Universidade do Minho
Escola de Economia e Gestão

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Monetary policy, financial frictions and business cycles

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Statement of integrity

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

Resumo

Nas últimas décadas, a sofisticação e complexidade dos mercados financeiros tem exposto cada vez mais a fragilidade da economia real a atritos financeiros, o que levanta questões importantes sobre o papel do crédito nos ciclos económico. A textit Grande Recessão é um lembrete gritante de que atritos financeiros podem desempenhar um papel fundamental nas flutuações do ciclo económico, com o acúmulo de desequilíbrios durante tempos tranquilos a conduzir a uma destruição grande e persistente de riqueza quando a bolha estoura, que pode então espalhar-se para a economia real.

O objetivo desta tese é explorar a interação entre fricções financeiras e os ciclos económicos, em primeiro lugar abordando a relação entre as restrições aos empréstimos e seu impacto sobre as variáveis macroeconômicas e, em segundo lugar, analisando como as flutuações no risco afetam os ciclos económicos. Para este fim, baseamo-nos em dois modelos encontrados na literatura, que possuem os ingredientes-chave que levaram os autores a argumentar que atritos financeiros podem, em grande escala, ser responsáveis por flutuações nas variáveis macroeconômicas.

No Capítulo 1, abordamos o modelo de Jermann and Quadrini (2012), que introduz choques diretamente no sistema financeiro que se propagam para a economia real; foi realizada uma análise das propriedades do modelo nos domínios temporal e da frequência. O uso de ôndulas permitiu uma avaliação de como o modelo se ajusta aos dados em diferentes frequências e em momentos específicos no tempo. Uma característica específica desse modelo é que ele introduz choques diretamente no sistema financeiro, que se propagam para a economia real. É também um dos primeiros a abordar este canal dentro de uma estrutura de Equilíbrio Geral Estocástico Dinâmico (DSGE).

Poucas pesquisas foram realizadas sobre o papel desempenhado pelos mercados financeiros e

de crédito durante as recessões dos anos 1970 e início dos anos 1980. No Capítulo 2, seguindo algumas evidências sobre o endurecimento dos padrões de crédito antes ou durante os períodos de recessão, bem como as conclusões de Bernanke et al. (1999) de que fricções financeiras podem afetar o tamanho das flutuações do ciclo de negócios, estendemos o modelo de Jermann and Quadrini (2012) para introduzir choques no preço do petróleo. O objetivo era analisar a contribuição das fricções financeiras durante este período, onde as recessões foram atribuídas principalmente a grandes aumentos nos preços do petróleo.

Os atritos financeiros podem amplificar os ciclos económicos, levando a flutuações macroeconômicas mais pronunciadas, seja por choques iniciados na economia real ou no próprio sistema financeiro. O papel da política monetária também pode depender da fonte do choque e do canal de transmissão.

No Capítulo 3, estabelecemos uma comparação entre as séries temporais empíricas dos principais agregados macroeconômicos durante o primeiro trimestre de 1985 até o último trimestre de 2019, e as séries simuladas a partir das contribuições dos choques incluídos em dois modelos DSGE distintos. O primeiro modelo é a versão neo-keynesianos do modelo de Jermann and Quadrini (2012), que estende Smets e Wouters (2007) com uma *restrição de execução* que pode ser interpretada como o grau de disposição dos bancos em conceder empréstimos, como uma proxy de padrões de crédito. O segundo modelo é o de Christiano et al. (2014b), que é baseado no mecanismo de acelerador financeiro do modelo de Bernanke et al. (1999), introduzindo choques de risco. Finalmente, comparou-se as duas abordagens distintas de modelagem de atritos financeiros, recorrendo às diferentes fontes e origens de choques. Para a comparação, foram empregues as ferramentas decorrentes das ôndulas para analisar o quanto os atritos financeiros podem explicar das flutuações observadas em diferentes frequências.

Palavras-chave: Fricções financeiras, choques petrolíferos, ôndulas, ciclos económicos, modelo de equilíbrio geral estocástico dinâmico, choques de risco, padrões de crédito.

Abstract

Over the last decades, the sophistication and complexity of financial markets has increasingly exposed the fragility of the real economy to financial frictions, which raises important issues regarding the role of credit in business cycles. The *Great Recession* is a stark reminder that financial frictions can play a key role in business cycle fluctuations, with the buildup of imbalances during tranquil times leading to the large and persistent destruction of wealth when the bubble bursts, which may then spill over to the real economy.

The purpose of this thesis is to explore the interaction between financial frictions and business cycles, firstly by addressing the relationship between borrowing constraints and their impact on macroeconomic variables and, secondly, by analyzing how fluctuations in risk affect business cycles. To this end, we relied on two models found in literature, which possess the key ingredients that have led the authors to argue that financial frictions may, on a large scale, be responsible for fluctuations in macroeconomic variables.

In Chapter 1, one began with the Jermann and Quadrini (2012) model, which introduces shocks directly in the financial system that propagate to the real economy; an analysis was undertaken of the model properties in the time-frequency domains. The use of wavelet tools allowed for an evaluation of how the model fits the data at different frequencies, and at specific moments in time. A specific feature of this model is that it introduces shocks directly in the financial system, which then spill over to the real economy. It is also one of the first to address this channel within a Dynamic Stochastic General Equilibrium (DSGE) framework.

Little research has been conducted on the role played by financial and credit markets during the

1970s and early 1980s recessions. In Chapter 2, following some evidence on the tightening of credit standards before or during the recession periods, as well as the findings by Bernanke et al. (1999) that financial frictions can affect the size of business cycle fluctuations, we extended the Jermann and Quadrini (2012) model to introduce oil price shocks. The aim was to analyze the contribution of financial frictions during this period, where the recessions were mainly attributed to large increases in oil prices.

Financial frictions can amplify business cycles, leading to more pronounced macroeconomic fluctuations, either due to shocks starting in the real economy or in the financial system itself. The role of monetary policy may also be dependent on the source of the shock and the transmission channel.

In Chapter 3 we established a comparison between the empirical time series of major macroeconomic aggregates during the first quarter of 1985 to the last quarter of 2019, with simulated series computed from the contributions of the shocks included in two distinct DSGE models. The first model is the Jermann and Quadrini (2012) New Keynesian version of the model, which extends the Smets and Wouters (2007) with an enforcement constraint that may be interpreted as the degree of willingness of banks to lend, as a proxy of credit standards. The second model is the Christiano et al. (2014b) model, which is based on the Bernanke et al. (1999) financial accelerator mechanism, thus introducing risk shocks. Finally, one compared two distinct approaches of modelling financial frictions, using different sources and origins of shocks. For the comparison, wavelet tools were employed to analyze how deeply financial frictions can explain the observed fluctuations at different frequencies.

Keywords: Financial frictions, oil shocks, wavelets, business cycles, dynamic stochastic general equilibrium model, risk shocks, lending standards.

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Chapter 1.

Financial frictions and business cycles: A wavelet analysis

Using wavelet tools, the time-frequency properties of the time series obtained from the Jermann and Quadrini (2012) model were explored and compared with the empirical counterparts. It was found that overall, and with the exception of consumption, the model is able to perceive the main features of the empirical time series, which are mostly explained by financial shocks. Although productivity shocks seem to be of low impact, when both shocks are combined, they generally enhance the synchronism of results between the model time series and the respective empirical counterparts.

1.1. Introduction

The link between financial markets and real economy has become pertinent once again due to the recent crisis in international financial markets, so that interest in this topic has gained another dimension. The result of this crisis points to a reduction in the capacity of financial institutions, for example banks, in the contexts of intermediate borrowing and lending between households and firms, and between financial institutions themselves. However, benchmark models used by central banks and policymakers in the analysis of the business cycle - such as the Real Business Cycle (RBC) and the

Dynamic New Keynesian (DNK) models - strongly assume that the financial and credit markets are perfect and complete.[1] It is for this reason that these models do not take into account the borrowing and lending between agents in equilibrium, where there are no financial frictions due to information asymmetry, non-convex transaction costs or limited contract enforcement.

Information asymmetry is not the only source of financial frictions presented in literature. Bai and Zhang (2010) have quantitatively investigated the impact of limited enforcement and limited spanning as a source of financial frictions, and its correlation with long-term average savings and investment rates across countries, thus solving the Feldstein–Horioka puzzle. Other works have explored multiple sources of financial frictions, such as Bigio (2015), who built a DSGE model with interaction between asymmetric information and limited enforcement. This model is able to reveal the magnitude and patterns for variables such as consumption, investment, hours and output-per-hour during the *Great Recession*.

The importance of the issue of financial frictions after the crisis of 2008 has been approached in many other works. Calza et al. (2009) used a two-sector DSGE model to evaluate how the structure of housing finance affected the transmission of monetary policy shocks. The model used collateral constraints and price stickiness to see how consumption and residential investment responded to monetary policy shocks. Gerali et al. (2010) studied the role of credit-supply factors in business cycle fluctuations, also using a DSGE model with financial frictions. In the model, banks issued collateralized loans to households and firms, and the manner in which they obtained funds was through the deposits and accumulated capital from retained earnings. Finally, for their estimation, the authors used Bayesian techniques with data from the Euro area. Studies in optimal monetary policy with financial frictions were undertaken by Cúrdia and Woodford (2009), who used an extended New Keynesian model to analyze this theme. The model allowed for a spread between the interest

[1] These markets are characterized as being perfect if they are frictionless and competitive, with no transaction costs or contract enforcement problems. The same markets are considered complete if they are fully capable of eliminating all risks. With the assumption of perfect and complete financial and credit markets, capital structure is irrelevant to the course of the real economy.

rate to savers and borrowers, which can vary. Brzoza-Brzezina and Makarski (2011) used a DSGE model for the banking sector to analyze the impact of the credit crunch during the Great Recession on a small open economy, where the banking sector operated under monopolistic competition. As an application, the authors estimated the model for the context of Poland.

There are many studies which model financial frictions on macroeconomics; however, most of the literature prior to Jermann and Quadrini (2012) only focuses on the role played by the financial markets in the propagation of shocks, the source of which does not reside in the financial sector. Jermann and Quadrini (2012) attempted to introduce shocks ensuing from the financial system by developing a model with debt and equity financing. In their study, the authors explored the effect of financial shocks in the dynamics of real and financial variables. They explored the link between a firm's debt and equity flows, and financial frictions, such as the firm's limited ability to borrow. The authors found that financial shocks contributed significantly to the observed dynamics of real and financial variables, such as GDP, debt repurchase, equity payout, as well as investment and hours worked. This model also revealed that the last three recessions, especially the *Great Recession*, were strongly influenced by changes in credit conditions, with a decline in firms' ability to borrow.

A few authors followed some of the key concepts of this model in their research. For example, Zanetti (2015) indicated that financial shocks generated fluctuations in labor market variables - such as vacancy posting, unemployment and wages - through an extended model created by Jermann and Quadrini (2012). Garín (2015), on the other hand, implemented a model that is rather similar to Jermann and Quadrini (2012), but which was enhanced by frictions in the labor market, to study the properties of unemployment and job creation. Zhao (2013a) applied the Jermann and Quadrini (2012) model to the Japanese economy. In the preliminary results, it seems that financial shocks generated a minor impact on the case of Japan, when compared to results for the U.S economy. The extended model presented different results, with financial shocks contributing heavily to the dynamics of financial flows. Despite these results from the extended model, and in the specific case of the Japanese economy, productivity shocks seem to have had a dominant impact on the fluctuations of economic variables. Zhao (2013b) also developed a two-country model, which was based on the

Jermann and Quadrini (2012) model and applied to the economies of the U.S. and Japan. The main results of this study indicated that, during normal periods, productivity shocks could explain most of the dynamic behavior of real variables, such as output or investment; on the other hand, financial shocks could explain variables, like labor, as consumption during periods of financial crisis. A similar study was carried out by Feng and Lin (2013), which used a two-country DSGE model with an enforcement constraint subject to random financial shocks, very much like Jermann and Quadrini (2012). Their aim was to understand the mechanism through which credit tightness affected the extensive and intensive margins of exports. Bergin et al. (2014) assessed the response of firms' entry in financial shocks, and the propagation of these shocks to the real economy. To do so, they used using a model which included a credit constraint – like that of Jermann and Quadrini (2012). The main model novelty of the model is that firms have the choice to finance the up-front entry costs through a combination of debt and equity, linking the fall in new firm creation to financial shocks. In order to assess the importance of financial shocks, when compared to others, Huang et al. (2014) focused on the explanation of slow recoveries using a model similar to that of Jermann and Quadrini (2012), with an intra-period loan and an enforcement constraint, which limited the borrowing capacity of firms. The estimation of the model showed that financial shocks can constitute a key factor in the case of slow recoveries after financial crises. Shirai (2016) used the Jermann and Quadrini (2012) model with 32 different specifications of the borrowing constraint to explore which factors generated persistent and/or amplified output responses to productivity and financial shocks. The main findings pointed to the trade-off between the persistence and amplification of shocks, as well as the important role of investment wedge in generating persistence. In their model, Kobayashi and Shirai (2016) considered two borrowing constraints (in the inter-period and in the intra-period loans), following a modeling methodology close to Jermann and Quadrini (2012). This model is unique in the sense that, even without financial shocks, accumulated debt can depress the economy persistently. Ikeda and Kurozumi (2014) introduced financial frictions to a DSGE model similar to Jermann and Quadrini (2012), which was enhanced by means of the Comin and Gertler (2006) endogenous TFP growth mechanism. The purpose was to describe slow recovery after negative financial shocks, such as the recoveries presented by many economies after the 2008 financial crisis. Mimir (2016) built a model to include four types of agents: households, financial intermediaries, firms and capital producers. In this case, the financial intermediaries played a key role in the model, since it is in this sector that financial frictions are implemented and modeled, as can be seen in Gertler and Karadi (2011). In order to assess the accuracy of the model, two different methodological approaches were used: the construction of a simulated time series similar to that of Jermann and Quadrini (2012); and an assessment of the model by means of Bayesian methods. In both cases, the findings were in line with Jermann and Quadrini (2012): financial shocks contributed significantly to short-term and long-term fluctuations in GDP, investment and hours, as well as in the financial variables used in this model (bank credit, deposits, net worth, leverage ratio and credit spread). Using a model which included two similar borrowing constraints – *a la* Kiyotaki and Moore (1997) and *a la* Jermann and Quadrini (2012) –, Finocchiaro et al. (2015) and Finocchiaro and Mendicino (2016) demonstrated that it was only in the Jermann and Quadrini (2012) version that one saw an interaction between financial frictions and labor demand. Furthermore, and in response to a negative financial shock, asset prices and consumption showed a substantial and persistent tendency to drop. Some concepts and references to the Jermann and Quadrini (2012) model can also be found in studies by Sarte et al. (2015), Miao et al. (2016), Lopez and Olivella Moppett (2014), Carvajal (2015), Dellas et al. (2015), Kamber et al. (2014), Biljanovksa (2015), Karabarbounis et al. (2014), Boz and Mendoza (2014), Bianchi and G. Mendoza (2015), and Finocchiaro et al. (2015).

More recently, Gareis and Mayer (2020) used a modified version of the Jermann and Quadrini (2012) model to explore how both tangible and intangible investment were affected by financial shocks. In this context, productive capital was distinguished as tangible and intangible, where only the former can be pledged as collateral in debt contracts.

The main goal of this chapter is to study the time-frequency properties of the Jermann and Quadrini (2012) model. In order to do so, a time-frequency analysis was carried out by means of a set of continuous wavelet tools. In the first phase, wavelet spectrum was used to describe some properties in the time-frequency domain of each of these, as well as their impact on the time series of the model (credit standards, GDP, equity payout, debt repurchase, investment, capital and hours worked). A comparison was also established between the empirical and simulated time series. During the second stage, one used wavelet coherency, partial wavelet coherency, phase-difference and partial phase-difference; this enabled one to measure, across time and frequency, the degree of synchronism between the empirical and respective simulated time series of the Jermann and Quadrini (2012) model.

Section 2 of this chapter proceeds with a literature review on credit standards and their relations with - or impact on - some real and financial variables. Section 3 presents a brief overview of the Jermann and Quadrini (2012) model, where a description is provided of the firm and household sectors, as well as the respective maximization problem which leads to the first order condition. Having discussed the key features of the model, one proceeded with a presentation of the data and process used to construct the shocks applied to the model simulations. The results shown are based on a comparison between the empirical and simulated time series using wavelet tools, namely wavelet power spectrum and wavelet coherence with the respective phase-difference. Section 4 summarizes the main conclusions.

1.2. Literature Review

The Federal Reserve conducts the Senior Loan Officer Opinion Survey on Bank Lending Practices. In this process, loan officers of approximately 60 domestic banks and several branches and agencies of foreign banks are asked about changes in their standards of approving loan applications for commercial and industrial (C&I) loans or credit lines. This is rated on a scale of 1 to 5 (1 - eased considerably, 2 - eased somewhat, 3 - remained about unchanged, 4 - tightened somewhat, 5 - tightened considerably).[2]

Historically, academics have overlooked or neglected information on credit standards. More re-

[2] The Senior Loan Officer Opinion Survey on Bank Lending Practices began in 1964 but the results were only publicized in 1967. In 1984, the issue of lending standards was dropped until 1990.

cently, however, several studies have been conducted using surveys on credit standards, mainly from the Federal Reserve and European Central Bank (Kirti, 2018; Rodano et al., 2018; Jiménez et al., 2018; Mian and Sufi, 2018; Swarbrick, 2019; Altavilla et al., 2019; Fishman et al., 2020; Darst et al., 2020; Vojtech et al., 2020; Jiménez et al., 2020; Apergis and Chatziantoniou, 2021; Chen et al., 2021). There are several reasons which make credit standards worth studying: firstly, credit standards may indicate the degree of frictions in the credit allocation process (Andersen and Kuchler, 2016); secondly, in the presence of financial frictions such as asymmetric information, credit standards can play an important predictive role on the GDP growth (de Bondt et al., 2010).

Survey measures of non-price credit conditions were not usually adopted in the construction of Financial Condition Indexes (FCI). Nonetheless, given the strong correlation between credit standards and some economic variables, it was later incorporated into such indexes. This is the case of Swiston (2008), as well as Guichard and Turner (2008), who included lending standards in FCIs to account for non-price credit conditions. Swiston (2008) showed that a tightening in credit standards reduced economic activity. More specifically, a 20 % net tightening of credit standards accounted for a reduction of 0.75% in economic activity on a one-year horizon, and 1.25% on a two-year horizon. The authors argued that their FCI was an accurate predictor of real GDP growth, anticipating turning points six to nine months ahead. Guichard and Turner (2008) also found that credit standards produced a great impact on GDP growth in the United States. Lown et al. (2000) observed that the Senior Loan Officer Opinion Survey contains meaningful information to forecast commercial loan growth. The reported changes in credit standards also help to predict some measures of business activity, revealing a strong correlation between the tightening of credit standards and the slowdowns in commercial lending and GDP. Also documented was the negative impact of credit standards on business fixed investment and overall industrial production. The results for the latter are in line with those presented by Lown and Morgan (2006), who found that recessions are commonly preceded by a tightening in credit standards.

Using data relating to credit standards for the United States and the Euro area, Ciccarelli et al. (2015) showed that the credit channel amplified the impact of a monetary policy shock on GDP and inflation. Bassett et al. (2014) found that, through unexplained changes in bank lending standards, there were large and asymmetric effects of lending supply shocks on GDP.[3] Using data for the Euro area, Cappiello et al. (2010) provided empirical evidence that changes in credit standards produce significant effects on real economy activity. By means of panel regressions, de Bondt et al. (2010) indicated that the Bank Lending Survey for the Euro area includes pertinent information to explain real GDP growth and its main components (residential investment growth, non-residential investment growth and real private consumption growth). Blaes (2011) and Del Giovane et al. (2010) made use of German and Italian banks' individual responses to the bank lending survey to determine asymmetric reaction on loan growth in the context of the tightening and easing of credit standards. They found that it is only when the indicator signals a tightening that the relation is significant.

The impact of credit standards, and their possible relation to and with other macroeconomic variables, deserved attention from the academic community, even before the *Great Recession*. For example, Asea and Blomberg (1998) showed that cycles in bank lending standards generated a considerable influence on aggregate unemployment fluctuations. More recently, Haltenhof et al. (2014) studied the effects of credit standards on employment in the manufacturing sector during the *Great Recession*. They concluded that the tightening of credit standards contributed to almost one third of the drop in employment during this period. Madsen and Carrington (2012) showed that the banks' willingness to lend, measured by credit standards, was a statistically significant driver of investment in long-term equilibrium; the shocks in a bank's willingness to lend have explained most of the investment growth cycles over the past two decades.

Despite all these results concerning credit standards and some macroeconomic variables, a causal relationship between them has not been fully explored. For instance, Driscoll (2004) and Ashcraft (2006) did not find compelling evidence for a strong causal relationship between credit supply and the GDP.

[3] The unexplained changes in lending standards were approximated by the residuals from the regression of credit standards - publicized by the Senior Loan Office Opinion Survey (SLOOS) - on controls for loan demand and observable bank-specific factors.

As stated by Jermann and Quadrini (2012), the time series used as financial shocks in the model provided a rather fair tracking of the Senior Loan Officer Opinion Survey on Bank Lending Practices. Indeed, the results obtained from the model favored the importance of this variable to explain business cycles. However, it is still important to understand whether this variable influences the behavior of the GDP and other macroeconomic variables, or if it simply reflects the state of the economy.

Bearing in mind the importance of credit on economic outlook, many macroprudential authorities have started to monitor this issue more closely; they have also proceeded with the development of several measures to act on credit flow, both directly or indirectly. Some of these measures can affect the willingness of banks to grant credit to households and non-financial corporations (such as LTV ratios, DSTI ratios or even risk weights). Other measures can also affect lending standards - although they are not designed with that goal in mind - throughout the banks financing costs (such as the CCyB, systemic risk buffers or even structural capital requirements). The results presented by De De Schryder and Opitz (2021) revealed that the macroprudential policy stance[4] might impact on internal credit standards, while senior loan officers do not seem to anticipate macroprudential shocks or effects.

Monetary policy can also play an important role in banks' credit standards. This was emphasized by Jiménez et al. (2018), who used monthly data from the Banco de España Central Credit Register. Some evidence was found of the softening of banks' credit standards during periods of loose monetary policy, and tightening when there was a rise in short-term interest rates. This result is in line with the findings by Zhang and Xu (2020), who used a DGSE model to test the contribution of monetary policy and financial market innovations to the U.S. housing boom between 2001 and 2006. It was concluded that the model predicted a softening in lending standards, following a drop in the benchmark interest rate. This view was also shared by Afanasyeva and Güntner (2020), who claimed that a low-interest-rate environment might induce banks to lower their credit standards, thus raising their credit volume and their portfolio risk, with an increase in riskier loans.

[4]The macroprudential stance is based on an index computed from the answers in the MacroPrudential Policies Evaluation Database (MaPPED), which measures whether implemented macropudential policies are tighter or looser.

1.3. Jermann and Quadrini Model

In this brief description of the model, only two sectors of the model will be described: the sectors of firms and households. In this sense, the primary focus will be on understanding how the model behaves. For more details, see Jermann and Quadrini (2012).

1.3.1. Households sector

One contemplated a continuum of households wishing to maximize expected life-time utility $\mathbb{E}_o \sum_{t=0}^{\infty} \beta^t U(c_t, n_t)$, where c_t is consumption, n_t is labor and β is the discount factor. Since the households are shareholders of firms - who also possess noncontingent bonds issued by firms - they are confronted by the following budget constraint:

$$w_t n_t + b_t + s_t (d_t + p_t) = \frac{b_{t+1}}{1 + r_t} + s_{t+1} p_t + c_t + T_t, \tag{1.3.1}$$

where s_t is the equity share, p_t is the market price of shares and T_t are lump-sum taxes which finance the tax benefit of debt for firms. Given the optimization problem of households, the first-order conditions are:

$$w_t U_c (c_t, n_t) + U_n (c_t, n_t) = 0, \tag{1.3.2}$$

$$U_c (c_t, n_t) - \beta (1 + r_t) \mathbb{E}_t U_c (c_{t+1}, n_{t+1}) = 0, \tag{1.3.3}$$

$$U_c (c_t, n_t) p_t - \beta \mathbb{E}_t (d_{t+1} + p_{t+1}) U_c (c_{t+1}, n_{t+1}) = 0. \tag{1.3.4}$$

1.3.2. Firm sector

For a continuum of firms in the $[0, 1]$ interval, the production function is given by $F(z_t, k_t, n_t) = z_t k_t^{\theta} n_t^{1-\theta}$, where z_t is the stochastic level of productivity (common to all firms), k_t is the capital (chosen at $t - 1$ and predicted at t), and n_t is labor (flexibly changed at t). For capital accumulation, one followed the specification with adjustment costs on investment. As such, the law of motion for the stock of capital takes the form of:

$$k_{t+1} = (1-\delta)k_t + \left[\frac{\varrho_1 \left(\frac{i_t}{k_t} \right)^{1-\upsilon}}{1-\upsilon} + \varrho_2 \right] k_t,$$

with δ being capital depreciation, while υ determines the sensitivity of the cost to investment, and i_t relates to investment.

Firms use debt and equity; owing to tax benefits, firms will prefer debt over equity. So as to formalize this, given the interest rate r_t, the effective interest rate for firms is $R_t = 1 + r_t\,(1-\tau)$, where τ is a tax benefit. Apart from debt (b_t), firms also finance themselves through an intra-temporal loan l_t. It is assumed that this intra-temporal loan was repaid at the end of a certain period, with no interest. Since payments were made before the realization of revenue, firms chose $l_t = w_t n_t + i_t + d_t + b_t - b_{t+1}/R_t$. [5]

At this moment, the firms' budget constraint is given by:

$$b_t + w_t n_t + k_{t+1} + d_t = (1-\delta)\,k_t + F\,(z_t, k_t, n_t) + b_{t+1}/R_t, \tag{1.3.5}$$

where, w_t is the wage and d_t is the equity payout.

Given the chosen l_t, and the firms' budget constraint, one obtained $l_t = F\,(z_t, k_t, n_t)$. Assuming that the decision of default happens after the realization of revenue, but before repayment of the intra-temporal loan, and that the liquidity $l_t = F\,(z_t, k_t, n_t)$ held by firms can be easily diverted, the only asset available for liquidation is capital k_{t+1}. Supposing that when the loan is made, the liquidation value of capital is uncertain: with probability ξ_t, the lender recovers the full value; and with $1-\xi_t$, the recovered value is null.[6] With this uncertainty concerning the liquidation value of capital, the firms

[5] Before production occurred, firms chose labor n_t, investment i_t, and equity payout d_t. At this point, they also had liability b_t, and chose a new inter-temporal debt b_{t+1}.

[6] The variable ξ_t can be interpreted as the probability of finding a buyer. Assuming that the price of sale is bargained on a take-it-or-leave-it offer, the ξ_t would be the probability of the offer made.

will be subject to the following enforcement constraint:

$$\xi_t \left(k_{t+1} - \frac{b_{t+1}}{1+r_t} \right) \geq l_t. \tag{1.3.6}$$

One possible interpretation for the variable ξ_t is the banks' willingness to grant a loan. The higher the values, the looser the enforcement constraint; the intra-temporal loan is thus more easily granted to firms, which means the banks have lowered their lending standards. In contrast, the lowering of ξ_t implies a tightening in the enforcement - or borrowing - constraint, thus reducing the amount of credit granted for the same collateral k_{t+1}, which is perceived as an increase in banks' lending standards. In this way, one concludes that ξ_t directly affects the tightness of the enforcement constraint, as well as the ability of firms to access intra-temporal loans and finance their pre-revenue costs.

Since firms can choose between debt and equity, in order to formalize rigidities in the adjustment of all funding sources, it is assumed that equity payout has a quadratic cost. Thus, given d_t, the actual cost for firms is $\varphi(d_t) = d_t + \kappa\left(d_t - \overline{d}\right)^2$, where $\kappa \geq 0$ and $\overline{d}$ is the value of the equity payout at the steady-state.

The optimization problem for firms is given by:

$$V(\mathbf{s_t}; k_t, b_t) = \max_{d_t, n_t, k_{t+1}, b_{t+1}} \left\{ d_t + \mathbb{E}_t m_{t+1} V(\mathbf{s_{t+1}}; k_{t+1}, b_{t+1}) \right\}$$

subject to

$$(1-\delta) k_t + F(z_t, k_t, n_t) - w_t n_t + \frac{b_{t+1}}{R_t} = b_t + \varphi(d_t) + k_{t+1} \tag{1.3.7}$$

$$\xi_t \left(k_{t+1} - \frac{b_{t+1}}{1+r_t} \right) \geq F(z_t, k_t, n_t), \tag{1.3.8}$$

where m_{t+1} is the discount factor.[7]

[7] Since the firms' optimization is consistent with household optimization, the discount factor is $m_{t+1} = \beta U_c(c_{t+1}, n_{t+1}) / U_c(c_t, n_t)$

The first order conditions are:

$$F_n\left(z_t, k_t, n_t\right) = w_t \left(\frac{1}{1-\mu_t \varphi_d\left(d_t\right)}\right), \tag{1.3.9}$$

$$\mathbb{E}_t m_{t+1}\left(\frac{\varphi_d\left(d_t\right)}{\varphi_d\left(d_{t+1}\right)}\right)\left[1-\delta+\left(1-\mu_{t+1}\varphi_d\left(d_{t+1}\right)\right)F_k\left(z_{t+1}, k_{t+1}, n_{t+1}\right)\right]+ \\ +\xi_t \mu_t \varphi_d\left(d_t\right) = 1, \tag{1.3.10}$$

$$R_t \mathbb{E}_t m_{t+1}\left(\frac{\varphi_d\left(d_t\right)}{\varphi_d\left(d_{t+1}\right)}\right) + \xi_t \mu_t \varphi_d\left(d_t\right)\left(\frac{R_t}{1+r_t}\right) = 1, \tag{1.3.11}$$

where μ_t is the Lagrange multiplier associated to the enforcement constraint.

There are two types of shocks in this model: financial and productivity. By log-linearization of the production function one obtains:

$$\hat{z}_t = \hat{y}_t - \theta \hat{k}_t - \left(1-\theta\right)\hat{n}_t, \tag{1.3.12}$$

where $\hat{z}_t$, $\hat{y}_t$, $\hat{k}_t$ and $\hat{n}_t$ are the log-deviations from the deterministic trend.

By following the same approach and resorting to the equation (1.3.8) the log-linearized version is obtained as:

$$\hat{\xi}_t = -\frac{\overline{\xi k}}{\overline{y}}\hat{k}_{t+1} + \frac{\overline{\xi b}}{\overline{y}}\hat{b}_{t+1} + \hat{y}_t, \tag{1.3.13}$$

where $\hat{\xi}_t$, $\hat{k}_{t+1}$, $\hat{b}_{t+1}$ and $\hat{y}_t$ are the log-deviations from the deterministic trend, and $\overline{\xi}$, $\overline{k}$, $\overline{y}$ and $\overline{b}$ denote the steady-state values.

Given the empirical series for $\hat{z}_t$, $\hat{y}_t$, $\hat{k}_t$, $\hat{n}_t$, $\hat{k}_{t+1}$ and $\hat{b}_{t+1}$, one constructed both the $\hat{z}_t$ and $\hat{\xi}_t$ series. Using these two time series, one is then able to estimate the autoregressive system:

$$\begin{pmatrix}\hat{z}_{t+1}\\ \hat{\xi}_{t+1}\end{pmatrix} = \mathbb{A}\begin{pmatrix}\hat{z}_t\\ \hat{\xi}_t\end{pmatrix} + \begin{pmatrix}\epsilon_{z_{t+1}}\\ \epsilon_{\xi_{t+1}}\end{pmatrix}, \tag{1.3.14}$$

where $\epsilon_{z_{t+1}}$ and $\epsilon_{\xi_{t+1}}$ are i.i.d. with standard deviations σ_z and σ_ξ, respectively. At this point, the series of financial and production shocks has been obtained to feed the model. The index of credit

Description	
Discount factor	$\beta = 0.9825$
Tax advantage	$\tau = 0.35$
Utility parameter	$\alpha = 1.8834$
Production technology	$\theta = 0.36$
Depreciation rate	$\delta = 0.025$
Enforcement parameter	$\bar{\xi} = 0.1634$
Payout cost parameter	$\kappa = 0.146$
Standard deviation productivity shock	$\epsilon_{z_{t+1}} = 0.0037$
Standard deviation financial shock	$\epsilon_{\xi_{t+1}} = 0.0067$
Matrix for the shocks process	$\mathbb{A} = \begin{bmatrix} 0.7908 & -0.0987 \\ 0.0725 & 0.8983 \end{bmatrix}$

Table 1.1.: *Parameters*

tightness in the model is given by symmetric innovation ϵ_{ξ_t}, which is a good proxy for the changes in ξ_t.

