Essays in Empirical and Theoretical Labor Market Models

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A thesis submitted for the degree of
Doctor of Philosophy

Trinity 2016

Abstract

This DPhil thesis is a collection of three theoretical and empirical papers studying labor markets in several advanced economies. Two chapters examine the relationship between the banking sector and the labor market in the US and the UK, while one evaluates a policy that has been proposed to help labor markets in the Euro Area adjust to economic shocks. In the first chapter, I develop a New Keynesian DSGE model that integrates a banking sector subject to moral hazard with a standard random search model of the labor market. I estimate the model using US data and study the role of the banking sector in determining labor market fluctuations. In the second chapter, I estimate a structural VAR model of the UK and US economies and identify bank lending shocks using a mix of sign and short-run exclusion restrictions. Consistent with the predictions of the DSGE model, an expansionary loan supply shock decreases job-destruction and increases job-creation, reducing the unemployment rate persistently. Bank lending shocks are also important drivers of labor market fluctuations, particularly during the Great Recession. Lastly, in the third chapter, I calibrate to the Euro Area a currency union DSGE model to evaluate the aggregate properties of European Unemployment Insurance (EUI). I find that EUI cannot contemporaneously stabilize the monetary union and achieve convergence in regional unemployment and inflation rates.

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This thesis is dedicated to
my grandma Rosa
who passed away
a few months before
I could defend this work.
With love,
Fede

Acknowledgements

The path to becoming a doctor is littered with distractions. I would like to thank those distractions for making me the person I am.

First, I would like to express my sincere gratitude to my advisors Prof. Simon Wren-Lewis and Dr. Francesco Zanetti for the continuous support of my DPhil study, for their patience, experience, and knowledge. Their guidance helped me in all the time of research and writing of this thesis. This work would have not been possible without their encouragement.

Besides my advisors, I would also like to thank the participants attending the seminars and conferences where I presented some of the chapters of this thesis. Their insightful comments and feedback, but also challenging questions, helped widen my research from various perspectives. In particular, I would like to thank the members of the Monetary Assessment and Strategy Division at the Bank of England who hosted me for a three-month internship. My conversations with them improved tremendously the quality of my work.

I would also like to thank my examiners for accepting the invitation and taking the time to review, assess, and challenge my work.

I am also thankful for and would like to acknowledge some of the most inspiring teachers I had the honor to learn from throughout my studies from when I was a little boy in Montale onward: my primary school teacher Dora Tonini, my high school literature instructor Lucia Chiti at the Instituto Tecnico Industriale (Pistoia, Italy), my tutors Eyad Shabaneh and Ravi Parashar at the United World College (Montezuma, USA), who first showed me the beauty of Economics, and my undergraduate tutor Rosemary Orr and Economics mentor Joost de Laat at University College Utrecht (Netherlands). Thanks for making me a better student, and, above all, a curious, informed, and responsible citizen of the world.

I would also like to thank my friends in the Economics Department for their endless support, for our chats and discussions, and for all the coffee we drank together: Carlo Pizzinelli, Francesca Brusa, Pawel Gola, Karan Nagpal, Nikki Shure, and James Wisson. A special thanks to Nikki and James for proof-reading this thesis, to Carlo for his macro feedback, and to Francesca for her technical support, her comfortable couch in time of need, and for submitting our theses together. A thanks also goes to my close friends Elena Netsi, Liam Cattell and Thom Fröhlich for being there for me. Above all, I would like to thank all of them for making me feel at home in Oxford.

Last but not least, I would like to thank my family: my parents Massimo and Graziella, my brothers Alessio, Simone, and Lorenzo, my dog Fuliggine, and my grandparents Anelio, Rosa, and Valeria, for supporting and loving me throughout these years. Even if I have been away from them for a long time, they are always close to my heart. I would not be the person that I am, and I would have not made it this far, without their love and encouragement.

Abstract

This DPhil thesis is a collection of three theoretical and empirical papers studying labor markets in several advanced economies. Two chapters examine the relationship between the banking sector and the labor market in the US and the UK, while one evaluates a policy that has been proposed to help labor markets in the Euro Area adjust to economic shocks. In the first chapter, I develop a New Keynesian DSGE model that integrates a banking sector subject to moral hazard with a standard random search model of the labor market. I estimate the model using US data and study the role of the banking sector in determining labor market fluctuations. In the second chapter, I estimate a structural VAR model of the UK and US economies and identify bank lending shocks using a mix of sign and short-run exclusion restrictions. Consistent with the predictions of the DSGE model, an expansionary loan supply shock decreases job-destruction and increases job-creation, reducing the unemployment rate persistently. Bank lending shocks are also important drivers of labor market fluctuations, particularly during the Great Recession. Lastly, in the third chapter, I calibrate to the Euro Area a currency union DSGE model to evaluate the aggregate properties of European Unemployment Insurance (EUI). I find that EUI cannot contemporaneously stabilize the monetary union and achieve convergence in regional unemployment and inflation rates.

Contents

List of Figures

List of Tables

1 Introduction

Several years after the deepest economic crisis since the Great Depression, labor markets across the world remain disrupted. Unemployment continues to be above its pre-crisis level, productivity is low, and real wages are stagnant in many countries. Overall, labor markets have not yet fully recovered from all the negative effects of the crisis. In this context, economists are still seeking a convincing explanation of the reasons why a crisis originating in the financial sector has had such a long-lasting impact on the labor market. There is also a need to devise innovative policies that can help labor markets cope with economic shocks. Quickly re-absorbing the unemployed would in fact reduce the long-term impact of severe consequences such as the financial crisis.

In this thesis, I contribute to the understanding of labor markets in advanced economies and to the current policy debate by studying several theoretical and empirical macro models in three different studies. In particular, Chapters 2 and 3 examine the relationship between the banking sector and the labor market in the UK and the US. In Chapter 4 I discuss a policy proposal that has been put forward to help the Euro Area (EA) adjust to economic shocks, namely European Unemployment Insurance (EUI).

