research.

In the following years, growing evidence of lengthy fluctuations in economic growth has been provided. Comin and Gertler (2006) firstly focused on U.S. business phases, also detecting the increasing time between high and low growth periods; what emerged through an optimal detrending procedure[14] is that these oscillations occur over a longer time pattern if compared to business cycles,' whose effects could be related to both high growth and prolonged stagnations. Then, the intuition is to include these *more permanent* components in traditional business cycle analysis, given the possibility that these cycles may be quite more persistent than what conventional stylized facts suggest.[15] Empirical evidence on real data is also confirmed by a relatively simple RBC model, which was able to replicate such dynamics in real GDP cycles, total factor productivity[16] and various capital utilization. A graphical representation of medium-term cycles and components' analysis by Comin and Gertler (2006) for per capita GDP and total factor productivity is presented in figure 1.3.

What can be interpreted from both descriptive and structural

[14]Which is the core of a proper spectral analysis, especially in this case, Comin and Gertler (2006).
[15]Comin and Gertler (2006).
[16]Which is allowed to be endogenous.

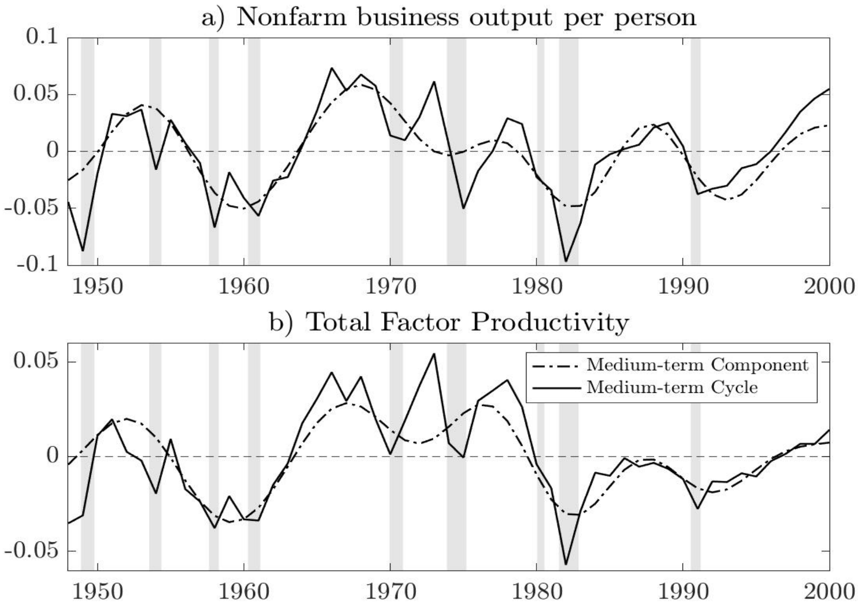

Figure 1.3.: Medium-term components and cycles for a) Nonfarm business output per person and b) Total Factor Productivity. Grey shaded areas depict NBER recession dates. *Source*: Comin and Gertler (2006), author's replication

analyzes of this seminal paper can be summarized as follows: (*i*) the RBC model generates artificial data which adequately fits moments of real data, (*ii*) dynamics of total factor productivity are well captured, especially at medium-term frequencies, (*iii*) variations in output are captured at high, medium and low frequencies, similarly to what has been suggested by former descriptive spectral analysis. Reviewing these results, straightforward conclusions lead to the idea that U.S. business cycles have a consistent portion of variability related to *lower* frequencies, which have been systematically neglected in traditional business cycle analysis. Developments in spectral analysis, detrending techniques, and theoretical modelling are strongly suggested, accordingly adjusting macroeconomic research to assess late results.

From the date Diego Comin and Mark Gertler published their paper, the *medium-term side* of macroeconomics rapidly bred multiple theme expansions; several authors started to embody the prolonged *anatomy* of business cycles in various macroeconomic areas, such as Cuddington and Jerrett (2008), Braun et al. (2008), Comin et al. (2009), Aghion et al. (2012), Ma and Wohar (2013), Comin et al. (2014), Schwark (2014).

Therefore, the link between business cycle and macro-financial modeling has been established through few fundamental research articles; Drehmann et al. (2012) and Borio (2014) embodied these novel evidences into financial cycles' analysis, whose extended fluctuations[17] naturally fitted a *medium-term* characterisation. They mainly reported that financial cycles' peaks are very closely associated with financial crises, and their length and amplitude have markedly increased since the mid-1980s. Aikman et al. (2014) identified medium-term fluctuations in credit that, over the last century, have most strikingly coincided with crises.[18]

A very recent paper by Queralto (2020) provided a sort of link between two sides of the same phenomenon of interest. It is proven that financial frictions[19] produce real aggregate recessionary phases which are quite more prolonged and severe if coinciding with banking defaults, resulting in medium-term contractions and recoveries.

An influential consequence arising from the presence of such results is the immediate link with the upcoming *medium-term* macroeconomics: the existence of clear improvements in the discipline cannot be ignored as new research efforts take place, then the interconnection between mainstream macroeconomics and the newborn *medium-run* has been immediately established, resulting into a vast production of articles and academic progress. Section 1.4 will follow with a condensed review of main methodological approaches, which consequently led to results listed in previous sections.

[17]Previously described in section 1.2.
[18]Figure 1.2 previously reported an example of the author's findings.
[19]Implemented into a structural macroeconomic model, with endogenous total factor productivity, R&D, and banking crises, a quantitative setup which is very similar to Comin and Gertler (2006).

1.4. Methodologies and data

To recap the whole set of methods and instruments applied to this vast ensemble of disciplines would be an immense effort. This cannot be said for the data employed, as literature generically relied on macroeconomic aggregate data. Real GDP is employed for most times, as the typical representative variable for real activity, i.e. the real business cycle; up to the same extent, financial data including mortgages, household debt, house price index, and gross data have been widely used as a benchmark for the so-called financial and housing cycles.

In pioneering works, the credit-to-GDP ratio has been considered an appropriate variable for determining the financial cycle; however, due to its cyclical characteristics[20] it may be considered a *mixture* of financial and business cycle indicators, which may hinder the analysis.[21] A growing number of empirical applications is assessing the role of asset markets together with investment volatility[22] and other market variables, as the real-financial interaction mechanism tends to be stronger in countries with a market-based financial system, see Stockhammer et al. (2019).

Modelling options include a broad set of choices, briefly summarised in:

(i) macroeconomic models (real business cycle and new keynesian-based DSGE models), as in Iacoviello (2005), Comin and Gertler (2006), Nolan and Thoenissen (2009), Sala (2015), Guerrieri et al. (2015), Rünstler and Vlekke (2018), Fehrle (2019), Schuler and Corrado (2019) Queralto (2020),

(ii) econometric modelling frameworks such as Bayesian VARs, multivariate VAR setups and structural VARs: examples are Iacoviello (2000), Schularick and Taylor (2012), Favara and

[20] Which have been reported by Hiebert et al. (2014), Schüler et al. (2015) and Rünstler et al. (2016).

[21] Hiebert et al. (2018).

[22] Bezooijen and Bikker (2017).

Imbs (2015), Miranda-Agrippino et al. (2015), Filardo et al. (2018), Lubik et al. (2019), Kaufmann (2020), Berger et al. (2020). Estimation of dynamic factor models also contributed shaping business and financial cycle empirical properties (Ng, 2011; Menden and Proaño, 2017; Miranda-Agrippino and Rey, 2020; Avarucci et al., 2021).

(*iii*) spectral analysis devices and the extraction of cyclical components.

Next section will cover the turning point analysis method and the main filtering techniques used in macroeconomics. This follows the historical perspective of business cycle analysis, which started with the dating of cyclical phases observed in raw data; then, advances in filtering techniques suggested the *extraction* of cycles.

1.4.1. Turning point analysis

As argued by a large part of literature, the detection of cycles in time has been performed by locating turning points analysis on macroeconomic time series. While in the last decades this procedure was exclusively used for the study of real business cycles, the recent adoption by the financial counterpart of research has been actual and natural. The methodological infrastructure for this technique goes back to Burns and Mitchell (1947), especially for the analysis of the U.S. business cycle. The National Bureau of Economic Research (NBER) dictates the main principles of the Business Cycle Dating Committees, also valid for the Center for Economic Policy Research (CEPR).[23]

Its employment in financial cycle research first evidenced the absence of time synchronicity between real and financial aggregates, see Borio (2014) for a fundamental example; although empirical work on the financial cycle was more limited than nowadays,[24] re-

[23]Concerning euro area business cycles.

[24]Drehmann et al. (2012), whose approach combined turning point location and frequency-based statistical methods.

sults encouraged its usage, which consequently increased.

Many studies, such as Claessens et al. (2011), Claessens et al. (2012), and Drehmann et al. (2012), demonstrated that real GDP ultimately showed a major presence of peaks and troughs if compared to housing prices and credit activities; however, when economies experiment periods of credit and housing booms, the coincidence between the two turning points may signal the overcoming of a financial crisis (contraction). Empirical evidences have been also provided by Filardo et al. (2018), Rünstler et al. (2018), Agnello et al. (2019), Kulish and Pagan (2021), Aldasoro et al. (2020a).

Other studies tried to employ results from turning point analysis for exercises of financial crisis predictions and policy advising. Aprigliano and Liberati (2019) exploited data produced by the Bank of Italy for the ECB[25] detecting turning points to estimate the probability of recessions in real-time, whose results support the ability of credit variables to detect the turning points and to correctly estimate the probability of contractionary phases for the economy. A more historical study by Bartoletto et al. (2019) located cycles for Italy's economy on more than a century of data, which is able to detect periods of policy stabilization for the national credit imbalances and confirms the main stylized facts for Italy's financial cycle. As this approach has been usually applied to individual series, it is worth remembering that it can also be exploited for the interpretation of global financial factors, as pointed out by Miranda-Agrippino and Rey (2020).

1.4.2. The extraction of cycles

The collection of business cycle's stylised facts began with the work of Hodrick and Prescott in 1975, as they provided a first *guideline* to analyse recurrent regularities for the business cycle phenomenon. The existence of detrending methods produced debates about their effectiveness in properly spotting the cycle, as these methodologies

[25] More than 100 financial time series have been employed.

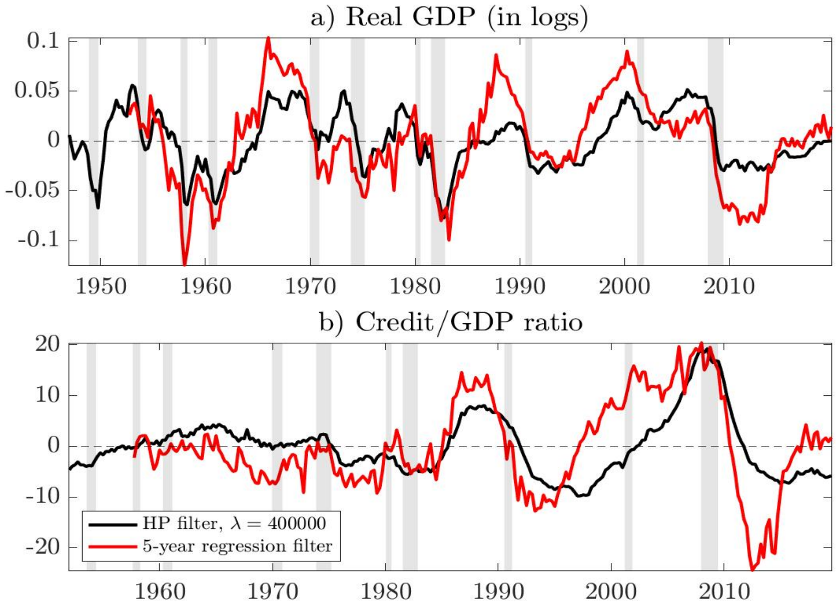

Figure 1.4.: Extraction of Hodrick and Prescott (1997) and Hamilton (2018) cyclical components for a) Real GDP (in logs) and b) Credit/GDP ratio. Grey shaded areas depict NBER recession dates. *Source*: Schüler (2018), author's replication

tend to measure it without any kind of theoretical support; the dichotomy between statistical and economic cycle decompositions is still actual,[26] as a non-appropriate detrending choice would result into a drastic modification of series' variability and mismatch of empirical regularities. Therefore, what is suggested is to concentrate on the best procedure to extract the cycle of interest, according to its ability in replicating cycles' properties; this is valid for both business and financial cyclical components, as their importance (especially in the latter case) increased in the last decade for macroeconomic purposes.

The Hodrick and Prescott (1997) filter (HP) has been widely used to remove the long-run component of a series as a standard computing tool; most of its capability relies on the smoothing parameter

[26] A consideration explained in Canova (1998).

λ, which must be properly set up according to the frequency of data. However, the choice tends to be controversial,[27] as the nature of data *requires* a proper detrending (filtering) choice. A strong criticism by Hamilton (2018) describes how the HP filter may produce spurious cycles; a regression-based filter, then, is proposed as an alternative for nonstationary time series, as the true generating process of data is considered as unknown.