In order to set the parameters for the model, one followed the same approach as Jermann and Quadrini (2012). In Table 2.1, the full set of parameters used to run the model is reported. Some values differ from Jermann and Quadrini (2012) due to differences in the length of the sample used in the calibration, as the data sample was extended from 2010 Q2 to 2019 Q4.

In the equation of the law of motion of capital, the parameters ϱ_1 and ϱ_2 are set by two steady-state targets. In the first, the depreciation rate is equal to δ; in the second, it is $\partial k_{t+1}/\partial i_t = 1$.[8]

Induced by the series of financial and production shocks (given by the $\epsilon_{\xi_{t+1}}$ and $\epsilon_{z_{t+1}}$, respectively), the GDP, debt repurchase, equity payout, hours, wages, investment and capital time series were simulated.

For the empirical time series, one used quarterly data from the first quarter of 1985 to the last quarter of 2019. To construct the debt repurchase and equity payout time series, we used data from

[8]The second condition implies that the Tobin's q is equal to 1 in the steady state.

the Flow of Funds Accounts of the Federal Reserve Board, following the same approach as Jermann and Quadrini (2012). Debt repurchase is the negative of ‘net increase in credit market instruments of nonfinancial business’; equity payout is the sum of ‘net dividends of nonfarm, nonfinancial business’ with ‘net dividends of farm business’, minus the sum of ‘net increase in corporate equities of nonfinancial business’ with ‘proprietors’ net investment of nonfinancial business’. Both these time series are divided by the business value added from the National Income and Product Accounts. For the real gross domestic product (GDP), the data was obtained from the Federal Reserve Bank of St. Louis.

With regard to capital stock k_{t+1}, one used data from the Flow of Funds Accounts of the Federal Reserve Board. Given the law of motion of capital stock $k_{t+1} = k_t - \delta k_t + i_t$[9], one measured capital depreciation as ’Consumption of fixed capital in nonfinancial corporate business’, adding ’Consumption of fixed capital in nonfinancial noncorporate business’ and investment as ’Capital expenditures in nonfinancial business’. For Labor, one used the ’total private aggregate weekly hours’ from the Current Employment Statistics national survey. In the case of wages, one used the ’wages and salaries paid in Nonfinancial corporate business’ from the Flow of Funds Accounts of the Federal Reserve Board. For consumption, we used the ’Real Personal Consumption Expenditures’ [PCECC96] from the Federal Reserve Bank of St. Louis. As in Jermann and Quadrini (2012), the time series are in log values. While Jermann and Quadrini (2012) adopted a linear detrend for the time series, we used the Hodrick-Prescott (HP) filter here[10] (with $\lambda = 1600$ as suggested - for quarterly data - in Hodrick and Prescott, 1997).

In order to measure credit standards, one used an index from the Senior Loan Office Opinion Survey of the Federal Reserve Board. In this survey, credit standards are constructed as the percentage of senior loan officers at banks who tightened their lending standards for commercial and industrial

[9] To build the capital stock series, we disregarded the adjustment costs on investment, assuming - as the formula shows - that all investment made is transformed into capital.

[10] Despite criticism from Hamilton regarding the use of the HP filter, the alternative Hamilton filter has been also criticized by some studies, such as those by Astofli et al. (2019), Drehmann and Yetman (2018) and Hall and Thomson (2020), suggesting the use of the HP filter instead.

loans. This data separates large and middle-market firms from small firms; accordingly, an average of the two time series was calculated.[11]

1.3.3. Wavelet Analysis

In the following section, the empirical time series are compared with those provided by the model. In order to do so, one implemented the Wavelet Power Spectrum (WPS), the Global Wavelet Power Spectrum (GWPS) and Wavelet Coherence (WC). The WPS provides information as to how the variance of the time series changes at a given frequency and at a chosen moment in time. The color code for power ranges from blue (low power) to red (high power) - the color blue means that there is low volatility, while the color red indicates a high volatility of the time series. The white line shows the maxima of WPS undulation. The darkest area indicates the region affected by edge effects - in this area, the results should be interpreted carefully. The GWPS is simply an average of the wavelet power for each frequency. Through the WC, one can identify common oscillatory behavior of the empirical and simulated time series, thus enabling an examination of their co-movements in the domains of time and frequency. The color code for power is the same as in the WPS; however, in this case, the blue means lower covariance, and the red higher covariance. Once again, the darkest area indicates the region affected by edge effects. Although the WC depicts the interaction between two time series, it is unable to distinguish positive from negative correlations; neither can it identify the lead-lag relationship. For this purpose, we made use of phase-difference methodology, which provides information concerning the relation between two time series in terms of their co-movement. Given this, when we consider the WC between the time series x and y, if we have a phase-difference of 0, it means that the time series move together at the specified time-frequency. If the phase-difference is on the $]0, \pi/2[$ range, the two time series are moving in phase, with x leading. On the other hand, if the phase-difference is on the $]-\pi/2, 0[$, the two time series are in phase but with y leading, in this case. If the phase-difference is on the $]\pi/2, \pi[$ range, then the two time series are moving out-of-phase,

[11] Although we used an average of the two time series, the results of their separate values do not lead to a significant change: both present rather similar behavior.

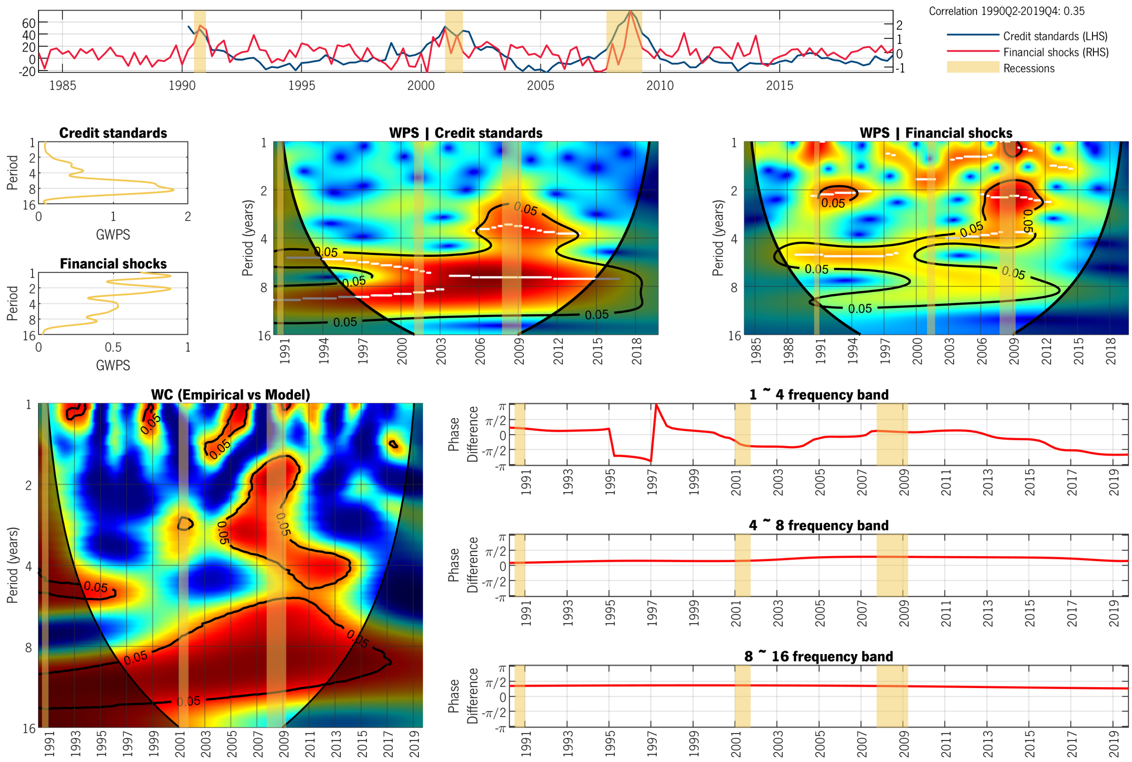

Figure 1.1.: *Above are the credit standards (quarterly) for the USA – from the Senior Loan Office Opinion Survey (blue line) and computed credit tightness (red line). Below is the GWPS for both time series, as well as the WPS of the credit standards and computed credit tightness. The dashed contour designates the 5% significance level based on an AR(1), while the dashed white line is the local maxima. At the bottom is the WC between the two time series and the phase-difference.*

with y leading. For a phase-difference on the $]-pi, -\pi/2[$, the two time series are also out-of-phase; in this case, it is x that is leading. For a phase-difference equal to π or $-\pi$, the two time series have an anti-phase relation. For a more detailed explanation on the fundamentals of wavelet tools, see Aguiar-Conraria and Soares (2014). For a better understanding of continuous wavelet transform and its application, see Aguiar-Conraria et al. (2012a,b); Aguiar-Conraria et al. (2013).

In Figure 1.1, one can observe that the computed credit tightness (from now on, this will be referred to as financial shocks) used to run the model is able to track the credit standards from the SLOOS reasonably well; however, the correlation between them is rather weak (only 0.37). The credit standards are smoother than the series of financial shocks but, in both cases, we have the observations of the top percentiles of both series[12], which occur during or just before recession periods. An analysis of the WPS for both time series, and despite the obvious differences, allows one to detect a few minor similarities. The main observable difference is that, while the higher power in the WPS of data is in the 4- to 8-year frequency band, in the WPS for the model the region of high power is mainly in the 1- to 4-year frequency band. There is, thus, stronger short-term volatility in the financial shocks series, as would be expected, given that this series results from the residuals of a VAR; however, a smoother transition is expected for credit standards.[13] This fact is supported by the GWPS for both time series. Despite these differences, both WPS show a larger region of higher power around 2008, thus reflecting the strong tightening of credit conditions. When focusing on the WC, one will observe that the two time series share common oscillatory behaviors, mainly in the second half of the sample. With the support of phase-difference, we can conclude that the financial shocks series tracks the behavior of credit standards quite fairly, despite some lag. For the 4- to 8-year frequency band, the two time series are found to be in-phase, with credit standards leading; however, they never reach a level of synchronization. For the 1- to 4-year frequency band, and with the exception of a short period after 1995, the two time series are also in-phase; however, in this case - after 2005 and during the *Great Recession* - they are practically synchronized. Lastly, for the frequency band of 8 to 16 years, the two time series remain in-phase but with a larger lag between the two, when compared to the 4- to 8-year frequency band. Despite the differences on the WPS for both series, the WC shows high covariance between both for an 8- to 16-year frequency across the entire time span.

Overall, the financial shocks used to simulate the model bear similarities with the credit standards series from SLOOS, mainly around the *Great Recession* period, with the two series showing a higher

[12]Since tightening of the enforcement constraint occurs when negative financial shocks happen, for the top percentiles we are referring - in this specific case - to the left tail of the distribution of financial shocks, i.e., to the top percentiles (95^{th} percentile) of $-\varepsilon_{\xi_t}$.

[13]Economic agents do not expect the frequent occurrence of great changes in credit conditions. Yet, several reasons can explain shifts in banks' willingness to lend, such as economic outlook or deleveraging driven by macroprudential measures, for example.

correlation across all frequencies during those years. There are undeniable differences (as expected, given the source and the way the financial shocks were computed) that are clearly shown in the WPS, with financial shocks exhibiting stronger volatility at higher frequencies, which reflects the short-term movements of the series. Despite the differences, financial shocks are considered to be a good proxy of the banks' credit standards.

After looking into the financial shocks' series used to simulate the model, one proceeded with an analysis of the main model variables, the most relevant of which is the GDP. At the top of the Figure 1.2 is the plot for the GDP, obtained from the data and the three time series derived from the model (simulated GDP with financial shocks only, with productivity shocks alone, and with both shocks included). From the plots, one can clearly observe that there is a stronger similarity between the empirical GDP and the simulated time series with financial shocks alone, than between the empirical GDP and the time series generated from productivity shocks. This fact is corroborated by the correlation between the empirical GDP and each one of the simulated time series. When financial shocks were considered, one obtained a correlation of 0.59; for productivity shocks, we only obtained a correlation between the time series of 0.35. Despite the stronger correlation between the empirical GDP and the simulated time series with financial shocks only, one observed a slight increase in correlation to 0.74 when both shocks were considered. From the plotting of the series (both the empirical and simulated), one observed that the time series obtained through financial shocks, as well as with both shocks, replicated the downturn of the product in the last three crises (1990-1991, 2001 and mainly 2008-2009). On observing the WPS of the empirical GDP, a higher volatility was detected, with a greater concentration in the 4- to 12-year frequency band for the whole sample. Around 2008, the region of high variance extended to a frequency band from 2 to 8 years. When we moved to the WPS of the simulated time series with financial shocks, we saw a similar result to the previous one, with local maxima exhibiting almost identical patterns around same frequencies. The WPS of the simulated GDP with financial shocks only was, however, much closer to the WPS of the empirical time series than to the WPS of the simulated time series with productivity shocks only. Taking into consideration the local maxima during the *Great Recession*, one can clearly see

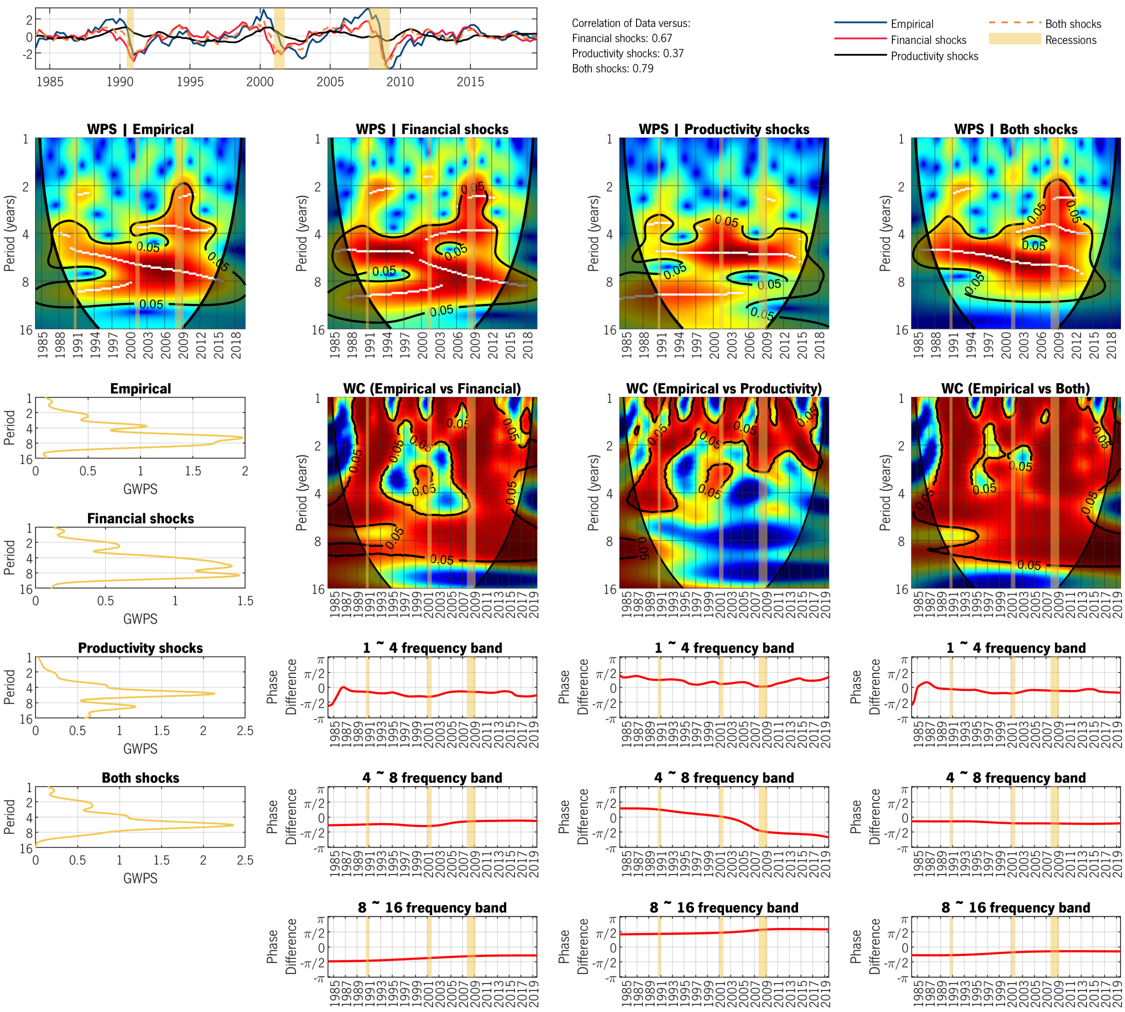

Figure 1.2.: *Above is the GDP (quarterly) for the USA (blue line), the simulated GDP with financial shocks only (red line), the simulated GDP with production shocks only (green line), and the simulated GDP, which includes both shocks (dashed black line). Below is the WPS of the empirical GDP and the simulated time series with financial shocks only, productivity shocks alone and both shocks included. The dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between the empirical GDP and each of the simulated time series.*

that, for the WPS of the empirical GDP, they are concentrated around three different frequencies (2 years, 4 years and around 6 to 8 years). There is also a clear downward trend in the local maxima at the 4- to 8-year frequency band, starting close to the 5-year frequency in 1990 and ending close to the 8-year frequency in 2015. Between the recessions of 1990-91 (Iraq's invasion of Kuwait and the oil price shocks) and 2001 (the collapse of the speculative dot-com bubble), one also observed a local maximum around the 10-year frequency. This is also broadly reflected in the GDP simulated with financial shocks, as well as with both shocks (apart from the local maxima around the 10-year frequency between the two previous recessions). However, when the productivity shocks were taken into account separately, only one local maximum was considered on a frequency band between 5 and 6 years, and one between 10 and 12 years, which was extended from the beginning of the sample to 2006. For simulation with both shocks, one obtained an approximation to the empirical series at frequencies under 8 years (for higher frequencies); yet, the local maxima were lost in the first half of the sample at the 10-year frequency. The similarities between the empirical GDP and each one of the simulated series was corroborated by the GWPS, showing better results when both shocks were used. The proximity of the simulated GDP (with financial shocks only) to the empirical GDP was also revealed through the WC and respective phase-difference. In this case, as well as when both shocks were considered, the WC gave a wider region of high covariance. This was even greater when both shocks were considered. The phase-difference was expressed differently across the frequency bands. For the 1- to 4-year frequency band, both series from each shock (financial and productivity) were in-phase with the empirical counterpart. Nevertheless, while the empirical series led the one simulated with productivity shocks, the series from financial shocks led the empirical GDP. When the two simulated series were summed up, one saw that the result revealed close synchronism with the GDP empirical series. For the 4- to 16-year frequency band, there were not many regions of strong covariance between the empirical and the one simulated from the productivity shocks' series. Thus, one cannot rely on the results for phase-difference regarding this case. Focusing on the results for the series of financial shocks, as well with both shocks, one observed that for the 4- to 8-year frequency band the results were quite similar: the series was in-phase and the simulated GDP took the lead.

For frequencies between 8 and 16 years, the series were in-phase in after 2000 in both cases; however, when both shocks were considered, the series drew significantly closer to synchronism. Lastly, one should remark on the stability of the phase-difference between the empirical GDP and the series simulated with financial shocks only: both series were in-phase across the frequency bands, with the simulated series always taking the lead. These results, along with those from the comparison between the credit standards of the SLOOS and financial shocks (credit standards leading the financial shocks), could indicate that the last recessions were mainly driven by the tightening in banks' lending standards, which restricted financing to the economy, both exposing and amplifying accumulated risks and vulnerabilities.

The next set of variables analyzed were equity payout and debt repurchase. The interest of looking into the behavior of these two series was due to the fact that: (i) the model is built under the roles for debt and equity financing, with a pecking order in firms' decisions; and (ii) the model is an approximate reflection of empirical cyclical properties, as argued by the authors.

From the plots for equity payout, one can observe that the simulated financial shocks series generally track the behavior of their counterparts, while the productivity shock series seem to be uncorrelated and unable to follow the movements of the empirical counterpart. This is reflected in the correlation between the empirical and simulated series. Although financial shocks produced a series that normally follows empirical equity payout movements, there was a major improvement of the fit after 2000. Indeed, and for example, in the 1990-91 crisis, the financial shocks introduced a significant reduction in equity payouts, which was not observed in the data (in this particular case, the inverted "U" shape of the productivity shocks seem to provide a closer replication of what is observed in the data). When considering the WPS, one observed regions of high volatility in the empirical series, mainly after 2000, with a predominance at lower frequencies, namely in the 3- to 12-year frequency band. The WPS of the simulated series with financial shocks only was very similar to the WPS for the GDP.[14]. When compared to the WPS of the empirical equity payout, one observed some

[14]Using the set of parameters adopted to calibrate the model, the financial shocks produced series for equity payout and debt repurchase. These were highly correlated with the GDP (positively and negatively, respectively). In order to

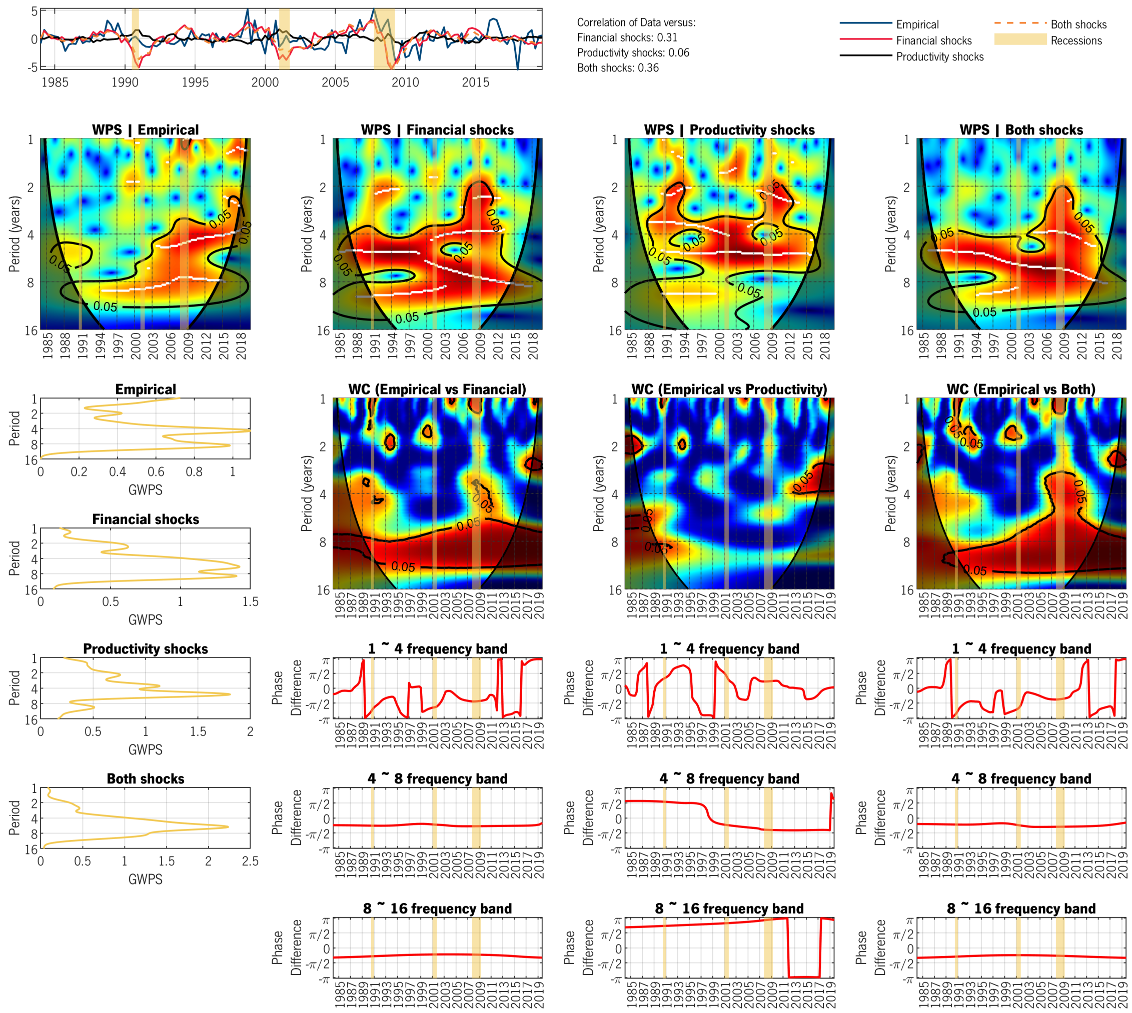

Figure 1.3.: *Above is the equity payout (quarterly) for the USA (blue line), the simulated equity payout with financial shocks only (red line), the simulated equity payout with productivity shocks only (green line), and the simulated equity payout with both shocks (dashed black line). Below is the WPS of the empirical equity payout and the simulated time series with financial shocks only, productivity shocks only, and including both shocks - the dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between empirical equity payout and each of the simulated time series.*

similarities after 2000, but not before. Furthermore, the financial shocks were unable to replicate the short-term volatility (in the 1- to 2-year frequency band) observed in the data. In contrast to the financial shocks, the productivity shocks were able to produce higher volatility regions in the 1- to 2-year frequency band, which are rather similar to the data; yet, there were larger differences in the WPS of the empirical series at lower frequencies, namely above 4 years. For the series produced from both shocks, the results for the WPS were quite similar to those for the financial shocks alone. One also saw some similarities after 2000; the series did not reveal areas of strong volatility at high frequencies (below 2 years). Observed in the WC were the consequences of the results detailed in the WPS, with the WC between empirical equity payout and the series of financial shocks exhibiting a region of strong covariance at lower frequencies. The productivity shocks were unable to produce a series of strong covariance with the empirical counterpart. Despite this, when added to financial shocks, they seemed to improve the area of strong covariance between the simulated series and the empirical counterpart. Taking into account the results of the WPS, the phase-difference for 1 to 4 years does not provide relevant results as there is no high covariance between the series. Nonetheless, one observed that the series were out-of-phase for the financial shocks during the 1990-91 crisis, while for the productivity shocks proved to be in-phase during this specific period, which is in line with the previous observation. For the 4- to 8-year and 8- to 16-year frequency bands, the simulated series with financial shocks only were in-phase, taking the lead over the empirical counterpart. This can be interpreted as a consequence of the financial shocks, or the tightening in banks' lending standards, which can somehow anticipate medium- to long-term movements (or deviations from the deterministic trend) of firms' equity payout decisions. In the case of productivity shocks, the phase-difference was meaningless, whereas for both shocks the results were globally equal to financial shocks alone.

Compared to equity payout, one saw an increase in the correlation between the empirical debt repurchase series and the simulated series with financial shocks only. The series of productivity

reduce the correlation between the GDP and equity payout/debt repurchase, one had to set $\tau = 0$, eliminating the friction on the cost of equity adjustment. The side effect of such an approach is that there is an even lower correlation between the equity payout/debt repurchase series from the model and the empirical counterparts.

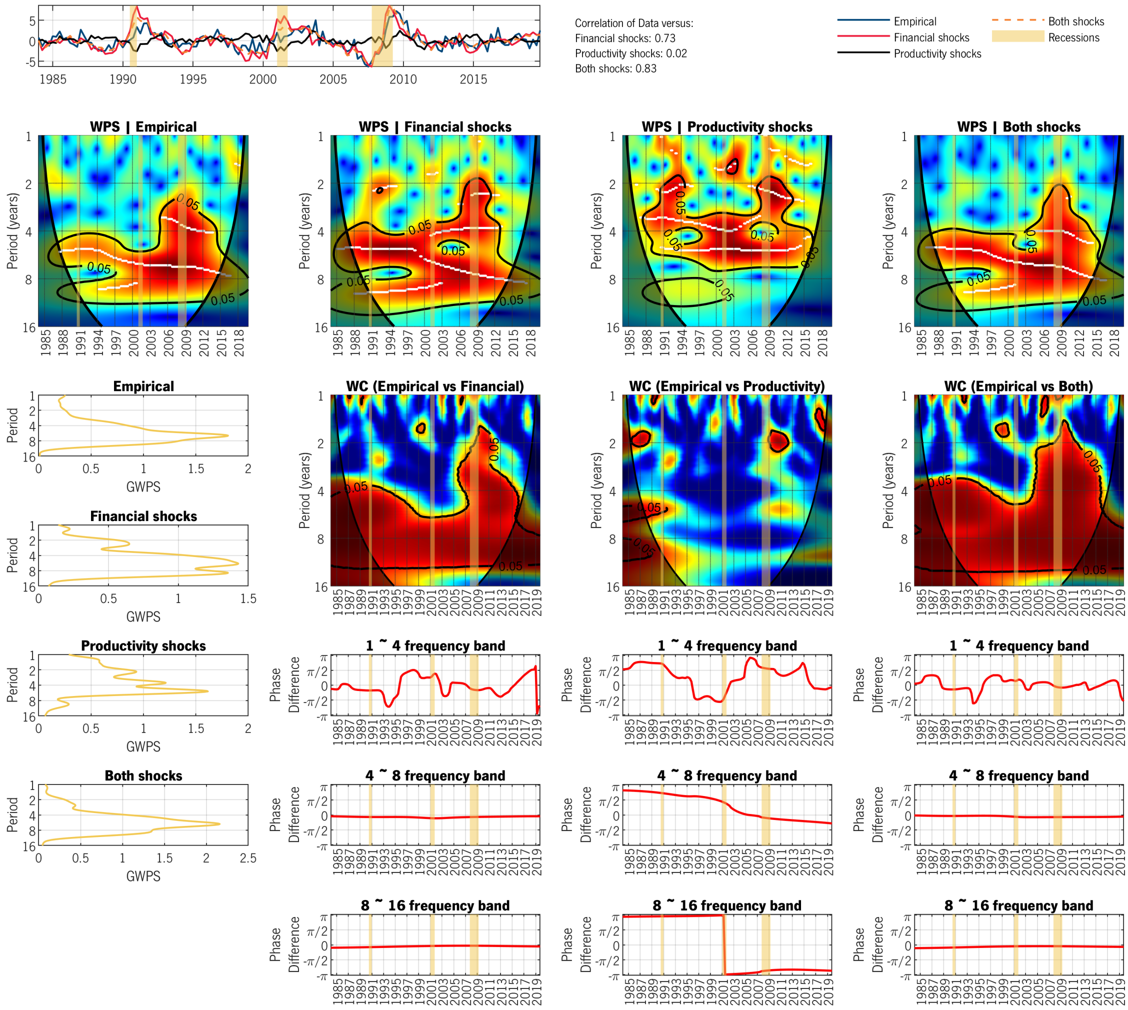

Figure 1.4.: *Above is the debt repurchase (quarterly) for the USA (blue line), the simulated debt repurchase with financial shocks only (red line), the simulated debt repurchase with production shocks only (green line), and the simulated debt repurchase with both shocks (dashed black line). Below is the WPS of the empirical debt repurchase and the simulated time series with financial shocks only, productivity shocks only, and with both shocks -the dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between empirical debt repurchase and each of the simulated time series.*

shocks remained uncorrelated with their empirical counterpart, which also occurred in equity payout. Yet, when both shocks were summed up, the correlation between the simulated and empirical series showed improvement. On observing the WPS of empirical debt repurchase in Figure 1.4, there were some similarities with those of the empirical GDP (Figure 1.2). Namely, the local maxima were close to the 4-year frequency around the *Great Recession* period, a trend in the local maxima in the 4- to 8-year frequency band (moving from closer to the 4-year frequency at the beginning of the sample to the 8-year frequency at the end), and the local maxima between the 1990-91 and 2001 crises around the 10- year frequency. For the simulated series, the WPS was identical to that of equity payout since there was a symmetry between the two series in the model.[15] In spite of the differences between the WPS of empirical debt repurchase and the WPS for productivity shocks, when both shocks on the model were summed up, the end result pointed to a WPS which was very similar to that of the empirical counterpart. This is consistent with the increase in correlation between the series (from 0.68 of the financial shocks to 0.79 of both shocks). In the GWPS, one observed a clear resemblance between the empirical and simulated equity payout with both shocks, with a cyclical component of around 6 years. When each of the shocks was considered separately, one observed that the simulated series had more periodic components, which were not overtly detected in the data. The results for the WC were aligned with those of the equity payout series, but in this case the area of strong covariance was wider for the financial shocks and for both shocks as well. In the case of the productivity shocks, as well as equity payout, there were once again very small regions of high covariance between the simulated and empirical counterpart over time and frequency. The phase-difference was, in itself, a reflection of the previous results. In the 1- to 4-year frequency band, the simulated equity payout with financial shocks only was, for most of the sample, in-phase with the empirical time series; after 2005, it was close to synchronism, with a small lag between the series during the *Great Recession*. The series simulated with financial shocks led over the empirical counterpart. When both shocks were used, the simulated series was even closer to synchronism with empirical debt repurchase; yet,

[15] The correlations between equity payout the debt repurchase from the model are -0.998, -0.987 and -0.983 for financial shocks, productivity shocks and both shocks, respectively.

in the case of productivity shocks, the results were, in themselves, meaningless. Despite the results of productivity shocks, in some periods it helps to approximate the simulated series with financial shocks to the data, namely between 1996 and 2004, as well as between 2007 and 2015. For the 4- to 8-year and 8- to 16-year frequency bands, the results were approximately the same as for equity payout, although the series from financial shocks and both shocks was slightly closer to synchronism with its empirical counterpart.