From a macroeconomic perspective, it is crucial to understand how conditions in the banking sector affect the supply of credit and labor market outcomes. This is the goal of Chapters 2 and 3. Since bank funding in an important source of external finance for many firms across advanced economies (de Fiore and Uhlig, 2011; Contessi *et al.*, 2013; Farrant *et al.*, 2013), financially impaired banks have important consequences for firms' hiring decisions (Bentolila *et al.*, 2013; Chodorow-Reich, 2014). Existing theoretical and empirical macroeconomics models, however, have neglected how the deterioration of the balance sheet of financial intermediaries affects equilibrium in the labor market.

In Chapter 2, I present a dynamic stochastic general equilibrium (DSGE) New Keynesian model in which financial intermediaries and credit supply shocks affect the labor market via a bank lending channel and labor demand. This model integrates a standard labor market with random search frictions *á* la Mortensen and Pissarides (1994) with a banking sector subject to moral hazard as in Gertler and Karadi (2011). In this framework, non-financial firms borrow from banks to finance vacancy-posting. When aggregate shocks change the ability of financial intermediaries to raise funds, the credit supply curve shifts, affecting the labor demand curve and labor market equilibrium. The net worth of financial intermediaries plays an important role in the propagation and amplification of aggregate shocks. In particular, I study the impact of negative credit supply shocks, namely unexpected changes to the net worth of financial intermediaries or to their incentive problem. Moreover, I estimate the model with Bayesian techniques and find that credit supply shocks are important explanatory variables of labor market fluctuations in the US.

Chapter 3 re-examines the relationship between the banking sector and the labor market from a more empirical perspective. Using UK and US data, I estimate a structural autoregressive (SVAR) model to provide evidence about the nature of the propagation mechanism of credit supply shocks on the labor market. While the Bayesian estimation in Chapter 2 relies on a fully specified structural model, in Chapter 3 I use a mix of sign and short-run exclusion restrictions to remain as agnostic as possible about the nature of this transmission mechanism. I assume that an expansionary bank lending shock increases the amount of available credit and lowers borrowing costs for firms and the inflation rate. While this shock has no contemporaneous effect on the labor market variables, I impose no other restrictions on these variables.

I find that an expansionary credit supply shock lowers the job-separation rate and increases vacancy-posting and the job-finding rate. Unemployment falls persistently as a result. This transmission mechanism is consistent with the one described in Chapter 2. I also use historical and forecasting decomposition analysis to assess the importance of bank lending shocks in explaining labor market fluctuations. In both the US and the UK, negative credit supply shocks are responsible for the large rise in the unemployment rate during the Great Recession, but they also explain labor market fluctuations during other periods in the past few decades.

The financial crisis has also revitalized interest in the appropriate policy response to economic shocks, particularly when constraints such as the zero lower bound, debt sustainability concerns, or membership in a monetary union bind. In Chapter 4 I assess the quantitative properties of EUI, under which workers in a region of the EA would partly finance unemployment benefits for residents of another region. While its proponents stress that EUI acts as an automatic counter-cyclical stabilization mechanism and helps achieve convergence among heterogeneous labor markets (Dullien, 2007, 2013; Allard *et al.*, 2013; Claeys *et al.*, 2014), its macroeconomic properties have not been studied in a general equilibrium framework. Thus, I use a DSGE model of a two-region currency union based on Mueller and Abbritti (2013) to measure the quantitative impact of EUI on the regional and aggregate unemployment and inflation volatilities (i.e. *stabilization*) and the volatilities of the unemployment and inflation differentials (i.e. *convergence*). I find that EUI can help achieve convergence in inflation and unemployment differentials, but its stabilization properties are more questionable. Several trade-offs between unemployment and inflation volatility, and between regional and aggregate volatility, exist because EUI cannot achieve the constrained efficient allocation. This is because EUI acts via income effects and has only an indirect effect on relative prices.

I contribute to the understanding of the functioning of labor markets in advanced economies from both an empirical and a theoretical perspective. This thesis is organized as follows. Chapter 2 presents the theoretical DSGE model and its Bayesian structural estimation. Chapter 3 identifies the labor market impact of bank lending shocks using a SVAR model. Lastly, Chapter 4 assesses the quantitative properties of EUI using a DSGE model of a currency union.

2 How Do Credit Supply Conditions Affect the Labor Market? Estimating a New Keynesian DSGE Model with Labor and Credit Market Frictions

2.1 Introduction

New micro-empirical evidence shows that the health of the banking sector affects the corporate behavior of non-financial firms, including hiring decisions and wage offers (Bentolila *et al.*, 2013; Campello *et al.*, 2011; Greenstone *et al.*, 2014; Chodorow-Reich, 2014). Yet, the macroeconomic DSGE literature lacks a model in which labor market outcomes depend on banks' financial conditions. Recent models studying the interaction between the financial sector and the labor market have focused exclusively on financial frictions at the firm-level (Nolan and Thoenissen, 2009; Jermann and Quadrini, 2012; Zanetti, 2012; Zanetti and Mumtaz, 2016). In these models, the banking sector is irrelevant, and labor market fluctuations depend on the financial conditions of non-financial firms. While credit demand conditions and agency problems between intermediaries and borrowers are important for labor market outcomes, the Great Recession has also highlighted the disruptive effects that impaired banks have on the real economy (Bean, 2010).

Thus, in the labor market business cycle literature, there is a need to put more emphasis on agency problems between financial intermediaries and their funders. This is why I present and estimate a New Keynesian DSGE model to study the role of financial intermediation on employment outcomes and answer the following questions: *1) How do credit supply conditions affect the labor market? 2) Does a banking sector improve the empirical fit of the search model with US labor market* *data? 3) Can credit supply shocks explain fluctuations in the US labor market at business cycle frequencies? 4) How are credit supply shocks transmitted to the labor market?* Using Gertler and Karadi (2011)'s model of financial intermediation, I embed a banking sector subject to a moral hazard problem into a sticky-price random search model of the labor market. Unlike models with financial frictions at the firm-level, the model does not have a financial accelerator mechanism.

Frictions at the bank-level result in a bank credit channel. This makes the state of the banking sector crucial for determining labor market equilibrium. When financial and real shocks affect, directly or indirectly, the balance sheet of the banking sector, the ability of financial intermediaries to raise funds and provide loans to firms changes. This shifts the credit supply curve, affecting the quantity and price of loans that firms can obtain. For instance, if firms received less and more expensive credit, they would hire fewer workers. This supply-driven credit contraction would increase the unemployment rate, and reduce the real wage and the probability of finding a job for unemployed workers.