Another approach to extract the cyclical component of a series consists in isolating it according to frequency bands, properly chosen by the researcher (Baxter and King, 1999; Christiano and Fitzgerald, 2003). This is the first tool which allows to detect cycles according to a set of thresholds, coinciding with the beginning and the end of the considered *period*. A vast number of articles suggest that the traditional business cycle component can be isolated into the $(6, 32)$ quarters interval. Comin and Gertler (2006) used the band-pass filter to isolate the medium-term component up to 200 quarters, Drehmann et al. (2012) and Borio (2014) consider a maximum threshold of 120 quarters.

Schüler (2018) provided additional empirical evidence of the fact that the Hamilton filter is not subject to the same drawbacks as the HP filter, as this might be more suitable anytime the researcher is interested in cycles that exceed the duration of regular business cycles. The specification of the filter, however, strongly depends on assumptions about the lag order of the regression,[28] although producing a smaller end-of-sample bias and emphasising cycles that exceed regular business cycle frequencies. A graphical illustration for part of Schüler (2018) results is presented in figure 1.4. One of the empirical features the author focused on is the amplification of cycles' medium-term frequencies, a key detail that tailors and accommodate what has been said until now. The presence of a cyclical component above the usual business cycle threshold of 32

[27] Ravn and Uhlig (2002) suggest that λ should be adjusted according to the fourth power of a change in the frequency of observations.

[28] Which is established to be, by default, a 2-years of 5-years regression filters.

quarters allows for the presence of larger variance of fluctuations and it spots contractionary phases which tend to be longer and more severe, a stylised fact coinciding with a huge part of research literature already mentioned here.

1.5. Concluding remarks

With this chapter, the objective was to provide a condensed picture of a novel economic phenomenon, adding new interpretations for complex dynamics. The importance of defining new stylised facts regarding the medium-run and the basic features of main financial variables conducted all the research works explained so far in previous sections. This body of literature can be divided into two groups: the "pioneering" one includes all those influential advances which helped to shed light on the *medium-run financial* macroeconomics, while the more "recent" percentage of articles empirically contributed in shaping the topic. The multitude of approaches used and the combination of different theoretical frameworks helped to challenge the researcher's knowledge about an *updated* analytical concept for the business cycle, naturally extending the whole set of empirical tools for other purposes.

What many researchers argue on is the importance of these developments in terms of policy implications. As the importance of the financial accelerator mechanism has been already established during the last two decades,[29] what has been discussed so far includes many other aspects in the matter of recurrent cyclical phases of the economy, especially in modern years. The presence of medium-term macroeconomic fluctuations in many key variables emphasise the need for further improvements in both theoretical and empirical frameworks; once credit and housing markets have been identified as critical sources of economic and financial instabilities, the next step would be to determine the existence of links between monetary

[29] Nolan and Thoenissen (2009).

and macro-prudential policies,[30] to both accommodate and model the arising of multiple cyclical dynamic patterns, as pointed out by Stockhammer et al. (2019). One of the most important advice by Drehmann et al. (2012) is not to lose sight of the medium-run component into financial cycle analysis; although the first notions we take from Comin and Gertler (2006) are not born into a financial *boom-bust* framework, including it for further modeling developments would be a proper choice. Moreover, monetary and fiscal policies must focus on the medium-term nature of phenomena involved, as the financial backlashes into real sectors would potentially last for years. This is also directly linked with the international synchronization between cycles since financial vulnerabilities take different periods to grow and, likely, need a long time to be absorbed.[31] From a cross-country point of view, this would require a special focus, due to the interconnectedness of financial markets and the different timing and magnitude of both national and global recessions.

[30] Rünstler et al. (2018).
[31] Borio (2014).

Chapter 2.

Are financial, housing, and business cycles medium-term phenomena?

A continuous Wavelet analysis

Abstract

Financial cycle stylized facts have been collected during the last two decades of research, mainly employing traditional spectral analysis and econometric methodologies. Here, continuous wavelet methods are proposed to further investigate dynamic correlations between the business cycle and a set of financial variables, which I assume to represent financial and housing cycles. Such stylized facts are robustly confirmed by coherence and partial coherence analyses, which identify a large amount of correlation above business cycle's frequency domain.

Introduction

What we are experiencing during these last two decades of research is the rapid inclusion of Wavelet methods for basic and advanced time series analysis. This is motivated by the flexibility of the proposed instruments, by their rigorous mathematical framework and the variety of topics where it is applied nowadays. The amount of research proposals for applied works has received a notable influence by the introduction of such a methodology, whose results have been related to a "direct extension of traditional time series modelling choice," where the decomposition of a time series into *frequency components* would lead to a major source of informations related to the series itself. The suitability of this tool also allows for a variety of multivariate analysis, relating the spectral variability and correlation of several frequency components between two or more series of interest. Empirical literature using Wavelet methods, then, has largely increased during the last years, primarily due to the flexibility of the instruments adopted and due to the evolution of recent research purposes, which found its natural applications with distinct sets of statistical procedures.

It is noteworthy to shortly describe the evolution of this methodology. As it has been already explained above, one of its most important features is the multitude of research disciplines where it is employed: areas such as engineering of electronic and magnetic signals, medicine, physics, climatology and many vastly explored their phenomena of interest exploiting traditional spectral analysis. One of the first contributions in time, which then resulted in the development of the Morlet Wavelet, comes from Goupillaud et al. (1984) and Grossmann and Morlet (1984); they also included one of the first definitions for a *wavelet*, that is, a function which is limited in both time and frequency domain. An initial review of the method can be found in Daubechies (1992), while several reviews such as Ganesan et al. (2004), Labat (2005), Sang (2013) and Li and Chen (2014), among with many others, revised the generic body of methodology according to their precise sector of application. An exhaustive review of the main papers produced for Wavelet Analysis applied to geophysics is provided by Foufoula-Georgiou and Kumar (2014), where the main time-frequency relationship is established and most notable technical advantages are described.

The passage from natural and scientific phenomena to the field of economics took a long time to emerge. Ramsey (2002) produced the first discussion about the relevance of this methodology in economic disciplines, underlying its potential importance for future research in economics and finance. From that moment on, technical progress has grown, so many researchers employed such methods to isolate frequency components of data, extracting localised information in both time and frequency domains. An extensive revision of application in economics and finance is presented in section 2.1.

From a computational point of view, several packages and software toolboxes have been released according to the main platform they're based on. Grinsted et al. (2004) introduced a set of software routines[1] to implement the main instruments for Geophysical data analysis, although this has become one of the most used in a multitude of research fields. The first contribution in economic analysis comes from Aguiar-Conraria and Soares (2014), as an update for an existing MATLAB Toolbox written by the same authors in 2008.[2] Other software (such as R[3] and Python[4]) proposed their suites for discrete and continuous wavelet computation.

The aim of this chapter is to explore the main features of this widely used instrument, in order to use it for macroeconomic empirical analysis, specifically for business cycle and financial aggregates, lately establishing the recent definition of *financial cycle*. This will also rely on more traditional instruments' results, comparing them with the more recent ones.

The organisation of the chapter is explained here. After the introduction, section 2.1 explains the peculiarities of Wavelet applications in economics. A brief review of the instruments employed is provided in section 2.2; a simple application of these tools compared with traditional Fourier transform is used as an example. Main empirical output takes place in sections 2.3, which respectively analyse the data and interpret the results. After these comments, section 2.4 concludes.

2.1. Wavelet methods in economics

One of the main advantages related to the adoption of such an instrument is to put two different analyses, the time domain and the frequency domain, into the same computational framework. While time series econometrics is mainly used to manage the former, the latter case has been used discrete Fourier transform to detect frequency peaks in the spectrum of time series data. The key ele-

[1] https://sites.google.com/a/glaciology.net/grinsted/wavelet-coherence.
[2] https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/the-astoolbox.
[3] CRAN, https://cran.r-project.org/web/packages/wavelets/index.html
[4] PyWavelets, https://pywavelets.readthedocs.io/en/latest/.

ments which made possible to shed light into an instrument such a Wavelet, after listing the well-known properties of traditional spectral analysis, are accurately described by Crowley (2007). As it will be shown later with an example applied on macroeconomic variables, it is clear that such an instrument provides an incomplete outline of the *spectral* informations available.[5] Discrete and continuous wavelet methods help avoiding this computational deficiency, allowing for a representation of time series which includes time and frequency scales, providing a richer anatomy of the variable involved.

The list of advantages is not over. Wavelet methods support multivariate analysis; it is possible to detect specific frequency and time areas in which two series are strongly correlated, i.e. describing the leading or lagging tendency between several frequency bands. Grinsted et al. (2004) describe these instruments, although an introductive revision of the main methodology is provided in most of the related published articles.

Research efforts including Wavelet methods applied to economics have been very limited until the beginning of '00s. An alphabetical list of those pioneering articles has been written by Crowley (2007), as the amount of related literature produced has largely increased until nowadays. In particular, the *discrete* approach has been considered very advantageous for applied economists and macroeconometricians, whose interest for cyclical and spectral periodicities can be properly inspected and analysed.

An increasing number of applications have been employed in oil market analysis (Yousefi et al., 2005; He et al., 2012; Tiwari et al., 2013; Jiang and Yoon, 2020; Adebayo et al., 2020); many others investigated the *multiscale resolution* of financial series, also employing them for forecasting purposes (Norsworthy et al., 2000; Fernandez, 2007; Rua and Nunes, 2009; In and Kim, 2013; Alexandridis and Zapranis, 2014; Addison, 2017; Rhif et al., 2019; Qiao and Yang, 2020). A more recent collection of articles is provided

[5]See section 2.2.2.

by Gallegati and Semmler (2014), who revisited applications in macroeconomics, asset market volatility and spectral forecasting. More recently, interdependencies between economic sectors and the Covid-19 pandemic have been also examined (Choi, 2020; Mustafa et al., 2020; Singh et al., 2020; Sharif et al., 2020; Sharma et al., 2021).

This work is devoted to the implementation of these techniques into financial cycle and medium-run research fields, whose developments have been naturally related to those of real business cycle's. The potential in explaining economic fluctuation is considerable.[6] Then, the adoption for these purposes was immediate, as the aims of this chapter are:

(*i*) to provide additional evidence of synchronisation between real and financial aggregate variables, sectioning them into several frequency bands of influence,

(*ii*) to detect whether these relationships do take place somewhere in the medium-run, i.e. at frequencies which exceed the classical *short-term* bound of 32 quarters (8 years),

(*iii*) to assess causality relationships between key macroeconomic variables.

The number of available wavelets is huge. According to methodology's prerequisites, the most used functional form in economics is the MODWT discrete approach. From a specular point of view, the results obtained through continuous approaches such as Wavelet spectra and coherencies add an easier interpretation (Aguiar-Conraria and Soares, 2014).

[6] It is worth to recall the recent criticism by Hamilton (2018), also for the suggestion of alternative procedures. A Wavelet decomposition of macroeconomic series would also be a proper option, avoiding controversial choices on data filtering procedures.

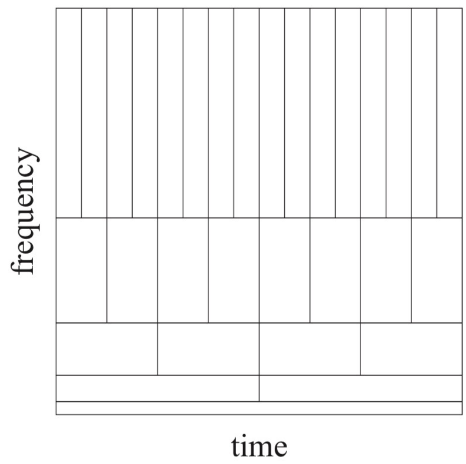

Figure 2.1.: A graphical example for multi-resolution decomposition, in both time ($x-$axis) and frequency ($y-$axis) domains.

2.2. Main methodology and instruments

In this section, a list containing the main computational tools for discrete and continuous Wavelet analysis is presented. It is common to divide them in *discrete* and *continuous* approaches, according to the nature of data and the number of observations considered. For the former case, the most common approach in economics is the *maximal overlap discrete wavelet transform* (MODWT), while for the latter we refer to the *continuous wavelet transform* (CWT) and its analytical extensions such as wavelet coherence, phase-difference angles and continuous wavelet gains.