In Figure 1.5, one has presented the results for labor, measured as hours worked. The correlations (above 0.5) between the empirical series of hours worked and simulated labor with financial shocks only, and with both shocks, showed a strong positive relation. Between the empirical series and simulated labor with productivity shocks only, a much lower correlation was obtained. Indeed, the productivity shocks were unable to replicate the reduction in the number of hours worked, which was observed during the recession periods. On analyzing the WPS and GWPS, the results approximately resemble those obtained for debt repurchase. Once again, the simulated time series with financial shocks only presented a WPS closer to the empirical one, when compared with the WPS of simulated labor with productivity shocks only. The same is true of the GWPS, which showed improved results when both shocks were used in the construction of the simulated series. These facts resulted in fewer regions of strong and significant covariance when one considered the WC between the empirical series of hours worked and simulated labor with productivity shocks only. The regions of higher coherency of the WC, between the empirical time series and simulated labor with financial shocks only, and with both shocks, were more pronounced after 2005, with these areas extending to almost all of the frequencies. Lastly, concerning the WC, the covariance between the series increased when both shocks were included in the simulated series. The phase-difference for the 1- to 4-year frequency showed that, overall, for the periods where the WC revealed a strong and statistically significant covariance, the empirical and simulated series were in-phase, differing mainly with regard to which of the two was in the lead. In greater detail: the simulated series systematically took the lead over the empirical counterpart, with the exception of the period around 2015, when they seemed to reach simultaneous synchronism. In contrast, in the case of productivity shocks, the opposite was

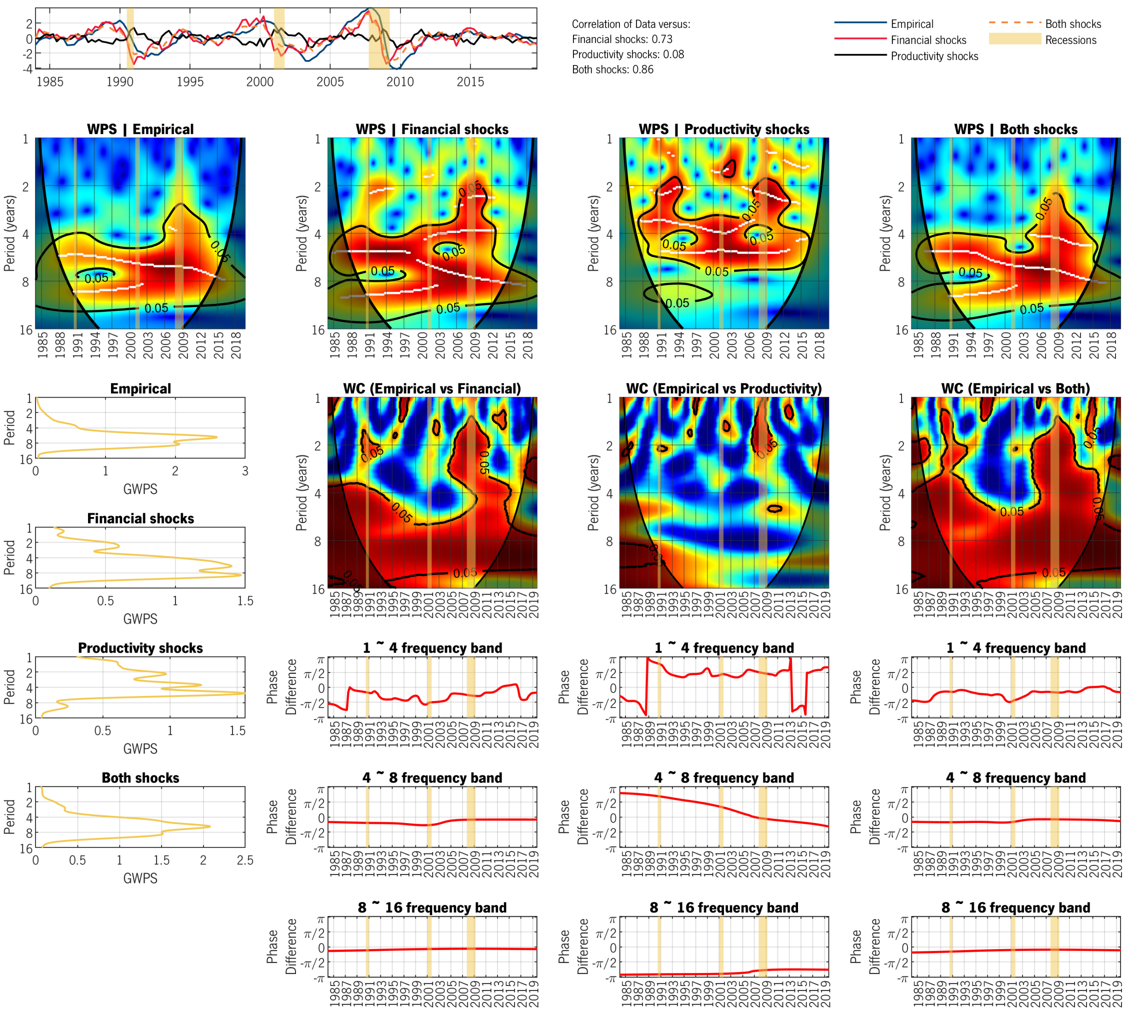

Figure 1.5.: *Above is the number of hours worked (quarterly) (blue line), simulated labor with financial shocks only (red line), simulated labor with production shocks only (green line), and simulated labor with both shocks (dashed black line). Below is the WPS of the empirical hours worked and the simulated time series with financial shocks only, productivity shocks only and with both shocks - the dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between the empirical hours worked and each of the simulated time series.*

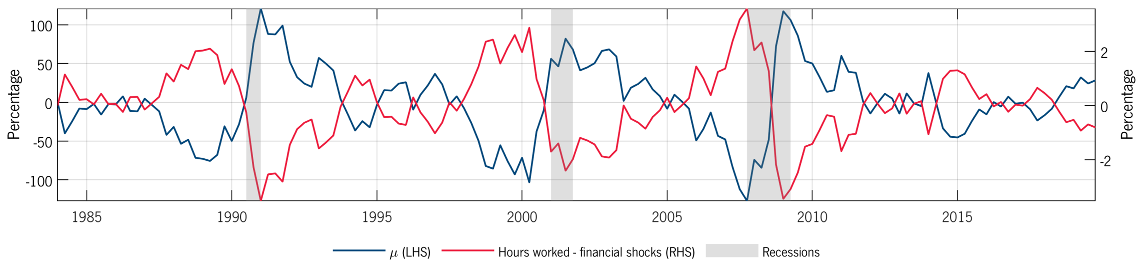

Figure 1.6.: *Lagrange multiplier μ and the hours worked*

observed: the empirical series of hours worked was in the lead and, around 2015, they seemed to be out-of-phase, with productivity shocks predicting a reduction in labor, which was not verified. The combination of the two shocks, which had been produced series with different lags when compared to the empirical counterpart, seemed to result in a series that was generally closer to synchronism with the empirical series of hours worked at higher frequencies. However, the financial shocks exercised greater influence and, consequently, the simulated series led over the empirical counterpart. For the 4- to 8-year and 8- to 16-year frequency bands – and although the results are irrelevant due to the low covariance level between the series - at the beginning of the sample, where covariance was stronger, the results for phase-difference seem to point to the two series being out-of-phase. For the simulated series with financial shocks only, and with both shocks, the results were similar for the two frequency bands; the series was in-phase and the simulated series took the lead over the empirical series for labor.

In fact, labor plays an important role in the model since it is the main channel through which financial shocks are transmitted to the real sector of the economy. In order to illustrate this, the enforcement constraint - given in equation (1.3.8) - can be rearranged to:

$$\left(\frac{\xi_t}{1-\xi_t}\right)\left[(1-\delta)\,k_t - b_t - w_t n_t - d_t\right] \geq F\left(z_t, k_t, n_t\right). \tag{1.3.15}$$

Assuming that at the beginning of the period k_t and b_t are given, then the only variables that are under the firm's control are labor n_t and equity payout d_t. In the presence of an adverse financial shock, i.e., a drop in ξ_t, and in order to maintain the production plan, the firm must reduce equity payout d_t. If this reduction - which depends on the flexibility of changes in the financial structure - is not possible, then the firm will be forced to reduce labor input n_t.[16]. In the equation 1.3.9 from the FOC, the marginal productivity of labor is equal to the marginal cost; however, the marginal cost is given by the wage rate, augmented by the factor that depends on $\xi_t \varphi\left(d_t\right)$, which is the "effective" tightness of the enforcement constraint. This means that, in the presence of a negative financial shock in the form of a tightening of the enforcement constraint, the effective cost of labor increases. This, in turn, leads to a shrinkage in the demand for labor, which is clearly illustrated in Figure 1.6. It presents the series for the Lagrange multiplier and simulated labor with financial shocks only, with the two time series showing almost perfect symmetrical behavior. These results can be interpreted as the tightening of banks' lending standards, thus affecting the firm's decision with regard to production, namely the necessary investments to be made and, consequently, the amount of labor required for it to operate.

The plots of the time series in Figure 1.7 show that the financial shocks produced a series for investment, which shared the behavior of their empirical counterpart. This can be seen in the drop in investment during the crises, with greater emphasis during the *Great Recession*. On the other hand, productivity shocks were unable to produce these reductions; however, when both shocks were taken into account, the simulated time series obtained seemed to draw closer to the empirical series of investment, as the correlations suggest. The WPS and the GWPS produced very similar results to those obtained for the GDP. Regarding the WC, and as usual, the results showed a smaller region of high coherency when only productivity shocks were used to construct the simulated series. These were mainly concentrated at higher frequencies, namely between 1 and 4 years. The phase-difference indicates that, for the 1- to 4-year frequency band, all the three simulated time series are generally in-phase with the empirical series of investment. Contrary to what was observed for other series are the productivity shocks, which produced a series closer to synchronism with the empirical counterpart. This result could be understood, in the short-term, as being more conditioned by productivity/technological innovations rather than by the financial conditions themselves. Additionally,

[16]The flexibility to change the firm's financial structure is reduced by the adjustment cost of equity payout $\varphi\left(\cdot\right)$

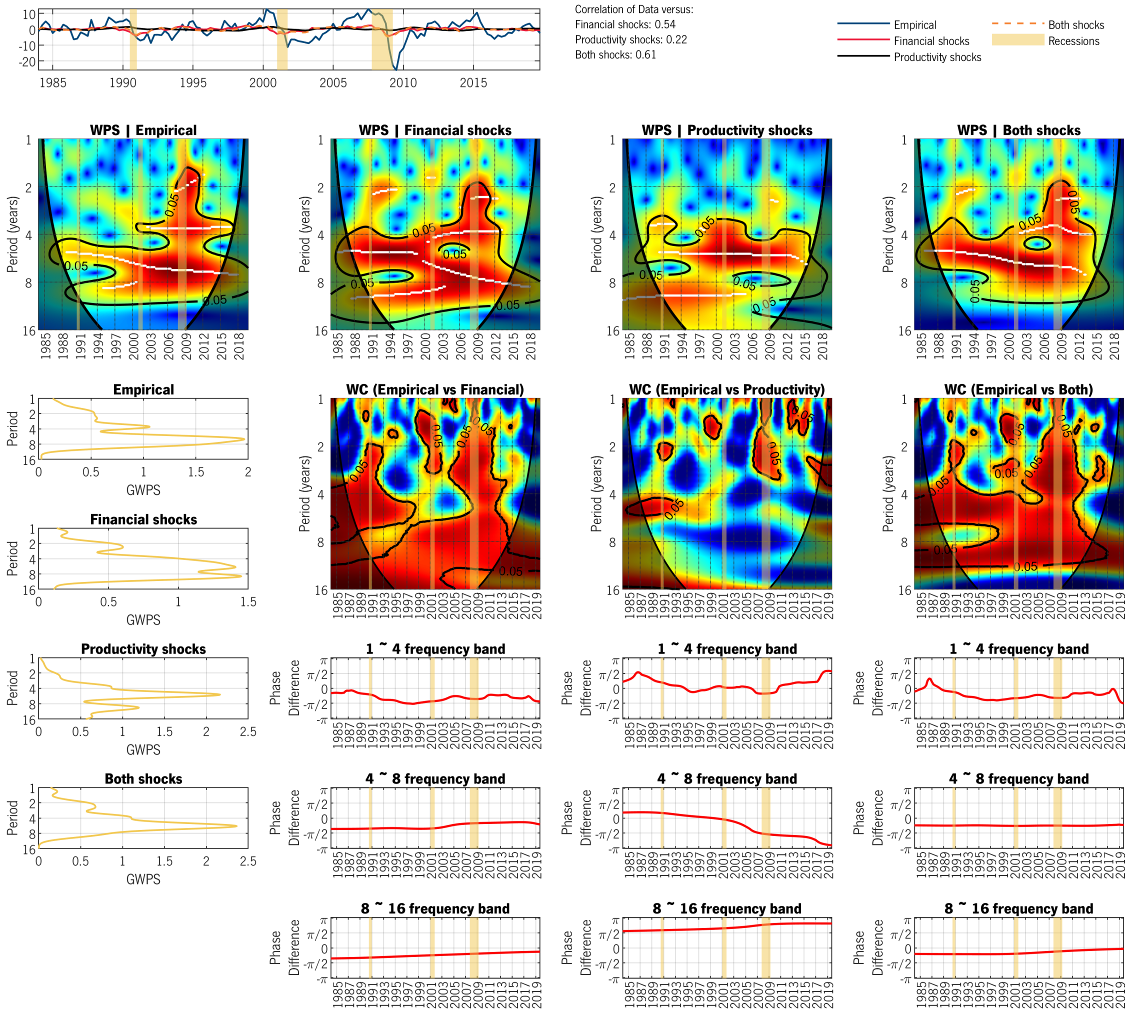

Figure 1.7.: *Above is the investment (quarterly) (blue line), simulated investment with financial shocks only (red line), simulated investment with production shocks only (green line), and simulated investment with both shocks (dashed black line). Below is the WPS of empirical investment and the simulated time series with financial shocks only, productivity shocks alone and with both shocks - the dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between empirical investment and each of the simulated time series.*

at this frequency band, and between 1996 and 2001, the simulated series with financial shocks only seem to be neither in-phase nor out-of-phase with the empirical series of investment; this also coincides with the reduced coherence observed during most of this period at these frequencies. In relation to the remaining periods, the simulated series and the empirical counterpart were in-phase, with the series built from the model usually leading the empirical series of investment , which is also the case in all the time periods when there is strong and statistically significant coherence. For the 4- to 8-year frequency band, the results showed an approximation to synchronism between the series produced from the financial shocks and the empirical ones, across the time span considered. The simulated series of investment took the lead, but the lag between them showed a reduction after 2005, which remained stable from then onwards. For the productivity shocks, one observed only a small area of strong covariance between the simulated series and the empirical counterpart; the latter was in the lead in this case, similarly to what was observed for the 1- to 4-year frequency band. When both shocks were taken into account, the phase-difference was quite stable along the entire time span, with the simulated series in the lead. Lastly, for the 8- to 16-year frequency band, one observed an approximation of the simulated series with financial only and both shocks showing synchronism with the empirical series of investment. However, there was always some lag between them, with the simulated series leading. In the case of productivity shocks, one did not observe any region of strong coherence; accordingly, the results relating to phase-difference are meaningless.

For capital stock, and as shown in Figure 1.8, the productivity shocks were unable to replicate the ups and downs of capital stock; thus, it is not surprising that the Pearson p-values demonstrated that they were uncorrelated. In contrast, the simulated series of capital with financial shocks only tracked the behaviors of the empirical counterpart reasonably well. The same applies to the simulated series with both shocks. On analyzing the WPS of each of the time series, they all presented a concentration of higher power at lower frequencies in common, exhibiting low volatility at the 1- to 4-year frequency band. As is usually seen in other series, the financial shocks produced a simulated series with a WPS that was more similar to the empirical counterpart, which is extended to the simulated series with both shocks. Taking into consideration the local maxima, the WPS for the simulated capital with

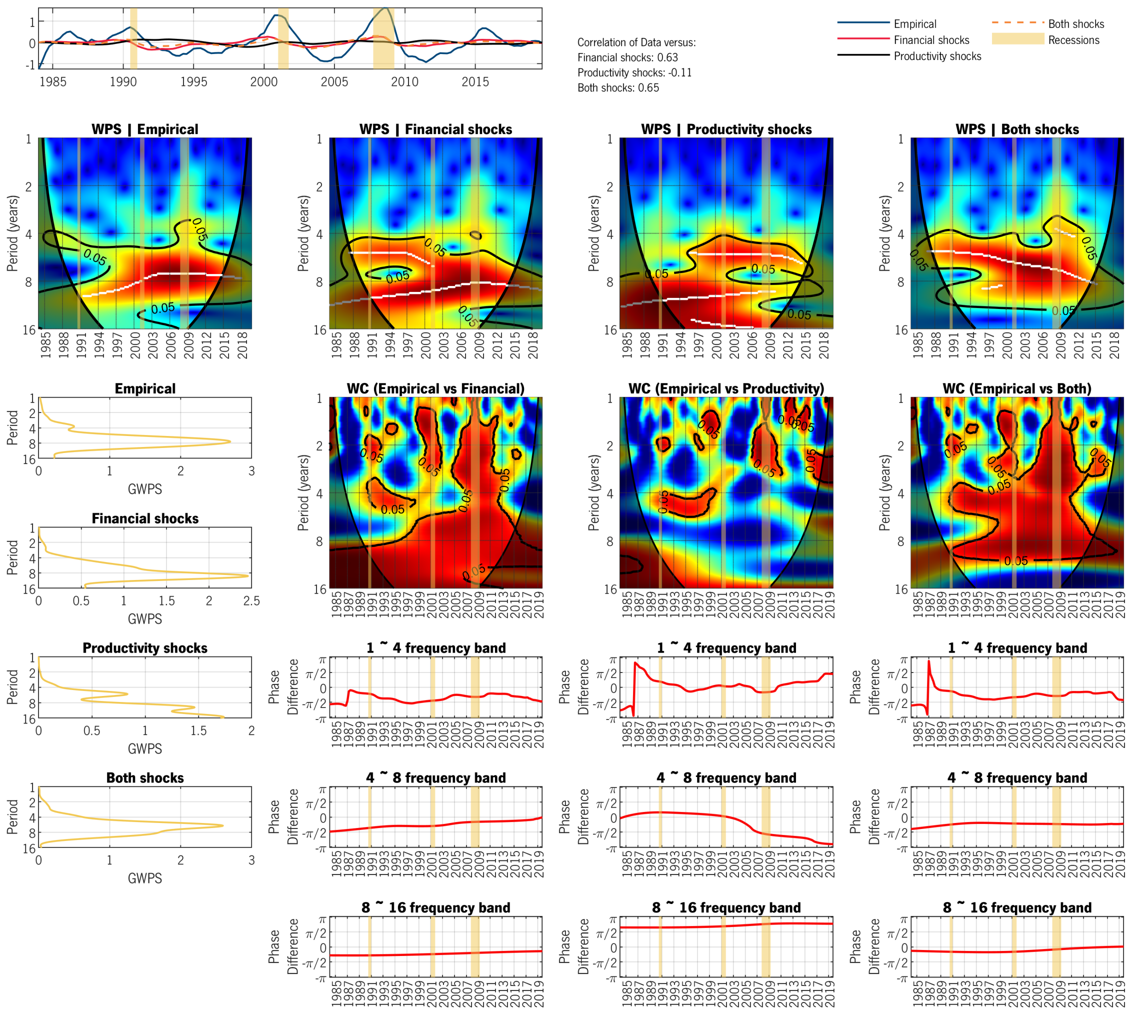

Figure 1.8.: *Above is the capital (quarterly) (blue line), the simulated capital with financial shocks only (red line), the simulated capital with production shocks only (green line) and the simulated capital with both shocks (dashed black line). Below is the WPS of empirical capital and the simulated time series with financial shocks only, productivity shocks only and with both shocks - the dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between empirical capital and each of the simulated time series.*

financial shocks only is the one that showed a greater approximation to the WPS for the empirical time series, especially in the second half of the sample. This is corroborated by the GWPS, which was concentrated at the 8-year frequency for both series (the simulated series for financial shocks and the empirical counterpart). The results indicated that financial shocks produce series with larger areas of strong covariance when compared to the empirical series of capital. For productivity shocks, which is also the case of the investment series, the areas of strong coherence were concentrated mainly in the 1- to 4-year frequency band, with the exception of a region of high covariance between the 1990-01 and 2000 crises, as well as around a 6-year frequency. Despite the similarities in the WPS and GWPS for high frequencies, such as between 1 and 4 years, the productivity shocks produced a series very close to synchronism with the empirical counterpart. This was also observed in the case of investment. At this frequency band, the results for the series produced from the financial shocks, as well as with both shocks, were remarkably similar to those of investment, with the series being in-phase most of the time (with the exception of the period between 1996 and 2001, which also occurred in the investment series), and the simulated series leading. The results for the other frequency bands resembled those of the investment series: the simulated series with financial and both shocks was in-phase (leading), while both the empirical counterpart and productivity shocks produced a series close to synchronism when coherence was strong and statistically significant at the 4- to 8-year frequency band.

Figure 1.9 shows the results obtained for the wages time series. Although the simulated series were uncorrelated with the empirical series of wages, the plots revealed that the financial shocks produced a series that was able to replicate wage decreases during the crises of 1990-91, 2001 and 2008. The productivity shocks, however, cannot explain these changes, and even generated an increase in wages during the 1990-91 and 2001 crises. For the WPS, one observed that the simulated wages with both shocks showed the closest approximation to the WPS of the empirical time series. Despite being the most similar, there were significant differences. Namely, after the 2001 crisis, and for the empirical series of wages, one observed that high volatility was concentrated mainly at higher frequencies (1- to 4-year frequency band), which was not replicated by financial shocks. On

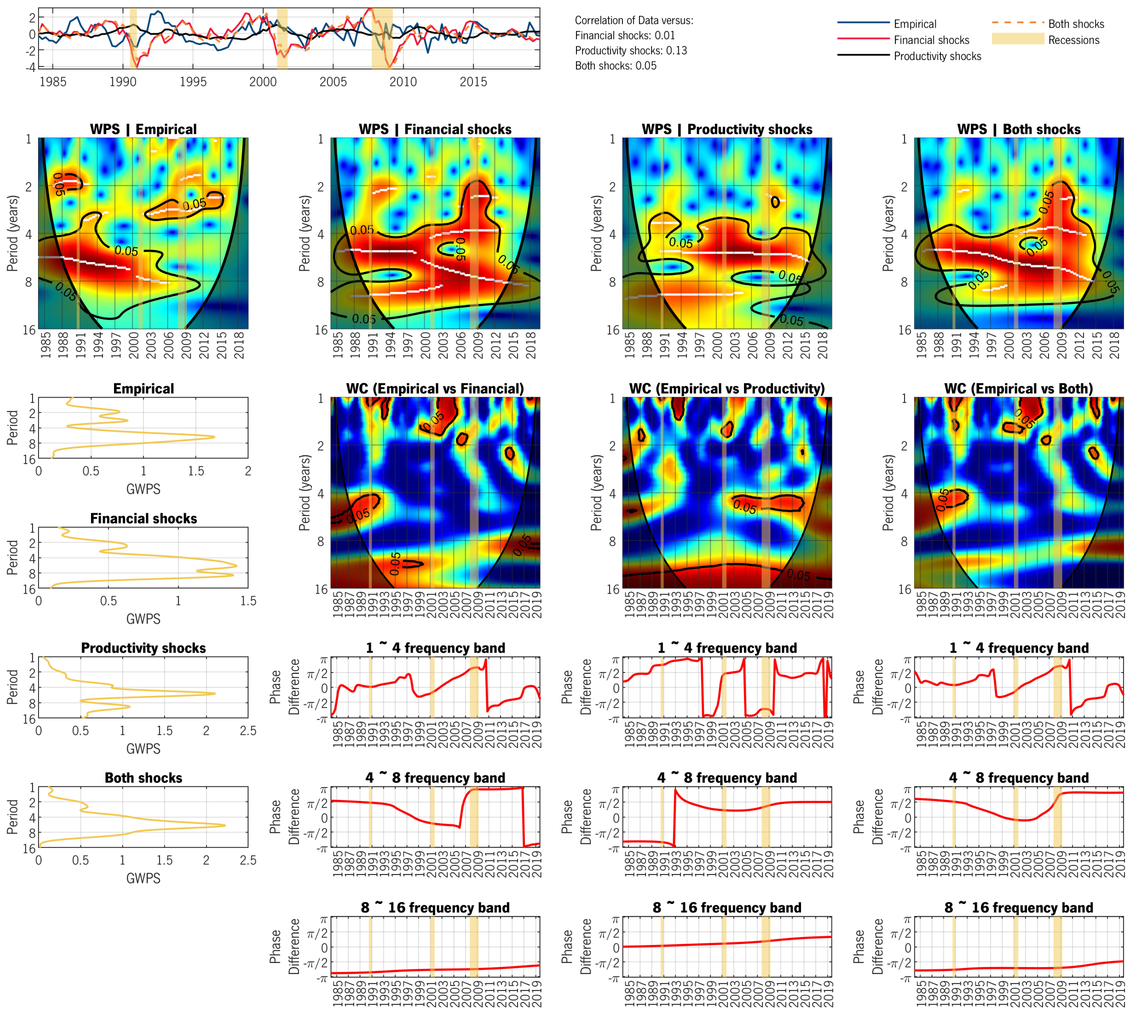

Figure 1.9.: *Above is wages (quarterly) (blue line), simulated wages with financial shocks only (red line), simulated wages with production shocks only (green line) and simulated wages with both shocks (dashed black line). Below is the WPS of empirical wages and the simulated time series with financial shocks only, productivity shocks only and with both shocks - the dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between empirical wages and each of the simulated time series.*

the GWPS, there were some similarities between the simulated series with financial and both shocks, but to a lower degree when compared to what had been observed previously. The WC, unlike the previous variables, did not present large regions of strong coherence. Due to this, the results of the phase-difference should be regarded with extra caution. For the 1- to 4-year frequency band, whenever there was a region of strong and statistically significant coherence, the simulated series with financial shocks only seemed to be in-phase with the empirical counterpart, while the series for productivity shocks was out-of-phase. For the remaining frequencies, the series produced from the model containing financial shocks seemed to be out-of-phase during periods of strong coherence. For productivity shocks, in the 4- to 8-year frequency band, the series were also out-of-phase, with a few exceptions. However, the results were rather clear, namely between 2003 and 2008. Continuing with productivity shocks, for the 8- to 16-year band, one observed a region of high covariance; in this case, the series were in-phase, with the empirical series leading.

For consumption, there was a positive correlation between the series produced from the financial shocks and with both shocks, and the empirical series of consumption. Once again, the productivity shocks produced a series that was uncorrelated with the empirical counterpart. From the results in Figure 1.10, it is clear that the Jermann and Quadrini (2012) model is unable to replicate the magnitude of consumption movements. On analyzing the WPS, one saw some resemblances between the empirical series and the simulated series. Nevertheless, there were also some undeniable differences, namely: for the empirical series of consumption, the region of high volatility was concentrated mainly between 3 and 12 years, while for the simulated series (except when both shocks were used), one observed areas of strong volatility in the 12- to 16- year frequency band. The local maxima were also quite different; this is reflected in the GWPS, where only the simulated series with both shocks was close to that obtained for the empirical counterpart, with a concentration around the 6-year frequency. Consequently, the results for the WC showed a larger area of high coherence when both shocks were considered in the building of the simulated series; as usual, the productivity shocks were those which produced a series with fewer and smaller areas of high coherence. Surprisingly, for the 1- to 4-year frequency band, the simulated series with financial shocks only was the one that was

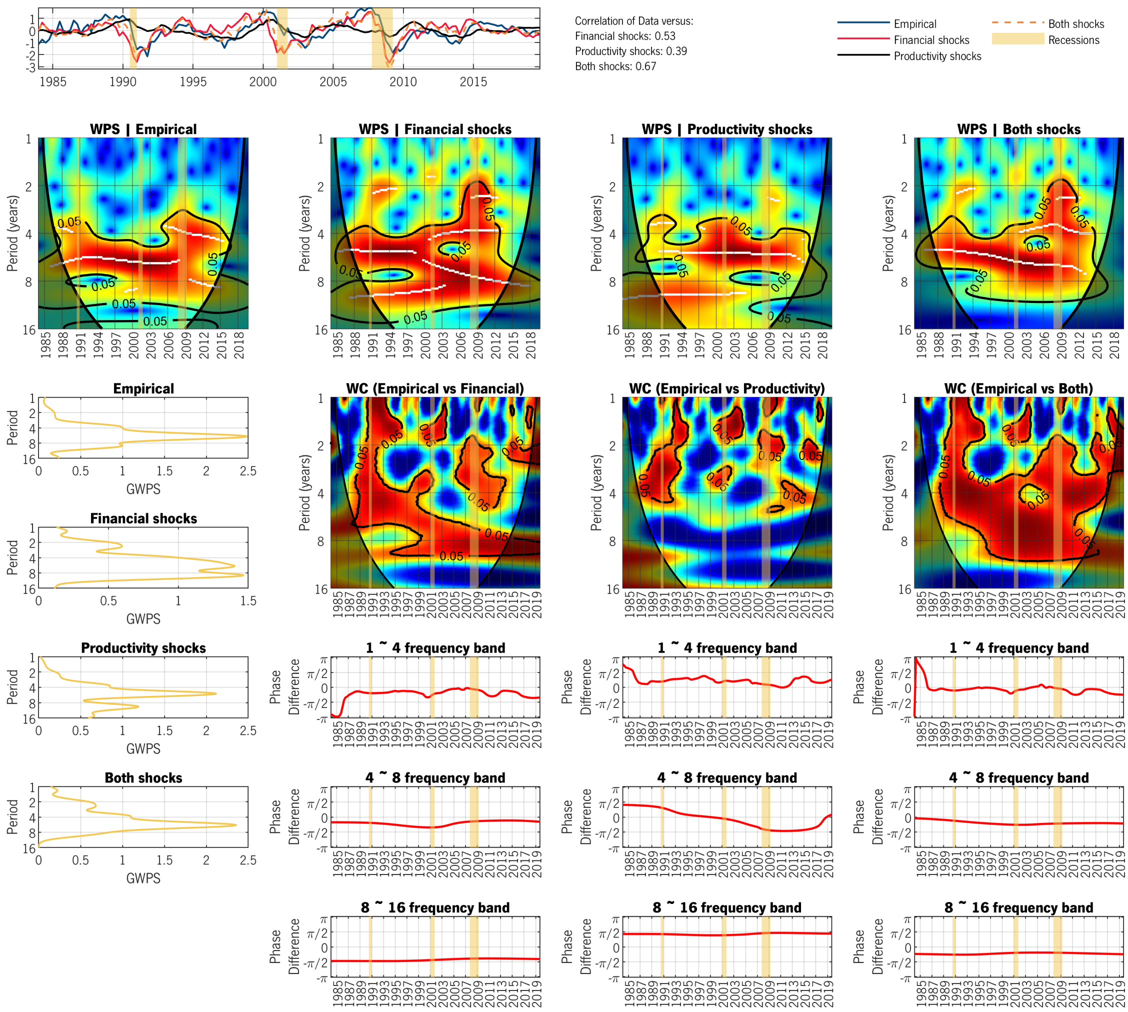

Figure 1.10.: *Above is consumption (quarterly) (blue line), simulated consumption with financial shocks only (red line), simulated consumption with production shocks only (green line), and simulated consumption with both shocks (dashed black line). Below is the WPS of empirical consumption and the simulated time series with financial shocks only, productivity shocks only and with both shocks - the dashed contour designates the 5% significance level based on an AR(1). The white line is the local maxima. At the bottom is the GWPS of the four time series, as well as the WC between empirical wages and each of the simulated time series.*

in-phase, and close to synchronism with the empirical counterpart, taking the leading position. For the 4- to 8-year frequency band, the simulated series with financial shocks only and with both shocks were in-phase with the empirical counterpart, with the latter leading. Lastly, for the 8- to 16-year frequency band, the simulated series with financial shocks was in-phase, and led the empirical series of consumption. This contrasts with what was observed for both shocks: while still in-phase, it was the empirical series which took the lead whenever there was strong and statistically significant coherence between the series.