I first present a theoretical model to capture this mechanism. This model links the hiring decision of non-financial firms to credit supply conditions. Integrating a financial intermediation model with an otherwise standard New Keynesian DSGE random search model *à* la Mortensen and Pissarides (1994) follows naturally from the idea that workers have value beyond their period-by-period cash-flow. Workers are financial assets from the firm's point of view because they enable firms to save on future vacancy costs. Moreover, I extend Gertler and Karadi (2011)'s banking model to include heterogeneity and search frictions in the labor market.

This model emphasizes the role that the net worth of financial intermediaries has in the propagation and amplification of aggregate shocks. This contrasts with models with financial frictions at the firm-level in which the net worth, or collateral, of non-financial firms plays this function. Thus, different mechanisms drive business cycle fluctuations and labor market movements. The interaction between the banking sector's net worth accumulation process and the firms' forward-looking vacancy-posting condition allows me to study how the banking sector and the labor market interact with one another in propagating and amplifying the impact of aggregate disturbances.

Then, using a Bayesian likelihood approach, I estimate this model using US data on the unemployment rate, the vacancy stock, labor market tightness, the real hourly wage, real productivity, real output, the inflation rate, and the short-term policy rate from 1964 until 2013. Finally, I use the model to study the response of the economy to productivity and financial disturbances, and to examine a number of empirical questions on the behavior of labor market variables. In particular, I conduct a forecasting variance decomposition and compare the theoretical moments the model predicts with their empirical counterparts.

The main findings of this chapter are as follows. First, the full model with a banking sector explains the time-series properties of the joint distribution of key labor market variables better than a restricted model with no financial frictions. The marginal likelihood of the full model (i.e. a measure of out-of-sample prediction performance) is greater than the marginal likelihood of the restricted model. Second, I use the model at the posterior mode to examine whether it can replicate the second moments of key labor market variables. It generally underestimates the volatility and persistence of the variables, but the signs of the cross-correlation coefficients are correct. Given the lack of many of the nominal and real frictions such as consumption habits or variable vacancy costs typically used to improve the empirical fit of New Keynesian DSGE models with search frictions, the model performs reasonably well.

Third, I use the model to assess the theoretical contribution that different structural disturbances have on the volatility of these labor market variables. Seven structural disturbances drive the stochastic dynamics of the model: total factor productivity (TFP) shocks, monetary policy shocks, matching elasticity shocks, intertemporal preference shocks, demand elasticity shocks, net worth shocks, and shocks to the incentive constraint of financial intermediaries. I refer to disturbances to the net worth or to the incentive constraint of financial intermediaries as credit supply, or bank lending, or loan supply, shocks because they originate in the banking sector and have a direct effect on the supply of bank credit.

I find that the banking sector is a quantitatively important source of business cycle fluctuations. Shocks to net worth are the most important driver of labor market tightness and make a substantial contribution to the volatility of the vacancy stock, the real wage, and, to a lesser extent, the unemployment rate. Shocks to the elasticity of the matching function are the most important driver of the unemployment rate and the vacancy stock. TFP shocks, and to a lesser degree monetary policy and preference shocks, explain the volatility of real output and the real wage. Overall, these findings suggest that the financial status of the banking sector has important implications for the behavior of labor market variables.

Fourth, I study the dynamic response of the economy to productivity and credit supply shocks originating in the banking sector. The banking sector represents both an amplification and a propagation mechanism for aggregate shocks. Credit supply frictions amplify the impact of aggregate shocks. For instance, a negative productivity shock lowers workers' marginal productivity and squeezes firms' profits. This reduces the incentive for firms to post vacancies, leading to a lower job-finding rate for unemployed workers and a higher unemployment rate. Since firms find it easier to fill their vacancies, the value of an employed worker falls. Workers are the only real asset in this economy; hence, the fall in the value of workers corresponds to a decline in the price of financial assets. As results, financial intermediaries face an unexpected loss on their balance sheet which worsens their incentive problem and limits their ability to raise funds from households. Banks provide less and more expensive credit to firms. Combined with lower productivity, higher borrowing costs further reduce firms' profits and their incentive to post vacancies, amplifying the impact of the initial impulse on the labor market.

I also find that that the model has a strong internal propagation mechanism. This is due to the state-variable nature of net worth accumulation that occurs via retained earnings. An exogenous fall in the value of the banking sector's net worth or a worsening of the incentive problem raise borrowing costs for firms. This lowers firms' profits and their incentive to post vacancies, reducing job-creation and economic activity substantially. As asset prices fall, intermediaries face an unexpected loss on their balance sheet which amplifies the initial impact of the shock. To relax their incentive constraint, intermediaries must rebuild their net worth through retained earnings. Thus, an exogenous reduction in net worth has long-lasting effects on the labor market despite the original impulse having little persistence.

The remainder of this chapter proceeds as follows. Section 2.2 reviews the existing literature studying the relationship between labor and financial markets. Section 2.3 presents the model. Section 2.4 discusses the empirical methodology used to estimate the model with US data. Section 2.5 presents the quantitative results of the estimation and some applications. Section 2.6 concludes.

2.2 Literature Review

This chapter builds on past contributions from: the micro-empirical literature studying the impact of credit supply conditions on firms' corporate decisions; the DSGE literature on banking models; and the macro-finance literature on labor markets with search frictions.

Several microeconometric contributions have shown that unexpected bank-credit supply shocks affect the corporate decisions of non-financial firms. In a survey of US, European, and Asian chief financial officers, Campello *et al.* (2011) find that firms that were less likely to obtain credit from banks planned cuts in investment, employment, and capital spending prior and during the 2008 crisis. Greenstone *et al.* (2014) find that US counties in which weak banks had larger market shares experienced a larger fall in employment than otherwise similar counties. They estimate that a negative credit supply shock can account, at most, for 20 percent of job losses in small businesses and 16 percent of total job losses between 2007 and 2009. Chodorow-Reich (2014) combines data from the Dealscan syndicated loan database with proprietary employment data from the US Bureau of Labor Statistics Longitudinal Database. He finds that firms attached to weak banks before the crisis were less likely to receive a loan after the Lehman bankruptcy and more likely to cut employment. This channel can explain between one-third and one-half of the fall in employment in small and medium enterprises. Bentolila *et al.* (2013) combine information from the balance sheet of private non-financial firms and the Spanish credit register to produce a sample that essentially covers all firms operating in Spain and all firm-banking relationships. They find that between 2006 and 2010 non-financial non-real estate firms with a higher exposure to weak banks were more likely to cut employment than similar firms attached to stronger banks. The identified credit supply shock can explain between 8 and 36 percent of aggregate job losses over the period.