It is worth to shortly describe discrete wavelet applications. The discrete approach for Wavelet analysis finds its roots into the multi-resolution analysis (MRA), a practical way to observe both time and frequency scaling at several resolutions. A graphical example of this kind of partition is provided in figure 2.1. Wavelet analysis produces a multi-resolution decomposition of data, which allows to separate components from aggregate series; this is crucial especially for economic variables, which tend to be at low frequencies and resulting

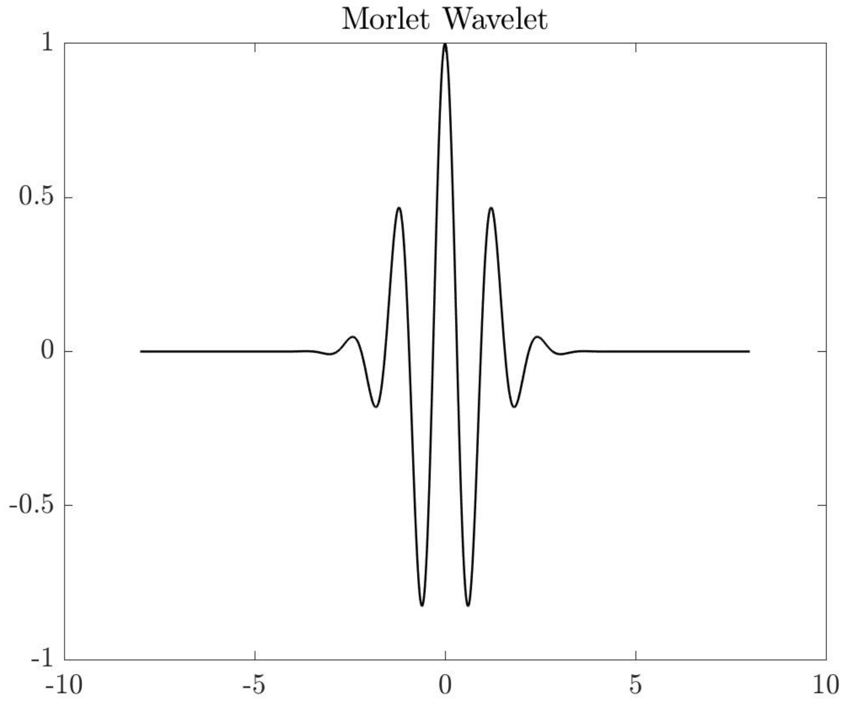

Figure 2.2.: An example of *mother* Morlet wavelet.

from the aggregation of several other series. Although MODWT may be considered an important pioneering tool for economics (Gallegati and Semmler, 2014), in this chapter we will only consider results obtained through the continuous approach.

2.2.1. Continuous wavelet transform

The *continuous wavelet transform* (CWT) helps the researcher to picture a function of time (typically a time series) into a function of two variables (time and frequency scales). The main apparatus requires the existence of a *mother* wavelet $\psi(t) \in \mathcal{L}^2(\mathbb{R})$, where $\mathcal{L}^2(\mathbb{R})$ is the set of square integrable functions,[7] which must satisfy

[7] Which is referred as the space of finite energy functions, see Aguiar-Conraria and Soares (2014).

the admissibility condition

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|}{|\omega|} d\omega \tag{2.1}$$
$$0 < C_\psi < \infty,$$

where $|\Psi(\omega)|$ is the Fourier transform and ω is the angular reference. Once these conditions are met, the subset of *wavelet daughters* is

$$W_{x,\psi}(\tau, s) = \int_{-\infty}^{+\infty} x_t(|\boldsymbol{s}|)^{-\frac{1}{2}} \psi^* \left[\frac{t-\tau}{s}\right] dt, \tag{2.2}$$

which results from a scaled/translated mother wavelet $\psi(t)$, x_t is the time series of interest, τ represents the position in time domain and $\boldsymbol{s}$ is the *frequency scaling parameter*. The asterisk (*) denotes a complex coniugate. Then, the *local* wavelet power spectrum $(WPS)_{x,\tau,\boldsymbol{s}}$ is defined as

$$(WPS)_{x,\tau,\boldsymbol{s}} = |W_{x,\psi}(\tau, s)|^2. \tag{2.3}$$

The complex wavelet coherence $\varrho_{x,y}$ between two series x_t and y_t is

$$\varrho_{x,y} = \frac{S(W_{x,y})}{[S(|W_x|^2)S(|W_y|^2)]^{\frac{1}{2}}}, \tag{2.4}$$

whose absolute value leads to the following definition of $R_{x,y}$,

$$R_{x,y} = \frac{|S(W_{x,y})|}{[S(|W_x|^2)S(|W_y|^2)]^{\frac{1}{2}}}, \tag{2.5}$$

with $0 \leq R_{x,y}(\tau, s) \leq 1$, where the smoothing operator S scales the complex wavelet coherence in both time and frequency domains. The phase lead of x_t over y_t is the *phase-difference angle* $\phi_{x,y}$, i.e the ratio between, respectively, the imaginary and the real parts of

Interval	Description
$\phi_{x,y} = 0$	x_t and y_t move together
$\phi_{x,y} \in \left[\frac{\pi}{2}, \pi\right]$	Out-of-phase, y_t is leading
$\phi_{x,y} \in \left[0, \frac{\pi}{2}\right]$	In-phase, x_t is leading
$\phi_{x,y} \in \left[-\frac{\pi}{2}, 0\right]$	In-phase, y_t is leading
$\phi_{x,y} \in \left[-\pi, -\frac{\pi}{2}\right]$	Out-of-phase, x_t is leading

Table 2.1.: Interpretation of phase-differences' angles $\phi_{x,y}$.
Source: (Aguiar-Conraria and Soares, 2014, p. 356).

the smoothed daughter wavelet:

$$\phi_{x,y} = \arctan\left[\frac{\Im(S(W_{x,y}))}{\Re(S(W_{x,y}))}\right] \tag{2.6}$$

$$= \phi_x - \phi_y. \tag{2.7}$$

Equation (2.7) clarifies why this is computed as a difference between two "converted" angles $\phi_{x,y} \in [-\pi, \pi]$. Such angles are used to interpret the lag-lead relationships between series x_t and y_t; all cases are described in detail in table 2.1. Several frequency bands can be chosen and implemented for phase-differences' analysis; from hereon they will be divided in short, medium and total cycles, as previously described at the beginning of section 2.2. Furthermore, we are interested in co-movements of these correlations (that is, we always consider two variables or more), then we omit single phases for each series, avoiding the presence of confusing graphs and misleading data.

These concepts can be similarly extended to the study of partial correlations for multiple time series. This is done with the introduction of *partial wavelet coherence* $\boldsymbol{\varrho_{1j,q}}$, where 1 recalls the first variable and $2 \leq j \leq q$ are the auxiliary controlling variables. Partial wavelet coherence allows us to investigate the partial correlation between two variables x_t and y_t *after controlling* for the effect of a third series z_t. That is, after estimating the wavelet coherence between x_t and y_t, if we notice that it exhibits remarkable reductions in high-powered areas, then the lowering of the former interdependence may be attributed to z_t. In our case we will consider the three-variable formulation.

Equation (2.8) computes the partial coherence $\varrho_{xy,z}$,

$$\varrho_{xy,z} = \frac{\varrho_{xy} - \varrho_{xz}\varrho^*_{yz}}{[(1 - R^2_{xz})(1 - R^2_{yz})]}, \tag{2.8}$$

where ϱ_{xy} and ϱ_{xz} are bivariate complex wavelet coherencies, R^2_{xz} and R^2_{yz} are their corresponding squared absolute values. Of course, the same definitions introduced for wavelet coherence and phase-differences are adapted to this case, defining the *partial wavelet coherence* as the absolute value of equation (2.8) and *partial phase-delay (partial phase-difference)*, respectively, as the phase angle of ϱ_{xz}, defined as $\phi_{xy,z}$:

$$r_{xy,z} = |\varrho_{xy,z}|, \tag{2.9}$$

$$\phi_{xy,z} = \arctan\left[\frac{\Im(S(\varrho_{xy,z}))}{\Re(S(\varrho_{xy,z}))}\right]. \tag{2.10}$$

Wavelet coherencies and partial wavelet coherencies are graphically represented as a plot with time on *horizontal* axis and frequency domain on *vertical* axis. Each high-powered zone (that is, where the interdependence between x_t and y_t is significantly high) is coloured in red and contoured by a thick black line, which defines the confidence interval at $\alpha = 0.05$. To compute these confidence intervals, many procedures are available;[8] in this case, they are computed through a large number of Monte Carlo simulations.[9]

Another measure which has been recently included in this body

[8]See Aguiar-Conraria and Soares (2014), section 5.

[9]Aguiar-Conraria et al. (2018a) consider $n_{sur} = 5000$ a *reasonably large* number of replications.

of analysis is the *wavelet gain coefficient*. Introduced by Aguiar-Conraria et al. (2018a) and Aguiar-Conraria et al. (2018b), the simple bivariate formulation allows to compute a dynamic regression coefficient of one series into another, evaluating it at different frequency bands.

The complex wavelet gain of y over x is defined as

$$\mathcal{G}_{yx} = \frac{S_{yx}}{S_{xx}} = \varrho_{yx} \cdot \frac{\sigma_y}{\sigma_x}, \tag{2.11}$$

whose real counterpart is the wavelet gain $G_{yx} = |\mathcal{G}_{yx}|$. Extending this formulation to the partial framework, where a third series z_t is included into the regression, the *partial wavelet gain* is

$$\mathcal{G}_{yx,z} = \frac{\varrho_{yx} - \varrho_{yz}\varrho^*_{xz}}{1 - R^2_{xz}} \cdot \frac{\sigma_y}{\sigma_x}, \tag{2.12}$$

where, again, the absolute value $G_{yx,z} = |\mathcal{G}_{yx,z}|$ is considered. In this case, the dynamic coefficients regard the effects of a regression of variable y on both x and z series.

2.2.2. An application to macroeconomic data

We estimate the Discrete Fourier transform and the Wavelet power spectrum using quarterly series for the U.S; data includes (*i*) real GDP, (*ii*) the amount of mortgages borrowed by families to buy residential properties, and finally (*iii*) the average sales price of houses. All series are expressed in quarterly growth rates. For a further description of data sources, see appendix A.

The advantage we can exploit here is that, using house price series in US dollars, the transformation in growth rate is quite straightforward.[10] Therefore, these key variables will be used to detect any linkage in time and frequency with the business cycle together

[10] While this cannot be said for any *index* series, for example the most available property price index for the US. To manipulate this series a filter in necessary, but the transformation in growth rate cannot be economically justified.

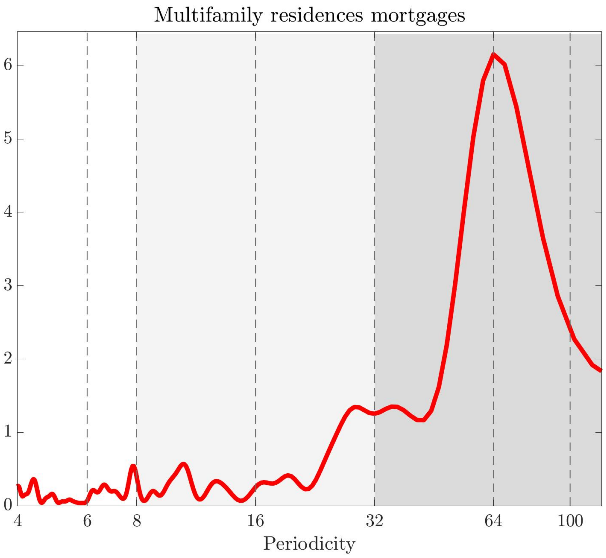

Figure 2.3.: Discrete Fourier transform, Multifamily Residences Mortgages

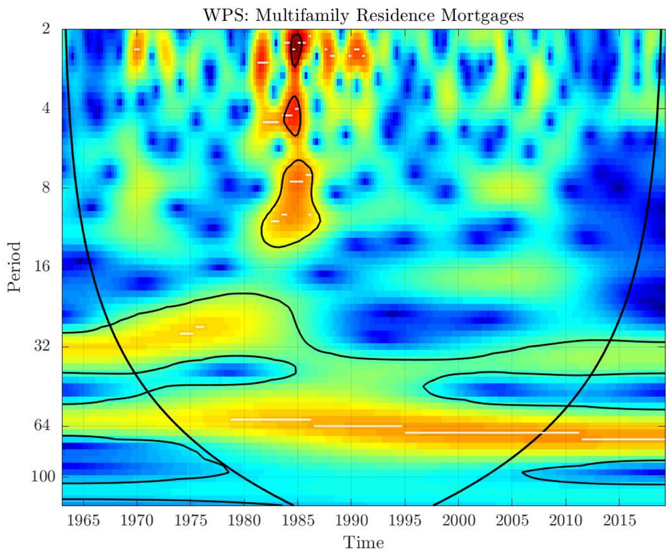

Figure 2.4.: Wavelet power spectrum, Multifamily Residence Mortgages

with other financial variables; the whole multivariate analysis is contained in section 2.3.

Discrete Fourier transform vs Wavelet power spectrum

To properly focus on predominant frequencies of a given series, we typically rely on its *spectral density*, to check whether it exhibits substantial peaks in its spectral representation *at* a certain frequency, suggesting the presence of a cycle at that specific periodicity.

In order to do this, it is required that series do not exhibit any trend component, then it is necessary for them to be stationary or near-stationary. This is done, as previously said, transforming our variables into quarterly percentage growth rates,[11] then the spectral density is computed using a non parametric power spectral representation, i.e. the discrete Fourier transform of the series. The periodicity axis in figures 2.3 and 2.5 is reversed, reflecting the convention of wavelet methods. Therefore, these preliminary results are compared with the Wavelet Power Spectrum, which gives us the advantage to extend the same frequency analysis in time.

Figure 2.3 depicts the spectral density of real multifamily residences mortgages growth rate for the US. The light grey area in the middle represents the interval for business cycle's frequencies (8-32 quarters), while the darker grey area on the right presents the *medium-term frequency domain*, which extends from 32 quarters up to 120, reflecting what has been postulated by Comin and Gertler (2006), Drehmann et al. (2012) and others.[12] Then, figure 2.4 helps us in graphically detecting the cycle and locating it in time through wavelet power spectrum estimation.

It is clear that once we detect a peak in its power spectrum at a

[11] That is, the log-difference multiplied by 100 is computed for each variable.