1.4. Conclusions

In this chapter, one analyzed the Jermann and Quadrini (2012) model in the time-frequency domain. In order to assess the accuracy of the model, both the empirical and simulated series were compared by means of wavelet tools, such as wavelet coherence, as the respective phase-difference.

From the comparison of the empirical series with the respective simulated counterparts, one observed that - with the exception of wages - financial shocks produced strongly correlated series, which were able to perceive most of the cyclical behaviors of the empirical counterparts. It is also true that the use of both shocks usually enhanced results, thus resulting in series closer to synchronism, and which globally pick up the frequency properties of the empirical series. In the case of wages, one can clearly see that the simulated time series was unable to replicate the cyclical behavior of the empirical series. Along with consumption, this was also the only case, where the productivity shocks seemed to produce simulated time series with a more similar behavior at higher frequencies, such as between 1 and 4 years. However, in a broader context, they were still far from replicating their empirical counterparts.

Globally, the wavelet analysis performed indicated that the Jermann and Quadrini (2012) model is able to grasp most of the properties of the empirical series. The main conclusions are that, with a few exceptions, there were better results for the series generated from financial shocks than from productivity shocks. Moreover, the financial shocks were able to explain most of the drops which occurred in the variables during the last three crises. Nonetheless, and with no exception, the difference in results for the financial and productivity shocks saw an improved outcome when both shocks were taken into account. It was also revealed that productivity shocks generated more volatility at higher frequencies than financial shocks, and are thus more relevant in short-term decisions. Aiming to reflect banks' lending standards, financial shocks ultimately lead to medium- to long-term decisions based on credit conditions. Furthermore, they are responsible for amplifying shocks that ensue from the financial system itself, thus exposing dependence of the economic outlook on the financial intermediation role of banks as a funding channel for the economy.

Chapter 2.

Financial frictions and oil shocks

Historically, oil price shocks have been pointed out as being chiefly responsible for the recessions in the U.S. economy during the 1970s and 1980s. Nonetheless, several studies have shown that these shocks cannot account for most of the drops in economic variables such as the GDP. In order to attempt to provide an explanation for the behavior of such economic variables during this period, we used a model with financial frictions which was augmented by oil price shocks. One was thus able to show that, through credit conditions, financial frictions may significantly explain the behavior of an economy during periods of recession and expansion.

2.1. Introduction

For many years, oil price shocks have customarily been strong contenders when providing an explanation for major U.S. recessions. Yet, this is not the only explanatory factor pointed out as playing an important role in recessions. Others, such as monetary policy or credit conditions, have been pursued in an attempt to explain the behavior of the economy during these periods of downturns. Contrary to expectations, and even after long periods of time, the reasons for recessions are not unambiguously associated with one single cause. If one considers as an example the last crisis of 2008-09, when the U.S. economy suffered a dramatic downturn, one will see different approaches to explain the reasons for this severe recession. On the one hand, there are the studies by James D. Hamilton (2009), and Ramey and Vine (2011), who highlighted the role of oil shocks in the economic slowdown. On the other hand, there is a wide range of literature relating financial frictions and global credit conditions to the "*Great Recession*", such as the work undertaken by Christiano et al. (2010), Gerali et al. (2010), Haltenhof et al. (2014), Christiano et al. (2014a), Garín (2015) and Bigio (2015). There is also the case of Stock and Watson (2012), who did not discard the role played by two forces - oil price shocks and global credit conditions - in the worsening of the U.S. economy during this period.

The *Great Recession* does not constitute an isolated case of multiple explanations and factors that affected the economy during recessions. An analysis of past occurrences has shown how difficult it is to separate the role of oil price shocks and the tightening of monetary policy and/or credit conditions; as was highlighted by Hoover and Perez (1994), and Barsky and Kilian (2002), most recessions are preceded by both. This is illustrated in Figure 2.1, which presents a plot of the credit standards from the Senior Loan Office Opinion Survey and the net oil price increase, following the approach proposed by Hamilton (1996). Credit standards reached a peak in the middle of the 1973-74 recession, immediately after the oil price shock, but most of the sharp increase in lending standards took place at the same time. This crisis was also preceded by a tightening of credit standards in the second quarter of 1973, i.e. half a year before the beginning of the recession. However, a different pattern in subsequent recessions also emerged. In the middle of 1979 there was, simultaneously, an oil price shock and a tightening of credit standards, which anticipated the 1980 recession. The tightening in credit standards was then followed by a softening in the period between crises, which countered the direction of monetary policy. Curiously, and since 1955, the second highest value of the effective federal funds rate was observed in January 1981 (19.08%)[1], when credit standards hit a trough. These two opposing forces may heighten credit risk as one increases the cost of credit, while the other means an increase in the willingness to grant more credit. When both occur simultaneously, this may lead to credit being channeled to riskier borrowers, which might also have contributed to

[1] Historically, this level of the effective federal funds rate was only surpassed by its value in June of that same year, while credit standards were still negative, thus pointing to a continuous softening in lending standards.

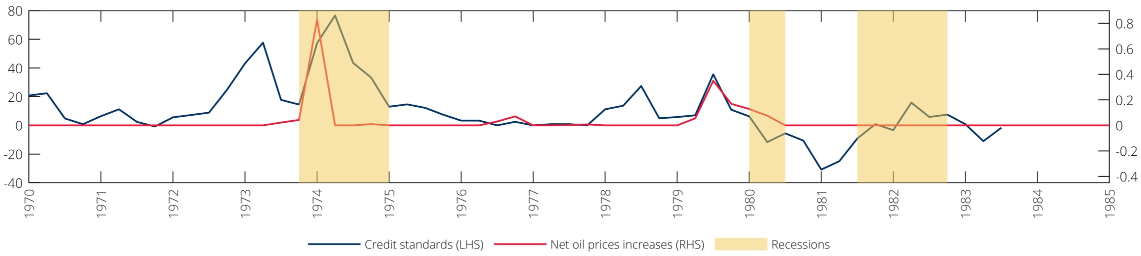

Figure 2.1.: *Time series of the credit standards from the Senior Loan Office Opinion Survey and the Hamilton (1996) net oil price increase. The shaded areas refer to the periods of Economic Recession in the U.S. by the NBER.*

the 1981-80 recession. Despite these facts, one of the main explanations proposed for the recession in 1974-75 was the increase in oil prices. However, most of the models with oil shocks experienced some difficulties when attempting to explain the strong recovery of the economy verified immediately afterwards, between 1976 and 1978; during this period, oil prices remained high and even continued to increase progressively. In this context, Barsky and Kilian (2002) argued that the recession of 1974-75, followed by an immediate strong recovery, might not have been driven by oil shocks. Another issue associated to models with oil prices is the fact that the results usually show that oil price shocks can only account for a small fraction of the drop in economic variables. This is possibly motivated by the lack of a strong multiplier-accelerator mechanism to amplify and propagate the impact of oil shocks. To bypass this, Rotemberg and Woodford (1996) argued that models of imperfect competition, particularly if they involved implicit collusion in the product market, could amplify the effects of oil shocks on output and wages. In contrast to this theory, Finn (2000) argued that, if firms' capacity utilization rate was allowed to vary in response to oil shocks, then it would be possible to have perfect competition and a deep recession in response to oil price increases. Although these two models constitute an improvement in the modelling of oil price shocks, their simulations with actual oil prices predict - in both cases - an immediate recession after the sharp increase in oil prices in 1973-74. In fact, this was to last throughout the 1970s, with no recovery, which contradicts the empirical facts.

The channels of financial frictions which are generally used are those of asymmetric information and agency costs, which contribute to moral hazard and adverse selection problems. From this point of view, aspects of debt contact provide support for the explanation of the nature of financial instability: for example, the tightening of credit as interest rates rise and asset prices fall. Frederic S. Mishkin (1991) for instance, pointed out some possible problems of asymmetric information with adverse selection in the postwar period, which could have significant adverse consequences for the U.S. economy.

One of the possible factors of a shrinkage in economic growth lies in the deterioration of credit conditions. The increased difficulty experienced by firms when trying to raise funds through the main channels can be reflected in economic developments. For example, Cappiello et al. (2010) showed that, for the Euro area, changes in credit supply - both in terms of volume and credit standards applied to loans to firms - generated a meaningful impact on economic activity. This result was supported by the results presented by Bennani et al. (2020), who employed a mixture VAR model to show that shocks in credit standards, as well as shocks in spreads, negatively affected GDP growth. Additionally, the authors highlighted the transmission of the effects of credit conditions to the labor market. Apergis and Chatziantoniou (2021), applied an Autoregressive Distributed Lag (ARDL) model for Canada, Germany, Japan, the UK and the US. In this study, they also documented the significant role of credit standards in real economic activity. The main transmission channel of credit standards to the real economy is by means of lending effects. While tightening in credit standards may enhance the quality of the credit granted - through less risky borrowers - this might also lead to a decline in economic activity since firms' funding costs may increase, thus leading to a decline in credit and encouraging a contraction in investment. Orame (2020) found a link between credit standards and lending to firms in the Italian credit market, with the former explaining about 40% of the decline in the latter during the *Great Recession* and subsequent years. To a certain extent, credit standards constitute a measure of the willingness of the banking sector to lend. The Federal Reserve conducts the Senior Loan Officer Opinion Survey on Bank Lending Practices and, as in other surveys, it contains some inherent biases. The surveys' qualitative nature, small sample size and possible reporting bias are some of the potential pitfalls when using these types of surveys in econometric models. Stacey

L. Schreft and Raymond E. Owens (1991) also emphasized the possible bias in survey data due to the fact that reports were not carried out anonymously. Despite these problems of bias, Lown et al. (2000) believe that the credit standards survey is informative and helpful in the improvement of a forecast accuracy for some of the economic variables. After examining this survey in the search for a proxy for credit availability, Lown et al. (2000) - as well as other authors such as Lown and Morgan (2006), Swiston (2008) and Beaton et al. (2009) - concluded that the survey of senior officers was a reasonable proxy for overall credit conditions. In an extension of the studies by Lown et al. (2000), Lown and Morgan (2006) estimated a VAR model over two disjointed sample periods: 1969-1984 and 1990-2000. Impulse response functions revealed a link between the tightening in credit standards and output drop. Similar results were obtained by Beaton et al. (2009), with a one standard deviation shock to the credit standards, which is equivalent to a net tightening of 8.6%, thus reducing the GDP to roughly 0.6% after two years. Guichard and Turner (2008) also reported that the survey data was statistically significant, with a 1% tightening in credit standards leading to a reduction of approximately 0.25% in GDP growth.

For our model, we followed the approaches of Jermann and Quadrini (2012) to introduce financial frictions. In this model, financial frictions are presented in the form of an enforcement constraint, limiting the amount of credit available to the sector of firms. One also included oil price shocks, as in Finn (2000). One of the particularities of such a model is the manner in which the capacity utilization rate interacts with the remaining variables. Firstly, there is the depreciation rate of capital as a function of the capacity utilization rate. This follows the notion that the intensity of the utilization of capital impacts on its depreciation, i.e, a higher use leads to more capital destruction. Secondly, the ratio between energy and capital depends on the capacity utilization rate for each of the periods.

Many authors - such as Mork (1989), Hamilton (1996, 2003) and Hooker (1996, 2002) - have documented a structural change in the relationship between oil prices and the economic environment of the 1980s. As was emphasized by Jermann and Quadrini (2012), there were also significant changes in the financial sector during the 80s, with regulatory amendments encouraging share repurchase, consequently impacting on firms' equity payout policy. A major change was also observed in the volatility of financial variables in the 80s, with equity payout and debt repurchase proving to be less volatile before 1984. Furthermore, the strong negative correlation between these two financial variables, as was documented by Jermann and Quadrini (2012), was not observed in the 70s. Despite these caveats, and since we introduced financial frictions to *a la*, as was done by Jermann and Quadrini (2012), as well as oil shocks, like Finn (2000), we chose to begin our analysis in 1964 and extended it to 1985. The objective was to study the possible contribution of financial friction to the 1974-75, 1980 and 1981-82 crises, the explanation of which is mainly attributed to oil shocks and monetary policy tightening in the pursuit of containing inflation.

The chapter proceeds as follows. In section 3.2, the model is described in detail, which includes the insertion of financial, oil price and productivity shocks. As mentioned previously, this model is an extension of Jermann and Quadrini (2012) model, which allowed for oil price shocks. In section 3.3, the data used for each variable is presented first, which is then followed by the parametrization and calibration of the model, as well as the building of the series used as financial, oil price and productivity shocks. This section concludes with an analysis of results for the simulated series. In section 2.4, a summary is presented of the main results and of the observation retained by the model proposed in this chapter.

2.2. The model

The model follows those developed by Jermann and Quadrini (2012), as well as Finn (2000). Like the Jermann and Quadrini (2012) model, one considered a closed economy, comprising three sectors - households, firms and the financial sector, it is also assumed that firms prefer to use debt financing instead of equity financing. In addition, one considered that firms face an enforcement constraint and incur additional costs when adjusting equity payout. Oil shocks were included in the model, like in Finn (2000), with the introduction of the utilization factor as described below.

2.2.1. Firms sector

For a continuum of firms in the $[0,1]$ interval, the production function is given by:

$$F(z_t, u_t, k_t, n_t) = z_t (u_t k_t)^{\theta} n_t^{1-\theta}, \tag{2.2.1}$$

where z_t is the stochastic level of productivity (common to all firms),u_t is the utilization rate ,k_t is the physical capital chosen at the time $t-1$ and n_t is labor, which can be changed flexibly at time t. At the beginning of each period, firms hold physical capital k_t and intertemporal liabilities b_t. Before production takes place, firms repay their previous debt b_t and choose the level of labor l_t, investment i_t, equity payout d_t, energy e_t, as well as the next period of debt b_{t+1}.

Assuming adjustment costs on investment, the stock of capital follows the law of motion:

$$k_{t+1} = (1 - \delta(u_t)) k_t + \phi(i_t, k_t), \tag{2.2.2}$$

with the depreciation rate of capital being an increasing convex function of u_t defined by:

$$\delta(u_t) = \frac{\omega_0 u_t^{\omega_1}}{\omega_1}, \tag{2.2.3}$$

$$0 < \delta(\cdot) < 1, \quad \omega_0 > 0, \quad \omega_1 > 1,$$

as in Finn (2000). $\phi(i_t, k_t)$ defines the adjustment cost on investment, i.e., the units of investment that are effectively turned into physical capital, which is given by:

$$\phi(i_t, k_t) = \left[\frac{\varrho_1 \left(\dfrac{i_t}{k_t} \right)^{1-\upsilon}}{1-\upsilon} + \varrho_2 \right] k_t, \tag{2.2.4}$$

The ν determines the sensitivity of costs to investment[2]. In other words, the greater the ν, the lower the number of units of capital produced by the same investment level. The parameters ϱ_1

[2]Note that if $\nu = 0$ then the law of motion for capital is given simply by $k_{t+1} = (1 - \delta(u_t)) + i_t$.

and ϱ_2 were set by imposing steady state targets, like in Jermann and Quadrini (2012)[3]. With the depreciation rate defined as a function of the utilization rate, one observed that a higher utilization of capital implies a higher depreciation of the same, and that more investment is then needed to maintain a constant stock of capital.

As in Finn (2000), we also assumed that capital utilization requires energy, which implies that firms also demand energy as an (indirect) input of the production function. This notion is formalized as:

$$\frac{e_t}{k_t} = a\left(u_t\right), \tag{2.2.5}$$

where

$$a\left(u_t\right) = \frac{\upsilon_0 u_t^{\upsilon_1}}{\upsilon_1}, \tag{2.2.6}$$

$$\upsilon_0 > 0, \quad \upsilon_1 > 1,$$

Firms are financed through debt and equity; however, due to tax advantages, firms will prefer debt over equity. In order to formalize this, and given the interest rate r_t, the effective interest rate for firms is $R_t = 1 + r_t\left(1-\tau\right)$, where τ is a tax benefit, since firms must effect payments before the realization of revenue from production. Apart from inter-temporal debt, firms also obtain financing through an intra-temporal loan l_t. It has been assumed that this loan will be repaid at the end of a time period, and at no interest.[4] In order to meet payments before the realization of revenue, the firms chose $l_t = w_t n_t + i_t + b_t + p_t e_t - b_{t+1}/R_t$.[5] Unlike Jermann and Quadrini (2012), we

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[3]We imposed that, in the steady state, the depreciation rate was equal to $\delta \equiv \delta\left(\overline{u}\right)$ and $\dfrac{\partial k_{t+1}}{\partial i_t} = 1$, thus obtaining $\varrho_1 = \delta^{\nu}$ and $\varrho_2 = -\left(\dfrac{\nu}{1-\nu}\right)\delta$. The second condition implies that the Tobin's *q* is equal to 1 in the steady state.

[4]Intra-temporal debt at no interest can be seen as firms holding cash and/or liquidity from one time period to another. Intra-temporal debt formulation is a shortcut to avoid including additional variables in the model when considering the retained earnings used to pay dividends and to finance working capital (including wages, investment and energy).

[5]Before production occurs, the firms choose labor n_t, investment i_t and energy e_t. At this point, they also have liability b_t and define the new inter-temporal debt b_{t+1}.

assumed that the intra-temporal loan cannot be used to distribute dividends; as such, equity payouts d_t were left out of the equation.

At this point the firms' budget constraint is given by:

$$b_t + w_t n_t + k_{t+1} + d_t + p_t^e e_t = (1-\delta)\, k_t + F\,(z_t, u_t, k_t, n_t) + b_{t+1}/R_t, \qquad (2.2.7)$$

where, w_t is the wage and p_t^e is the price of energy.

Given the chosen l_t and the firms' budget constraint, we obtained that $l_t = F\,(z_t, u_t, k_t, n_t) - d_t$. Assuming that the decision of default happens after the realization of revenue but before repayment of the intra-temporal loan, and that the liquidity l_t held by firms can easily be diverted, the only asset available for liquidation is capital k_{t+1}. Supposing that at the time of the loan, the lender acquires the right to liquidate the firm's capital in case of default, the liquidation value of capital is uncertain and has the probability ξ_t. The lender will recover the full value and, with $1-\xi_t$, the value recovered is thus null.[6] With this uncertainty as to the liquidation value of capital, and given that the liquidation value cannot be observed before the default occurs, it is assumed that firms are in possession of full bargaining power in the renegotiation process; as such, the lender only gets the threat value. On proceeding with a separate analysis of the two possible outcomes for the liquidation value, we see that: (i) if the lender can recover the full value of the capital k_{t+1}, the firm should pay an amount that renders the lender indifferent to either liquidation or keeping the firm in normal operation. In order to meet this condition, the firm needs to pay $k_{t+1} - b_{t+1}/(1+r_t)$ under the pledge of paying b_{t+1} at the beginning of the next period, when the inter-temporal debt is due. Therefore, the ex-post value of defaulting is:

$$l_t + \mathbb{E} m_{t+1} V_{t+1} - \left(k_{t+1} - \frac{b_{t+1}}{1+r_t} \right), \qquad (2.2.8)$$

where V_{t+1} is the cum-dividend market value of the firm; (ii) if the liquidation value of the capital is null, the lender's best option is not to liquidate the capital. Instead, the next period should be awaited,

[6]The variable ξ_t can be interpreted as the probability of finding a buyer. Assuming that the price of sale is bargained on a take-it-or-leave-it offer, the ξ_t would be the probability of the offer being made.

when b_{t+1} is due. Hence, the ex-post value of defaulting is:

$$l_t + \mathbb{E}m_{t+1}V_{t+1}. \tag{2.2.9}$$

Given the two possible outcomes for the liquidation value and the associated probabilities, we get that, when the debt is contracted, the expected liquidation value is:

$$\underbrace{\xi_t\left(l_t + \mathbb{E}m_{t+1}V_{t+1} - \left(k_{t+1} - \frac{b_{t+1}}{1+r_t}\right)\right) + (1-\xi_t)\left(l_t + \mathbb{E}m_{t+1}V_{t+1}\right)}_{l_t + \mathbb{E}m_{t+1}V_{t+1} - \xi_t\left(k_{t+1} - \frac{b_{t+1}}{1+r_t}\right)}. \tag{2.2.10}$$

The enforcement requires the value of not defaulting to be greater or equal to the expected value of defaulting; that is:

$$\mathbb{E}m_{t+1}V_{t+1} \geq l_t + \mathbb{E}m_{t+1}V_{t+1} - \xi_t\left(k_{t+1} - \frac{b_{t+1}}{1+r_t}\right). \tag{2.2.11}$$

By re-arranging the previous equation, one concludes that firms will be subjected to the following enforcement constraint:

$$\xi_t\left(k_{t+1} - \frac{b_{t+1}}{1+r_t}\right) \geq l_t. \tag{2.2.12}$$

One possible interpretation for the variable ξ_t is that it provides us with the banks' willingness to finance firms. In this way, ξ_t affects the tightness of the enforcement constraint.

Since firms can choose between debt and equity, and in order to formalize the rigidities in the adjustment of all funding sources, it is assumed that equity payout has a quadratic cost; thus, given d_t, the actual cost for the firms is $\varphi(d_t) = d_t + \kappa\left(d_t - \overline{d}\right)^2$, where $\kappa \geq 0$ and $\overline{d}$ is the value of equity payout at the steady state.

The optimization problem of the firms is given by:

$$V\left(\mathbf{s_t}; k_t, b_t\right) = \max_{d_t, n_t, u_t, k_{t+1}, b_{t+1}} \left\{d_t + \mathbb{E}_t m_{t+1} V\left(\mathbf{s_{t+1}}; k_{t+1}, b_{t+1}\right)\right\} \tag{2.2.13}$$

subject to

$$\left(1-\delta(u_t)\right)k_t + F\left(z_t, u_t, k_t, n_t\right) - w_t n_t + \frac{b_{t+1}}{R_t} = b_t + \varphi\left(d_t\right) + k_{t+1} + p_t^e e_t \tag{2.2.14}$$

$$\xi_t\left(k_{t+1} - \frac{b_{t+1}}{1+r_t}\right) \geq F\left(z_t, u_t, k_t, n_t\right) - d_t \tag{2.2.15}$$

$$\frac{e_t}{k_t} = a\left(u_t\right) \tag{2.2.16}$$

where m_{t+1} is the discount factor.

The first order conditions, in order to n_t, u_t, k_{t+1} and b_{t+1}, are:

$$F_n\left(z_t, u_t, k_t, n_t\right) = w_t\left(\frac{1}{1 - \frac{\mu_t}{1-\mu_t}\varphi_d\left(d_t\right)}\right), \tag{2.2.17}$$

$$F_u\left(z_t, u_t, k_t, n_t\right) = \frac{\left(1-\mu_t\right)\left(p_t^e a_u\left(u_t\right)k_t\phi_i\left(i_t, k_t\right) + \delta_u\left(u_t\right)k_t\right)}{\left(1-\mu_t\left(1-\varphi_d\left(d_t\right)\right)\right)\phi_i\left(i_t, k_t\right)}, \tag{2.2.18}$$

$$\begin{aligned}
&\mathbb{E}_t m_{t+1}\left(\frac{\varphi_d\left(d_t\right)\left(1-\mu_{t+1}\right)}{\varphi_d\left(d_{t+1}\right)}\right)\left[\left(1 - \frac{\mu_{t+1}\varphi_d\left(d_{t+1}\right)}{1-\mu_{t+1}}\right)F_k\left(z_{t+1}, u_{t+1}, k_{t+1}, n_{t+1}\right) - \right.\\
&\quad\left. - p_{t+1}^e a_u\left(u_{t+1}\right) + \frac{1-\delta\left(u_{t+1}\right) + \phi_k\left(i_{t+1}, k_{t+1}\right)}{\phi_i\left(i_{t+1}, k_{t+1}\right)}\right] + \\
&\quad + \xi_t\mu_t\varphi_d\left(d_t\right) = \frac{1-\mu_t}{\phi_i\left(i_t, k_t\right)},
\end{aligned} \tag{2.2.19}$$

$$R_t\mathbb{E}_t m_{t+1}\left(\frac{\varphi_d\left(d_t\right)}{\varphi_d\left(d_{t+1}\right)}\right) + \xi_t\mu_t\varphi_d\left(d_t\right)\left(\frac{R_t\left(1-\tau\right)}{R_t-\tau}\right) = 1, \tag{2.2.20}$$

where μ_t is the Lagrange multiplier associated with the enforcement constraint.

These equations can provide some insights into the model. Equation (2.2.17) presents the optimality condition for labor, where the marginal utility of labor equals its marginal cost. The marginal cost differs from the usual form. In this case, the marginal cost of labor is equal to the wage rate, and is augmented by a wedge that depends both on the tightness of the enforcement constraint, as well as on the rigidity of financing substitution κ. A higher value of μ_t, which means a tighter enforcement constraint, increases the marginal cost of labor and there is, consequently, a decrease in this demand. Additionally, a higher value of κ leads to the same reaction, since the cost of changing the funding source is higher, thus inducing an increase in the labor wedge. This gives us the main channel through which financial shocks influence the real economy in the model. For a better insight of the equation (2.2.18), and the sake of simplicity, let us consider the case of $\nu = 0$. In this case, it is $\phi_i\left(i_t, k_t\right) = 1$, and one then obtains the equation:

$$F_u\left(z_t, u_t, k_t, n_t\right) = \left(p_t^e a_u\left(u_t\right) k_t + \delta_u\left(u_t\right) k_t\right)\left(\frac{1}{\left(1 - \underbrace{\left(1 + 2\kappa\left(d_t - \overline{d}\right)\right)}_{\varphi_d(d_t)} \mu_t\right)}\right). \tag{2.2.21}$$

In this case, one sees that the marginal utility of use is equal to the sum of the cost of energy and marginal depreciation augmented by a wedge. As in the previous equation, this wedge depends on the tightness of the enforcement constraint, as well as on the marginal cost for firms to change their equity payout policy.

For equations (2.2.19) and (2.2.20), let us consider the case where firms do not incur adjustment costs on equity payout, i.e., $\kappa = 0$. Also, and for simplicity's sake, we continue with no adjustment costs on investment by setting $\nu = 0$ as we did previously, and consequently $\phi_i\left(i_t, k_t\right) = 1$ and

$\phi_k(i_t, k_t) = 0$. By re-arranging the equations, one ends up with:

$$F_k(z_{t+1}, u_{t+1}, k_{t+1}, n_{t+1}) = \frac{1 - \mu_t - \xi_t\mu_t + \mathbb{E}m_{t+1}\left[p^e_{t+1}a_u(u_{t+1}) - (1 - \delta(u_{t+1}))\right]}{\mathbb{E}m_{t+1}\left(1 - \dfrac{\mu_{t+1}}{1 - \mu_{t+1}}\right)} \tag{2.2.22}$$

and

$$\xi_t\mu_t = \left(\frac{1}{R_t} - \mathbb{E}m_{t+1}\right)\left(\frac{1 - \tau}{R_t - \tau}\right). \tag{2.2.23}$$

From the latter equation, we have that: taking as given R_t and $\mathbb{E}_t m_{t+1}$, a decrease in ξ_t - which means a lower liquidation value of capital - leads to a higher value for μ_t since the two variables are negatively correlated. Furthermore, as was seen in equation (2.2.17), this implies a lower demand for labor. By joining equations (2.2.22) and (2.2.23), we are able to conclude that a marginal productivity of capital does not depend directly on financial innovations but rather on: the Lagrange multiplier (μ_{t+1}), the effective interest rate (R_t), and the marginal cost of capital utilization ($p^e_{t+1}a_u(u_{t+1})$). If the enforcement constraint becomes tighter, then the denominator becomes smaller, thus increasing the marginal productivity of capital ensuing from a reduction in the capital stock used in production. A similar effect is observed when the effective interest rate is reduced: it increases the present value of firms' debt, thus tightening the enforcement constraint. Lastly, the positive contribution of the marginal cost of capital utilization to the marginal productivity of capital is explained by the efficiency of capital utilization on the production function, as can be seen in the equation (2.2.20).

All of these mechanisms are reinforced when $\kappa > 0$ since it will become costly to adjust the financing structure of firms and innovations to ξ_t, and will amplify the movements in μ_t , which was seen as being the main transmission channel of financial shocks to the real economy.

2.2.2. Households sector

Let us consider a continuum of households wishing to maximize their expected life-time utility :

$$\mathbb{E}_o \sum_{t=0}^{\infty} \beta^t U\left(c_t, n_t\right), \tag{2.2.24}$$

where c_t is consumption, n_t is labor and β is the discount factor. Since the households arethe shareholders of firms, who also possess non-contingent bonds issued by firms, they face the following budget constraint:

$$w_t n_t + b_t + s_t\left(d_t + p_t\right) = \frac{b_{t+1}}{1+r_t} + s_{t+1} p_t + c_t + T_t, \tag{2.2.25}$$

where s_t is the equity share, p_t is the market price of shares and T_t is lump-sum taxes, which finance the tax benefit of debt for firms. Given the optimization problem of households, from the first-order conditions we have:

$$w_t U_c\left(c_t, n_t\right) + U_n\left(c_t, n_t\right) = 0, \tag{2.2.26}$$

$$U_c\left(c_t, n_t\right) - \beta\left(1+r_t\right)\mathbb{E}_t U_c\left(c_{t+1}, n_{t+1}\right) = 0, \tag{2.2.27}$$

$$U_c\left(c_t, n_t\right) p_t - \beta \mathbb{E}_t\left(d_{t+1} + p_{t+1}\right) U_c\left(c_{t+1}, n_{t+1}\right) = 0. \tag{2.2.28}$$

The equations (2.2.26) and (2.2.27) determine labor supply w_t, and the interest rate r_t. From equation (2.2.28) and using forward substitution we get:

$$p_t = \mathbb{E}_t \sum_{s=1}^{\infty} \left(\frac{\beta^s U_c\left(c_{t+s}, n_{t+s}\right)}{U_c\left(c_t, n_t\right)}\right) d_{t+s}. \tag{2.2.29}$$

Since the firms' optimization is consistent with the households' optimization, the discount factor is $m_{t+1} = \beta U_c\left(c_{t+1}, n_{t+1}\right) / U_c\left(c_t, n_t\right)$

2.2.3. Market-clearing conditions

One can now proceed with the definition of a general equilibrium. We assume that large characters represent aggregate variables, and small characters indicate variables of individual agents. When the market clears, one assumes that the total quantity of equity shares is equal to 1, i.e, $S_t = 1$. Since all the market participants are assumed to be identical and to act the same, we get $s_t = 1$ for the representative agent.

The aggregate states that $\mathbf{s_t}$ are: productivity z_t, energy price p_t^e the variable ξ_t, aggregate capital K_t, and aggregate bonds B_t.

Definition 2.2.1 (Competitive equilibrium)**.** *A recursive competitive equilibrium is defined as a set of functions for:*

(i) household's policies $c^h(\mathbf{s_t})$, $n^h(\mathbf{s_t})$ and $b^h(\mathbf{s_t})$;

(ii) firms' policies $d(\mathbf{s_t}; k_t, b_t)$, $n(\mathbf{s_t}; k_t, b_t)$, $u(\mathbf{s_t}; k_t, b_t)$, $k(\mathbf{s_t}; k_t, b_t)$ and $b(\mathbf{s_t}; k_t, b_t)$;

(iii) firms' value $V(\mathbf{s_t}; k_t, b_t)$;

(iv) aggregate prices $w(\mathbf{s_t})$, $r(\mathbf{s_t})$, $p(\mathbf{s_t})$ and $m(\mathbf{s_t}, \mathbf{s_{t+1}})$;

(v) law of motion for the aggregate states $\mathbf{s_{t+1}} = \Psi(\mathbf{s_t})$,

such that

(i) household's policies meet conditions (2.2.26) and (2.2.27);

(ii) firms' policies are optimal and $V(\mathbf{s_t}; k_t, b_t)$ meet Bellman's equation (2.2.13);

(iii) w_t and r_t clear the labor and bond markets and $m(\mathbf{s_t}, \mathbf{s_{t+1}}) = \beta \frac{U_c(c_{t+1}, n_{t+1})}{U_c(c_t, n_t)}$;

(iv) the law of motion $\Psi(\mathbf{s_t})$ is consistent with individual decisions and the stochastic processes for z_t, p_t^e and ξ_t.

2.3. Quantitative analisys

This section presents a quantitative evaluation of the effects of productivity, as well as those of oil and financial shocks. It is shown that these shocks are able to explain much of the economic activity occurring since the 70's. The fact that these shocks explain much of the fluctuation in the economic variables does not mean that other shocks were not important during this period.