Overall, this evidence highlights the importance of bank credit conditions on firm's hiring decisions, with quantitatively important aggregate effects. This effect is particularly pronounced for SMEs which are more heavily reliant on bank credit and less likely to have access to bond and equity markets. Motivated by findings in this area, I build and estimate a micro-founded model that can study the aggregate effects of credit supply shocks that microeconometric studies cannot account for.

DSGE models incorporating financial frictions in the banking sector assume competitive labor markets and have little to say of how credit supply shocks affect unemployment, vacancies, and the job-finding rate.[1] Dib (2010) models a costly state verification mechanism at the firm-level as in Bernanke *et al.* (1999) and an interbank market in which net borrowing banks can strategically default on their debts. Although he studies the interaction between credit supply and credit demand frictions, the labor market is perfectly competitive. Compared to that paper, I abstract from credit demand frictions and focus on the impact of credit supply frictions on labor market outcomes. Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) model financial intermediaries as facing a moral hazard problem. Financial shocks worsen this incentive problem, reducing the amount of deposits banks can raise from households, and increasing the interest rate charged to firms. This has a large negative impact on real activity.

[1] Wasmer and Weil (2004) and Petrosky-Nadeau and Wasmer (2013) are an exception because they develop a double search and matching model with frictions in both credits and labor markets. This modeling strategy, however, is a reduced-form approach to link labor and financial market frictions which does not distinguish between credit supply and credit demand frictions.

I essentially extend this banking model by adding a labor market with search frictions. I also abstract from other modeling devices such as consumption habits and physical capital to focus on the interaction between credit and labor markets. Moreover, I put more emphasis on disturbances originating in the banking sector rather than shocks originating outside as Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) do. The basic propagation mechanism of the original model remains unchanged. However, the interaction between banks' net worth accumulation process and firms' vacancy posting leads to some interesting dynamics which are absent in the baseline banking model.

Departures from perfectly competitive or monopolistic competition in the labor market have only been explored in the context of firm-level financial friction models. To the best of my knowledge, no DSGE model has studied the labor market impact of agency problems between banks and their funders. The model I propose is best seen as complementary to the existing business cycle literature with search frictions in the labor market and an agency problem between banks and borrowing firms. Within this literature, financial frictions have either been modeled assuming limited enforceability (Kiyotaki and Moore, 1997) or costly state verification (Bernanke *et al.*, 1999) at the firm-level.

In the first approach, lenders cannot enforce debt contracts, and borrowers must pledge some collateral. Jermann and Quadrini (2012) embed this mechanism into a real business cycle model with no banking sector and a competitive labor market. Firms issue equity, inter-temporal to finance capital accumulation and intra-temporal debt to pay workers. With inter-temporal debt predetermined and costly equity adjustment, a financial shock diminishes the firm's ability to issue intra-temporal debt and hire workers. They find that financial shocks can replicate well the series of output, investment, and hours worked in the US. Zanetti (2012) adds a non-competitive labor market to Jermann and Quadrini (2012)'s model to study and quantify the interactions between financial and labor market variables. When firms are constrained in the amount of intratemporal debt they can take, the financial shock is transmitted in the labor market through adjustments in labor demand.

In the costly state verification approach borrowers are subject to idiosyncratic productivity shocks that lenders can only observe by paying a monitoring cost. Using this setting, Nolan and Thoenissen (2009) construct a New Keynesian model with monopolistic competition in goods and labor markets. They find financial shocks to entrepreneurial net worth to be as important as TFP shocks in explaining fluctuations in output and hours worked. Zanetti and Mumtaz (2016) perform a Bayesian estimation of a similar model with and without search frictions in the labor market. They find that financial frictions at the firm-level improves the empirical fit of the financial accelerator model, and that TFP and preference shocks are the main drivers of macroeconomic fluctuations. Chugh (2013), Petrosky-Nadeau and Zhang (2013), and Petrosky-Nadeau (2014) calibrate a search model with costly state verification to replicate the empirical moments of labor market variables. Using either spillover effects between a common and an idiosyncratic TFP shock, a time-varying monitoring cost, or a bargaining wage-setting mechanism based on Hall and Milgrom (2008), these models propose mechanisms making the real wage less responsive to TFP shocks. Thus, they show that financial frictions at the firm-level can amplify the impact of TFP shock and match particular moments of labor market variables.

I conduct a similar quantitative analysis to the abovementioned papers. Nevertheless, assuming a moral hazard problem in the banking sector changes the model dynamics, the transmission mechanism, and the interpretation of the financial shock. For instance, the net worth of the banking sector, rather than the net worth or collateral of borrowing firms, propagates aggregate shocks. Moreover, financial shocks in the model I propose directly affect the behavior of financial intermediaries, whereas in the existing literature the direct effect is on firms. In practice, which type of financial friction is relatively more important in explaining labor market fluctuations is an empirical question which requires a more complex general equilibrium model. Nonetheless, the model I present contributes to the existing labor and financial friction literature by highlighting a different transmission mechanism that micro-empirical evidence has shown to be quantitatively important.

2.3 Model

I model the core economy is a standard New Keynesian DSGE model with search frictions in the labor market and a banking sector. The economy includes households, financial intermediaries, firms, and the government. Household members are either workers or bankers. Workers provide labor, while bankers manage financial intermediaries. Firms are either competitive producers producing a homogeneous intermediate good or retailers repackaging this input into differentiated final goods. This separates the production from the pricing decision, simplifying the analysis, but with no consequence on the model predictions. Financial intermediaries channel household savings to the productive sector. Producers borrow to hire labor and pay workers beyond what current revenues would allow. Financial intermediaries are subject to a moral hazard problem and face an endogenous leverage constraint limiting their ability to provide funds. Finally, the government conducts an active monetary policy and a passive fiscal policy. I discuss each of these economic actors in turn.