[12] It is safe to assume that *medium-term* frequencies exceed 32 quarters, up to an ideal limit of 100 quarters. Several literature contributions do not agree with the upper bound of the interval, therefore its specification is not unique.

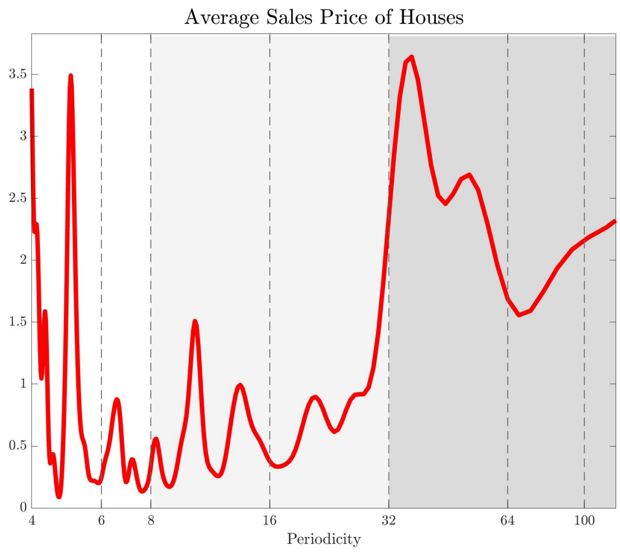

Figure 2.5.: Discrete Fourier transform, Average sales price of Houses

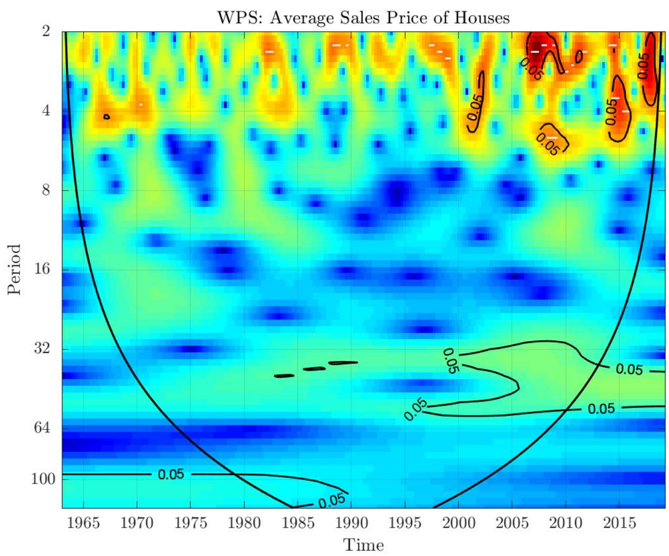

Figure 2.6.: Wavelet power spectrum, Average sales price of Houses

certain frequency, then it is a strong suggestion that a cycle appears at that given frequency. Here, a peak at 64 quarters frequency is clearly spotted, which is confirmed by the high-powered red zone plotted in the wavelet power spectrum; moreover, figure 2.4 provides additional information, allowing us to locate this cycle in time between early '70s and the end of the sample. Together with this *lower frequency cycle*, several other significant regions at high frequencies may be noticed in figure 2.4, which are hardly traceable in the former Fourier processed series.

This is even more visible if we consider a second key variable, which is the *average sales price of houses* for the US. Figure 2.5 presents a typical high-frequency spectrum with peaks at, approximately, 5, 10 and 32 quarters. However, the wavelet power spectrum in figure 2.6 exposes additional results; it depicts few high-frequency significant regions, which extend from early '00s for at least 15 years, *and* an extended cycle which lasts from 1975 to 2019 with frequency above 32 quarters, *plus* a nearly contemporaneous cycle between 1975 and 1995, whose frequency is above 64 quarters.

Such a preliminary comparison exploited one major improvement, which is the location in time of frequency-based informations which traditional spectral analysis tools could not highlight, if not partially.

2.3. Business and financial cycles' applications

The following section employs the entire set of methodologies explained in section 2.2 to analyse macroeconomic data. This specifically examines real GDP, multifamily residences mortgages and the average sales price of houses for the U.S.[13] to compute spectral correlations, phase difference angles and lag-lead relationships, also including dynamic regression coefficients such as wavelet gains.

[13] See appendix A for a review of variables' sources.

The basic setup considers the interconnection between a real variable (i.e. real GDP) and a financial series. Aggregate financial variables have been chosen as proxies for both the financial and the housing cycles: these will be used to check whether financial aggregates do produce any impact on real GDP in several frequency bands, particularly in both *short* and *medium-run*.

The procedure follows four steps: (i) detection of significant high-power zones, bordering the resulting correlation in time and frequency with confidence intervals; (ii) phase-differences analysis, to detect lag-lead relationships. This is a rough but straightforward method to detect whether these variables had a role in determining a strong correlation (*in* or *out* of phase) between the growth rate of output and financial aggregates or not; (iii) computation of wavelet gains and partial wavelet gains, in order to evaluate the impact of one variable to another according to the value of a frequency-based regression coefficient; (iv) comparison with the results obtained through *partial* coherence, where the financial variable of interest, again, is used as a *controlling variable* for the coherence between GDP and house prices. As it will be explained in next sections, results produce support to existing stylised facts for both financial and housing cyclical phenomena, developing a detailed dissection of their interconnection.

2.3.1. Wavelet Coherence results

Graphical results are organised as follows: for each figure, plot (i) depicts the Wavelet Coherence between GDP and, respectively, mortgages and house prices. Coherencies' frequency interval (in $y-$axis) extends from 2 to 120 quarters, while the time span ($x-$axis) ranges from 1963:Q1 to 2019:Q4. Subplot (ii) includes various phase-difference angles at, respectively, $(6, 32)$, $(6, 100)$ and $(32, 100)$ intervals, listed in legend for each figure. This is done in order to curb three cyclical components, ideally coinciding with a business cycle frequency range, a *total cycle* and a medium term component,

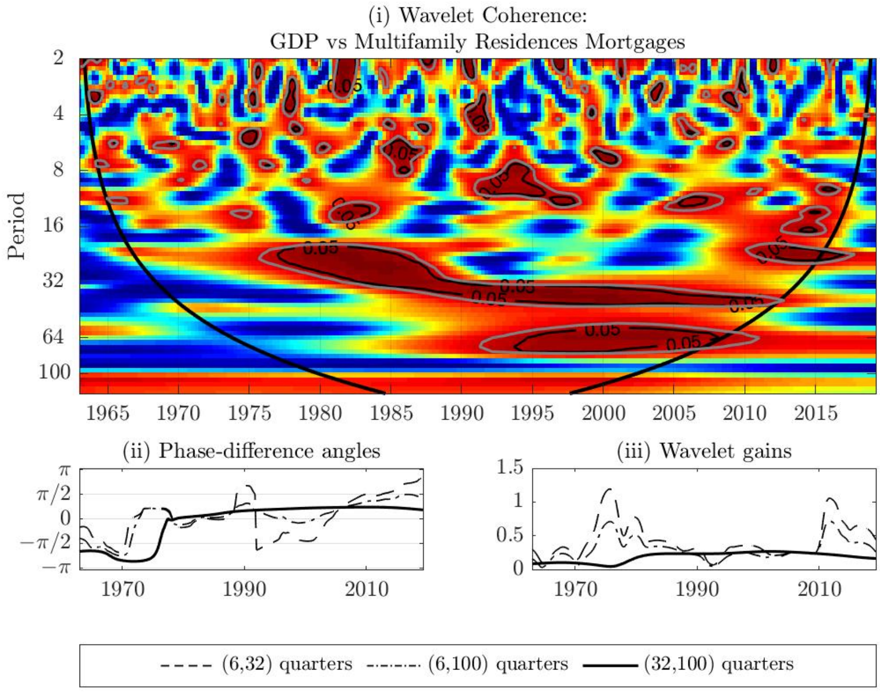

Figure 2.7.: Wavelet Coherence between real GDP and Multifamily Residences Mortgages. Wavelet gain coefficients $\boldsymbol{\beta}_i$ are obtained from $y_t = \alpha + \boldsymbol{\beta}_t m_t + \epsilon_t$ dynamic regression.

respectively. Last subplot (*iii*) illustrates wavelet gains according to the same frequency intervals applied for phase-differences. This setup will also be used for Partial Wavelet coherence, partial phase-angles and partial wavelet gains, collected in section 2.3.2.

Figure 2.7 shows the wavelet coherence between real GDP and multifamily residences mortgages. High powered zones mostly concentrate into the 6-32 quarters frequency interval, with a remarkable cycle between 16 and 32 quarters from late '70s to, approximately, 2012. A medium-frequency cycle takes place from 1994 to 2008, with frequency above 64 quarters. The presence of strong correlation above 64 quarters suggests that, during the last three decades, real GDP and mortgages shared medium-term fluctua-

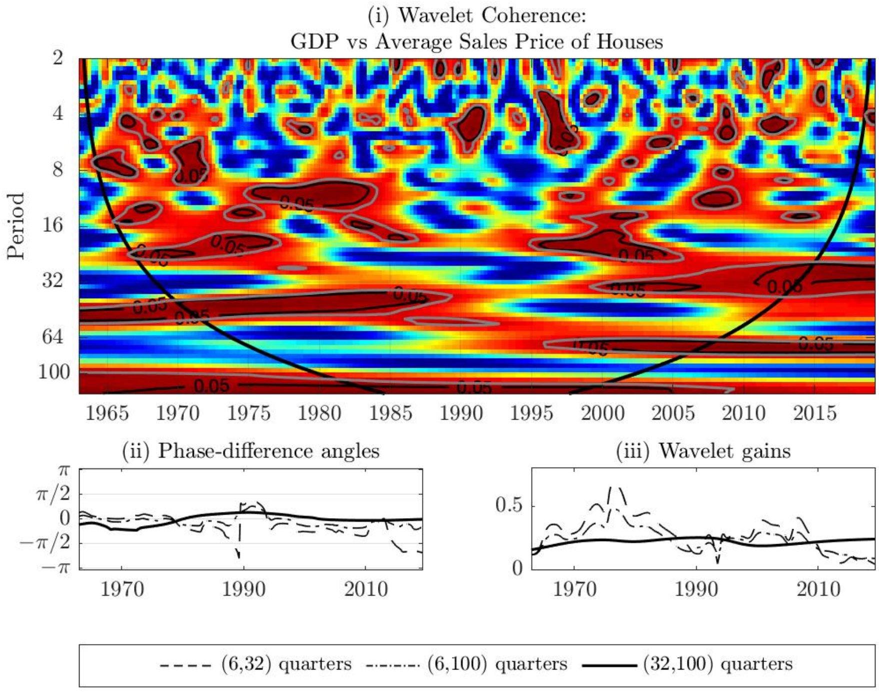

Figure 2.8.: Wavelet Coherence between real GDP and Average Sales Price of Houses. Wavelet gain coefficients $\boldsymbol{\gamma}_i$ are obtained from the $y_t = \alpha + \boldsymbol{\gamma} h_t + \epsilon_t$ dynamic regression.

tions.

Short-term phase difference exhibits pronounced peaks and troughs, avoiding a clear interpretation of the lag-lead relationship. Conversely, the medium-term phase difference is more stable, with GDP leading mortgages quantities in-phase (positive correlation) from half of the '70s onwards. It is very important to remark the fact that phase-difference angles should be considered only related to highly-significant power zones identified by the wavelet coherence.

Wavelet gains may be considered as a measure of impact which one variable has to another, exploiting once again the advantage of frequency fractioning.[14] It is noteworthy that the maximum

[14] Aguiar-Conraria et al. (2018a).

level of the coefficient is reached during half of '70s at business cycle's frequencies, while for the medium-run interval its relative maximum value coincides in time with the significant power zone above 64 quarters. Coefficients tend to stabilize in value at each frequency interval during the half '90s - 2010 period. This suggests the presence of dynamic correlation between real GDP and mortgages, which is also marginally driven by frequencies above the business cycle.

Our next analysis considers the relationship between business cycle and housing sector, providing additional evidence of their joint spectral dependency. Figure 2.8 reproduce the wavelet coherence between GDP and the *average sales price of houses*. High powered regions are even thinner and allocated at high-frequencies, although a clear cycle between 32 and 64 quarters is bounded from 1963 to late '80s. Hence, from 1995 several significant coherencies highlight a more persistent medium-term cycle.

From 1963 for at least twenty years (coinciding with the high-powered correlation area), the medium term phase difference angle lies in $[-\pi/2, 0]$ interval. House prices, then, lead real GDP at medium-run frequencies, with positive correlation sign (in-phase) in two different medium-term significant cycles.

Wavelet gain coefficients exhibit a similar pattern to those in figure 2.7. The most stable value is reached by the $(32, 100)$ frequency coefficient, and it is near the total cycle coefficient during the high significant cycles in figure 2.8-(i). Peaks in short-term wavelet gains coincide with the high-frequency cycles in the entire sample, distinctively plotted in same figure.

Our results confirm stylised facts about financial and housing cycle dynamics. The existence of cycles which extend up to a *medium-term* range[15] is confirmed by spectral analysis; it is also worth to mention that the housing cycle significantly leads real GDP in two medium-term cycles, a result also visible in other frequency bands.

[15]Drehmann et al. (2012), Borio (2014), Benk et al. (2016), Comin et al. (2014), Stockhammer et al. (2019).