2.3.1. Data

For the empirical time series, we used quarterly data from the first quarter of 1970 to the first quarter of 1985. In order to construct the debt repurchase and equity payout time series, data was used from the Flow of Funds Accounts of the Federal Reserve Board, following the same approach as Jermann and Quadrini (2012). Debt repurchase is the negative of 'net increase in the credit market instruments of nonfinancial business', while equity payout is the sum of 'net dividends of nonfarm, nonfinancial business' with 'net dividends of farm business' minus the sum of 'net increase in the corporate equities of nonfinancial business' with 'proprietors' net investment of nonfinancial business'. Both these time series are divided by the business value added from the National Income and Product Accounts. For the real gross domestic product (GDP), the data was obtained from the Federal Reserve Bank of St. Louis. As for oil prices, these were provided by the 'Spot Crude Oil Price: West Texas Intermediate (WTI)'. Since this data is monthly, we considered the quarter as being the three-month average. The capacity utilization was given by 'Capacity Utilization: Total Industry (TCU)' from the Federal Reserve Bank of St. Louis. For capital stock k_{t+1}, data was used from the Flow of Funds Accounts of the Federal Reserve Board. Assuming the law of motion of capital stock $k_{t+1} = k_t - \delta k_t + i_t$[7], capital depreciation was measured as 'Consumption of fixed capital in nonfinancial corporate business' plus 'Consumption of fixed capital in nonfinancial noncorporate business', and investment as 'Capital expenditures in nonfinancial business'. For Labor, we used the 'total private aggregate weekly hours' from the Current Employment Statistics, a national survey. For wages, we used the 'wages and salaries paid in Nonfinancial corporate business', from the Flow of Funds Accounts of the Federal Reserve Board. For consumption, one used the 'Real Personal Consumption Expenditures', from the Federal Reserve Bank of St. Louis. As in Jermann and Quadrini (2012), the time series are in log values. For the detrend of the time series, the Hodrick-Prescott filter was used.

[7] This is a special case where, for $\upsilon = 0$

In order to measure credit standards, we used a Senior Loan Office Opinion Survey from the Federal Reserve Board. In this survey, credit standards were constructed as the percentage of senior bank loan officers who tightened their lending standards for commercial and industrial loans. This data separates large- and middle-market firms from small firms; accordingly, an average of the two series was determined.[8]

2.3.2. Parametrization

For model parametrization, we began with the parameters calibrated by the steady state targets, and then moved to the parameters given by the model relationships, since they cannot be set by steady state targets.

For the β parameter, we followed Jermann and Quadrini (2012). We set β equal to 0.9825, which implies that the annual steady state return from holding shares was 7.32%.[9] For the tax wedge, we set τ equal to 0.05, which corresponds to the benefit of debt over equity if the marginal tax rate is 5%. This value differed considerably from the 0.35 (or 35%) in Jermann and Quadrini (2012). The main reason for this is that, during the 70s and early 80s, observation of the data did not point to a strong negative correlation between debt repurchases and equity payout, which suggests that the relation of the firms' funding source with the business cycle was not significant. This can also be understood as an absence, or at least a weaker benefit of debt over equity. Given the households' utility function $U\left(c_t, n_t\right) = ln(c_t) + \alpha(1 - n_t)$, and in order to get the hours worked in a steady state equal to 0.3, we set α equal to 1.9106. The Cobb-Douglas parameter in the production function was set to θ equal to 0.36 and the depreciation to δ 0.025. We chose the mean value of $\bar{\xi}$ by setting a steady state ratio of debt over the product equal to 2.55, which is the average ratio over the period from 1970 to 1985 for the non-financial business sector, based on data from the Flow of Funds and National

[8]Although an average of the two time series was implemented, the results of using each one separately do not change significantly.

[9]We chose β to imply that $\left(\frac{1}{\beta}\right)^4 = 1.0732$

Income and Product Accounts for debt and business GDP, respectively. To this end, we obtained $\bar{\xi}$ equal to 0.157. We set u equal to 0.83, so as to match the average value of capacity utilization from 1970 to 1985 of 83%. Like Finn (2000), we set $p^e ey$ equal to 4.3%. Productivity z and oil prices p^e were normalized to 1.

For the calibration of the remaining variables and parameters, model equations were used to obtain their values. In this process, two steps were followed. Firstly, we used the equations (2.2.2), (2.2.7), (2.2.12), (2.2.17), (2.2.19), (2.2.20), (2.2.25), (2.2.26), (2.2.27) and the assumption that $p^e ey$ is equal to 0.043 to find the steady state values for the variables c, d, w, R, μ, k, b, i, e and y. In the second step, we used the equation (2.2.22), and followed the same methodology as Finn (2000) to find the values for parameters υ_0, υ_1, ω_0 and ω_1.

The parameter κ, which cannot be set by means of the steady state targets, was chosen so that the standard deviation of equity payout - simulated by the model over the period from 1970 to 1985 - would be equal or, at least, close to the standard deviation of its empirical counterpart. Thus, we set κ to be equal to 0.6, which is a much larger value than that used in the Jermann and Quadrini (2012) model calibration. This is justified by the lower volatility of the equity payout series during this period, when compared to the post-85 time period, which shows a higher reluctance of firms to change their dividend distribution policy.

In this model, there are three types of shocks: financial, productivity and oil prices. For the financial and productivity innovations, we followed the same procedure as Jermann and Quadrini (2012). From the linearization of the production function we obtained:

$$\hat{z}_t = \hat{y}_t - \theta\hat{k}_t - (1-\theta)\,\hat{n}_t, \tag{2.3.1}$$

where $\hat{z}_t$, $\hat{y}_t$, $\hat{k}_t$ and $\hat{n}_t$ are the log-deviations from the deterministic trend.

Following the same approach, and making use of the equation (2.2.15), we obtain the linearized version as:

$$\hat{\xi}_t = -\frac{\overline{\xi k}}{\overline{y}-\overline{d}}\hat{k}_{t+1} + \frac{\overline{\xi b}}{\overline{y}-\overline{d}}\hat{b}_{t+1} + \hat{y}_t - \frac{\overline{d}}{\overline{y}-\overline{d}}\hat{d}_t, \tag{2.3.2}$$

where $\hat{\xi}_t$, $\hat{k}_{t+1}$, $\hat{b}_{t+1}$, $\hat{y}_t$ and $\hat{d}_t$ are the log-deviations from the deterministic trend, and $\overline{\xi}$, $\overline{k}$, $\overline{y}$, $\overline{b}$ and $\overline{d}$ denote the steady state values.

Given the empirical series for $\hat{y}_t$, $\hat{k}_t$, $\hat{n}_t$, $\hat{k}_{t+1}$, $\hat{b}_{t+1}$ and $\hat{d}_t$, we constructed the $\hat{z}_t$, $\hat{\xi}_t$ series for the time period from 1970 to 1985. With the $\hat{z}_t$ and $\hat{\xi}_t$ series, along with the oil price $\hat{p}^e$ log-deviations from the deterministic trend, we were then able to estimate the autoregressive system:

$$\begin{pmatrix} \hat{z}_{t+1} \\ \hat{\xi}_{t+1} \\ \hat{p}^e_{t+1} \end{pmatrix} = \mathbb{A} \begin{pmatrix} \hat{z}_t \\ \hat{\xi}_t \\ \hat{p}^e_t \end{pmatrix} + \mathbb{B} \begin{pmatrix} \hat{z}_{t-1} \\ \hat{\xi}_{t-1} \\ \hat{p}^e_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{z_{t+1}} \\ \epsilon_{\xi_{t+1}} \\ \epsilon_{p^e_{t+1}} \end{pmatrix}, \tag{2.3.3}$$

where $\epsilon_{z_{t+1}}$, $\epsilon_{\xi_{t+1}}$ and $\epsilon_{p^e_{t+1}}$ are i.i.d. with standard deviations σ_z, σ_ξ and σ_{p^e}, respectively. By following this approach, we assumed that all three shocks were correlated. This is a plausible assumption, since any change in one of the three variables can have implications for the other two. For example, an oil shock can change the banks' willingness to lend as it can increase the risk of default by firms. Similarly, an oil price shock can reduce the productivity of firms.

At this point, we obtained the series of financial and production shocks to feed the model, given by the innovations $\epsilon_{z_{t+1}}$ and $\epsilon_{\xi_{t+1}}$. Using the Hamilton (1996) concept to measure net oil price increases, we then built our oil price shocks by using the innovations $\epsilon_{p^e_{t+1}}$ obtained from the autoregressive regression. The measure of net oil price increases, proposed by Hamilton (1996), is defined as the amount by which oil prices in quarter t exceeded their peak values over the last 12 quarters. In the absence of a surplus in the previous peak, then it is considered to be zero. Following the assumption that the impact of an increase in oil prices is not significant when it is of a higher value in the previous recent past, we only considered the innovations higher than those verified in the previous 12 periods. In other words, given the errors from the autoregressive system $\epsilon_{p^e_{t+1}}$, we built the time series $\dot{\epsilon}_{p^e_{t+1}}$ given by:

$$\dot{\epsilon}_{p^e_{t+1}} = \begin{cases} \epsilon_{p^e_{t+1}} & \text{if} \quad \epsilon_{p^e_{t+1}} > \max\left(\epsilon_{p^e_t}, \ldots, \epsilon_{p^e_{t-11}}\right) \\ 0 & \text{if} \quad \epsilon_{p^e_{t+1}} \leq \max\left(\epsilon_{p^e_t}, \ldots, \epsilon_{p^e_{t-11}}\right). \end{cases} \tag{2.3.4}$$

In Table 2.1 we report the full set of parameters and steady state variables values used to run the model.

Parameters			Steady state variables	
$\beta = 0.9825$	$\tau = 0.05$	$\nu = 0.3$	$d = 0.0941$	$c = 0.6645$
$\alpha = 0.9106$	$\theta = 0.36$	$\varrho_1 = 0.331$	$w = 1.8137$	$n = 0.3$
$\delta = 0.025$	$\kappa = 0.6$	$\varrho_2 = -0.011$	$\xi = 0.157$	$R = 1.0116$
$\mathbb{A} = \begin{bmatrix} -0.1027 & -0.0130 & 0.6477 \\ 1.0331 & -0.0141 & -0.1516 \\ 0.0834 & 0.8113 & -2.1852 \end{bmatrix}$			$b = 2.2982$ $z = 1$ $i = 0.1824$	$\mu = 0.0378$ $k = 7.294$ $y = 0.8849$
$\mathbb{B} = \begin{bmatrix} 0.0257 & 0.0014 & -0.0088 \\ -0.2688 & -0.0069 & 0.5659 \\ -0.1137 & -0.1815 & -1.6400 \end{bmatrix}$			$e = 0.0381$ $u = 0.83$	$p^e = 1$

Table 2.1.: *Parameters and steady state values*

The model was then fed with the series of financial, oil price and productivity shocks (given by the $\epsilon_{\xi_{t+1}}$, $\dot{\epsilon}_{p^e_{t+1}}$ and $\epsilon_{z_{t+1}}$ respectively), and obtained the simulated time series.

2.3.3. Data Analysis

In this section we will begin to look into impulse response. Only then will a subsequent analysis be undertaken of the results for the simulated time series obtained from the model with productivity, oil price and financial shocks, comparing these with the empirical counterparts.

Impulse responses to a one-time shock are reported in Figure 2.2. The variable μ is important when attempting to gain a better understanding of the model's behavior. This is the multiplier for enforcement constraint, and determines the labor wedge presented in equation (2.2.17). One can observe that only a negative financial shock increased μ in the first quarter, leading to a tightening of the enforcement constraint, and increasing the labor wedge. In the case of impulse response to hours worked, n, this provides an explanation for why the one-time negative financial shock led to a decrease in hours worked, when the same was not verified in the other two negative shocks.

When one considered the impulse response for capacity utilization, we observed that financial and

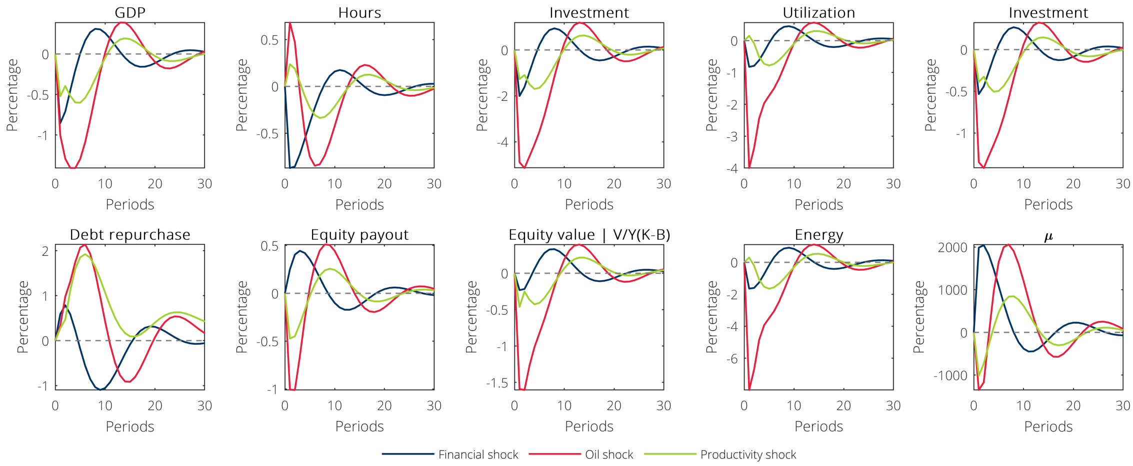

Figure 2.2.: *Impulse responses to a one-time financial, oil price and productivity shocks.*

oil price shocks produced a negative impact, while the productivity shock had the opposite effect. The impact of financial and oil price shocks is explained by the equation (2.2.22), where we can see that an increase of p_t^e or μ_t implies a higher marginal cost of capacity utilization. On the other hand, in the presence of a negative productivity shock, and if firms wish to maintain an unchanged output, they must increase capacity utilization. Equity payout reacted positively to a tightening in the enforcement constraint but one then saw a drop in the equity value of firms. For the other two shocks, one observed the same effect on the equity value of firms but not on equity payouts, which were negatively affected by oil price and productivity shocks. Regarding debt repurchases, the financial shocks began by having a slightly positive effect, which was rapidly inverted. The productivity shock generated an opposite effect on these variables, with a positive effect over the first 12 quarters. Investment and consumption reacted similarly to the shocks, with a fall in the first quarters, but the recovery from the financial shock was faster. All the shocks generally produced a negative impact on the energy used for production, with a response identical to that observed for the utilization rate. These results present some similarities to those identified in Jermann and Quadrini (2012); however, here we found some loop effects, which ensued from the second order VAR.

The Figure 2.3 presents the plot for credit standards obtained from the Senior Loan Office Opinion

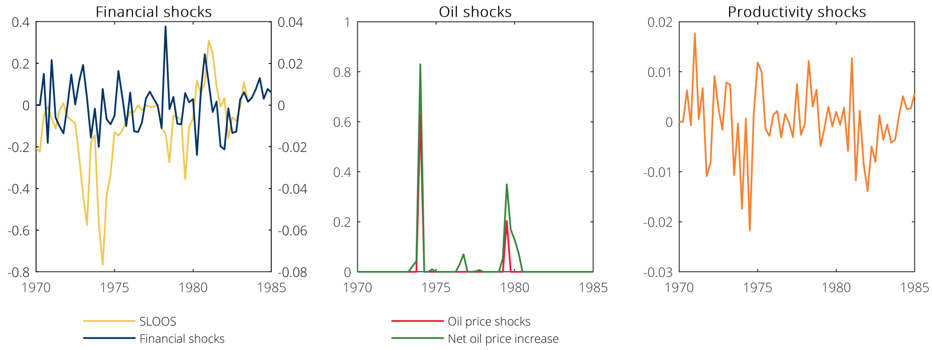

Figure 2.3.: *Time series of credit standards from the Senior Loan Office Opinion Survey, financial shocks, oil price shocks, the Hamilton (1996) net oil price increase and productivity shocks. The shaded area represents the period of Economic Recession in the U.S. by the NBER.*

Survey. Started in the fourth quarter of 1966, it was discontinued at the end of 1983, only returning in the second quarter of 1990. During the time period when the survey was conducted, one can observe that before - or during - the major recession, there was a significant increase in credit standards. On analyzing the financial shocks series, it generally seems to constitute a good indicator of the tightening of credit standards. In the plots for the time series used as oil price shocks in the model, as well as the net oil price increase measured, and proposed by Hamilton (1996), one can see that much of the increase is common to both time series, with a few slight variations in their magnitudes. Some of the differences in these two time series, and their implication for the model, will be discussed later. For productivity shocks, there was a negative sign occurring mainly during the recessions, as expected.

Figure 2.4 presents the results for the GDP, hours worked, investment, consumption and capacity utilization. For all these variables, one computed the simulated series to include all three shocks (financial, oil price and productivity), as well as with each of the shocks. These were then compared to the empirical time series.

In the results for the GDP, it can be concluded that the simulated series for financial shocks tracks the empirical counterpart reasonably well; it explains most of the cyclical behavior and generally reflects the fall of the product during the entire recession in the U.S. during this period. A closer

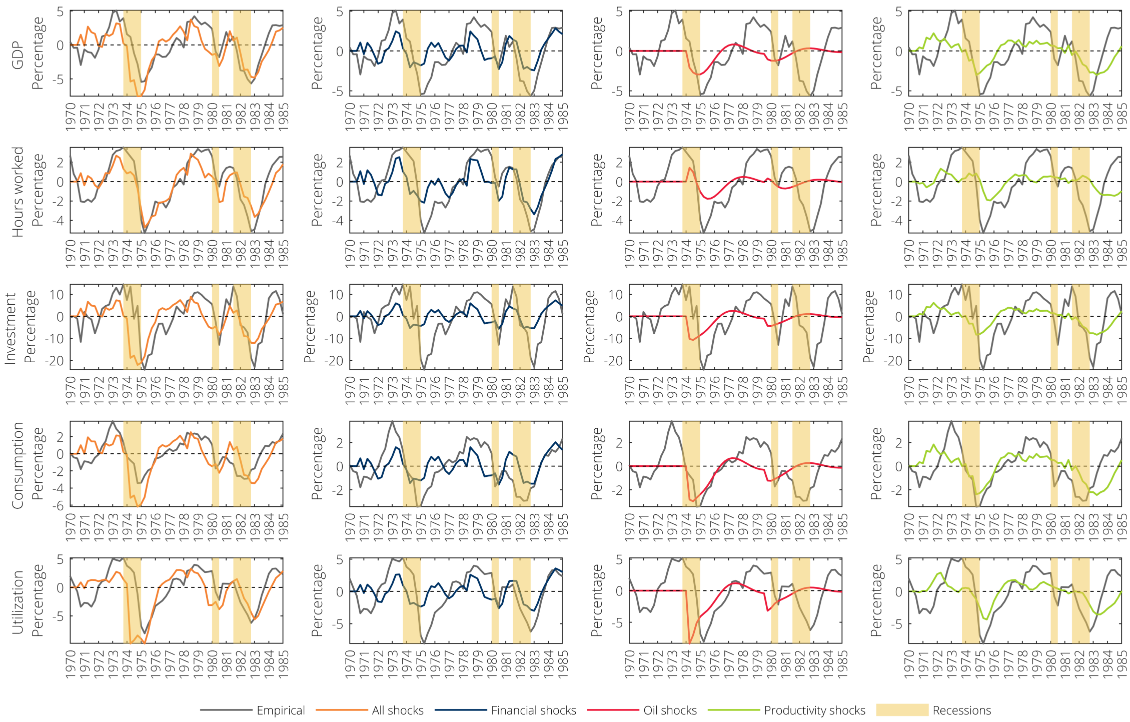

Figure 2.4.: *Simulated time series and empirical counterparts for the product, hours worked, investment, consumption and capacity utilization.*

analysis of the recession periods reveals that: (i) for the 1973-75 recession, the three shocks contributed to a decrease in GDP at different moments in time. There was, firstly, a financial shock that triggered a downfall in GDP around the second quarter of 1973. This decrease was later amplified by the oil price shocks that occurred in the first quarter of 1974, and which continued to contribute to the downward trend in GDP during the entire recession period, unlike the financial shocks. Lastly - and in addition to the financial and oil price shocks - there were several incidences of productivity shocks, which significantly contribute to explaining this recession, with the last negative shock in the middle of 1974. (ii) The fall in GDP during the 1980 recession seems to have been anticipated by both the financial and oil price shocks; however, the former is the only one of the three which is able to explain, at least partially, the great drop in GDP during the first half of 1980. Regarding productivity shocks, they cannot explain this recession in spite of a slight decrease in the simulated series for this period. (iii) For the 1981-82 recession, financial and productivity shocks explain most of the fall in GDP, as well as its posterior recovery, despite a small delay at the beginning of the upward trend in the simulated series with productivity shocks. It should also be highlighted that between the 1980 and 1981-82 recessions, none of the shocks - with the exception of financial shocks - can explain the sharp recovery in GDP. As was seen previously, after the tightening of credit standards in the middle of 1979, the following period was mainly characterized by an overall softening in credit standards. This, in turn, may have fostered an increase in investment, which then reverberated on the GDP.

As was mentioned previously in the analysis of impulse responses, the financial shock is the only one which presents a short-time negative effect on the hours worked. Given this, it is not surprising that only the simulated series with financial shocks successfully replicated the behavior of the empirical counterpart, which followed a very similar path. Both the oil price and productivity shocks showed a positive effect during the 1973-75 recession, with the emergence of a decrease only at the end of this period. The same pattern was observed for the simulated series with productivity shocks in the 1981-82 crises. Nevertheless, the fall was more prolonged in the post-crisis periods, and was unable to accompany the recovery that began in 1983 and lasted until 1985. Besides the drops in employment, the financial shocks were also able to follow the path of recovery, namely between the 1980 and 1981-82 recessions and after 1983, during which most of the observed recovery can be explained.

The results for investment consumption are similar to those for the GDP, and can be intuitively explained by the fact that both of these - investment and consumption - are components of the GDP. As such, their behavior is quite similar, apart from the magnitude of deviations from the trend, or steady state.

Capacity utilization plays an important role in the model since it changes the ratio of energy over capital, as well as the rate at which capital stock depreciates. Using financial shocks alone, the model was able to apprehend almost all of the behavior observed in the data. While explaining both the ups and downs of the series, the greatest recovery was predicted to occur between the 1980 and 1981-82 crises, which is not reflected in the empirical counterpart. This stronger positive impact of financial

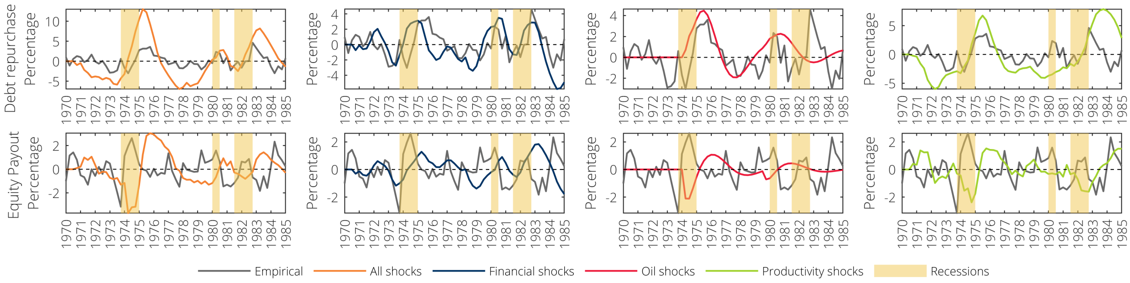

Figure 2.5.: *Simulated time series and empirical counterparts for debt repurchase and equity payout.*

shocks, compared to what is observed in the data, was also shared by the results for investment and consumption; these, however, occurred on a lower scale since the recovery for those two variables was also higher. In the case of oil price shocks - and taking into account that only the negative ones were considered - these led to a large drop in capacity utilization, which is consistent with the empirical counterpart, anticipating the greatest fall in both the 1973-75 and 1980 recessions by two quarters. Given the absence of oil price shocks to explain the 1981-82 recession, they were also unable to explain the fall in capital utilization over this period. Productivity shocks partially explained the fall around the 1973-75 and 1981-82 crises; but, as is observed in other variables, it failed to do so for the 1980 recession.

In general terms, one can conclude that the simulated series with financial frictions only explains most of the movements of the empirical counterparts, and is mainly responsible for the fit in the recovery periods. Since only the largest negative shocks (an increase of oil prices) were considered for the last 12 quarters, oil price shocks only impacted on the economic downturns. Accordingly, they were only able to provide a partial explanation for the behavior of the series during the 1973-75 and 1981-82 recessions. Like oil price shocks, productivity shocks cannot explain the fall of variables during the 1980 recession; neither can they explain the strong recovery observed after 1983 in all of the variables presented in Figure (2.4).

The results for debt repurchase and equity payout are presented in Figure 2.5. For debt repurchase, one observed that financial shocks produced a simulated series which generally apprehended the behavior of its counterpart. During the recessions, it followed an upward trend in accordance with the data but could not reproduce the drop in the middle of the 1973-75 crisis. Although the fit is similar to that of other variables, one observed the overall cyclicality of debt repurchase in the financial shocks series. Surprisingly, the oil shock in 1974 produced an oscillation in the simulated series, which closely mimics the pattern of its empirical counterpart until almost 1979, although one cannot guarantee a causality between this shock and the debt repurchases of the following period. Lastly, productivity shocks also produced an upward trend during the recessions; however, they seem to have followed the previous trend only in the 1980 recession. Results were rather distinct for equity payout. The financial shocks were generally able to track the data until 1976. After this period, the model only occasionally followed the same pattern as its empirical counterpart. The inability of financial shocks to track the data may reside in the apparent lack of correlation between the business cycles and equity payout. For example, during the first crisis, although one observed a great increase in equity payout, the same was rather unclear in the one which followed. An inversion of equity payout was also observed during the recessions, which was not apprehended by the financial shocks, thus inducing an increase over the full recession period. During the 1973-75 crisis, oil prices seem to have had the opposite effect to what was observed in the empirical counterpart. Lastly, the simulated series with productivity shocks revealed a strong negative correlation with the empirical equity payout, due to symmetric behavior across almost all of the time span.

2.4. Conclusions

Globally, the model tracks the behavior of the main economic variables – such as GDP, hours worked, investment and consumption – rather well. With regard to financial variables, like equity payout and debt repurchases, the model performs poorly when tracking the empirical counterparts. While financial shocks produced a simulated series that generally followed the path of data in the case of debt repurchase, the same cannot be said for equity payout, where one saw great differences in the behavior of the series. In this case, there is clearly a negative correlation between the simulated series with productivity shocks and the data. These results were expected up to a certain point, since the negative correlation between equity payout and debt repurchase only appeared in the post-1984 period. These were caused by major changes in the financial markets, which were spurred by regulation implemented in the early 80s that may have caused a structural change, as was emphasized by Jermann and Quadrini (2012).

If one analyzes separately the simulated series obtained through each of the three shocks, some different aspects of the model must be taken into account. Firstly, from the perspective of financial shocks, it seems that firms' ability to raise funds generates a considerable impact on the main economic variables. With no exception in the variables considered, financial shocks are able to replicate the economic recession of 1973-75, followed by an immediate strong recovery. The same is true for the 1980 and 1981-82 recessions, with a revival of the economy in the interim period. Oil prices can replicate the greatest drops during the recessions, except for the hours worked, which are only able to account for a small fraction of the downturns. It is for this reason that we believe oil price shocks play an important role in the state of the economy. Indeed, they constitute part of the explanation for recessions; however, financial instability and credit conditions may also have exacerbated the downturns in the economy observed during the 70s and 80s. Additionally, attention must be drawn to the lags between the effects of each shock during the recessions: financial shocks occur first and are responsible for triggering the fall in variables; this is followed by oil price shocks; and productivity shocks are usually the last to contribute to the downward trend.

Although debt and equity play an important role in the model, the truth is that the simulated time series are unable to provide a clear explanation for the behavior of these two financial variables. Despite this fact, it is important to reinforce that financial shocks can explain the overall behavior of debt repurchase; yet, when all of the shocks are included, the simulated series exhibits greater volatility than that of the empirical counterpart.

Chapter 3.

Credit standards versus risk shocks

In this chapter, wavelet tools were used to analyze two different models embedded with financial frictions. Whereas the Jermann and Quadrini (2012) model makes use of an enforcement constraint that limits the ability of firms to raise funds, the Christiano et al. (2014b) model implements risk shocks along with news shocks, both of which amplify the effects of financial stress.

3.1. Introduction

The financial crisis that began in the summer of 2007 pointed to the importance of incorporating the financial sector into macroeconomic models in order to gain a better understanding of the dynamics of business cycles. The contributions made by Bernanke et al. (1999) (henceforth BGG), as well as those of Kiyotaki and Moore (1997), have become classic references for most of the work developed in this field. Much of the subsequent literature focusing on the amplification mechanisms proposed by BGG and Kiyotaki and Moore (1997), and relating to the presence of traditional shocks, has encountered some difficulty in supporting the real importance of financial frictions. Quadrini (2011) presented three possible channels which link the financial sector to real economy. In the first hypothesis, the financial sector is of reduced importance when explaining fluctuations in the real economy. This occurs when it is assumed that changes in investment and employment constitute a response to movements in real factors, such as productivity. The second is the amplification effect, which has been the focus of most studies in literature, with the financial sector considered responsible for the inflation of a shock, despite not being the main cause. This means that the financial sector would cause a longer and profound recession but could not generate one. In the third hypothesis, the financial sector is seen as chiefly responsible for a recession. In this case, the shock stems from the financial sector; as result, fewer funds are channeled from lenders to borrowers, thus leading to a contraction in economic activity and, ultimately, to a recession. In line with this perspective, two important contributions were made by Jermann and Quadrini (2012), as well as Christiano et al. (2014b), where both researchers considered shocks to have ensued from financial shocks, further arguing that these shocks may play an important role in macroeconomic fluctuations. Along these lines, it is also argued that, besides amplifying the downturn in economic activity, financial frictions can also be responsible for long-lasting recessions. Financial frictions may lead to the misallocation of resources among economic agents (Banerjee and Duflo, 2005; Buera et al., 2011; Gilchrist et al., 2013; Midrigan and Xu, 2014; Sahay et al., 2015; Karabarbounis and Macnamara, 2021); and, while some firms may overcome this issue through the internal generation of funds, this option may not be reliable for firms newly entering a market or requiring an investment far in excess of past profits. Since self-financing takes time, sizeable misallocations due to financial frictions could exist for long periods. Indeed, literature has pointed out that firms' investment decisions are highly sensitive to the ability to raise funds from the banking system, especially in countries with a large proportion of small firms (Cingano et al., 2016; Manaresi and Pierri, 2017, 2018).

Despite the interest shown by researchers and the scientific community in the interplay between the financial and real economy from approximately the 70s onwards, this topic has been the target of greater attention since the *Great Recession*, seeing exponential growth in the number of publications per year. Zabavnik and Verbič (2021) performed a bibliometric analysis on studies covering the relationship between financial and real economy. Two of the 50 most influential articles in this field are those of Christiano et al. (2014b) (henceforth CMR) and Jermann and Quadrini (2012) (henceforth

JQ).[1] These two contributions lean on two distinct transmission channels of financial friction to the real economy. While CRM focuses on risk fluctuations as a source of financial frictions, and examines their effects on fluctuations in GDP, JQ bases the study on how financial shocks affect firms' ability to finance themselves, which then impacts on macroeconomic fluctuations. According to Zabavnik and Verbič (2021), the CMR model was largely influenced by JQ, amongst others such as Gilchrist and Zakrajšek (2012), Ericsson et al. (2009) and Collin-Dufresn et al. (2001).

JQ introduced an enforcement constraint in a similar manner to that of the collateral constraint implemented in the Kiyotaki and Moore (1997) model. This enforcement constraint limits the amount of funds that firms are able to raise when addressing the issue of the costs incurred before production can begin. The financial shocks that feed the model are obtained from this same constraint, and the authors pointed to the similarities between *financial shocks* and credit standards. Moreover, the authors were able to demonstrate that changes in credit conditions have influenced economic downturns since the mid 80s, with financial shocks contributing to almost half of the volatility in GDP, and around 30 percent of the volatility in hours worked. The price-markup shock was considered to be responsible for nearly one quarter of GDP fluctuations, and more than half of debt repurchases.