2.3.1 Households

Households are made up of workers and bankers of measures f_W and f_B. Each period a proportion $1-\theta_B$ of bankers become workers, and a proportion $(1-\theta_B)f_B$ of workers become bankers. This prevents bankers from accumulating sufficient net worth so that they no longer need to borrow. It also maintains a fixed proportion of workers and bankers in the population. I normalize f_W to one. The household maximizes the expected lifetime utility of its members $j \in [0, f_W + f_B]$:

$$\max_{\{c_{t+s}(j)\}_{s=0}^{\infty}} \int_{j=0}^{f_W+f_B} \sum_{s=0}^{\infty} (\beta \exp^{\nu_t})^s \left(\log(c_{t+s}(j)) - D_{t+s}(j)\chi \frac{(hr_{t+s}(j))^{1+\omega_w}}{1+\omega_w} \right) dj \quad (2.1)$$

where $\beta \in (0,1)$ is the intertemporal discount rate, ν_t is an exogenous intertemporal preference shock to β that follows an AR(1) process with autocorrelation parameter ρ_ν and white-noise innovations ϵ_t^ν with variance σ_ν^2. $D_{t+s}(j)$ is an indicator variable with value 1 if a worker j is employed and zero otherwise (i.e. unemployed worker or banker), $c_{t+s}(j)$ indicate the member's level of consumption, and and $hr_{t+s}(j)$

the number of hours an employed worker provides,[2] χ measures the disutility of labor, and ω_w is the inverse of the Frisch elasticity of labor supply. Both the hourly wage rate and hours worked are determined in a non-competitive manner and taken as given in the household's problem.

Moreover, I assume perfect consumption insurance within the household, so all members consume the same amount c_{t+s} of the consumption bundle in all periods. In equilibrium, all employed workers spend the same amount of time working (i.e. $hr_{t+s}(j) = hr_{t+s} \forall j, \forall s$), reducing the problem to a representative agent framework. Aggregating over all members j, (2.1) simplifies to:

$$\max_{\{c_{t+s}\}_{i=0}^{\infty}} \sum_{s=0}^{\infty} (f_W + f_B) \left(\beta \exp^{\nu_t}\right)^s \left(\log(c_{t+s}) - \frac{l_{t+s}}{f_W + f_B} \chi \frac{(hr_{t+s})^{1+\omega_w}}{1+\omega_w} \right) \tag{2.2}$$

where $l_{t+s} = \int_{j=0}^{f_W + f_B} D_{t+s}(j) dj$ is the amount of workers employed in each period:

$$0 \leq l_{t+s} \leq f_W \tag{2.3}$$

In equation (2.2), the factor $\frac{l_{t+s}}{f_W + f_B}$ is the unconditional probability that a household member is employed. Under full participation and with the mass of workers normalized to one, l_{t+s} measures the employment rate at the beginning of the period. $u_{t+s} = 1 - l_{t+s}$ measures the unemployment rate and also equals the pool of unemployed workers.

In each period, each employed worker receives a real hourly wage w_t, which is transferred to the household. The household also receives profits Π_t^F from the firms it owns, and the net worth of exiting bankers net of the start-up funds the household provides entering bankers Π_t^B. In addition, households have access to a single financial instrument. At the end of the period, they can deposit an amount b_{t+1} of their income into a financial intermediary paying the riskless rate R_{t+1} in the next period. Thus, the household faces the following per-period budget constraint:

$$(1 + f_B) c_t + b_{t+1} = w_t l_t hr_t + \Pi_t^B + \Pi_t^F + R_t b_t \tag{2.4}$$

[2] Implicitly, I assume that a banker provides labor inelastically.

The household chooses a path of consumption $\{c_{t+s}\}_{s=0}^{\infty}$ to maximize (2.2) subject to (2.3) and (2.4). This yields the standard intertemporal equation for consumption:

$$E_t\left[\Lambda_{t,t+1}R_{t+1}\right] = 1 \tag{2.5}$$

where $\Lambda_{t,t+1} = \beta \exp^{\nu_t}\left(\frac{c_t}{c_{t+1}}\right)$ is the household's stochastic discount rate. I abstract from labor market choices and assume that workers are always willing to supply labor at the equilibrium wage rate and hours worked. This full participation assumption requires that in the neighborhood of the steady-state the marginal benefit of an additional worker participating in the labor market be strictly greater than his disutility from labor when l_t equals one for all time periods:

$$w_t > \chi \frac{hr_t^{1+\omega_w}}{1+\omega_w} c_t \tag{2.6}$$

This condition holds in the calibrated version of the model, and I also verify it holds on a grid over a parameter space of the estimated model.

2.3.2 Financial Intermediaries

Financial intermediaries channel savings from households to the productive sector. As in Gertler and Karadi (2011) there is an infinite number of financial intermediaries j on the unit interval. Each intermediary starts the period with deposits d_{t-1}^j and loans $s_{t-1}^j Q_{t-1}$ made in the previous period, where Q_{t-1} is the relative price of each claim expressed in units of the consumption good. Loans pay a gross interest rate $R_{k,t}$, and the bank repays a gross interest rate R_t to depositors. The banker decides the dividend payout dp_t^j transferred to the household. This determines net worth, or equity capital, n_t^j at the beginning of period t, which is simply the difference between the return on assets and the cost of funding inclusive of dividend payouts:

$$n_t^j = R_{k,t} Q_{t-1} s_{t-1}^j - R_t d_{t-1}^j - dp_t^j \tag{2.7}$$

Uncertainty about the status of existing bankers is then resolved. With probability $1-\theta_B$ the banker exits the market and transfers n_t^j to the household.

With probability θ_B he continues managing a bank. The banker raises an amount of deposits d_t^j from households and combines them with his net worth to finance s_t^j loans to firms. The bank balance sheet is:

$$Q_t s_t^j = n_t^j + d_t^j \tag{2.8}$$

Since n_t^j is predetermined, choosing the loan level s_t^j provides sufficient information to determine the required amount of deposit to be raised from households. Combining (2.8) and (2.7), I obtain a law of motion of net worth expressed in terms of past lending and previous-period net worth:

$$n_t^j = \rho_t Q_{t-1} s_{t-1}^j + R_t n_{t-1}^j - dp_t^j \tag{2.9}$$

where $\rho_t = (R_{k,t} - R_t)$ is the excess return on a loan, or interest rate spread. This equation shows that s_{t-1}^j and n_{t-1}^j are the state variables in the banker's problem at time t.