This is also consistent with empirical findings from Igan et al. (2011) and Leamer (2015).

2.3.2. Partial Wavelet Coherence results

It is clear that real GDP is strongly related to mortgages and house prices at several periodicities. Our specific aim, again, is to focus on periodicities above 32 quarters, i.e representing our *medium-term* cycle interval for both financial variables. In out three variable study, it is of solid interest to inspect the spectral dynamics already computed *after* the interdependence of a specific financial sector is removed. Once the coherence between variables x_t and y_t is computed, then, if we cut off the interdependence between x_t and z_t the resulting coherence will detect whether significant correlations are currently existing or not. Partial correlations are deeply related to the elimination of other effects, bringing them again to a bivariate approach. Instruments listed in equations (2.8)-(2.12) are computed below; the graphical setup is identical to what already used for wavelet coherences in figures 2.7 and 2.8.

Previous results underlined the presence of medium-term correlations between all variables, as a common feature in different time intervals, extending above the 32 quarters frequency. Now, the analysis proceeds with a similar setup, in which the main real and financial variables are, respectively, real GDP and mortgages, whose coherence is *controlled for* the second financial variable, i.e. the house prices series. Once the spectral partial correlation between real GDP and house prices is computed, then it is cancelled to check what are the remaining dynamic relationships. To make it more clear, if we choose to *clean up* the spectral effects of mortgages (whose medium-term correlation has been already spotted in previous figures), then we would expect to visualize a huge reduction of highly significant frequencies above the business cycle.

Figure 2.9 depicts the partial wavelet coherence between real GDP and multifamily residence mortgages, after the effect of house

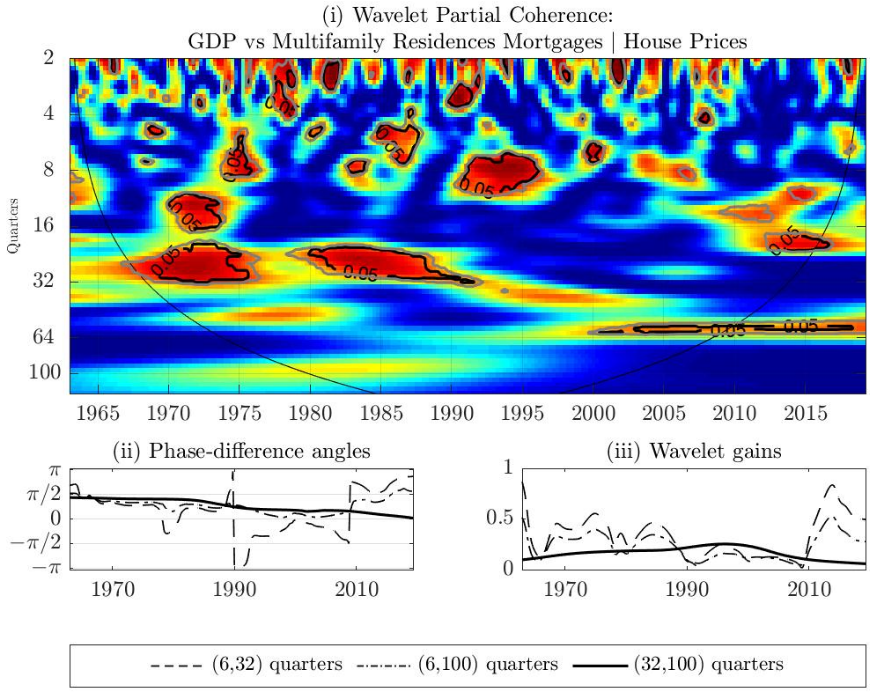

Figure 2.9.: Partial Wavelet Coherence between real GDP and Multifamily Residence Mortgages, after controlling for Average Sales Price of Houses. Partial wavelet gain coefficients $\boldsymbol{\beta}_i$ are obtained from the $y_t = \alpha + \boldsymbol{\beta} m_t + \gamma h_t + \epsilon_t$ dynamic regression.

prices has been cleaned out from the coherence. It is notable that highly significant correlations have reduced in number, presenting few significant cycles around 32 quarters before the 00s. A thin cycle at 64 quarters begins with the new century, signalling a *common* dynamic correlation. Other clear-cut cycles fall into the business cycle frequency interval, plus a portion of very-short term cycles between (2,8) quarters interval. A significant medium term cycle is spotted in common with the two previously computed coherences. Business and mortgages cycles share some recent co-movement, which turns out to be in-phase with business cycle leading mort-

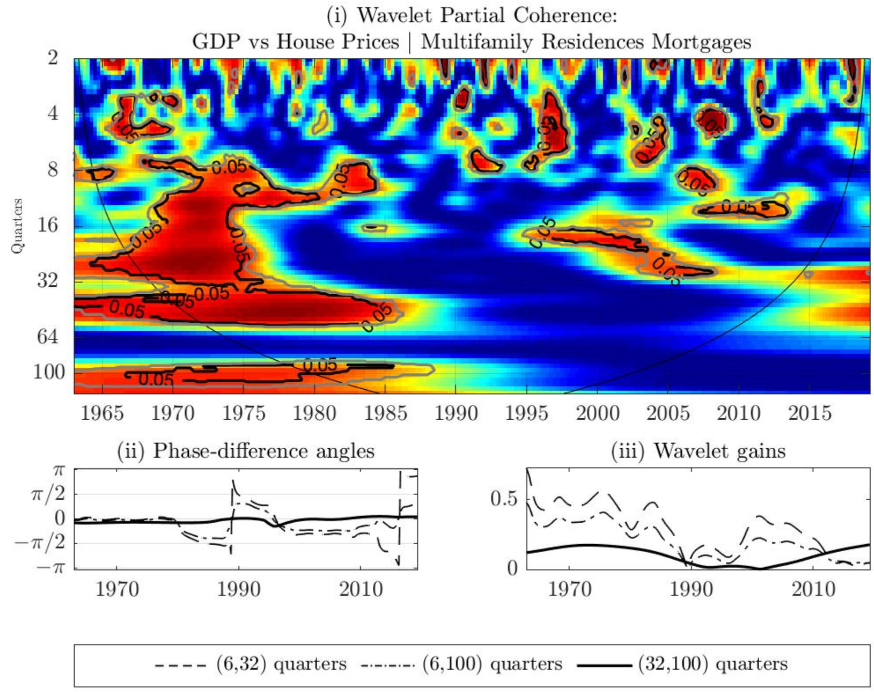

Figure 2.10.: Partial Wavelet Coherence between real GDP and Average Sales Price of Houses, after controlling for Multifamily Residence Mortgages. Partial wavelet gain coefficients $\boldsymbol{\gamma}_i$ are obtained from the $y_t = \alpha + \beta m_t + \boldsymbol{\gamma} h_t + \epsilon_t$ dynamic regression.

gages. The medium-term gain coefficients β_i indicate a decline from the '00s, reflecting the fact that several high-powered zones have been "cleaned out" by the effect of house prices. However, the presence of medium-term correlations independently from the influence of house prices is still clear. House prices, then, count as a medium run component of business and financial cycles.

Figure 2.10 presents the correlation between real GDP and house prices, once the influence of multifamily mortgages is removed. As previously done, "cleaned-out" cycles are examined: it is notable that, once we clean out the effect of mortgages, the recent medium-term correlations are not visible anymore. Nonetheless, a huge portion of significant correlations between 8 and, approximately, 40 quarters is still present, from the beginning of sample up to 1985. The frequency-based regression provide a medium-term value for γ which increases in early '00s, while the phase-difference causality angle suggests that, during the significant high-powered zones, house prices positively lead real GDP, even after the "cleaning" of the third financial variable, a result which is consistent with what previously found in figure 2.8. From the '90s onwards, the significant regions lie in the $(2, 32)$ quarters interval, suggesting that correlations between real GDP and house prices are predominantly in the short-term.

2.4. Concluding remarks

As a comprehensive time-frequency study for real and financial aggregates, collected results are quite encouraging. The extension from traditional spectral analysis to a more detailed inclusion of frequency bands and time domain greatly augmented the amount of information obtained.

We have empirical evidence that mortgages do play a role in determining business cycle correlations and co-movements, especially at frequencies above the usual business cycle convention. Starting from Fourier spectral decomposition, the main (although insufficient) results provided a good hint in determining what the most relevant characteristics of data are, to preliminarily confirm what the initial literature stated during last years of research. Medium term spectral peaks are clearly spotted in financial variables, and this is still present in more advanced spectral analyses.

Then, Wavelet coherence investigated the dynamic correlations between mortgages, house prices and real GDP; again, the "financial influence" is still present as we study real activity cross-correlations with both variables, a confirmation of what declared by Avouyi-Dovi and Matheron (2003), Nolan and Thoenissen (2009), Chen et al. (2012), Rünstler et al. (2018), Rünstler and Vlekke (2018), Fehrle (2019), Stockhammer et al. (2019) and others. Interconnections between financial sectors are still present and tend to increase in time.

Moreover, what emerges is the increasing presence of "medium-run" influences in real and financial cycles (Comin and Gertler, 2006; Drehmann et al., 2012; Borio, 2014). Finally, some advances in analysing housing cycles have been proposed, as results suggest that predictability relationship between real GDP and house prices is reversed in the medium-run. Some suggestions for monetary policy are proposed, then, as the financial stability purpose should also precisely target credit cycle phases (Badarau and Popescu, 2014) and housing markets (Bezemer and Zhang, 2014), to detect whether credit booms may trigger house price expansions and, lately, slow recoveries from recessions.

Chapter 3.

Medium-term financial and house price shocks

What are the cyclical effects on business cycle?

Abstract

Following the literature on financial cycles, the paper identifies business and financial shocks, which allow the propagation of cyclical changes in the economy. I identify real, mortgages and house price shocks in a structural VAR framework with sign restrictions, where shocks are assumed to have specific duration. Financial effects on the real side of the economy are present and do matter especially for business cycles' recessions. Results provide additional evidence on cyclical implications for both sectors, with empirical confirmation of house prices and mortgages determining business cycle variations in the medium run.

Introduction

The last decades of empirical economic research have experienced a massive usage of vector autoregressive models (VARs). After establishing the seminal roots for this econometric tool,[1] Sims et al. (1986) questioned whether the *residual* part of a model may be used to interpret an *independent stochastic contribution*, whose effect may produce significant consequences into the model.

The perception of an unpredictable exogenous change directly led to the evolution of the basic VAR tool, resulting into the introduction of *structural identification of shocks* in time series econometric modelling. Economic interpretation of shocks directly follows, quantifying their importance and contribution to the reduced-form errors of VAR model. However, shock identification is a challenging procedure, as methodologies' availability largely increased and

[1] Sims (1980).

modern literature further developed the main tools to identify certain phenomena of interest.

A huge amount of work employed monetary VARs, as in Gerlach and Smets (1995), Evans et al. (1998), Christiano et al. (1999), Canova and De Nicolo (2002), Van Aarle et al. (2003) and Dungey and Fry (2009). A former review of research improvements for this specific topic has been provided by Bagliano and Favero (1998).

The main idea was to add *zero (exclusion) restrictions* on structural shocks, according to different periods of influence,lately shifting attention to their domain. It became very popular, then, to set *sign restrictions* to check whether a certain sign for a particular impulse response may fit the model. This helps using them as flexible restrictions, rather than excluding the existence of such an effect.

The idea of employing the information contained into "signs" of significant statistical quantities firstly came from Faust (1998), Canova and De Nicolo (2002) and Uhlig (2005), rapidly becoming a popular approach to provide *set-identification schemes* in empirical models. The sign of the structural coefficients or, preferably, the shape of structural impulse response functions, is set up according to intrinsic economic information about their domain. Early contributions for this identification technique may be found in Paustian (2007), Kilian and Murphy (2012), Baumeister and Hamilton (2015) and Baumeister and Hamilton (2020), among others. This flexible methodology will therefore apply prior information given by economic theory and empirical results (Uhlig, 2005; Fry and Pagan, 2011; Baumeister and Hamilton, 2015; Kilian and Lütkepohl, 2017) to shocks' specification. The set of information used will be explained in next sections.

Review of financial shocks literature

As a first step, it is useful to illustrate major contributions which defined a proper definition of shock arising from financial sectors. Stock and Watson (2012) argue that most of output decline after

2008 financial crisis are estimated to come from financial shocks. Financial market disruptions emerge from a non-standard expansion of monetary and credit aggregates, exhibiting prolonged expansionary features which play a role in both crisis and normal conditions (Fornari and Stracca, 2013; Merola, 2015). The question is whether the nexus between expansionary and output collapse during the crisis in the U.S. can be originated by a single shock, adapting empirical findings to future research challenges.

Banking system actively determines the transmission of such *financial shocks* (Alpanda and Aysun, 2014; Iacoviello and Neri, 2010; Iacoviello, 2015; Altinoglu, 2021) and tends to amplify the effects on output, also due to the atypical nature of mortgaging contracts. This has been proven to set up the 2008 crisis, making the recessionary phase more persistent (Forlati and Lambertini, 2011; Laeven and Valencia, 2018). Brunnermeier et al. (2021) examine the capability of a credit expansion to trigger strong real effects in the economy, providing useful *warnings* for output contractions.