Several studies followed the key ingredients of the JQ model, namely with regard to the concept of the enforcement constraint, and the link between lending standards and GDP fluctuations. Credit supply shocks are an important driver of the countercyclical behavior of banks' lending standards, leading to significant fluctuations in loans and the GDP (Chen et al., 2021). Perri and Quadrini (2018) built a two-country model embedded with financial friction and credit shocks to show that, while the globalization of financial markets may reduce the frequent occurrence of financial crises, this may imply larger macroeconomic contractions. The main explanation resides in a higher incentive for borrowers to gain some leverage, as a result of less frequent downturns, thus amplifying the effects of forced deleveraging. Bianchi et al. (2019) built an endogenous growth model which included

[1] In the list presented by the authors regarding the 50 most influential articles, CMR is in 11th position, followed by JQ in the 17th. The metric used for the list consists of the average total of citations per year. JQ also appears in the top 25 of the most cited articles, in the last position, under the metric of total citations.

financial frictions on debt and an equity financing structure. Besides debt financing shocks, in the form of enforcement constraints – as is seen in JQ – equity financing shocks were also introduced. The results showed that the two financing shocks affected the economy over different horizons, with equity financing shocks producing a long-lasting effect on GDP growth. Ferrante (2019) extended a standard NK model to include a rich financial system, in which shocks to the collateral constraint reduced credit supply and led to an increase in lending rates. The collateral shocks are conceptually similar to the financial shocks included in the JQ model. The authors showed that, during the 2007-09 financial crisis, financial shocks affected the default premium; additionally, the liquidity premium could reproduce the behavior of some macroeconomic variables, such as GDP, investment or hours worked. Using a DSGE model with financial frictions along the lines of JQ and nominal rigidities, Kirsanova et al. (2021) showed that "modest" financial shock can underlie deep recession. The authors also identified two reasons for the results, which are: (i) the high levels of private indebtedness at the moment the shock occurs and (ii) when monetary policy is restricted by the zero lower bound. Under the model's specifications, over-lending can trigger a deep recession, since the reduction of debt requires deleveraging in the economy. The loop effect between the decrease of debt and the fall in capital stock – which in turn requires less financing – leads to a much greater reduction of capital, GDP and hours worked. Additionally, when monetary policy is conducted under discretion, the policy maker – following an optimal policy rule – will wish to lower interest rates. When the zero lower bound is reached, and if the constraint is binding interest rates above what is desirable, this will disrupt deleveraging. Consequently, firms will have to reduce labor and capital even further, thus amplifying the depth of recession. Kamber et al. (2017) extended the JQ model with (anticipated) news shocks on TFP. The expected shocks impacting on future GDP produced a positive co-movement between the GDP, hours worked, consumption and investment.[2]

Christiano et al. (2014b) (henceforth CMR) incorporated a BGG financial accelerator in a model with New Keynesian features. The authors found that the risk shocks proved to be the most important

[2]The financial frictions introduced, as in Jermann and Quadrini (2012), are responsible for the co-movement between the hours worked and consumption.

driver of GDP growth, with a contribution of 62% of the variation in the business cycle frequency. Their results contradict the findings of other papers, such as those by Bachmann and Bayer (2013), as well as Chugh (2016) and Dorofeenko et al. (2008); Dorofeenko et al. (2014). The main reason for these differences in results could lie in the introduction of a new component to the model. In this context, agents receive signals before the realization of a certain shock. The results reported by the authors suggest that risk shocks are the main drivers of GDP fluctuations, accounting for 62%. News shocks alone contribute to 38% of the variation in GDP. Excluding the anticipated component, risk shocks only explain 16% of GDP. Movements in financial variables – such as equity, spreads and credit – are also largely explained by risk shocks, with news shocks also playing an important role in the dynamics.

A similar specification of risk shocks by CMR is followed by Mendicino et al. (2020). In order to study the *Twin Default Crisis*, which is characterized by abnormally high defaults in firms and banks, two types of risk shocks were introduced (firms and island risk shocks). The results showed that the exposure of banks to shocks relating to non-diversifiable sources of borrowers' default risk plays an important role during deep recessions – when higher defaults are also observed in firms and banks. Becard and Gauthier (2021) explored the link between the fall in market sentiment and the tightening of banks' lending standards. A key ingredient in their model is the interaction between traditional and shadow banks. Sentiment shocks play an important role in explaining macroeconomic variable fluctuations since they trigger an increase in spreads. As these spreads increase, indebted households must reduce their purchase of goods and housing, and indebted firms cut back on capital purchases, thus anticipating a recession with the fall of employment, consumption and investment. Becard and Gauthier (2021) extended the CMR model in two directions by: (i) introducing heterogeneity in the household sector with patient and impatient households and (ii) including a banking sector subjected to capital requirements. Besides these features, the model also includes collateral shocks, which affect the fraction of housing capital (capital stock) that households (entrepreneurs) are able to pledge as collateral. Collateral shocks are interpreted as credit supply shocks, and are conceptually similar to JQ's financial shocks.[3] The results indicate that collateral shocks are the main drivers

[3]The authors show that there is a reasonably good match between the estimated collateral shock process and the bank

of GDP, investment and business credit, accounting for 32%, 83% and 68% of fluctuations in these three variables, respectively. Through an analysis of the long-run effects of risk, van der Kwaak et al. (2021) observed that, over more extended periods of time, deposit insurance leads to higher investment and GDP, as banks expand their balance sheets when risks increase. This enables banks to improve their profitability when the risk does not materialize, while the limited liability allows them to avoid the negative consequences. Using the risk shocks framework proposed by CMR, Carrillo et al. (2021) studied optimal policy rules and attempted to answer the question on whether financial stability considerations should be included in monetary policy rules, or if they ought to be dealt with as separate financial policy rules. The authors argue that the Tinbergen rule applies to the model since the two inefficiencies – sticky prices and costly state verification – require two instruments to be tackled. Welfare cost analysis showed that the standard Taylor rule, and an augmented Taylor rule to target credit spreads, produced lower welfare and larger fluctuations in response to risk shocks, when compared to a dual-rule-regime. In the latter, monetary policy follows a Taylor rule, thus addressing inflation and target spreads of the financial policy rule by setting a subsidy on financial intermediation. The improvement in welfare in the dual system is explained by the fact that the other two policy rules raise interest rates excessively when inflation increases; conversely, these rates do not fall sufficiently when spreads widen.

Despite the differences between the CMR and JQ approaches on financial frictions, Mumtaz et al. (2018) used, among others, the innovations to the financial conditions index from JQ, as well as the risk shocks from CRM, as proxy variables for credit supply shocks. The authors checked the reliability of these instruments using two statistics. For both tests, they pointed out that the measure proposed by JQ constitutes the most reliable and strongest instrument. Using a variety of VAR models, the authors concluded that credit supply shocks had been important during the last crisis, and were responsible for about half of the decline in GDP growth.

Our focus from now on will be on the JQ and CMR models, since we argue that these two important

lending standards from the Senior Loan Officer Opinion Survey on Bank Lending Practices conducted by the Federal Reserve.

mechanisms are transmitted to the real economy through financial frictions. On the one hand, there is the direct effect of banks' lending standards; and, on the other, are the effects of entrepreneurial risk. A common practice is to evaluate the relative contribution of the various shocks through variance decomposition. The results show that, in both models, financial friction plays a key role in financial and macroeconomic variable fluctuations. In this chapter, we attempt to evaluate the role of this financial friction by means of wavelet tools, which have allowed for an analysis of the contributions of the time and frequency domains simultaneously. Using wavelet tools, we looked into the properties of the series simulated from the models, and compared these with the actual data. For each model, we considered three sets of shocks to analyze their respective contributions: financial, monetary and others. Despite the simplicity of the RBC model set up by JQ, the NK version was used in a subsequent analysis as it shares more features with the CMR model, thus allowing one to focus on the distinctive ways financial frictions are introduced in the models.

The remainder of the chapter is organized as follows. Section 3.2 discusses the JQ and CMR models, presenting a brief description of the main shocks and the manner in which they are implemented in the model. Section 3.3 deals with the use of wavelet tools, namely the wavelet power spectrum (WPS) and wavelet coherency (WC). The implementation of these tools allows one to analyze the properties of some common series of the models, more specifically in the domains of time and frequency, with special emphasis placed on GDP. The main findings of this process are then discussed. The section 2.4 terminates the chapter.

3.2. The models

JQ developed a DSGE model to include debt and equity financing, in which the dynamics of real and financial variables was explored. The parsimonious model constructed by the author was fed with financial shocks, along with Solow residual-based TFP shocks, thus obtaining the simulated series of both financial and real economic variables. This RBC model was extended to include NK features. In the approach followed in the RBC version of the JQ model, the effects of financial shocks were considered independently, regardless of how many shocks were included in the model; on the other hand, structural estimation indicated that the lack of quantitatively important shocks may over-estimate the contribution of those included. It is for this reason that JQ departed from the model estimated by Smets and Wouters (2007) which already included seven shocks: productivity, investment-specific, intertemporal preferences, labor supply, price mark-up, government spending, and monetary policy. The model was extended by adding financial frictions and financial shocks, in line with the RBC model specifications, introducing debt and equity financing, as well as an enforcement constraint. By doing so, eight structural shocks were finally considered. The CMR model is richer due to the shocks included. It considers 12 aggregate shocks – exogenous measurement error, monetary policy, risk, intertemporal preferences, investment-specific, technological, productivity, marginal efficiency of investment, government spending, inflation target, growth rate and net worth. Besides these shocks, the model also features 8 news shocks (anticipated).

Below is a brief description of the main features included in the two models. Since the models share common features – following the standard NK models – we will not provide further details and will mainly focus on their distinguishing aspects. We will begin by describing the main differences in the household sector, moving on to how financial frictions are introduced and, lastly, a quick overview is presented of the shocks included in each model which were not discussed earlier. For a complete description of the models, please refer to the authors' articles

3.2.1. Households

The household maximizes the expected lifetime utility, subject to a lifetime budget constraint, whose preferences are defined over composite consumption (c_t), as well as labor (n_t), and utility function $U(c_t, n_t)$. Both models include a shock of preferences, which changes the expected lifetime utility, thus apprehending shocks to the intertemporal margin. The budget constraint presents some differences. In JQ, households receive equity payouts due to the ownership of firms; in CMR, however, households have access to both long-term (ten-year) and short-term (one-period) bonds, as well as being the owners of raw capital.

In the labor market, both models have wage rigidities, following Calvo's price rigidity. The main difference is that, while in JQ individual households are monopolistic suppliers of labor, in CMR a representative, competitive labor contractor aggregates differentiated labor services to homogeneous labor; and for each labor type, a monopolistic union sets the wage rate.

3.2.2. Financial frictions

Financial frictions and their associated shocks are introduced in the firms/entrepreneurs sector of the model. This is where the JQ and CMR models show great disparity. For that reason, each model was considered separately so as to provide further details of each approach.

JQ model

As is standard in literature, a continuum of firms produces differentiated intermediate goods – using capital and labor, subjected to productivity shocks – which are combined into the final product. This process of transforming a set of intermediate goods into a final product is subjected to a shock (the nominal price mark-up). Physical capital (k_t) is accumulated by firms, and investment is exposed to a specific technology shock. Capital utilization (u_t) is costly, and its cost is a function of the fraction of used capital over the capital owned. In the case of nominal price rigidity, Rotemberg's approach was followed, in detriment of Calvo's staggered prices.[4]

As in the simpler version of the JQ model, firms can finance themselves through debt (b_t) and equity (d_t), where debt is preferred due to tax advantages. Equity payouts are subjected to adjustment costs. Given the equity payout d_t received by shareholders, the cost for the firm is $\varphi(d_t) = d_t + \kappa \cdot \left(d_t - \overline{d}\right)^2$.[5] Lastly, the firms are subjected to an enforcement constraint given

[4]This option is justified by the fact that Calvo's approach would introduce heterogeneity in the financial structure of firms; consequently, it would not be possible to aggregate and work with a representative firm.

[5]The removal from the model of debt tax advantage and cost of adjusting equity will lead to an NK model with complete markets.

by:

$$\xi_t \left(k_{t+1} - \frac{b_{t+1}}{P_t \left(1 + r_t\right)} \right) \geq F(k_t, u_t, n_t; \mathbf{s_t}), \tag{3.2.1}$$

where $F\left(\cdot\right)$ is the production function, $\mathbf{s_t}$ is a vector of aggregate states, P_t is the aggregate nominal price index, r_t the nominal interest rate on bonds, and ξ_t is a variable which affects the tightness of the enforcement constraint and, therefore, the firm's borrowing capacity. JQ refers stochastic innovations as *financial shocks*.

The enforcement constraint in this structural NK version of the JQ model was derived in the same way, resulting in a simpler (RBC) version. It ensues from the renegotiation process between firms and lenders to settle the amount of collateral in the event of a firm's default on intertemporal debt.

CMR model

The main difference between the CMR model and other previous models with risk shocks is the presence of new shocks, and the manner in which they are introduced.

The main component of uncertainty in the CMR model lies in entrepreneurs' ability to transform the acquired raw capital into effective capital. In other words, entrepreneurs buy K units of raw capital and then turn them into ωK units of effective capital, where $\omega \geq 0$ is a random variable with mean unity, and is independently drawn by each entrepreneur. When ω is realized, the entrepreneurs know its value; however, the lenders must monitor the cost in order to determine its value. The realization of ω for each entrepreneur will also decide if the agent is able to meet the obligations required or declare bankruptcy. At the beginning of the period, the entrepreneur obtains financing through a standard debt contract. Given the cutoff value $\overline{\omega}_{t+1}$ – which divides entrepreneurs into those who can repay the interest and, principally, those who cannot – we have that:

$$R^k_{t+1}\overline{\omega}_{t+1}Q_{\overline{K},t}\overline{K}^N_{t+1} = B^N_{t+1}Z_{t+1}, \tag{3.2.2}$$

where $R^k_{t+1}\overline{\omega}_{t+1}$ is the rate of return, $Q_{\overline{K},t}$ is the price of raw capital, B^N_{t+1} is the debt, and Z_{t+1} is the gross nominal interest rate on debt. The equation (3.2.2) states that the cutoff value of $\omega \equiv \overline{\omega}_{t+1}$

is such that the value of effective capital equals the value of the debt to be paid (the interest plus the principal). Given this, one can conclude that all the agents with $\omega \leq \overline{\omega}_{t+1}$ will not be in a condition to repay their debt contracts, thus declaring bankruptcy. For such entrepreneurs, it is assumed that they are monitored by a mutual fund, which takes all of their assets.

The measure of *risk*, σ_t, is given by the cross-sectional standard deviation of $\log w$. The risk is assumed to have the first order autoregressive form:

$$\hat{\sigma}_t = \rho_\sigma \hat{\sigma}_{t-1} + u_t, \tag{3.2.3}$$

where u_t is i.i.d. univariate innovations to $\hat{\sigma}_t$. Unlike most of the business cycle models, where the agents do not learn about the shocks until they occur, CMR introduced a *new* component, so that the agents receive signals of the shocks before they arise. This is formalized in the u_t in the form of:

$$u_t = \xi_t^0 + \xi_{t-1}^1 + \xi_{t-2}^2 + \xi_{t-3}^3 + \xi_{t-4}^4 + \xi_{t-5}^5 + \xi_{t-6}^6 + \xi_{t-7}^7 + \xi_{t-8}^8, \tag{3.2.4}$$

where ξ_t^i are i.i.d with a standard deviation, where σ_i. ξ_t^0 is the unanticipated component of the risk shocks, while $\xi_{t-1}^1, \ldots, \xi_{t-8}^8$ relates to the signals received by the agents. Note that the entrepreneurs receive information regarding the shocks 2 years before they actually occur.

Along with the uncertainty of transforming raw capital into effective capital by entrepreneurs, the model also includes a shock in the marginal efficiency of investment when producing raw capital, $\zeta_{I,t}$. Raw capital is produced by households, following the technology:

$$\overline{K}_{t+1} = (1-\delta)\,\overline{K}_t + \left(1 - \mathbb{S}\left(\zeta_{I,t}\frac{I_t}{I_{t-1}}\right)\right) I_t, \tag{3.2.5}$$

where δ is the depreciation rate of raw capital, $\overline{K}_t$, I_t relates to investment, and $\mathbb{S}$ is an increasing and convex function of the adjustment cost for investment.

3.2.3. Shocks

The CMR model also includes 10 additional shocks. It has a stationary technology shock and a shock with a stationary growth rate, which both affects both the intermediate production of goods. It also accounts for equity shocks, as well as monetary policy shocks and the target inflation rate. The remaining shocks in the model relate to government consumption, the growth rate of z_t^*, households' preference in consumption, investment goods technology, and the term structure of interest rates (term premium shocks).

The shocks on the growth rate of z_t^* impact directly on wages. While a subset $1-\xi_w$ of monopoly unions sets the wages $W_{i,t}$ optimally, the remaining subset ξ_w sets the wages, as follows:

$$\begin{aligned} W_{i,t} &= (\mu_{z^*,t})^{\iota_\mu} (\mu_{z^*})^{1-\iota_\mu} \tilde{\pi}_{w,t} W_{i,t-1}, \\ \tilde{\pi}_{w,t} &\equiv (\pi^*)^{\iota_w} (\pi_{t-1})^{1-\iota_w}, \quad 0 < \iota_w < 1, \end{aligned} \tag{3.2.6}$$

where μ_{z^*} is the growth rate of z_t^*.

We have that z_t^* also affects producers. Namely, the intermediate j production of goods is as follows:

$$Y_{j,t} = \begin{cases} \varepsilon_t K_{k,t}^\alpha (z_t l_{j,t})^{1-\alpha} - \Phi z_t^* & \text{if } \varepsilon_t K_{k,t}^\alpha (z_t l_{j,t})^{1-\alpha} > \Phi z_t^* \\ 0 & \text{otherwise} \end{cases}, \tag{3.2.7}$$

where $0 < \alpha < 1$, z_t constitutes a shock with a stationary growth rate, ε_t is a covariance stationary technology shock, $K_{j,t}$ is the effective capital used to produce the intermediate product j, and $l_{j,t}$ relates to hired labor. We also have $z_t^* = z_t \Upsilon^{\left(\frac{\alpha}{1-\alpha}\right)t}$, where Υ is a growth parameter.

The final producer of goods uses a technology that combines all the intermediate goods to transform these into the final product, which is subjected to a unit root technology shock in the form of:

$$Y_t = \left[\int_0^1 Y_{j,t}^{\frac{1}{\lambda_{f,t}}} dj\right]^{\lambda_{f,t}}, \quad 1 \le \lambda_{f,t} < \infty, \tag{3.2.8}$$

where $\lambda_{f,t}$ constitutes a shock in production. A similar shock is found in the JQ model, as was mentioned earlier (the nominal price mark-up shock).

In the model, there are two types of technology which convert homogeneous goods into consumption, C_t, as well as into investment goods, I_t. While the conversion rate of homogeneous goods into consumption goods is one-to-one, from a unit of homogeneous goods one obtains $\Upsilon^t \mu_{\Upsilon,t}$ of investment goods, where $\Upsilon > 1$ and $\mu_{\Upsilon,t}$ refer to the technology shocks of investment goods.

The monetary authority's policy rule is subjected to two types of shocks: monetary policy shocks and the inflation target. The linearized form is given by:

$$R_t - R = \rho_p \left(R_{t-1} - R\right) + \left(1 - \rho_p\right)\left[\alpha_\pi \left(\pi_{t+1} - \pi^*\right) + \alpha_{\Delta y}\frac{1}{4}\left(g_{y,t} - \mu_{z^*}\right)\right] + \frac{1}{400}\varepsilon_t^p, \tag{3.2.9}$$

where ε_t^p is the monetary policy shock, R_t the net interest rate, π_{t+1} is anticipated inflation and π_t^* is the inflation target. $g_{y,t}$ is GDP growth, so the term $g_{y,t} - \mu_{z^*}$ refers to GDP growth in deviation from the steady state.

The CMR model also makes a distinction between short and long-term bonds. Households have access to short-term bonds B_{t+1}, which pay a gross nominal return R_t, and a long-term bond R_{t+40}^L, with a gross return R_t^L in the period $t + 40$. Given R_t^L, the long-term interest rate in the model and $\tilde{R}_t^L$ the long-term interest rate in the data, the term structure of the interest rate is as follows:

$$\left(R_t^L\right)^{40} = \left(\tilde{R}_t^L\right)^{40} \eta_{t+1} \cdots \eta_{t+40}, \tag{3.2.10}$$

where η_t is an exogenous measurement error shock that the authors refer to by using the term premium shock. The authors show that risk shocks account for some of the fluctuations in the slope of the interest rate term structure.

Equity shocks introduced in the CMR model directly affect entrepreneurs' net worth. In other words, once entrepreneurs have collected their earnings through the sale of undepreciated capital and capital rental during each period, and have settled their obligations, a fraction $1 - \gamma_t$ of their assets is transferred to the households, while the complementary fraction γ_t stays with the entrepreneurs. The entrepreneurs' net worth in then given by:

$$N_{t+1} = \gamma_t \left[1 - \Gamma_{t-1}\left(\overline{\omega}_t\right)\right] R_t^k Q_{\overline{K},t-1} \overline{K}_t + W_t^e, \tag{3.2.11}$$

where γ_t is the equity shock and W_t^e is a lump-sum transfer received by the entrepreneurs from the households.

At this point, one is left with the government consumption shock. Given government consumption, G_t, then we have $G_t = z_t^* g_t$, where g_t is a stationary stochastic process.

The JQ model includes 3 additional shocks to those mentioned previously.

The aggregate nominal wage index is given by $W_t = \left(\int_0^1 w_{j,t}^{1/(1-\nu_t)} dj\right)^{1-\nu_t}$, where $w_{j,t}$ is the nominal wage rate set by household j and ν_t is a stochastic variable apprehending shocks relating to the wage mark-up.

In the public sector of the model, two remaining shocks are found. The government faces a budget constraint:

$$P_t G_t + B_{t+1}\left(\frac{1}{R_t} - \frac{1}{1+r_t}\right) = T_t, \tag{3.2.12}$$

where G_t refers to real (unproductive) government purchases, r_t is the nominal interest rate, $R_t = 1 + r_t(1-\tau)$ is the effective gross interest rate paid by firms, and T_t relates to the lump-sum taxes paid by households to finance government expenditures. Government purchases follow the stochastic process:

$$\hat{G}_t + \rho_g \hat{G}_{t-1} + \rho_{gz}\left(\hat{z}_t - \hat{z}_{t-1}\right) + \epsilon_{g,t}, \tag{3.2.13}$$

where $\epsilon_{g,t} \sim N\left(0, \sigma_G\right)$ relates to government shocks.

Similarly to the CMR model, the monetary policy follows a Taylor rule, in which the interest rates respond to deviations from the steady state of inflation and GDP growth:

$$\frac{1+r_t}{1+\bar{r}} = \left(\frac{1+r_t-1}{1+\bar{r}}\right)_R^{\rho} \left[\left(\frac{\pi_t}{\bar{\pi}}\right)_1^{\nu} \left(\frac{Y_t}{Y_T^*}\right)_2^{\nu}\right]^{1-\rho_R} \left(\frac{\frac{Y_t}{Y_t^*}}{\frac{Y_{t-1}}{Y_{t-1}^*}}\right)^{\nu_3} \varsigma_t, \tag{3.2.14}$$

where ρ_R, ν_1, ν_2 and ν_3 are parameters and $\varsigma_t \sim N\left(0, \sigma_R\right)$ is the monetary policy shock.

3.2.4. Estimation

In order to proceed with estimation, the JQ and CMR approaches were followed for the respective models. We began with some parameters which were determined through steady state targets, while the remaining were estimated by using Bayesian methods, as described in An and Schorfheide (2007).

In line with the standard approach in this literature, one used as many empirical series as the number of unanticipated shocks in the models. This means that 8 series were used for the JQ, whereas 12 were implemented in the CMR. The series used are the same as those in the original papers; however, they were extended to cover the period between the first quarter of 1984 and the fourth quarter of 2019.

Like the JQ model, the estimates were developed by means of the empirical series of: the GDP (growth rate), personal consumption expenditures (growth rate), private domestic investment (growth rate), implicit price deflator for the GDP (growth rate), working hours in the private sector (growth rate), hourly wages in the business sector (growth rate), federal fund rate and debt repurchases in the nonfinancial business sector. For the estimation of the CMR model, we used the empirical series of: GDP (deflated by its implicit price deflator), consumption (sum of household purchases of nondurable goods and services, each deflated by its own implicit price deflator), investment (sum of gross private domestic investment plus household purchases of durable goods, each deflated by its own price deflator), inflation (measured as the logarithmic first difference of the GDP deflator), real wages (hourly compensation of all employees in nonfarm business, divided by the GDP implicit price deflator), relative price of investment goods (implicit price deflator for investment goods, divided by the implicit price deflator for GDP), hours worked (index of nonfarm business hours of all persons), the federal funds rate, credit to nonfinancial firms, slope of the term structure (difference between the ten-year constant maturity US government bond yield and the federal fund rate), entrepreneurial net worth (Dow Jones Wilshire 5000 index) and credit spread (difference between the interest rate on BAA-rated corporate bonds and the ten-year US government bond rate).[6] For the transformations applied to the data, we followed the respective authors' approaches.

Table 3.1 presents a report of the first set of parameters which, for both models, were calibrated to match steady state targets. In JQ, most of those parameters are the same as those of the simpler

[6]GDP, consumption, investment, hours worked and credit are converted to per capita terms by dividing by the population over 16. Annual population data was obtained from the Organization for Economic Cooperation and Development and linearly interpolated to obtain a quarterly frequency.

model. Average government purchases were set to have a steady state ratio of government purchases/consumption over output of 0.18. This target is close to the 0.2 used by CMR for the same purpose. The parameter for the disutility of labor differed significantly from the two models since the authors followed different targets. While JQ defined this parameter so that the average working time is 0.3, CMR targeted the unit as the steady state of hours worked. For the discount rate, JQ defined this as being 0.9825 – to have an annual steady state return from holding shares equal to 7.32 percent – while CMR set it equal to 0.9987.

The second set of parameters were then estimated by using Bayesian procedures. Tables 3.2 and 3.3 report the prior and posterior modes for the estimated parameters of the JQ and CMR models, respectively. For the JQ model, the posterior distribution was re-estimated since, as argued by Pfeifer (2016), some posterior modes – such as consumption habits and the interest rate smoothing parameter – exceeded the 90 percent highest posterior density intervals (HPDIs). Generally, this is a sign of parameter drift in the Markov Chain and of non-convergence. For the re-estimation procedure, we followed Pjeifer by using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm to find the modes, as well as the Monte Carlo Markov Chain, consisting of 10 million draws from the Metropolis-Hastings algorithm with a burn-in of 25 percent. The results of this re-estimation showed that the contribution of financial shocks to GDP fluctuations – given by the posterior mean variance decomposition for the observables – had decreased significantly, accounting on average for less than 5%, against the 46.4% originally reported by Jermann and Quadrini (2012). Conversely, one observed an increase in the contributions of financial shocks for the cases of inflation and debt repurchase.[7]

3.3. Quantitative analysis

The next section presents an analysis of four of the simulated time series for both models, comparing these with the empirical data. For the time series, one specifically focused on the GDP, investment,

[7] In the context of inflation, financial shocks are responsible, on average, for 18% of fluctuations, against the 9.5% in JQ. For debt repurchases, the average contribution is now almost 23%, while JQ reports 13.5%.

Parameter	**Description**	**Value**
Jermann and Quadrini (2012) model		
β	Discount factor	0.9825
τ	Tax advantage	0.35
α	Utility parameter	16.736
θ	Production technology	0.36
δ	Depreciation rate	0.025
$\overline{\xi}$	Enforcement parameter	0.199
$\overline{G}$	Average government purchases	0.179
Christiano et al. (2014b) model		
β	Discount rate	0.9987
σ_L	Curvature on disutility of labor	1.00
ψ_L	Disutility weight on labor	0.7705
λ_w	Steady state markup, suppliers of labor	1.05
μ_z	Growth rate of the economy	0.41
Υ	Trend rate of investment-specific technological change	0.42
δ	Depreciation rate on capital	0.025
α	Power on capital in production function	0.4
λ_f	Steady state markup, intermediate good firms	1.2
$1-\gamma$	Fraction of entrepreneurial net worth transferred to households	1-0.985
W^e	Tranfer received by entrepreneurs	0.005
ν_g	Steady state government spending – GDP ratio	0.2
π^{target}	Steady state inflation rate (APR)	2.43
π^c	Tax rate on consumption	0.05
π^k	Tax rate on capital income	0.32
π^l	Tax rate on labor income	0.24

Table 3.1.: *Parameters and steady state values*

			Prior Distribution		Posterior Distribution			
					JQ	Reestimation		
Parameter Description	**Par.**	**Dist.**	**Mean**	**Std**	**Mode**	**Mode**	**5%**	**95%**
Panel A. Economic parameters								
Risk aversion	σ	norm	1.500	0.370	1.090	1.540	0.855	1.731
Frisch elasticity	ε	norm	2.000	0.750	1.761	0.873	0.940	2.998
Habit parameter	h	beta	0.500	0.300	0.608	0.367	0.263	0.500
Calvo Wage adjustment	ω	beta	0.500	0.300	0.278	0.075	0.037	0.220
Rotemberg price adjustment cost	ϕ	invg	0.100	0.300	0.031	6.997	7.300	29.584
Investment adjustment cost	ϱ	invg	0.100	0.300	0.021	0.149	0.102	1.371
Capital utilization cost	ψ	beta	0.500	0.150	0.815	0.775	0.548	0.882
Equity cost	κ	invg	0.200	0.100	0.426	0.287	0.254	0.935
Average price markup	$\overline{\eta}$	beta	1.200	0.100	1.137	1.806	1.712	1.871
Average wage markup	$\overline{\upsilon}$	beta	1.200	0.100	1.025	1.140	1.057	1.374
Panel B. Shocks								
Productivity shock persistence	ρ_z	beta	0.500	0.200	0.902	0.920	0.864	0.949
Investment shock persistence	ρ_ζ	beta	0.500	0.200	0.922	0.913	0.623	0.928
Intertemporal shock persistence	ρ_γ	beta	0.500	0.200	0.794	0.949	0.920	0.979
Price markup shock persistence	ρ_η	beta	0.500	0.200	0.906	0.866	0.734	0.910
Wage markup shock persistence	ρ_υ	beta	0.500	0.200	0.627	0.981	0.945	0.996
Government shock persistence	ρ_G	beta	0.500	0.200	0.955	0.976	0.957	0.993
Interest policy shock persistence	ρ_ς	beta	0.500	0.200	0.203	0.213	0.131	0.338
Financial shock persistence	ρ_ξ	beta	0.500	0.200	0.969	0.990	0.978	0.998
Interaction production government	ρ_{gz}	beta	0.500	0.200	0.509	0.859	0.608	0.969
Taylor rule persistence	ρ_R	beta	0.750	0.100	0.745	0.784	0.767	0.849
Taylor rule feedback	ν_1	norm	1.500	0.250	2.410	2.202	1.984	2.505
Taylor rule feedback	ν_2	norm	0.120	0.050	0.000	-0.020	-0.032	0.050
Taylor rule feedback	ν_3	norm	0.120	0.050	0.121	0.176	0.141	0.232
Standard deviations, shock innovations								
Technology shock	σ_z	invg	0.001	0.050	0.005	0.005	0.004	0.005
Investment shock	σ_ζ	invg	0.001	0.050	0.006	0.009	0.007	0.049
Preference shock	σ_γ	invg	0.001	0.050	0.016	0.019	0.013	0.028
Price Markup shock	σ_η	invg	0.001	0.050	0.019	0.013	0.013	0.031
Wage Markup shock	σ_υ	invg	0.001	0.050	0.085	0.021	0.012	0.022
Government shock	σ_g	invg	0.001	0.050	0.028	0.016	0.014	0.018
Monetary shock	σ_ς	invg	0.001	0.050	0.002	0.001	0.001	0.002
Financial Shock	σ_ξ	invg	0.001	0.050	0.008	0.016	0.013	0.018

Table 3.2.: *Posterior estimates with JQ priors*

Parameter Description	Par.	Prior Distribution Dist.	Mean	Std	Posterior Distribution Mode	Std
Panel A. Economic parameters						
Calvo wage stickiness	ξ_w	beta	0.75	0.1	0.81	0.019
Habit parameter	b	beta	0.5	0.1	0.74	0.050
Steady state probability of default	$F(\overline{\omega})$	beta	0.007	0.0037	0.0056	0.0023
Monitoring cost	μ	beta	0.275	0.15	0.21	0.073
Curvature, utilization cost	σ_a	normal	1	1	2.54	0.70
Curvature, investment adjust cost	S''	normal	5	3	10.78	1.71
Calvo price stickiness	ξ_p	beta	0.5	0.1	0.74	0.035
Policy weight on inflation	α_π	normal	1.5	0.25	2.40	0.16
Policy smoothing parameter	ρ_p	beta	0.75	0.1	0.85	0.015
Price indexing weight on inflation target	ι	beta	0.5	0.15	0.90	0.049
Wage indexing weight on inflation target	ι_w	beta	0.5	0.15	0.49	0.11
Wage indexing weight on persistent technology growth	ι_μ	beta	0.5	0.15	0.94	0.029
Policy weight on output growth	$\alpha_{\Delta y}$	normal	0.25	0.1	0.36	0.099
Panel B. Shocks						
Correlation among signals	$\rho_{\sigma,n}$	normal	0	0.5	0.39	0.095
Autocorrelation, price markup shock	ρ_{λ_f}	beta	0.5	0.2	0.91	0.034
Autocorrelation, price of investment goods shock	ρ_{μ_Ψ}	beta	0.5	0.2	0.99	0.0085
Autocorrelation, government	ρ_g	beta	0.5	0.2	0.94	0.023
Autocorrelation, persistent technology growth	ρ_{μ_z}	beta	0.5	0.2	0.15	0.070
Autocorrelation, transitory technology	ρ_ϵ	beta	0.5	0.2	0.81	0.065
Autocorrelation, risk shock	ρ_σ	beta	0.5	0.2	0.97	0.0093
Autocorrelation, consumption preference shock	ρ_{ζ_c}	beta	0.5	0.2	0.90	0.031
Autocorrelation, marginal efficiency of investment	ρ_{ζ_z}	beta	0.5	0.2	0.91	0.017
Autocorrelation, term structure shock	ρ_η	beta	0.5	0.2	0.97	0.025
Standard deviations, shock innovations						
Std, anticipated risk shock	$\sigma_{\sigma,n}$	invg2	0.001	0.0012	0.028	0.0028
Std, unanticipated risk shock	σ_{σ_0}	invg2	0.002	0.0033	0.07	0.0099
Std, measurement error on net worth		Weibull	0.01	5	0.018	0.0009
Price markup	σ_{λ_f}	invg2	0.002	0.0033	0.011	0.0022
Investment price	σ_{μ_Ψ}	invg2	0.002	0.0033	0.004	0.0003
Government consumption	σ_g	invg2	0.002	0.0033	0.023	0.0016
Persistent technology growth	σ_{μ_z}	invg2	0.002	0.0033	0.0071	0.0005
Equity	σ_γ	invg2	0.002	0.0033	0.0081	0.001
Temporary technology	σ_ε	invg2	0.002	0.0033	0.0046	0.0003
Monetary policy	σ_{ε^p}	invg2	0.583	0.825	0.49	0.037
Consumption preference	σ_{ξ_c}	invg2	0.002	0.0033	0.023	0.003
Marginal efficiency of investment	σ_{ξ_I}	invg2	0.002	0.0033	0.055	0.012
Term structure	σ_η	invg2	0.002	0.0033	0.0016	0.0007

Table 3.3.: *CRM model Priors and Posteriors*

consumption and hours worked. JQ and CMR emphasized the importance of financial shocks to explain the drop in GDP during the *Great Recession*; both authors found them to be important when attempting to understand the cyclical behavior of the product. Accordingly, our main focus relied on the results for the GDP. Despite this similarity in perspectives, they both present significant differences in the process of introducing and exploring financial frictions.