The banker maximizes the discounted stream of payments to the household and discounts the future using the stochastic discount rate $\Lambda_{t,t+i}$. Let $V(n_t^j, Q_t s_t^j)$ be the end-of-period value of the bank. Then, it must satisfy the Bellman equation:

$$V(n_{t-1}^j, Q_{t-1} s_{t-1}^j) = E_{t-1}\left[\Lambda_{t-1,t} \max_{dp_t^j, n_t^j}\left\{dp_t^j + (1-\theta_B) n_t^j + \theta_B \max_{s_t^j} V(n_t, Q_t s_t^j)\right\}\right] \tag{2.10}$$

The banker faces an incentive constraint. After raising funds from households and providing new loans to firms, he can divert an endogenously determined fraction Θ_t of his assets back to his household. If this occurs, depositors can force the banker to default, but they can only recover a proportion $1 - \Theta_t$ of assets. I model the parameter Θ_t as time-varying and common to all bankers. Specifically, it follows the stochastic process $\Theta_t = \Theta \exp^{\delta_t}$, where Θ is the average fraction of assets the banker can divert and δ_t an exogenous AR(1) process with autocorrelation parameter ρ_Θ and white-noise innovations ϵ_t^Θ with variance σ_Θ^2. The banker chooses not to divert assets if and only if the value of the bank at t is at least as great as the fraction of assets he can divert:

$$V(n_t^j, Q_t s_t^j) \geq \Theta_t Q_t s_t^j \tag{2.11}$$

In a no-default equilibrium, this incentive constraint must be satisfied at all times.

The banker's problem consists of finding the value function that solves (2.10) subject to the constraints (2.9), (2.11), and the non-negative constraints $Q_t s_t^j \geq 0$ and $dp_t^j \geq 0$. Consider the problem at $t-1$, and let η_t, μ_t, ϖ_t, and λ_t be the multipliers associated with each of the above constraints. The first-order conditions associated with respect to dp_t^j, $Q_t s_t^j$, and n_t^j are:[3]

$$\lambda_t = \eta_t - 1 \tag{2.12}$$

$$0 = \theta_B \left[V_2(n_t^j, Q_t s_t^j) - \mu_t \left(\Theta_t - V_2(n_t^j, Q_t s_t^j) \right) \right] + \varpi_t \tag{2.13}$$

$$\eta_t = (1 - \theta_B) + \theta_B V_1(n_t^j, Q_t s_t^j) + \mu_t \theta_B V_1(n_t^j, Q_t s_t^j) \tag{2.14}$$

While the Benveniste-Scheinkman conditions are:

$$V_1(n_t^j, Q_t s_t^j) = E_t \left[\Lambda_{t,t+1} \eta_{t+1} R_{t+1} \right] \tag{2.15}$$

$$V_2(n_t^j, Q_t s_t^j) = E_t \left[\Lambda_{t,t+1} \eta_{t+1} \rho_{t+1} \right] \tag{2.16}$$

Since I am interested in an equilibrium in which bankers are willing to finance firms, the multiplier ϖ_t must be zero for all time periods. The non-negativity constraint on lending would otherwise bind.

Moreover, I can show that the banker chooses not to pay out any dividends. A unit of earning from one period to the next is worth more when retained as equity since this loosens the incentive constraint. Assume the transversality condition $lim_{T \to \infty} \theta_B^T E_{t-1} \Lambda_{t,t+T} \eta_{t+T} R_{t+T} = 0$ holds. Substituting (2.15) into (2.14) and solving for η_t yields the unique rational expectation solution:

$$\begin{aligned} \eta_t &= (1 - \theta_B) \sum_{i=0}^{\infty} \theta_B^i E_t \left[\Lambda_{t,t+1+i} R_{t+1+i} \right] + (1 - \theta_B) \sum_{i=0}^{\infty} \theta_B^i E_t \left[\Lambda_{t,t+1+i} R_{t+1+i} \mu_{t+i} \right] = \\ &= 1 + (1 - \theta_B) \sum_{i=0}^{\infty} \theta_B^i E_t \left[\Lambda_{t,t+1+i} R_{t+1+i} \mu_{t+i} \right] \end{aligned} \tag{2.17}$$

where the last step follows from the household Euler equation for consumption (2.5). Suppose that the incentive constraint is expected to never bind. The associated

[3]Strictly speaking, the banker chooses the number of loans s_t^j rather than their value $Q_t s_t^j$. However, since Q_t is market-determined and given from the banker's perspective, treating $Q_t s_t^j$ as a choice variable is inconsequential for the analysis and eases the mathematical derivation.

multiplier μ_t is expected to be zero for all time periods, and the previous expression reduces to η_t equals one. If the incentive compatibility constraint is binding for at least some periods, then in equilibrium η_t is strictly greater than one. Thus, (2.12) implies that the multiplier λ_t on the non-negativity constraint for dp_t^j is strictly positive. It follows that the banker chooses a zero dividend payout policy and keeps accumulating retained earnings. That is, the banker seeks to maximize his expected terminal wealth, and the value function $V(n_t^j, s_t^j)$ can be rewritten as:

$$V_t^j = E_t \sum_{i=1}^{\infty} (1-\theta_B)\theta_B^{i-1} \Lambda_{t,t+i} n_{t+i}^j \tag{2.18}$$

Furthermore, a positive excess return of the loan over the riskless rate arises in equilibrium. Solving (2.13) for $V_2(n_t^j, Q_t s_t^j)$ and using (2.16) yields:

$$E_t \left[\Lambda_{t,t+1}\eta_{t+1}(R_{k,t+1} - R_{t+1})\right] = \frac{\mu_t}{\mu_t + 1}\Theta_t \tag{2.19}$$

As long as the incentive constraint binds, there must be an excess return over the riskless rate. Some arbitrage opportunities are not exploited, but the moral hazard problem prevents bankers from borrowing more, otherwise they would violate the incentive constraint. This means financial markets are incomplete. In a frictionless market, or when the constraint does not bind, the multiplier μ_t equals zero, so no interest rate spread arises.