Numerous theoretical models stylised applications for financial shocks. Starting from the financial accelerator setup by Bernanke et al. (1999), many DSGE models attempted to explain transmission mechanisms through financial and real sectors. Miao et al. (2012) link stock bubbles to endogenous credit channels, while counter-cyclical repercussions on real business cycles have been examined by Furlanetto et al. (2019), also including a similar identification for house prices. Results from both theoretical and empirical models show that a significant portion of business cycle fluctuations is driven by financial shocks (Castelnuovo and Nistico, 2010; Christiano et al., 2014; Chen and Svirydzenka, 2017; Fève et al., 2019). These also account for a large portion of output and investment declines, once financial disruptions take place in the economy (Gilchrist and Zakrajšek, 2012; Ludvigson Sydney et al., 2018; Kátay et al., 2020).

Understanding the nature of these shocks requires a lot more efforts in research. The main contribution of this paper, then, is the identification of "financially driven shocks" which plausibly contribute to the origin of aggregate macroeconomic fluctuations into the economy. Similarly to Brunnermeier et al. (2021), identification deeply relies on recovering the effects of credit expansions and disturbances in financial markets. Shock identification is explained in the next section, also underlying the link between shocks' impact and cyclical fluctuations.

Identification of financial shocks

Up to this point in time, the revision of most frequently identified shocks did not contemplate perturbations arising from financial markets which could originate cyclical responses in macroeconomic variables. As these sources of fluctuations have been typically tied to financial crises, these are usually considered as "non-standard" shocks whose impact still needs to be quantified (Meeks, 2012). Both empirical and theoretical literature spent last recent years investigating the role of financial aggregates in propagating backlashes into the business cycle,[2] analysing causality relationships, or classifying recurrent properties of phenomena such financial cycles[3] and housing cycles.[4]

This chapter employs a small-scale structural VAR identified with sign restrictions, to identify a commonly known productivity (i.e. technology) shock and, additionally, a *financial shock* and a *housing shock*. Specifications of structural perturbations coming from financial factors have been produced so far, mainly regarding the source of credit supply shock in a manner of financial deregulation, as in Favara and Imbs (2015).

The link between credit expansion and the reaction of house

[2] Leamer (2015), Mian et al. (2017), Oman et al. (2019), Queralto (2020), are recent contributions to this field.

[3] Avouyi-Dovi and Matheron (2003), Drehmann et al. (2012), Claessens et al. (2011), Borio (2014), Stremmel (2015) and Aldasoro et al. (2020b) recently established this field.

[4] As documented by Igan et al. (2009), Rünstler et al. (2016), Jordà et al. (2015), Leamer (2015), Agnello et al. (2019).

prices is economically essential, being a potential candidate to explain the likelihood of financial crises (Davis and Heathcote, 2005; Woodford, 2010; Anundsen et al., 2016), although their joint identification could lead to *multiple shocks problem* (Fry and Pagan, 2011) and issues in interpreting structural results (Baumeister and Hamilton, 2020). The imposition of sign restrictions on impact has been chosen as a primary approach to identify multiple financial shocks, as in (Fornari and Stracca, 2012; Furlanetto et al., 2019).

This is done to find empirical evidence of *financially driven* business cycles and to recover a confirmation of the existence of prolonged business cycle's fluctuation. Beaudry (2005), Comin and Gertler (2006) and Drehmann et al. (2012) established the presence of significant medium-term real activity fluctuations. Stockhammer et al. (2019) identify endogenous financial-real interactions, especially at medium run frequencies,[5] which naturally consolidate with credit cycle definition (Aikman et al., 2014) and financial cycle theories (Drehmann et al., 2012; Borio, 2014; Strohsal et al., 2019).

Two financial variables are used here as representatives of both credit and housing sectors, whose dynamics are assumed to directly affect real GDP growth rate. To our knowledge, such a simplified financial identification scheme has not been proposed yet. A similar approach has been followed by Bergholt et al. (2022), where medium-run effects on labor share are inspected. Medium-run horizons are here examined by extending the number of restricted quarters in impulse responses, following advances from both theoretical models (Yépez, 2018; Iacoviello and Neri, 2010; Forlati and Lambertini, 2011; Lambertini et al., 2017) and empirical macroeconomic findings.

The chapter is organised as follows. Section 3.1 introduces the methodology of sign-identified structural VAR models. Data description and the actual set of restrictions are in sections 3.1.1 and 3.1.2, respectively. Main empirical results, consisting in impulse response functions, forecast error variance decompositions and his-

[5]Which expand up to more than 32 quarters (8 years).

torical decompositions are presented in section 3.2. Once these have been commented, section 3.3 concludes.

3.1. Structural VARs with sign restrictions

The econometric framework for a structural VAR is presented here. Consider a simple VAR(p) model as in Kilian and Lütkepohl (2017),

$$y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \boldsymbol{u_t} \tag{3.1}$$

where structural shocks $\boldsymbol{u_t} = \widehat{\mathbf{C}}\varepsilon_t$ are linear combinations of the reduced form shocks ε_t, variance-covariance matrix is $\hat{\Sigma}_\varepsilon = E(\varepsilon_t \varepsilon_t')$ and $\widehat{\mathbf{C}}$ is the triangular Cholesky decomposition of $\hat{\Sigma}_\varepsilon$. It is also assumed that $V(\epsilon_t) = I$ and $V(\boldsymbol{u_t}) = \widehat{\mathbf{C}}\widehat{\mathbf{C}}'$. Estimation of coefficients for $\boldsymbol{\Phi}_i$ and $\hat{\Sigma}_\varepsilon$ matrices in the VAR(p) model is performed via OLS. The VMA representation of (3.1) is

$$\begin{aligned} y_t &= \Theta_0 \mathbf{D}\boldsymbol{u_t} + \Theta_1 \mathbf{D}\boldsymbol{u_{t-1}} + \dots && (3.2) \\ &= M_0 \boldsymbol{u_t} + M_1 \boldsymbol{u_{t-1}} + \dots, && (3.3) \end{aligned}$$

then, $\mathbf{D}$ matrix can be rewritten as

$$\mathbf{D} = \widehat{\mathbf{C}}Q, \tag{3.4}$$

where Q is an orthogonal matrix.[6] To determine "rotation" matrices, the algorithm by Rubio-Ramirez et al. (2010) is applied: it computes a large number of $\mathbf{D}_i$ matrices through QR decomposition,[7] and generates structural impulse responses M_i in equation (3.3), then verifies if the generated IRF satisfies the sign restriction. If all the imposed restrictions are verified, then the *draw* is accepted; otherwise, it is discarded. Once a sufficiently large number of structural models is retained,[8] a set containing k admissible

[6]Which must satisfy $Q'Q = QQ' = I$, Kilian and Lütkepohl (2017).
[7]Kilian and Murphy (2012)
[8]This will be explained in detail in section 3.2.1.

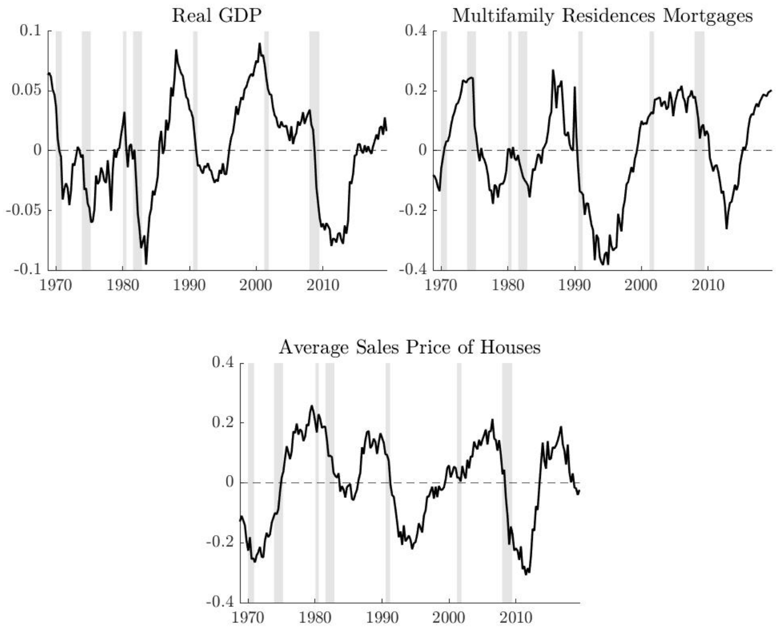

Figure 3.1.: Plot of variables y_t, m_t, p_t. Grey shaded areas depict NBER recession dates

structural impulse responses is obtained. As motivated by Kilian and Lütkepohl (2017), the percentage of all accepted models on the total number of models computed cannot be properly considered as a consistent measure of compatibility of the data with the restrictions applied.

3.1.1. Sign restrictions in practice

The model considers three variables in $\mathbf{Y_t} = \begin{bmatrix} y_t & m_t & p_t \end{bmatrix}'$, where y_t is real GDP, m_t is the amount of mortgages lent to purchase multifamily residences and p_t is the average sales price of houses. A description of series used is provided in appendix A.1. This simplified representation of the economy aims to provide evidence of the dynamics between the increase of property prices, the amount of credit lent to purchase such residences and, finally, their contributions in shaping the business cycle. The choice of variables is consistent with Berger et al. (2020).[9]

All variables are in logs and have been detrended through the Hamilton (2018) 5-year regression filter, as the presence of *medium-term frequencies* is emphasised and properly considered. A similar approach is followed by Huang et al. (2020), where a multiresolution wavelet analysis is used to extract cycle components of variables;[10] the resulting series are plotted in figure 3.1. The structural shock vector $\boldsymbol{u_t} = \begin{bmatrix} g_t & f_t & h_t \end{bmatrix}'$, then, includes a "real activity shock" g_t, a "financial shock" f_t and a "housing channel shock" h_t. Vector autoregressive lags are chosen according to the Bayesian Information Criteria (BIC), which suggests a lag order of $p = 1$.

3.1.2. Shock identification

Set restrictions applied are summarized in table 3.1. Bold signs in parentheses feature the requested set identifications for impulse responses, while the intervals below each sign are the *periods* when restrictions take place. These boundaries are expressed in quarters: as it has been proven by Kilian and Lütkepohl (2017), anytime a quarter is added to restrict the response (according to its sign) it has to be considered a restriction itself. The identification process considers two restrictions alternating in signs, i.e. *cycle restrictions*, and a third positive sign applied to the house prices' response; the idea is to only restrict those responses which are in diagonal, while the remaining responses are left unconstrained.

Anytime we consider the expansionary-contractionary pattern in a "cyclical" framework, we implicitly assume that, at a certain point, the pathway is reversed; when an expansion proceeds into a recessionary direction, according to business cycle research we are able to detect these peculiar points with procedures such as Bry

[9] Who represented the financial cycle as a combination between mortgages and house prices.

[10] These are used to estimate a structural VAR, where credit, housing and monetary shocks are identified.

	Technology shock $\boldsymbol{g_t}$	Financial shock $\boldsymbol{f_t}$	Housing shock $\boldsymbol{h_t}$
Real GDP (y_t)	$\{\underset{(0,18)}{(+)},\ \underset{(28,31)}{(-)}\}$	$\ldots$	$\ldots$
Mortgages (m_t)	$\ldots$	$\{\underset{(0,18)}{(+)},\ \underset{(28,36)}{(-)}\}$	$\ldots$
House prices (p_t)	$\ldots$	$\ldots$	$\underset{(0,18)}{(+)}$

Table 3.1.: Identification through sign restrictions, time intervals in quarters.

and Boschan (1971) turning points' calculation algorithm. Once the duration of these phases is estimated, turning points are only partially implemented in the model as a part of restrictions, as the purpose is to let the model determine what the turning point of restricted structural impulse responses will be.

Then, to properly specify the cyclical properties of filtered real GDP *after* a real activity shock hits, the sign of real activity shock g_t is set to be positive for eighteen quarters, subsequently turning to negative for three additional quarters after a "free" time window of ten quarters. This is imposed to represent what might be the reaction of the real business cycle once its peak is reached; therefore, we might expect this to drive a negative comeback of aggregate economic activity, arising the contractionary phase of the cycle which will last for, at least, three quarters.

The intention is to impose that, after a positive real shock hits the system, it tends to be absorbed in a limited amount of time, subsequently generating a fluctuation of opposite sign. It is possible to inspect recovery dynamics, then, after the shock hits the system. The actual specification leaves the responses for mortgages and house prices unconstrained, so there are not prior assumptions for their reactions to such a shock.

Next variables follow a technically similar setup, although the length of cyclical phases vary in time. It is assumed that mortgages' response to a financial shock would be positive for eighteen quarters, turning up to be negative for eight additional quarters. Again, real and housing responses to financial stimulation are unconstrained, leaving these additional dynamics free to emerge. The "free" time window considered when applying restrictions to real GDP and mortgages count ten quarters in both cases.

Finally, the housing channel shock is assumed to have an expansionary phase lasting for eighteen quarters. This is the only case where the negative sign is not specified, allowing the model to determine the length of subsequent response. The impact on both real GDP and mortgages is also determined by the structural model; transmission mechanisms between housing, mortgaging, and real activity would be determined by impulse responses whose sign has not been previously specified. A good candidate to explain these stylised dynamics can be found in Jordà et al. (2015): an increase in house prices would lead to, respectively, an increase in the value of mortgage's collateral and the aggregate value of real GDP,[11] also involving cyclical adjustments for house prices in the economy.