As mentioned previously, besides the differences in how financial frictions are introduced in the models, as shown in the section 3.2, there is a different number of shocks. JQ only considered eight, while CMR took twelve different shocks into account. In order to simplify our analysis, we organized shock contributions into three "categories": financial, monetary and other. In CMR, for the financial category, risk shocks were included with news (anticipated) shocks. In the other category, we included in the models all the shocks that did not fit in the other two categories – financial and monetary.

For the empirical and respective simulated series, in this analysis one used the quarterly data starting in the first quarter of 1984 to the last quarter of 2019. This provided a timespan of 36 years (144 observations) in which to apply the wavelet tools, namely the Wavelet Power Spectrum (WPS), Wavelet Coherency (WC) and the respective phase-differences. A more detailed explanation of wavelet tools can be seen in Aguiar-Conraria and Soares (2014). For a fully detailed explanation of the empirical data used in the model to produce the simulated series, we refer to Jermann and Quadrini (2012), and Christiano et al. (2014b).

3.3.1. Wavelet Analysis

Wavelets provide us with the tools to analyze time series in both the domains of time and frequency. The WPS shows the time-frequency level of volatility (red regions present a higher level of volatility, while the blue are of lower volatility). The WPS also allows one to compare time series at a "*superficial*" level, looking for the similarities between the regions of higher and lower volatility, as well as the local maxima (shown with a white line). This first overview allows for an indication of what the most relevant frequencies will be in the subsequent analysis. The WC is useful in the comparison of time series. The implementation of WC enables one to proceed with an in-depth analysis of crosscorrelation behavior (the red regions indicate a high correlation, while the blue represent low levels of correlation). Once WC is established, one can then compute the phase of wavelet transformation for each of the series, thus obtaining their phase-difference which, in turn, provides information as to their possible co-movements. Accordingly, if the phase-difference is in the $]-\pi/2, \pi/2[$ range, then the time series are in-phase; conversely, if it is in the $]-\pi, -\pi/2[$ or $]\pi/2, \pi[$ range, then the time series are out-of-phase. One considered three different frequency bands for phase-difference. One ranges from 1 to 4 years, which represents short-term (higher) frequencies; another ranges between 4 and 8 years, thus apprehending medium-term frequencies; the last of these ranges from 8 to 16 years, which we refer to as long-term (shorter) frequencies. Furthermore, if the phase-difference is in the $]-\pi, -\pi/2[$ or $]0, \pi/2[$ range, then the empirical time series leads; on the other hand, if it is on the $]-\pi/2, 0[$ or $]\pi/2, \pi[$ range, then it is the simulated time series which is in the lead. Lastly, when the phase-difference is equal to 0, one considers the series to be perfectly synchronized. For a more detailed explanation of wavelet tools, see Aguiar-Conraria and Soares (2014).

Figures 3.1 and 3.3 present the WPS relating to the GDP for the empirical series and the series from the JQ and CMR models, respectively. For the WPS, the pattern between the data and the JQ model is more similar than the one obtained for the CMR model, mainly at lower frequencies. This is shown by the regions of higher volatility and the local maxima. Using the JQ model, one observed great similarities between the series simulated with all the other shocks and the empirical counterpart, but not during the 2007-09 recession. During this period, one saw significant similarities in the simulated series with financial and monetary shocks, mainly at short-term frequencies. It is also evident that, in the JQ model, the financial shocks series presented more cyclical components than the empirical series for the GDP. Use of the CMR model led to rather different results. First of all, the high volatility of the simulated series with financial shocks was concentrated mainly in the medium to long-term frequencies, ignoring most the local maxima located at high frequencies in the empirical series. Secondly, the regions of high volatility at short-term frequencies were principally apprehended through the other shocks, including the period around the *Great Recession*.

The results from the WPS are more or less reflected in the WC (Figure 3.2 and 3.4). In the JQ model, WC between the empirical GDP and the simulated series with all the other shocks exhibits high coherence across all the frequencies and along the entire time span. In contrast, for the WC of financial shocks, the area of higher correlation with the empirical counterpart is mainly located in the short to medium-term frequencies. In the case of monetary policy, there is an area of high coherence, approximately in the 5- to 10-year frequency band, covering almost the entire time span. Besides this area, one observed that around the *Great Recession* period, the high levels of correlation between the simulated series and the empirical counterpart spread to lower frequencies, between 1.5 and 4 years. There were slightly different results in the CMR model. For the financial and monetary shocks, WC between the simulated and empirical series exhibited a greater correlation at medium-term frequencies, spreading to lower frequencies around the last recession period. For the simulated series with all the other shocks, the areas of high coherence were mainly located at higher frequencies, and after 2005.

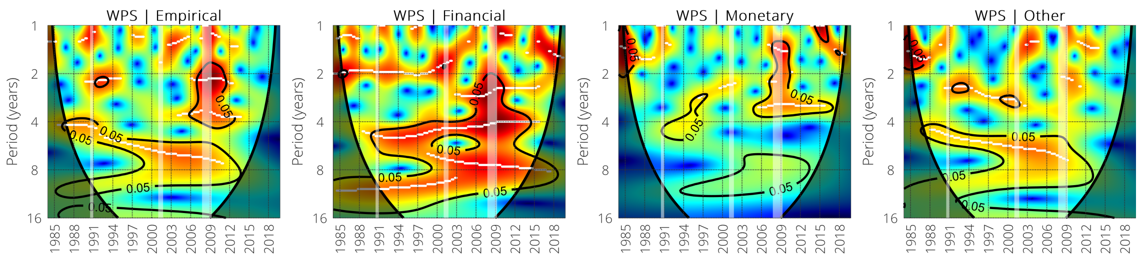

Figure 3.1.: *WPS of the empirical GDP and the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

Phase-difference showed that, for both models, the simulated series with financial shocks were in-phase with their empirical counterparts. Namely, and in greater detail: in the JQ model, one observed that these were near synchronism in the last recession, during the shorter and longer time horizons; in the medium-term time horizon, the empirical series was in the lead. A broader analysis across the time span indicated that the series was close to synchronism until 2003 in the 4- to 8-year frequency band; after 2005, this occurred in the long-term frequencies. The series never

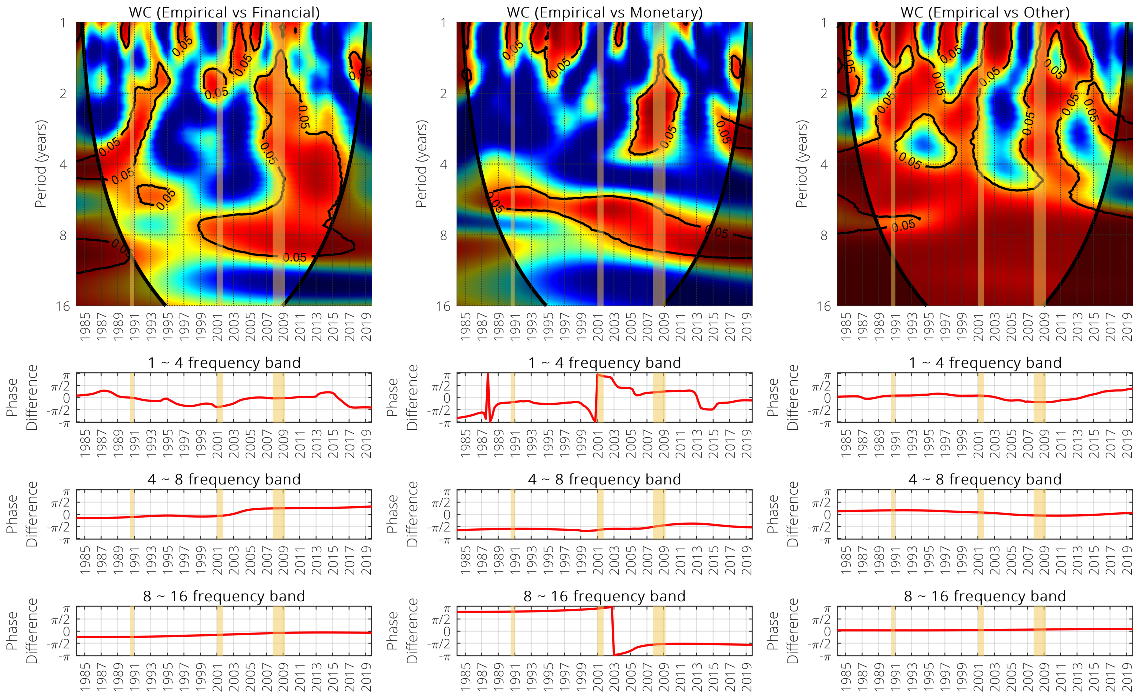

Figure 3.2.: *WC between the empirical GDP and each one of the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

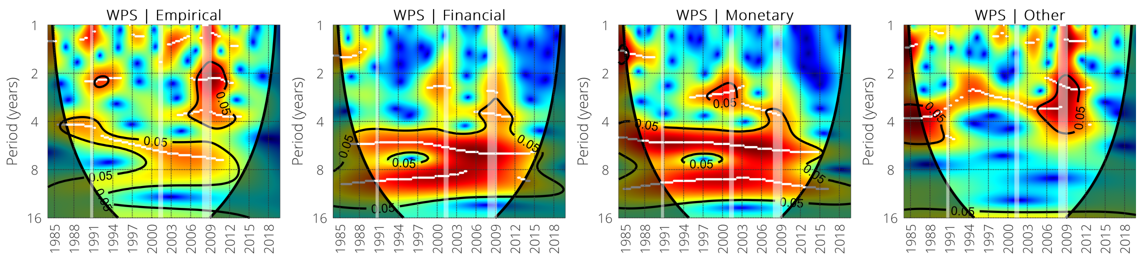

Figure 3.3.: *WPS of the empirical GDP and the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

reached this level of synchronism in the CMR model, with the empirical GDP series leading the one simulated from financial shocks during the entire sample period. Regarding monetary policy shocks, one observed distinct results for the two models when we focused on the period surrounding the *Great Recession* – from 2005 to 2011. Firstly, in JQ the phase-difference was meaningful only in

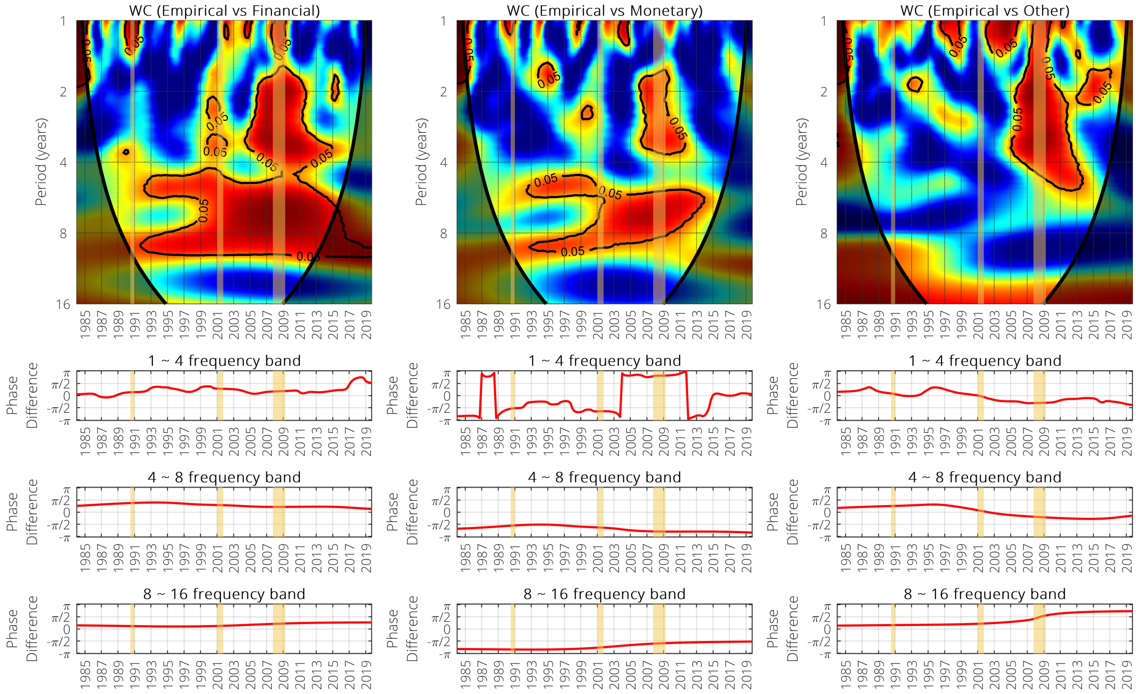

Figure 3.4.: *WC between the empirical GDP and each one of the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

the 1- to 4-year frequency band, while in CMR it was also significant at frequencies between 4 and 8 years. Secondly, while in JQ the simulated series of monetary policy shocks was in-phase with the empirical counterpart, in CMR they were out-of-phase in both frequency bands – the empirical GDP led in the 4 -to 8-year period and the simulated series took the lead at frequencies between 1 and 4 years. The results from the CMR model indicate that monetary policy helped to smooth the intensity of fluctuations in the GDP caused by the materialization of risks, meaning that the 2007-09 recession would have been deeper, had it not been for the monetary policy. This is in-line with the thought that expansionary monetary policy shocks, corresponding to a decline in the US federal fund rate, lead to the hump-shaped expansion of some macroeconomic variables, such as consumption, investment and output. In contrast, the results from monetary policy shocks in the JQ model follow the argument that price stability constitutes an insufficient condition for financial stability. As argued by Badarau and Popescu (2014), a more aggressive monetary policy would not have been fully successful at improving an economic response to the financial bubble underlying the last recession. This result is also aligned with the findings that, while monetary policy succeeded in mitigating financial market distress, GDP growth remained lower than expected in several advanced economies, with recovery being disappointingly sluggish (Pain et al., 2014; Jannsen et al., 2019). Additionally, the findings by Acharya et al. (2020) suggest that banks' capital constraints during an easing of monetary policy may affect the effectiveness of the bank-lending channel. Lastly, this result from the JQ model is also consistent with the conclusions drawn by Carrillo et al. (2021), which claim that two inefficiencies require two instruments if they are to be tackled. The results for the phase-difference related to the simulated series with all the other shocks shows, once again, that the JQ model generates series closer to synchronism. For the CMR model, the series is in-phase – except after 2010 in the 8- to 16-year frequency band; yet, these results should be interpreted carefully. There is, however, some oscillation in the leading one, whereas in the region of high coherency – approximately during the last crisis – it is the simulated series which leads.

Overall, the results obtained from the wavelet tools – WPS, WC and phase-difference – for investment are the same as those for GDP in both models (Figure 3.5, 3.6, 3.7 and 3.8).

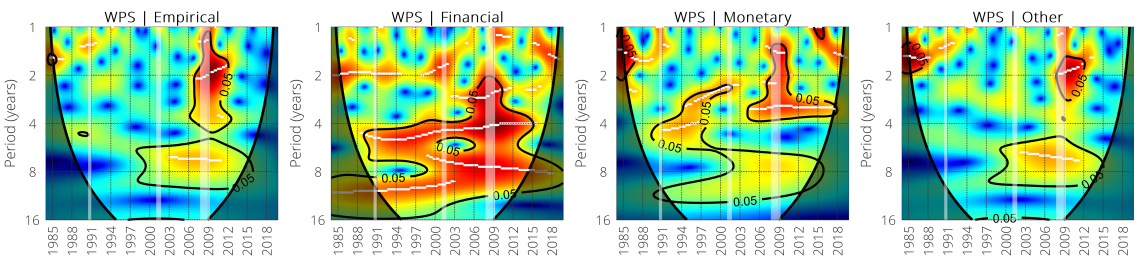

Figure 3.5.: *WPS of the empirical series for investment and the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

It is important to point out that the empirical series for investment differs in the two models. While JQ considers the empirical series for investment as 'Capital expenditures in nonfinancial business' (Table F.101, line 4), in CMR this is the sum of gross private domestic investment plus household

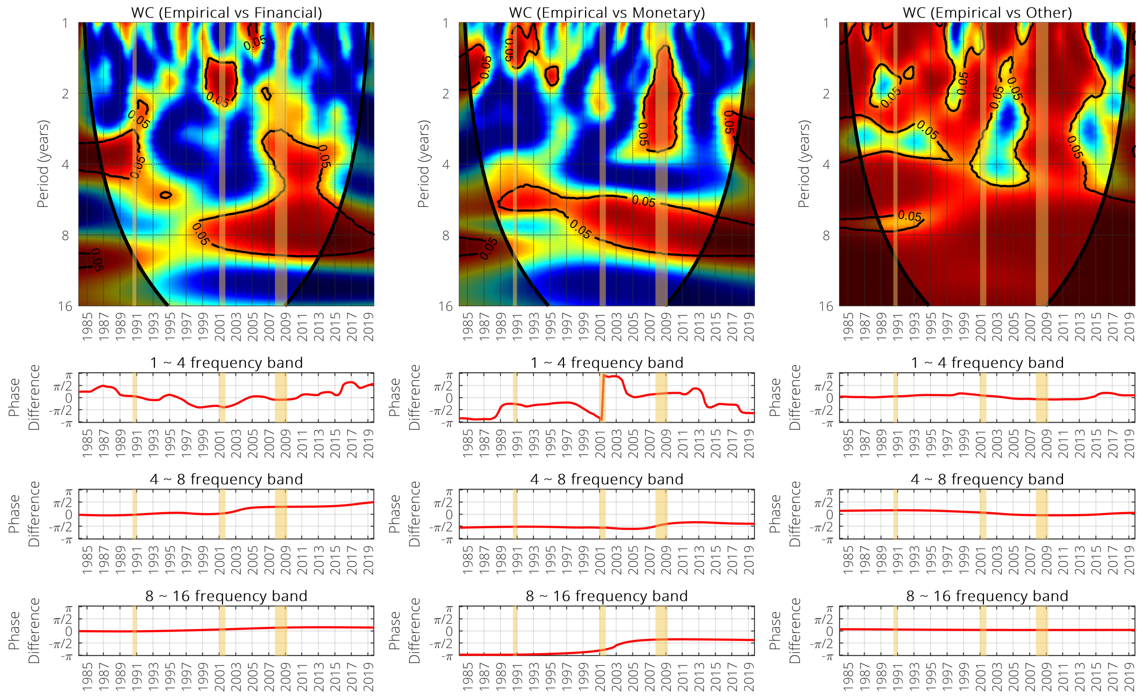

Figure 3.6.: *WC between the empirical series for investment and each of the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

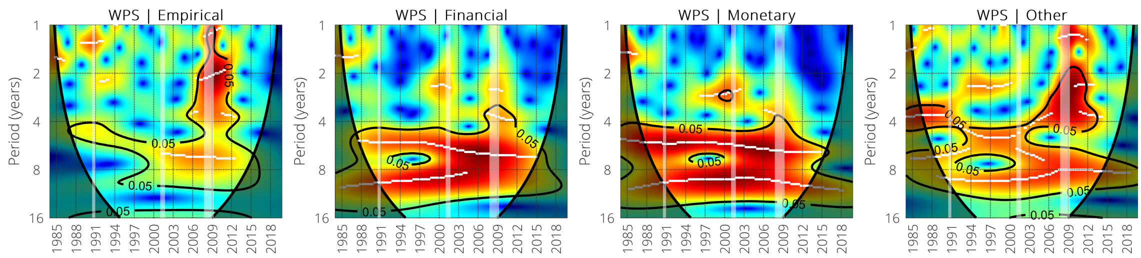

Figure 3.7.: *WPS of the empirical series for investment and the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

purchases of durable goods, each deflated by its own price deflator. The simulated series with financial shocks, as well as all the other shocks, were in-phase with the empirical counterpart in both the JQ and CMR models. For the CMR model, they are also those which show wider regions of high coherency. One should draw attention to the fact that, in the WPS for the simulated series with all the other

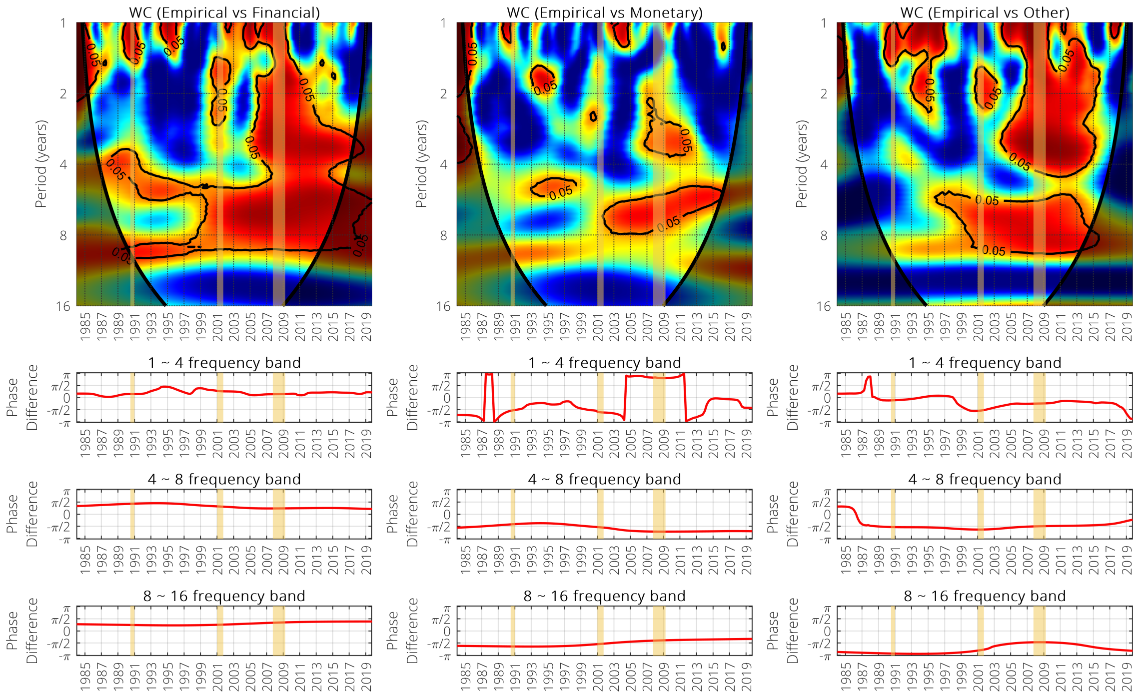

Figure 3.8.: *WC between the empirical series for investment and each of the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

shocks, the regions of higher volatility are no longer concentrated in the higher frequencies but are found mainly in the lower frequencies. Nonetheless, there are more similarities with the WPS for the empirical series of investment, mainly around the last financial crisis – in which it also seems to concentrate in the region of higher volatility in the empirical series during the short-term horizons. In the JQ model, as in the GDP, all the other shock contributions produce a simulated series that exhibits high correlation with the empirical counterpart at all frequencies, and across the entire time span. In the case of monetary policy shocks, one observed the same results as in the GDP, with the JQ model producing series which were in-phase with the empirical investment series, while these were out-of-phase in the CMR model.

As in the empirical series of investment, in the case of consumption one observed slight differences in the measures used in the two models. JQ considers consumption as being 'Real personal consumption expenditures' from the NIPA (Table 1.1.6); in CMR, it is the sum of the household purchases of nondurable goods and services, each deflated by its own implicit price deflator. From the WPS (Figure3.9 and Figure3.10) we have that, while in JQ the combination of other shocks – rather than financial or monetary – produce the most similar time series with its empirical counterpart, in CMR that is observed for the series from the monetary policy shocks – closely followed by the time series obtained from all other shocks. The financial shocks seems to play a more important role in the JQ model in explaining the changes in consumption, despites the stronger volatility at high frequency domains, that is not seen in the WPS for the empirical time series of investment.

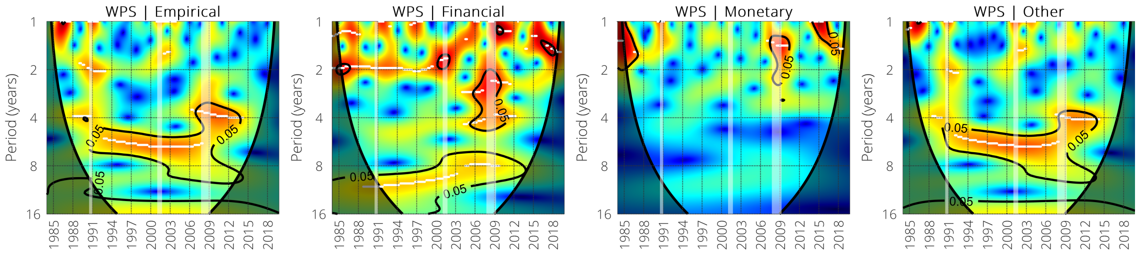

Figure 3.9.: *WPS of the empirical series for consumption and the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

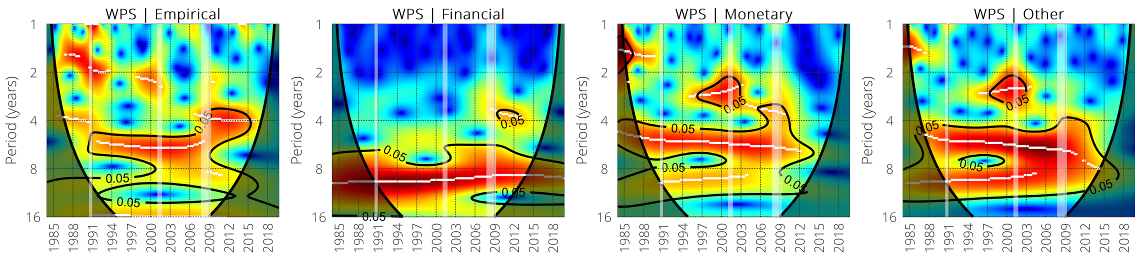

Figure 3.10.: *WPS of the empirical series for consumption and the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

For consumption, and when compared to the previous results for GDP and investment, the main difference lies in the phase-difference for financial shocks (Figure3.11 and 3.12). In the JQ model, the results are in-line with what was observed for other variables; on the other hand, in the CMR model, the simulated series with financial shocks are mainly out-of-phase for the short and medium-term horizons.

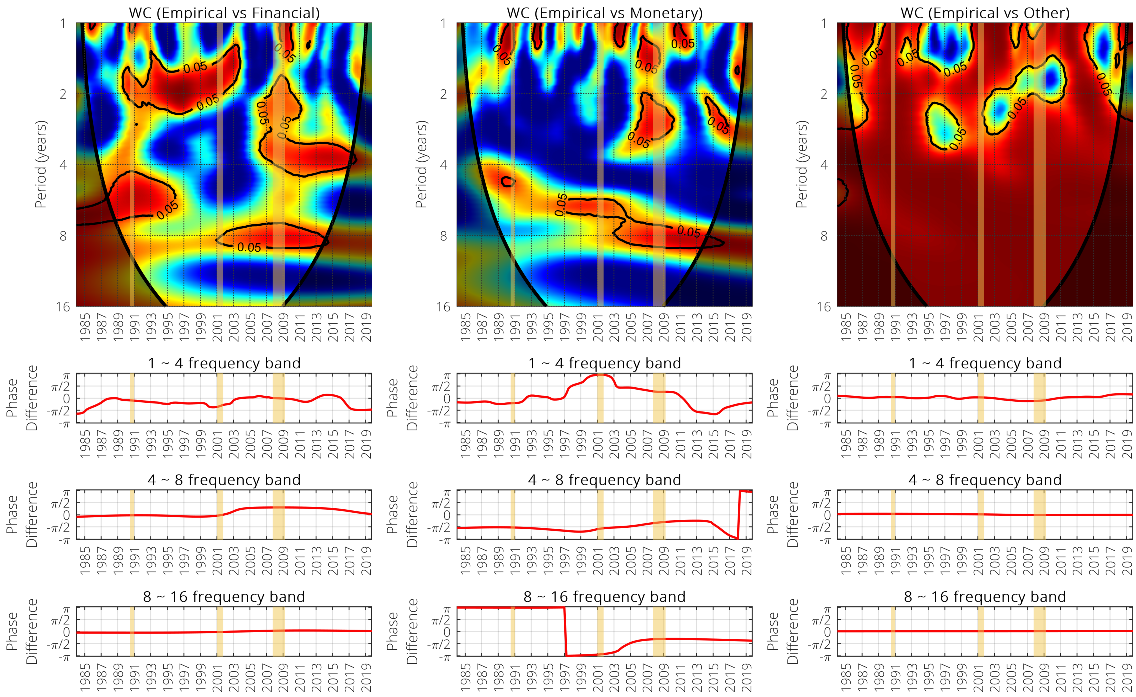

Figure 3.11.: *WC between the empirical series for consumption and each of the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

It is only the simulated series with all the other shocks that are in-phase with the empirical counterpart, highlighting the inability of risk shocks to explain fluctuations in consumption. These results would imply an increase (decrease) in consumption when the entrepreneurs' risks are lower (higher). They additionally indicate that financial shocks produce a smoothing effect on consumption, since the simulated series move in an opposite direction to what is observed in the data. As in previous results for the JQ model, regarding the WC results, one saw a wider region of high correlation for the series simulated with other shocks; the phase-difference showed that the series are synchronized along the entire sample period. Nonetheless, in the case of financial shocks, one still observed some

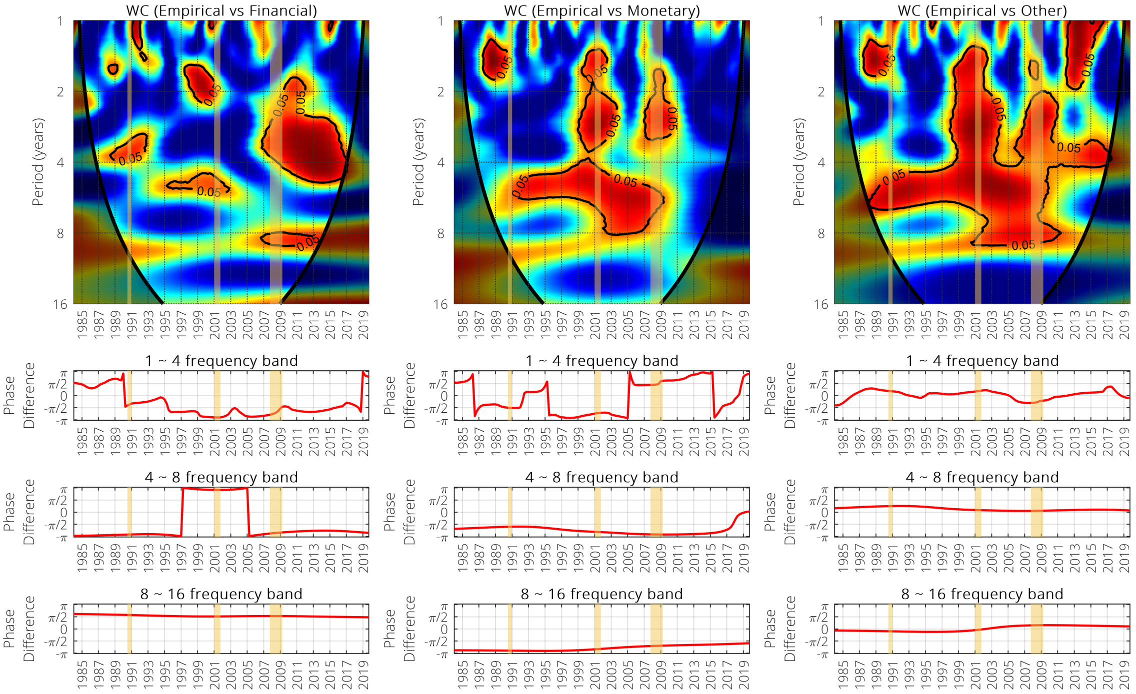

Figure 3.12.: *WC between the empirical series for consumption and each of the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

significant areas of high coherency, with phase-difference indicating that the series are in-phase and synchronized, or close to this most of the time – so that phase-difference is statistically significant. As for the other variables, in the JQ model the simulated series with monetary policy shocks are in-phase with the empirical counterpart.