Since this is a linear program, I guess that its solution is linear in the state variables n_t^j and s_t^j:

$$V(n_t^j, Q_t s_t^j) = g_{n,t} n_t^j + g_{s,t} Q_t s_t^j \tag{2.20}$$

where the coefficient $g_{n,t}$ is the expected discounted marginal gain to the banker of holding an extra unit of net worth while keeping assets constant. $g_{s,t}$ has a similar interpretation. It is the expected discounted marginal gain of increasing assets while holding net worth constant. Equating the Benveniste-Scheikman conditions (2.15) and (2.16) with the expected marginal value of net worth $g_{n,t}$ and asset $g_{s,t}$ yields:

$$g_{n,t} = V_1(n_t^j, Q_t s_t^j) = E_t \left[\Lambda_{t,t+1}\eta_{t+1} R_{t+1}\right] \tag{2.21}$$

$$g_{s,t} = V_2(n_t^j, Q_t s_t^j) = E_t \left[\Lambda_{t,t+1}\eta_{t+1} \rho_{t+1}\right] \tag{2.22}$$

This shows that these time-varying coefficients are independent of bank-specific characteristics. Define the banker's leverage ϕ_t^j at time t as the ratio between assets and net worth:

$$\phi_t^j \equiv \frac{Q_t s_t^j}{n_t^j} \tag{2.23}$$

Substituting (2.20) into (2.11) and solving for s_t^j yields:

$$Q_t s_t^j = \frac{g_{n,t}}{\Theta_t - g_{s,t}} n_t^j = \phi_t n_t^j \tag{2.24}$$

where the last step follows from the definition of leverage. In this equilibrium:

$$\phi_t^j = \frac{g_{n,t}}{\Theta_t - g_{s,t}} \tag{2.25}$$

An increase in either the expected discounted marginal gain of holding an extra unit of net worth or assets increases the value of the banker at time t and the opportunity cost for the banker to divert funds. This loosens the incentive constraint and increases the leverage the banker is allowed to take. Conversely, an increase in Θ_t decreases the amount of leverage, since the gain of diverting funds for the banker is higher. Leverage is independent of bank-specific characteristics, so all bankers choose the same leverage and I can drop the superscript j. Expression (2.20) can be rewritten as:

$$V(n_t^j, Q_t s_t^j) = (g_{n,t} + g_{s,t}\phi_t)\, n_t^j = G_t n_t^j \tag{2.26}$$

where $G_t \equiv \frac{\partial V(n_t^j, s_t^j)}{\partial n_t^j}$ is the marginal value of net worth, or the real price of the banker's net worth expressed in units of the final consumption goods. Substituting (2.26) into the Bellman equation (2.10) and using the solution $d_t^j = 0$ yields:

$$G_{t-1} n_{t-1}^j = E_{t-1}\left[\Lambda_{t-1,t}\left\{(1-\theta_B)n_t^j + \theta_B G_t n_t^j\right\}\right] \tag{2.27}$$

Using the law of motion of capital for net worth (2.9), I obtain a recursive formulation for the real price of net worth:

$$\begin{aligned} G_t &= E_t\left\{\Lambda_{t,t+1}\left[(1-\theta_B) + \theta_B G_{t+1}\right]\left[(R_{k,t+1} - R_{t+1})\phi_t + R_{t+1}\right]\right\} = \\ &= E_t\left\{\tilde{\Lambda}_{t,t+1}\left[(R_{k,t+1} - R_{t+1})\phi_t + R_{t+1}\right]\right\} \end{aligned} \tag{2.28}$$

where $\tilde{\Lambda}_{t,t+1} \equiv \Lambda_{t,t+1}\left[(1-\theta_B)+\theta_B G_{t+1}\right]$, following Gertler and Karadi (2012), is an augmented stochastic discount factor. In a frictionless market, the real price of net worth equals one. When frictions exist, however, net worth is more valuable to the banker, so G_t exceeds one.

Finally, I find expressions for the time-varying coefficients in the problem's solution. Solving (2.13) for the multiplier on the incentive constraint μ_t and using (2.22) yields:

$$\mu_t = \frac{g_{s,t}}{\Theta_t - g_{s,t}} \tag{2.29}$$

Substituting this expression into (2.14) and using (2.21):

$$\begin{aligned} \eta_t = (1-\theta_B) + \theta_B \left(g_{n,t} + \frac{g_{s,t}}{\Theta_t - g_{s,t}} g_{n,t} \right) = \\ (1-\theta_B) + \theta_B \left(g_{n,t} + \phi_t g_{s,t} \right) = (1-\theta_B) + \theta_B G_t \end{aligned} \tag{2.30}$$

where the last step follows using the equilibrium level of leverage (2.25) and the definition of the marginal value of net worth. I find an expression for the marginal value of a unit of net worth averaged across the exiting and continuing state. With probability $(1-\theta_B)$, the banker transfers the unit of net worth to the household which consumes it. With probability θ_B, it retains this unit and values it at price G_{t+1}. Note that the augmented stochastic discount factor $\tilde{\Lambda}_{t,t+1}$ equals $\Lambda_{t,t+1}\eta_{t+1}$ Thus, the expected marginal gain of net worth and assets and equilibrium leverage are:

$$g_{n,t} = V_1(n_t^j, Q_t s_t^j) = E_t\left[\tilde{\Lambda}_{t,t+1} R_{t+1}\right] \tag{2.31}$$

$$g_{s,t} = V_2(n_t^j, Q_t s_t^j) = E_t\left[\tilde{\Lambda}_{t,t+1} (R_{k,t+1} - R_{t+1})\right] \tag{2.32}$$

$$\phi_t = \frac{E_t\left[\tilde{\Lambda}_{t,t+1} R_{t+1}\right]}{\Theta_t - E_t\left[\tilde{\Lambda}_{t,t+1} (R_{k,t+1} - R_{t+1})\right]} \tag{2.33}$$