3.2. Results

Structural impulse response functions are plotted in figure 3.2. For each shock stimulating its variable of interest, the median (solid black curve) and the 68% confidence intervals (dotted black lines) are presented. Although these are considered confidence intervals, Fry and Pagan (2011) point out that these should be properly considered as a *credible set* containing the total amount of impulse responses obtained. Following the usual econometric convention, in forthcoming figures variables are listed in row and structural shocks in column.

Figure 3.3 contains all the accepted impulse responses generated from equation (3.4) through the QR decomposition, correctly identified by sign restrictions; estimation process retained $k = 256$ structural models. The main purpose is to judge whether these

[11] Although not inspecting any other transmission mechanisms, such as Stein (1995)'s "downpayment" theory.

impulse responses (plotted together) may provide some additional information about the overall tendency of *all* accepted models.[12] This may be used as a visual tool to check whether these responses move together or regularly cross themselves at a certain point in time, providing additional graphical results. For explanatory purposes, both results are reported, with forecast horizon set up to 64 quarters (16 years).

3.2.1. Structural impulse response functions

Here, model dynamics are examined through structural impulse response functions. It is worth recalling that, for both technology and financial shocks, a *cyclical restriction* is implemented, while housing shock follows a simple positive stimulation in the structural model, lasting for four years and half. According to the ample dimension of some specific confidence intervals, especially on impact, few responses cannot be interpreted as statistically significant; however, the entire set of responses for housing shock h_t is positive with reducing confidence interval as the forecast horizon increases, a feature which is recurrent for all model's responses. Responses outside the diagonal are free to be entirely determined by the model, as restrictions have not been imposed in these cases.

The cyclical technology shock produces an adverse effect on house prices, lasting for the entire forecast period, and a weak comeback for mortgages turning from negative to positive after, approximately, four years. The former contractionary response has a weaker effect if compared to credit reaction, even though its negative feedback lasts for the entire forecast time span without reaching its steady state level. Median mortgages' response turns out to be near zero value after 16 quarters, reflecting a less delayed reaction to the shock.

[12] The idea emerging from Fry and Pagan (2011), who recommend this "aggregate sight" of multiple models' responses rather than summarizing them into a more synthetic measure.

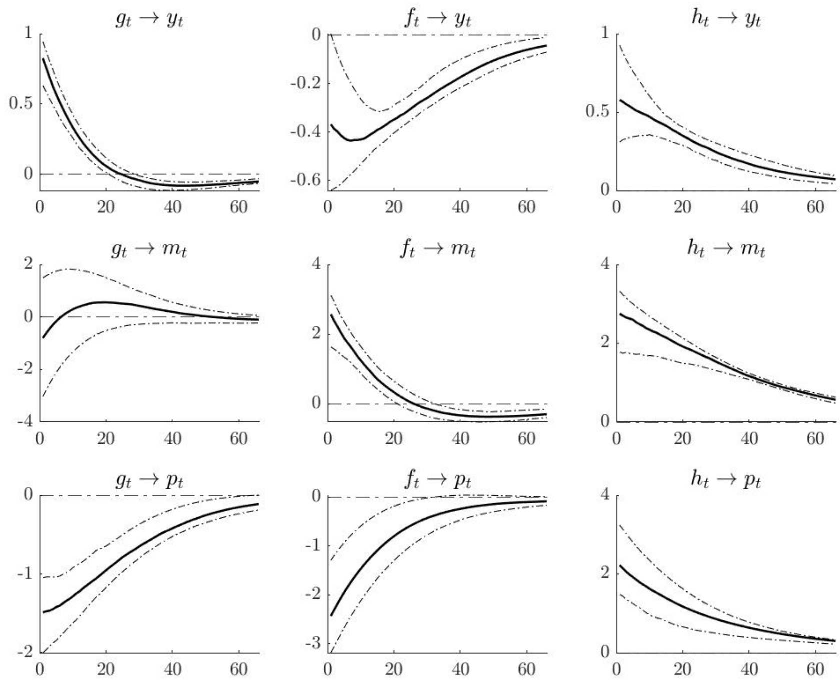

Figure 3.2.: Impulse response functions to a unit structural shock, expressed in percentage points. Solid black curve is the median of all computed IRFs, dotted lines coincide with 68% confidence intervals.

Financial shock responses are provided in second column of figure 3.2. House prices and real GDP exhibit a negative response, generating a long-lasting recovery phase near the zero value.[13] Findings which are partially consistent with Brunnermeier et al. (2021), as low (negative) real GDP growth may be predicted after credit expansions. These will be inspected in more detail with the overall representation of all accepted models below.

After the housing shock hits the system, the three variables feature very similar positive reactions. Real GDP significantly grows

[13]The absence of a complete recovery for real GDP has been reported by Leamer (2015).

by 0.5% and slightly declines to reach zero value after 64 quarters, a pattern strictly followed by mortgages and house prices themselves, whose median responses increase by 2.5% and 3%, respectively.

Once these primary results have been commented, to inspect in greater detail further variations in model responses we rely on several variance dissections for each response and variable, which are likely to generate relative financial backlashes on real activity. An investigation for real GDP contributions in forecasting financial aggregates is also provided, allowing for the presence of different time intervals. Before moving to further results, overall rotated models' results are presented.

Figure 3.3 depicts the impulse response functions *for each accepted structural model.* This aggregate representation has been firstly suggested by Fry and Pagan (2011) as a first "countermeasure" to the representation of *median-targeted*[14] impulse responses; this tends to simplify the inspection of each shock's impact, although losing information about the remaining $k-1$ accepted models. Each set of responses exhibit several leanings for all shock, reflecting different transmissions mechanisms into structural models computed by the "rotation matrices" in equation (3.4). According to Kilian and Lütkepohl (2017), these are *rotated models* whose ability to fit the data is equivalent by construction because these rotations do not depend on data. Therefore, anytime a small fraction of accepted rotated models is obtained, there is no evidence that this may be a result of a poor identification scheme, as it has been previously underlined by the critique of Fry and Pagan (2011).

The interpretation provided in section 3.2.1 is further developed here, as for each "rotated" model their inner dynamics can be inspected in detail. The previously spotted large dimension of confidence intervals is still evident here, although its interpretation is different; if we consider the mortgages' response to a technology shock, it is clear that a portion of rotated model produced a posi-

[14]That is, each response included in figure 3.2 is chosen if it is close to the median. This is also necessary to compute FEVDs and HDs.

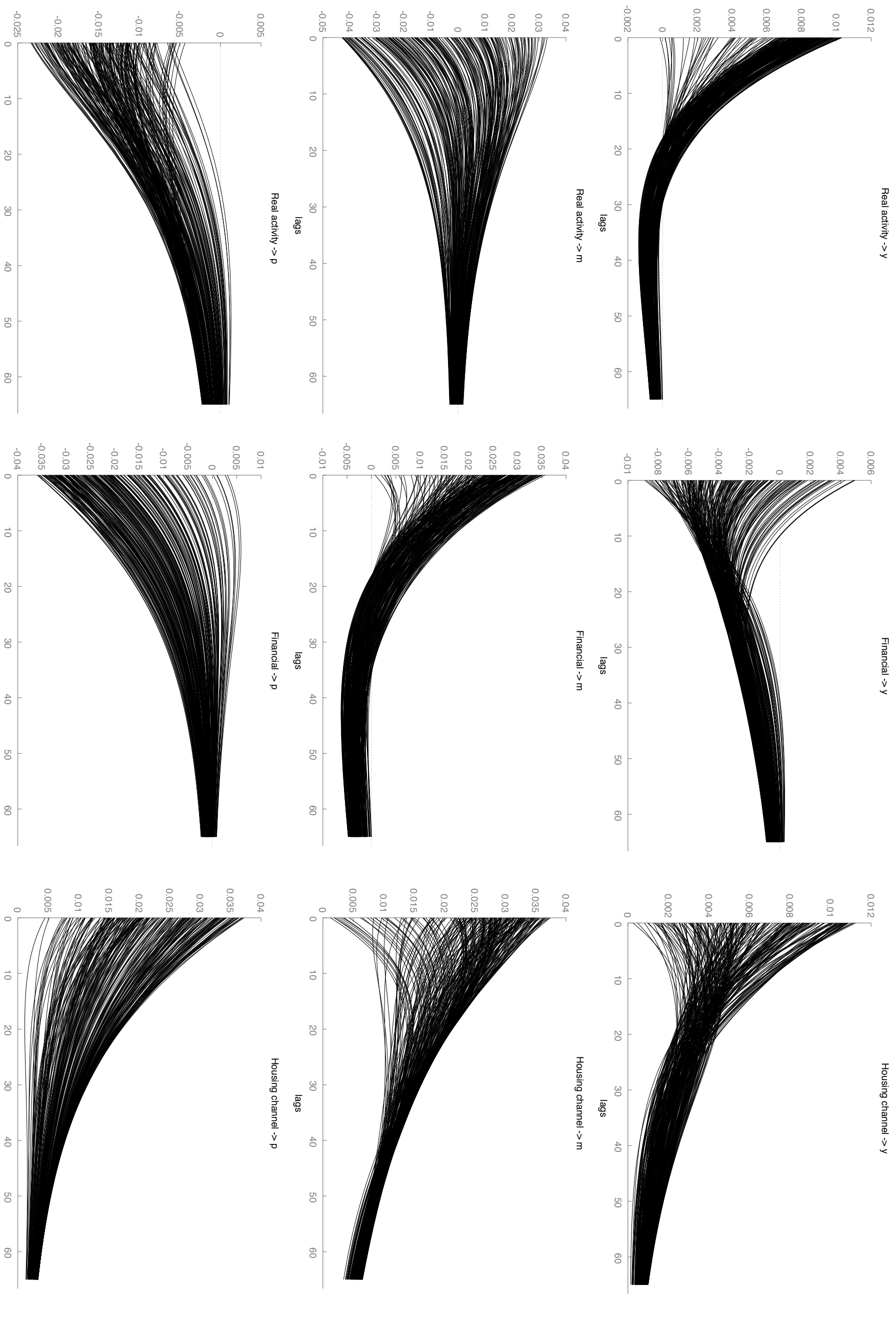

Figure 3.3.: Impulse response functions to a unit structural shock, all k accepted models ($k = 256$).

tive response, a result in line with both macroeconomy theory and recent empirical results.[15] However, an important portion of responses follow the opposite sign, being negative during the entire time span. This reflects the presence of many transmission mechanisms between financial aggregates such as multifamily (household) mortgages, house prices and the business cycle. A similar feature is spotted for all the responses which haven't been identified through restrictions, while in "diagonal" responses their tendency looks quite more common and less variable, as *medium-term* periodicities are reached in the forecast horizon.

3.2.2. Variance analysis

To further inspect the results produced by a set identified structural VAR model, we rely on Forecast Error Variance Decomposition and Historical Decomposition. While the former (FEVD) allows us to graphically detect the single contributions of each variable to a single shock after the forecasting horizon is established, the latter (HD) introduces the impact of each shock into the entire length of the series. To distinguish the capability of financial and housing shocks in forecasting the three variables included in the model, the focus is on their impact in both short and medium-term intervals. Lastly, for HD estimation the weight of each shock in determining variability of original variables is discussed, obtaining additional details of their influence.

Forecast Error Variance Decomposition

Figure 3.4 reproduces the contributions of each structural shock to the forecast error variance across the entire forecast horizon; all panels depict the decomposition for a single variable, following the ordering convention of the structural model. This computes the error produced in forecasting a variable, due to the presence of exogenous shocks. The distinct impacts follow the legend attached

[15] Schularick and Taylor (2012), Favara and Imbs (2015).

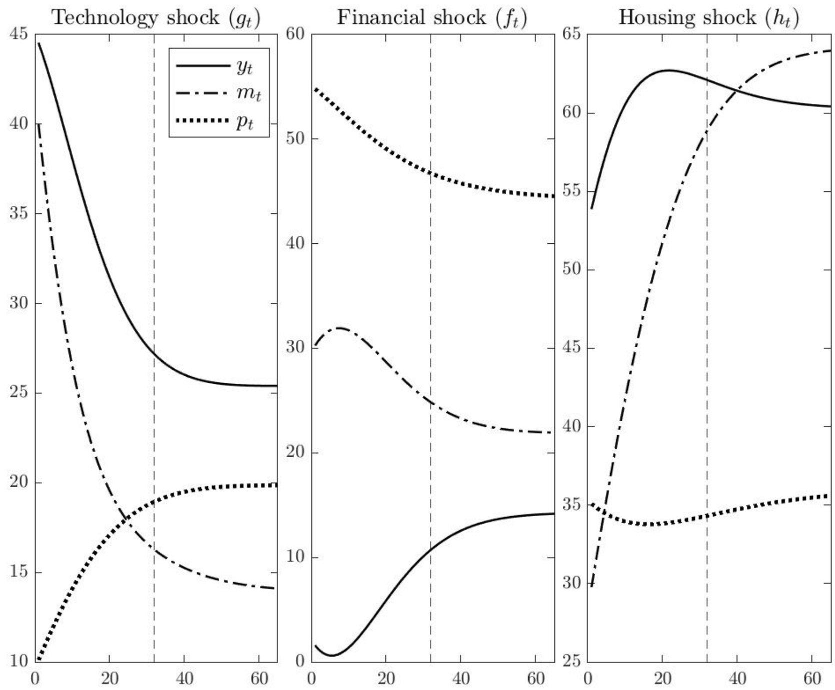

Figure 3.4.: Forecast Error Variance Decomposition (FEVD) for each variable of the system. Each panel lists variance innovations for every variable, as listed in legends. Vertical dotted lines identify the 32 quarters threshold.

at first panel. To distinguish between business cycle's periodicities and what can be considered a *medium-term* interval, table 3.2 summarises shocks' impacts on average, according to two different time intervals, respectively $(6, 32)$ and $(32, 64)$ quarters.