Once again, different measures of labor were used in the estimation of the two models. In JQ, this is measured as the 'total private aggregate weekly hours' from the Current Employment Statistics national survey, while the CMR uses an index of nonfarm business hours for all persons. Figures 3.13, 3.14, 3.15 and 3.16 present the results for the WPS, WC and phase-difference.

In the JQ model, one observed similar results to those found for other variables with regard to financial shocks and all the other shocks; however, there was a deviation of results in relation to monetary policy shocks. In the latter case, phase-difference indicates that, while in the 1- to 4-year

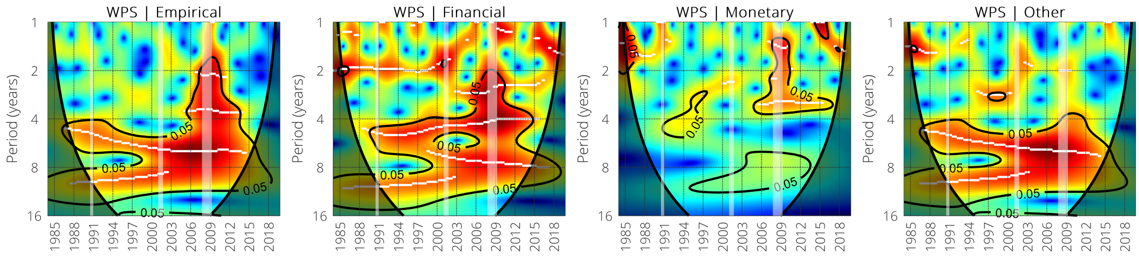

Figure 3.13.: *WPS of the empirical series for labor and the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

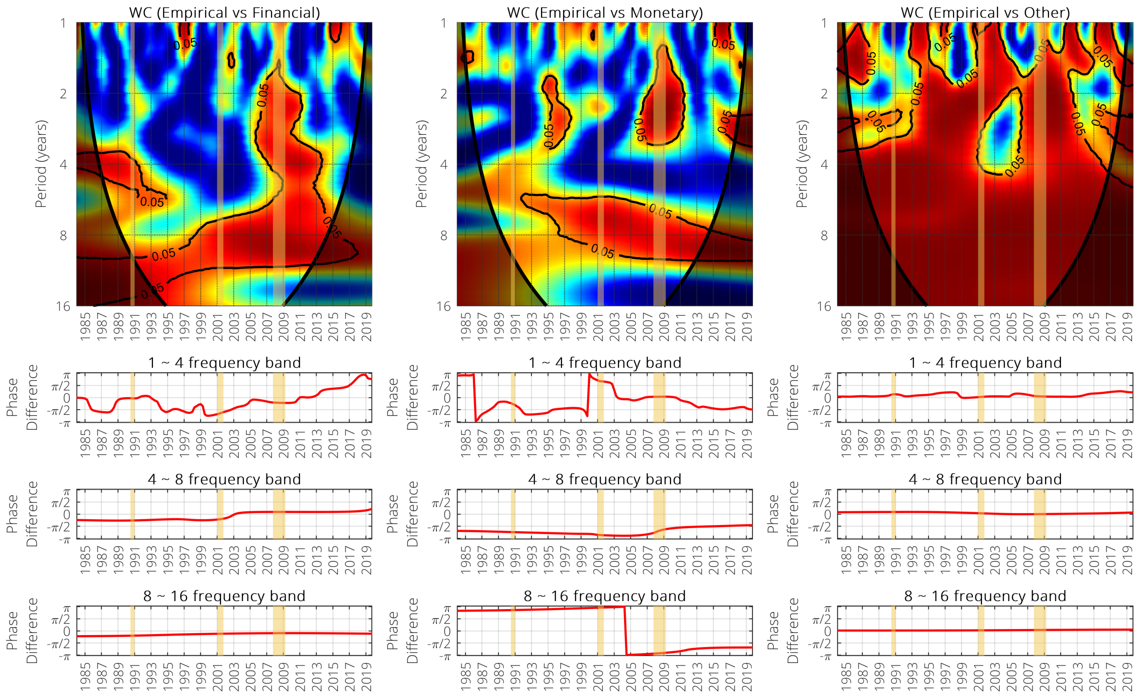

Figure 3.14.: *WC between the empirical series for labor and each of the simulated series from the JQ model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

frequency band the simulated series is in-phase with the empirical counterpart during the period around the last crisis, it is out-of-phase in the other frequency bands. For the CMR model, one saw that the WC for financial shocks presented a wider region of high coherency, when compared to the results for the other two simulated series. For the 1- to 4-year frequency band, the results are not

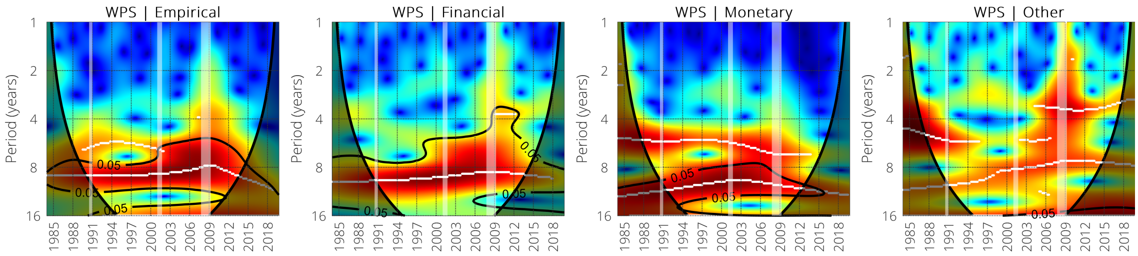

Figure 3.15.: *WPS of the empirical series for labor and the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

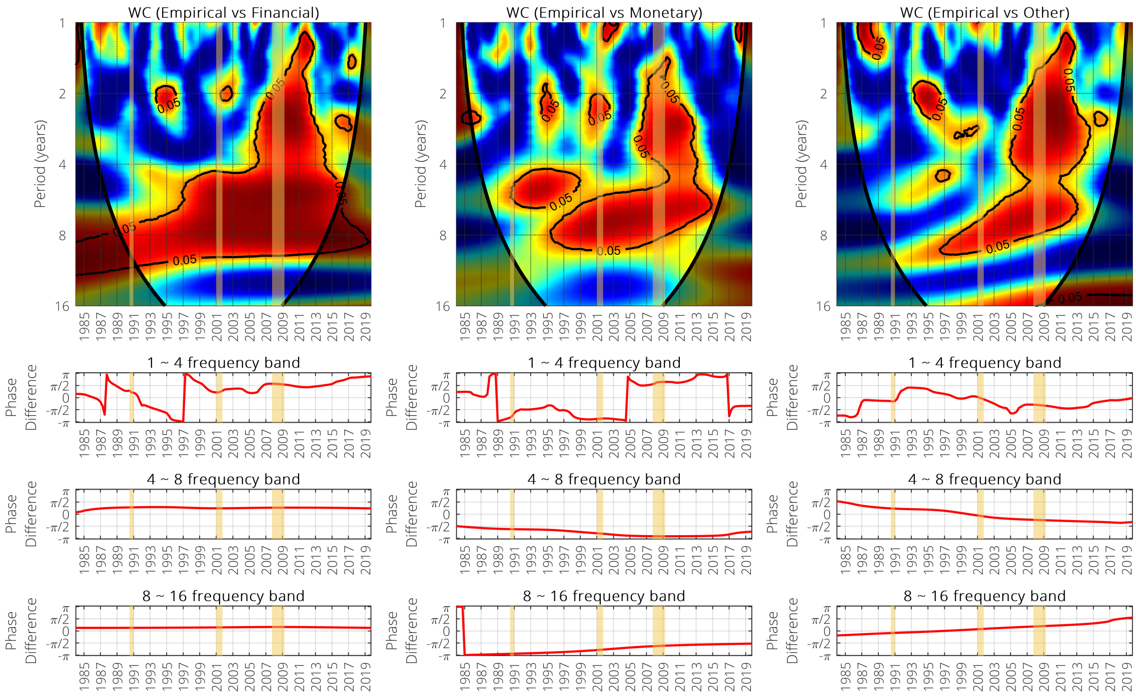

Figure 3.16.: *WC between the empirical series for labor and each of the simulated series from the CMR model. The dashed contour designates the 5% significance level based on an AR(1). The dashed white line is the local maxima.*

as relevant as in the regions of higher statistical significant coherency; phase-difference is mainly around $-\pi/2$ and $\pi/2$. For the remaining frequency bands, the results are aligned with previous observations of the other variables, with the series being in-phase. The empirical series of labor leads the simulated series with financial shocks, and there is a shift in the leadership of results for all the other shocks.

3.4. Conclusion

In this paper, wavelet tools were used to analyze the Jermann and Quadrini (2012), as well as the Christiano et al. (2014b) models, comparing the simulated time series from both models with the empirical counterparts. We began by comparing the WPS for each of the time series, proceeding to WC and the respective phase-difference.

Overall, both models exhibited interesting properties. While the risk shocks from the CMR model seem to present a strong fit with the medium to long-term fluctuations of the GDP, the enforcement constraint from the JQ model is able to explain short-term volatility in greater detail. Moreover, the financial shocks from the JQ present a stronger fit in variables such as consumption.

We observed major differences in the contribution of monetary policy shocks. Phase-difference indicated that, while the simulated series are out-of-phase with the empirical counterpart in the CMR model, they are mostly in-phase in the JQ model. The same occurs for the other two aggregated shocks considered in this analysis. This can be understood as two opposite overviews on the role of monetary policy during financial crises, such as the Great Recession: some researchers advocate that monetary policy impacts strongly on economic slowdown, aiding economic recovery; others argue that, due to its limitations, monetary policy may help GDP growth to remain lower than expected.

Chapter 4.

Conclusion

This thesis addresses the role of financial friction in the macroeconomic variables fluctuations. The main objective of the thesis was to explore how financial frictions may affect the link between the financial market and the real economy. There is a wide debate on the role played by the financial frictions in the propagation and amplification of shocks originated either on financial system or in the real economy, contributing for the deepness of the financial crises such as the *Great Recession*.

For that purpose, we start by looking at the Jermann and Quadrini (2012) model and by means of the wavelets tools to look at the model properties on the time-frequency domains. We also extend the model to include oil shocks to analyze the contribution of lending constrains to the recessions during the 1970s and early 1980s. The main reason found on the literature to those recessions are the oil price shocks, but at the same time, they miss to explain the sharp economic recovery between the 1980 and 1981-82 recessions. Lastly, we compare two models with financial frictions, namely the Jermann and Quadrini (2012) model and the Christiano et al. (2014b) model. These two models incorporate financial frictions without needing to explicit model the banking sector but they differ conceptually. While Jermann and Quadrini (2012) include an enforcement constraint that link the willingness of banks to lend to fluctuations on macroeconomic variables, Christiano et al. (2014b) studies how disturbances in the volatility of cross-sectional idiosyncratic uncertainty can originate realistic business-cycle dynamics.

In Chapter 1 we found that, as argued by Jermann and Quadrini (2012), financial shocks are able to explain most the fluctuations in macroeconomic and financial variables, with the simulate series being in phase and relatively close to the synchronism with the empirical counterpart at different frequencies, capturing most of the short and medium to long term fluctuations. Productivity shocks, despite the low contribution in the overall fluctuations of the variables, improves the fit of the model to the data, with an approximation to the synchronism of the simulated series to their empirical counterparts.

In Chapter 2, the results shows that the financial shocks, simulating the tightening and softening of lending standards can account for most of the fluctuation in macroeconomic variables such as the GDP, investment, consumption and hours worked. We found that productivity shocks have a non-negligible contribute to explain the fall on such macroeconomic variables during the 1973-75 and 1981-82 recessions, while oil shocks have their main contribution in 1973-75 recession – we also observe a mild decrease in macroeconomic variables around the 1980 recession due to oil price shocks. On the model we also found some sort of order in the effect of shocks with the financial shocks appearing first while the productivity shocks is the last one to be observed, creating a lag between the fall in the simulated series that when combined are able to track quite well the behavior observed in the data.

Lastly, in Chapter 3, the results shows that while the risk shocks from Christiano et al. (2014b) model seems to fit strongly the medium to long-term fluctuations of GDP, the enforcement constraint from JQ model is more suitable to explain the short-term volatility. Contrary to the results from the simpler version (RBC), in the New Keynesian version of the Jermann and Quadrini (2012) model the financial shocks accounts only marginally to the fluctuations on macroeconomic variables. Despite this lower contribution, the financial shocks in the model produces simulated series that are overall in-phase with their empirical counterparts at the different frequency bands, contributing for the fluctuations at the short to long-term cycles. This is less evident in the risk shocks from the Christiano et al. (2014b) model, despite the larger contribution to the global fluctuations. From the monetary policy shocks we have opposite results on both models. While in the Christiano et al. (2014b), the phase-difference shows that the simulated series are out-of-phase with their empirical counterpart, in Jermann and Quadrini (2012) they mostly in-phase. This can be perceived as a reflecting different views on the role of monetary policy in the financial stabilization. While some argue that monetary policy should also target financial stability though price stabilization, others may argue that price stability alone would not ensure financial stability and inflation targeting may have an adverse impact on financial stability.

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Appendix

A Brief introduction of Wavelet tools

The wavelets theory have its root in the Fourier analysis but with some remarkable distinctions. Overall, wavelet analysis can overcome some of the limitations from the Fourier analysis. Namely, it can be employed to noisy and strongly non-stationary time series and uncover relations at different frequencies, distinguishing transient relations and detecting structural changes (Aguiar-Conraria et al. (2008)).

A.1 Continuous Wavelet Transform

The Continuous Wavelet Transform (CWT), $W_x(\tau, s)$, is defined as the convolution over all time of the signal multiplied by scaled (s), shifted (τ) versions of the mother wavelet function $\psi(t)$ with a time series x_t:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\psi_{\tau,s}(t)dt \tag{A.1}$$

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\overline{\psi}\left(\frac{t-\tau}{s}\right), \quad s > 0, \tau \in \mathbb{R} \tag{A.2}$$

where the bar denotes complex conjugate. s is a scaling factor responsible for the stretching ($|s| > 1$), or compressing ($|s| < 1$), of the waveform.

If the mother wavelet is complex, the result of the convolution in the CWT will also be complex-valued. As result, one can extract the power and phase. If not, i.e., if the mother wavelet is real-valued, then we have only information concerning the power and is no longer possible to compute information regarding the phase of the time series.

A.2 Mother wavelet

For the wavelet analysis, many functions can be used as mother wavelet. In short, any continuous function $\psi(t)$ that has null moments and that decay quickly toward zero when t moves to $\infty(+/-)$ can be a candidate to be of mother wavelet.

Although, in short, many function can be thought for, a candidate function $\psi(t)$ to be a mother wavelets has to fulfil some "requirements". The first if that it has finite energy, i.e.:

$$\int_{-\infty}^{+\infty} |\psi(t)|^2 < \infty. \tag{A.3}$$

Second, the function $\psi(t)$ must satisfy the *admissibility condition* (which states that the Fourier transform of the wavelet function cannot have a zero-frequency component):

$$0 < C_\psi := \int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|}{|\omega|} d\omega < \infty, \tag{A.4}$$

where $\Psi(\omega)$ denote the Fourier transform of $\psi(t)$, given by:

$$\Psi(\omega) = \int_{-\infty}^{+\infty} \psi(t) e^{i\omega t} dt. \tag{A.5}$$

The admissibility condition implies that the Fourier transform of $\psi(t)$ vanishes at the zero frequency, i.e., $|\Psi(\omega)|^2_{\omega=0} = 0.$

For functions with sufficient decay, the admissibility condition (A.4) can be relaxed to the equivalent requirement:

$$\Psi(0) = \int_{-\infty}^{+\infty} \psi(t) dt = 0 \tag{A.6}$$

Third, a wavelet is a function with zero average, i.e.

$$\int_{-\infty}^{+\infty} \psi(t) dt = 0, \tag{A.7}$$

which means that it must oscillate.

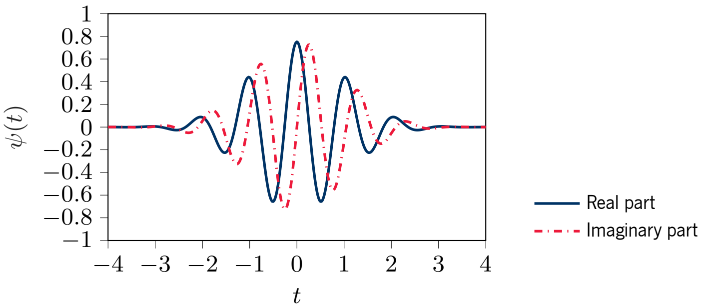

Figure 1: *Real (solid line) and imaginary (dash-dotted line) parts of the Morlet wavelet for* $\omega_0 = 6$.

Additionally, the wavelet is usually normalized $\|\psi(t)\| := \int_{-\infty}^{+\infty} \left(|\psi(t)|^2 dt\right)^{\frac{1}{2}} = 1$ and centered at $t = 0$.

The importance of the admissibility condition (A.4) is related to the preservation of the energy of the original function $x(t)$ that is assured with the holding of the following Parseval-type relation:

$$\int_{-\infty}^{+\infty} |x(t)|^2 dt = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} |W_x(\tau, s)|^2 \frac{d\tau ds}{s^2} \tag{A.8}$$

The admissibility condition then guarantees that the recovering of the original time series, $x(t)$, from its wavelet transform is possible.

Morlet wavelet

The Morlet wavelet is widely used it the related literature as it offers a good balance between time and frequency. It form follows:

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{1}{2}t^2}, \tag{A.9}$$

where $\pi^{-1/4}$ ensures the unity energy of the wavelet and $e^{-\frac{1}{2}t^2}$ ensures that it satisfies the admissibility condition (A.4).

One useful property of the Morlet wavelet, is related with how to convert scales into frequencies. The measures *energy frequency*:

$$\omega_\psi^E = \frac{1}{\|\Psi\|^2} \int_{-\infty}^{+\infty} \omega |\Psi(\omega)|^2 d\omega, \tag{A.10}$$

peak frequency, i.e., the frequency at which the magnitude of the Fourier transform of the mother wavelet ψ, $|\Psi(\omega)|$, is maximized:

$$\omega_{\psi}^{P} = \sup_{\omega \in \mathbb{R}} |\Psi(\omega)|, \tag{A.11}$$

and *central instantaneous frequency*:

$$\omega_{\psi}^{I} = \breve{\omega}_{\psi}(0), \text{ where } \breve{\omega}_{\psi}(t) = \frac{d}{dt}\Im\{\ln \psi(t)\} = \frac{d}{dt}\arg\{\psi(t)\}, \tag{A.12}$$

they all can be used to convert scale to frequency, being associated with an interpretation of it. In case of Morlet wavelet we have that they are all equal, and:

$$\omega_{\psi}^{E} = \omega_{\psi}^{P} = \omega_{\psi}^{I} = \omega_0. \tag{A.13}$$

This facilitate the conversion. When the frequency parameter $\omega_0 = 6$, the Morlet wavelet satisfies the admissibility condition and, by using the "Fourier" frequency, f we end up with $f(s) = \omega_0/(2\pi s)$. As a result, for a given wavelet scale, s, we have the inverse relation $f \approx 1/s$.

Localization properties

Assuming that the mother wavelet $\psi(t)$ is normalized, then $|\psi(t)|^2$ defines a probability density function. From that we can obtain the mean $\mu_{\psi,t}$ (called *center*) and the standard deviation $\sigma_{\psi,t}$ (called *radius*) of this distribution. Considering the Fourier transform of the mother wavelet, $\Psi(t)$, similarly we can obtain its mean $\mu_{\Psi,\omega}$ and standard deviation $\sigma_{\Psi,\omega}$ as well. More precisely, the quantities are defined as:

$$\mu_{\psi,t} = \frac{1}{\|\psi\|^2}\int_{-\infty}^{+\infty} t|\psi(t)|^2 dt \tag{A.14}$$

$$\sigma_{\psi,t} = \frac{1}{\|\psi\|}\left\{\int_{-\infty}^{+\infty} (t-\mu_{\psi,t})^2|\psi(t)|^2 dt\right\}^{\frac{1}{2}} \tag{A.15}$$

$$\mu_{\Psi,\omega} = \frac{1}{\|\Psi\|^2}\int_{-\infty}^{+\infty} \omega|\Psi(t)|^2 d\omega \tag{A.16}$$

$$\sigma_{\Psi,\omega} = \frac{1}{\|\Psi\|}\left\{\int_{-\infty}^{+\infty} (\omega-\mu_{\Psi,\omega})^2|\Psi(\omega)|^2 d\omega\right\}^{\frac{1}{2}} \tag{A.17}$$

These quantities are used to define the Heisenberg box in time-frequency domain:

$$\left[\mu_{\psi,t} - \sigma_{\psi,t}, \mu_{\psi,t} + \sigma_{\psi,t}\right] \times \left[\mu_{\Psi,\omega} - \sigma_{\Psi,\omega}, \mu_{\Psi,\omega} + \sigma_{\Psi,\omega}\right] \tag{A.18}$$

We are now in position to say that $\psi(t)$ is localized around the point $(\mu_{\psi,t}, \mu_{\Psi,t})$ of the time-frequency domain with an uncertainty given by $\sigma_{\psi,t}\sigma_{\Psi,\omega}$, with the Heisenberg's uncertainty principle establishing that $\sigma_{\psi,t}\sigma_{\Psi,\omega} \geq 1/2$.[1]

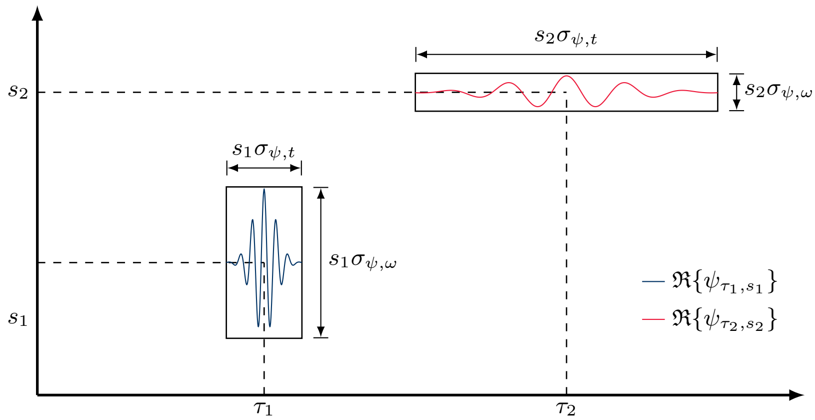

Figure 2: *Windows associated with a wavelet transform*

B Wavelet tools

In the following section we will define the tools that have been used in our analysis. It should be noticed that additional, and useful, tools are available within the wavelets framework, namely, the Partial and Multiple Wavelet Coherency, and Partial phase-difference (see Aguiar-Conraria and Soares (2014)).

[1] As any time-frequency analysis, it is limited by the Heisenberg's uncertainty principle which states that the more precise a particle is known, the more uncertain the momentum is, and vice versa. In terms of time and frequency domains, this means that we do not have the exactly information on the time and frequency in simultaneous, and a trade-off between time and frequency limits the analysis. Using the Morlet wavelet as our mother wavelet we assure that wavelet has optimal time-frequency concentration in the sense that $\sigma_{\psi,t}\sigma_{\Psi,\omega} = 1/2$. As so we can say that we have the optimal trade-off between time and frequency resolution.

B.1 Wavelet Power Spectrum

Similarly to the terminology used in the Fourier case, the (local) *Wavelet Power Spectrum* (WPS, also known as *Scalogram* or *Wavelet Periodogram*) is defined as

$$WPS_x(\tau, s) = |W_x(\tau, s)|^2. \tag{B.1}$$

The *Global Wavelet Power Spectrum* (GWPS), is defined as the averaged over time WPS_x, and is given by:

$$GWPS_x(s) = \int_{-\infty}^{+\infty} |W_x(\tau, s)|^2 d\tau. \tag{B.2}$$

Although we loose the time "property" it may provide useful hints on the overall periods of the time series, and the more relevant frequencies for deeper analysis.

B.2 Wavelet Coherency

Similarly to the Fourier analysis, the (complex) *Wavelet Coherency* ϱ_{xy}, given two time series $x(t)$ and $y(t)$, is defined as:

$$\varrho_{xy} = \frac{\mathscr{S}(W_{xy})}{\left[\mathscr{S}\left(|W_x|^2\right)\mathscr{S}\left(|W_y|^2\right)\right]^{1/2}}, \tag{B.3}$$

where $W_{xy} := W_x W_y^*$ denotes the Cross-Wavelet Transform of the two time series $x(t)$ and $y(t)$, and $\mathscr{S}$ a smoothing operator in both time and scale.

B.3 Phase-difference

To define the phase-difference one must start by the wavelet phase. By using a complex-valued wavelet ψ, the corresponding wavelet transform $W_x(\tau, s)$ is also complex-valued and we can separate it into its real part, $\mathfrak{R}\{W_x(\tau, s)\}$, and imaginary part, $\mathfrak{I}\{W_x(\tau, s)\}$. The *phase* (or phase-angle) is defined as:

$$\phi_x(\tau, s) = \arctan\left(\frac{\mathfrak{I}\{W_x(\tau, s)\}}{\mathfrak{R}\{W_x(\tau, s)\}}\right), \tag{B.4}$$

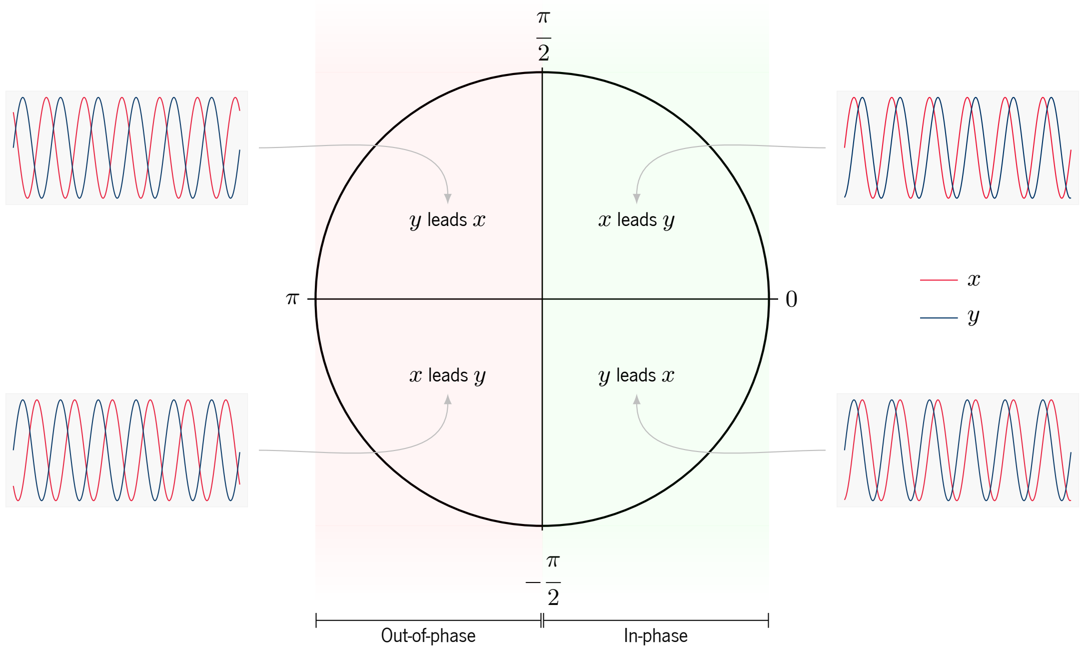

Figure 3: *Phase-difference circle*

where arctan denotes:

$$\arctan\left(\frac{b}{a}\right) = \begin{cases} \arctan\left(\frac{b}{a}\right) & a > 0, \\ \arctan\left(\frac{b}{a}\right) + \pi & a < 0, \quad b \geq 0 \\ \arctan\left(\frac{b}{a}\right) - \pi & a < 0, \quad b < 0 \\ \pi/2 & a = 0, \quad b \geq 0 \\ -\pi/2 & a = 0, \quad b < 0 \end{cases} \tag{B.5}$$

In case of a real-value wavelet function use, the imaginary part is non-existing (is constantly zero) and the phase is undefined. As so, in order to separate the phase and amplitude, ($|W_x(\tau, s)|$), the use of a complex wavelet is required.

Similarly, given the Cross-Wavelet Transform, W_{xy}, for two time series $x(t)$ and $y(t)$, we define the *Phase-Difference* (phase lead of x over y) as:

$$\phi_{xy} = \text{arctan}\left(\frac{\Im\{\mathscr{S}(W_{xy})\}}{\Re\{\mathscr{S}(W_{xy})\}}\right), \tag{B.6}$$

where, as previously, $\mathscr{S}$ denotes a smoothing operator in both time and scale.

C Discretization of the CWT

For computation purpose we must proceed with the discretization of the CWT. With time spacing δt and scale s, the CWT for a discrete time series $x = \{x_n; n = 0, \ldots, N-1\}$ is given by:

$$\begin{aligned} W_\psi(\tau, s) =& \frac{\sqrt{s}}{N}\sum_{k=0}^{N/2} \hat{x}_k \Psi^*\left(s\frac{2\pi k}{N\delta t}\right) e^{i\frac{2\pi k}{N\delta t}\tau} + \\ &+ \frac{\sqrt{s}}{N}\sum_{k=(N/2)+1}^{N-1} \hat{x}_k \Psi^*\left(s\frac{2\pi (k-N)}{N\delta t}\right) e^{i\frac{2\pi (k-N)}{N\delta t}\tau}, \end{aligned} \tag{C.1}$$

where the Fourier transform of the time series x, $\hat{x}_k$, is defined as:

$$\hat{x}_k = \sum_{n=0}^{N-1} x_n e^{-i\frac{2\pi n}{N}k}, \quad k = 0, \ldots, N-1 \tag{C.2}$$

and using the periodicity $\hat{x}_k = \hat{x}_{k-N}$.

Since in practice, the wavelet transform is computed for a restrict selection of scale values $s \in \{s_\ell, \ell = 0, \ldots, F-1\}$, which have a corresponding frequency ω_ℓ, the computed WPS of the discrete time series x will be defined by:

$$W_x(\ell, m) = \frac{\sqrt{s_\ell}}{N}\sum_{k=0}^{N-1} \hat{x}_k \Psi^*(s_\ell w_k) e^{i\frac{2\pi k}{N}m}, \tag{C.3}$$

with

$$w_k = \begin{cases} \frac{2\pi k}{N\delta t} & k = 0, \ldots, \frac{N}{2} \\ \frac{2\pi(k-N)}{N\delta t} & k = \frac{N}{2}+1, \ldots, N-1, \end{cases} \tag{C.4}$$

and $m = 0, \ldots, N-1$ ($m = \tau/(\delta t)$).