As it is commonly assumed and subsequently proven in real business cycle literature, technology shocks (or *productivity*, i.e. deeply linked to real economic activity perturbations) account for the majority of business cycle fluctuations.[16] This is confirmed by the first panel of figure 3.4, where the productivity shock accounts for more than 40% of the variability in the very short run, reaching

[16]Prescott (1986).

	Short-run (6,32)			Medium-run (32,64)		
	g_t	f_t	h_t	g_t	f_t	h_t
y_t	32.82	5.42	61.77	25.80	13.18	61.03
m_t	21.35	28.86	49.80	14.81	22.76	62.42
p_t	16.43	49.59	33.98	19.63	45.32	35.05

Table 3.2.: Forecast Error Variance Decomposition, calculated on average according to $(6, 32)$ and $(32, 64)$ quarters forecasting intervals, in percentage points.

a stable value after 40 quarters at, approximately, 26%. This also contributes to house prices and mortgages with large predominance in the former variable. Both reach stable values at, approximately, 15% and 20% in the medium run.

Examining the financial shock, its power in explaining real activity variability is very limited in the first interval, while its importance increases in the second interval, after roughly 5 years. The impact on both mortgages and house prices is more visible in the short run, with little variation after the 32 quarters threshold.

Other notable elements are spotted in the third panel, where forecast errors for the housing shock are plotted. It strongly accounts to mortgages variability, especially in the medium-run; its effect is also prominent in explaining real GDP volatility, suggesting that house prices contribute in determining real business cycles (Leamer, 2015).

Historical Decomposition

In this section, the relative importance of each specific shock is investigated for each variable. The nine panels contained in figure 3.5 present the historical decomposition for each variable of the model, including the percentage of variance which is explained by each structural shock.

Filtered real GDP volatility is partly explained by fluctuations of the real activity shock itself, exhibiting negative contributions from the '70s to the end of '80s and, notably, during the whole

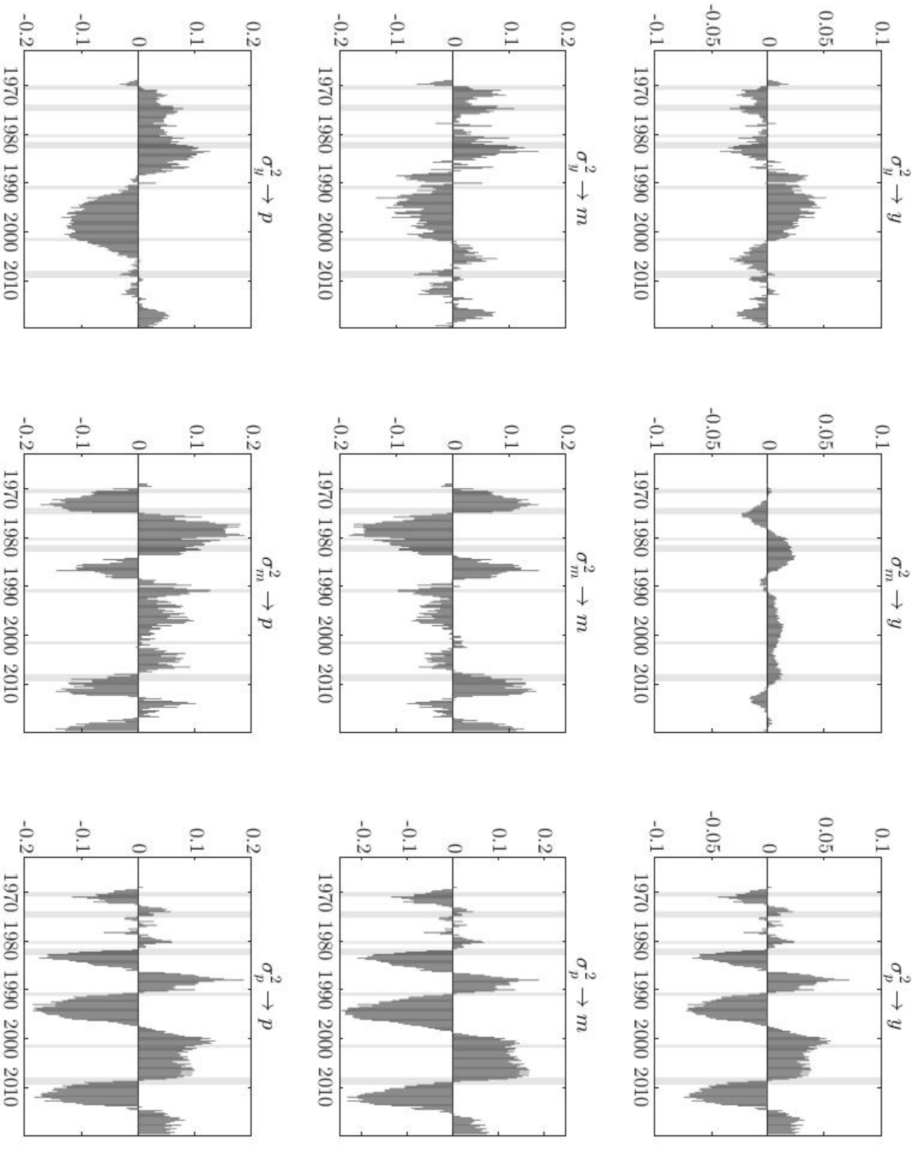

Figure 3.5.: Historical decompositions. Grey shaded areas depict NBER recession dates

period, despite declining in magnitude as we move to more recent times. The influence of the financial shock is less pronounced but still visible and alternating in sign; mortgages and house prices' shocks produce effects in determining business cycle variations, especially during the '90s and the Great Recession, a result which is in common with Meeks (2012). For the latter case, the major negative influence is related to the housing shock σ_p^2, which negatively produced long-lasting effects on aggregate activity.

Technology shocks positively contribute from '70s to half of the '80s to mortgages' variability, and as we move to more recent times its role is less relevant. The largest fluctuations in variance are provided by financial and housing shocks, where peaks and troughs in variability are evident and recurrent until the end of sample. Especially after 2008, financial factors and, mostly, house prices negatively contributed to the variance of mortgages, as a direct consequence of the "credit freezing" after the housing bubble disrupted. The increasing importance of both financial and housing shocks is consistent with a huge branch of related literature (Alpanda and Aysun, 2014; Furlanetto et al., 2019; Berger et al., 2020; Brunnermeier et al., 2021). Productivity shocks' effects, then, tends to be negligible, reflecting a less relevant contribution of technologic improvements.

Lastly, house prices' variance is predominantly driven by financial aggregates, although the presence of technology shock's influence cannot be disregarded especially from the '90s up to the early '00s. Financial and housing shocks' impact increase in time, with extensive adverse effects along the last three decades; although house prices have been strongly determined by both σ_m^2 and σ_p^2 during the Great Recession, the two shocks also positively influenced the long period of financial development and deregulation preceding the financial crisis (Bezemer and Zhang, 2014; Favara and Imbs, 2015; Chen and Svirydzenka, 2017).

3.3. Concluding remarks

Business and financial cycles' literature, in all their many developing forms, has largely increased nowadays. This is valid especially for studies that investigate financial impacts on the real business cycle and the composition of proper indexes to improve the predictability of financial disruptions and housing booms ready to bust.[17] However, this is done implementing several empirical procedures and research methodologies, therefore not allowing for a uniform and conforming interpretation of results.[18] Our attempt, then, is to find empirical confirmation of various results, confiding to obtain a clearer interpretation of these phenomena, whose importance is constantly increasing in modern macroeconomics. This is done using a small set of key variables implemented into a structural VAR, to keep analysis as simple as possible and to produce economically interpretable results.

The interpretation of structural impulse responses can be summarized as follows:

(i) *financial* and *housing* shocks both have a significant impact on GDP, resulting in pronounced responses;

(ii) the real activity shock g_t does not produce a unique interpretation on financial variables' effects, deriving a set of responses that can be either positive or negative in the short term. Even in longer time intervals, few main tendencies of the impulse responses can be spotted with opposite signs, although they cannot be statistically considered different from zero;

[17] As the number of articles is increasing, the most recent are Filardo et al. (2018), Fehrle (2019) and Schüler et al. (2020).

[18] For example, many researches consider a "cross-country" framework, investigating causes, magnitude, timing and impact on real variables *between* several countries, see Igan et al. (2011), Bezemer and Zhang (2014), Stremmel (2015), Stockhammer et al. (2019), Strohsal et al. (2019). These works, for obvious reasons, produced results that are hardly comparable with those obtained from univariate analyses.

	Expansions	Contractions	Tot. cycle
Real GDP (y_t)	27.4	3.6	31
Mortgages (m_t)	30.5	6.6	37
House prices (p_t)	18.1	4.1	22

Table 3.3.: Turning point analysis for $\log(\mathbf{Y})$, in quarters

(*iii*) the financial shock f_t produces an immediate negative reaction for GDP, whose readjustment requires the entire forecast horizon;

(*iv*) a housing shock p_t develops responses which tend to be consistent with one of the main transmission mechanisms exposed in Jordà et al. (2015): the mortgage values' increase, and so does real GDP.

Our shock specification is consistent with turning point analysis of U.S. business cycle expansions and contractions provided by NBER;[19] the dynamics of contractions-expansionary phases is also confirmed by turning point analysis provided in table 3.3.

Although the financial impact on real sectors does not always provoke recessions and bubble-dynamics in financial markets, the magnitude of this effect seems to be confirmed by the structural model, but its source still needs to be investigated. Sources such as the generic relaxing of financial market conditions (Claessens et al., 2012; Bezemer and Zhang, 2014), or fundamental macroeconomic conditions, i.e differences in housing and financial aspects, are all plausible candidates. This would also conduce to different propagation mechanisms (Oman et al., 2019).

A similar interpretation is caught from Forecast Error Variance Decompositions and Historical Decompositions. In the former case, the subdivision in short and medium-term intervals depicts the increasing importance of financial entities in explaining real aggregate

[19] The business cycle dating database, updated at 08/2020, can be found at https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

dynamics *above* 8 years. Moreover, the presence of financial factors affecting the business cycle was much smaller before the '90s, as these became larger and predominant in determining real GDP variability (Stockhammer et al., 2019; Berger et al., 2020). Historical decomposition depicts the positive financial effects on real GDP growth during the 2000s, as it turned out to be negative for the following decade.

Finally, further developments can be conducted into identification of *financial shocks*, employing alternative methodologies into a proper econometric framework. An interesting application would take place applying the identification methodology of Kilian and Murphy (2012) and Arias et al. (2018), where the joint use of zero (exclusion) and sign (set identified) restrictions is proposed, combining *strong* (zero) and *weak* (sign) restrictions into a single identification scheme. Alternatively, the usage of *narrative sign restrictions* as introduced by Antolín-Díaz and Rubio-Ramírez (2018) may be a proper technique to inspect crucial historical events, exploiting information about the sign of their impact on the economy. This is suggested as the availability of aggregate macroeconomic data would increase, in particular, to inspect COVID-19 pandemic's economic backlashes, whose influence has been neglected in this work, truncating data availability for estimation up to the last quarter of 2019.

Appendix A.

Data description

A.1. Data sources

All series are quarterly for the United States. Selected sample goes from 1963:1 to 2019:4. In chapter 2 series are detrended via log-differencing, while in chapter 3 these have been transformed in logs and filtered through Hamilton (2018) 5-years regression filter.

1. Real gross domestic product, inflation adjusted value of the goods and services produced by labor and property located in the United States. Billions of Chained 2012 Dollars, Seasonally Adjusted Annual Rate.

   Source: U.S. Bureau of Economic analysis, Real Gross Domestic Product [GDPC1], retrieved from FRED, Federal Reserve Bank of St. Louis.

   https://fred.stlouisfed.org/series/GDPC1.

2. Mortgage Debt Outstanding by Type of Property: Multifamily Residences. Millions of Dollars, Not Seasonally Adjusted.

   Source: Board of Governors of the Federal Reserve System (US), Mortgage Debt Outstanding by Type of Property: Multifamily Residences [MDOTPMFR], retrieved from FRED, Federal Reserve Bank of St. Louis.

   https://fred.stlouisfed.org/series/MDOTPMFR.

3. Average Sales Price of Houses Sold for the United States. Dollars, Not Seasonally Adjusted.

   Source: U.S. Census Bureau and U.S. Department of Housing and Urban Development, Average Sales Price of Houses Sold for the United States [ASPUS], retrieved from FRED, Federal Reserve Bank of St. Louis.

   https://fred.stlouisfed.org/series/ASPUS.

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