2.3.2.1 Aggregation

Let S_t and N_t denote the aggregate demand for assets and the aggregate net worth of financial intermediaries. Since ϕ_t does not depend on bank-specific characteristics, aggregating over both sides of (2.24) yields:

$$Q_t S_t = \phi_t N_t \tag{2.34}$$

To derive the law of motion for N_t, I follow Gertler and Karadi (2011). Aggregate financial intermediary's net worth is the sum of continuing and new bankers' net worth. The aggregate net worth of continuing bankers $N_{c,t}$ follows:

$$N_{c,t} = \theta_B \left[(R_{k,t} - R_t)\phi_t + R_t \right] N_{t-1} \tag{2.35}$$

Since the probability of exiting is i.i.d., exiting bankers at the end of period $t-1$ on the whole transfer $(1-\theta_B)Q_{t-1}S_{t-1}$ to the household. I assume that each household assigns a fraction $\frac{\omega}{1-\theta_B}$ of this value to new bankers as a start-up fund. Thus, the net worth of new bankers $N_{n,t}$ is:

$$N_{n,t} = \omega Q_t S_{t-1} \tag{2.36}$$

Combining (2.35) and (2.36), I obtain the law of motion for aggregate intermediary's net worth:

$$N_t = \theta_B \left[(R_{k,t} - R_t)\phi_t + R_t \right] N_{t-1} + \omega Q_t S_{t-1} + \exp \varepsilon_t^{NW} \tag{2.37}$$

where ε_t^{NW} is an exogenous shock to net worth that follows an AR(1) process with autocorrelation ρ_{NW} and white-noise innovations ϵ_t^{NW} with variance σ_{NW}^2. This is one of the two credit supply shocks I examine and corresponds to a transfer from bankers to households. In absence of financial frictions, this shock would have no impact, but in the presence of moral hazard it worsens the incentive problem bankers face.

The other financial shock I investigate has a direct impact on the ability of financial intermediaries to raise deposits from households. The agency problem exists because bankers can divert a fraction Θ_t of assets. The larger the fraction of divertable assets, the more severe the agency problem, and the higher the equilibrium level of interest rate spread. A positive incentive-constraint shock represents bankers having a higher ability to divert funds. This tightens the leverage constraint and leads to a higher return that firms must pay above the riskless rate to obtain funds. I assume that households can observe the realizations of this shock. There is no discrepancy between the ability of bankers to divert funds, and how households perceive it.

A positive incentive-constraint shock can be interpreted as financial innovations, lax regulations, and/or a poor governance structure that allows bank managers to promote their own short-term benefits rather than those of the institution they manage. Importantly, the nature of this shock differs from the financial shock in Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) who assume a financial shock affects the effective quality of the physical capital underlying the shares S_t. This indirectly lowers the value of the intermediary's financial assets and its ability to raise funds. Their goal is to model a shock originating outside the financial sector. In contrast, I am interested in examining the banking sector as a source of disturbances for the real economy.[4]

2.3.3 Wholesale Producers

The productive sector and the labor market are modeled in a relatively standard way. Competitive firms produce wholesale goods and sell them to final good producers, or retailers, at the relative price p_t^M. Labor is the sole input of production, and wholesale goods are produced according to a linear production function:

$$y_t = A_t l_t hr_t \tag{2.38}$$

where $A_t \equiv \exp^{z_t}$ is technology and $l_t hr_t$ is total hours worked. Total factor productivity is subject to an exogenous disturbance z_t that follows an AR(1) process with autocorrelation coefficient ρ_A and white-noise innovations ϵ_t^A with variance σ_A^2.

This production function incorporates both an extensive and an intensive labor margin. Including hours worked ensures that, in absence of TFP shocks, output can react to other aggregate shocks in each period. Otherwise, the predetermined nature of the stock of employed labor would allow output to react to other shocks only with a period lag.[5] The assumption of a linear production function is typical

[4] In this set-up, I cannot compare the implications of these two types of financial shock because the assumption of output linear in labor makes a financial shock observationally equivalent to a technological shock. Introducing physical capital would enable the model to include a shock affecting the effective quality of physical capital or labor.

[5] Including an intensive labor margin adds an equation to the model that serves to pin down hours worked. Although I am not primarily interested in distinguishing between the effects of financial shocks to the extensive and intensive labor margins, this richer model brings little

in the search and matching literature, and, in absence of physical capital, this restriction is necessary to derive the value of the firm. To introduce some concavity, I could generalize to a production function displaying diminishing returns to hours worked. This is a reasonable assumption, but it does not change the qualitative and quantitative results of the model.[6]

Labor is purchased in a non-Walrasian market. Workers and wholesale firms spend time and resources before matching successfully. Firms post vacancies V_t paying a linear cost κ, expressed in units of the final good, per vacancy. In addition to using per-period sale revenues, firms borrow from financial intermediaries to pay for vacancy costs and wages. For instance, when interest rates are low, firms can borrow to expand production beyond what current revenues can finance. Firms issue S_t claims that entitle intermediaries to earn a gross real return $R_{k,t+1}$ in the following period. In equilibrium, arbitrage ensures the value of these claims Q_tS_t equals the value of the firm. This links the financial to the real sector of the economy.

Each period, new matches are produced according to a constant-returns-to-scale matching function $m_t = m(u_t, V_t)$. The matching function is strictly increasing and strictly concave in both arguments. I define labor market tightness x_t as the ratio between vacancies V_t and the pool of unemployed workers u_t at the beginning of the period. Using the CRS properties of the matching function, the job-filling rate for a firm, or the probability of a vacancy being filled, equals:

$$q(x_t) \equiv \frac{m(u_t, V_t)}{V_t} = m\left(\frac{1}{\frac{V_t}{u_t}}, 1\right) \tag{2.39}$$

New gross hires h_t equal the number of posted vacancies times the job-filling rate, and they become productive only in the next period. Similarly, the probability

extra computational complexity. Alternatively, I could assume that new hires become productive immediately and abstract from intensive labor margin considerations. However, I can establish the value of the firm only if I impose that new hires become productive in the next period as in the standard random search model.

[6] I studied the response of the model with $y_t = A_t l_t hr_t^{\alpha}$ as the economy's production function. For $\alpha < 1$, the intensive margin becomes increasingly inelastic to aggregate shocks, but the effects are quantitatively small.

of finding a job for an unemployed worker s_t is:

$$s(x_t) \equiv \frac{m(u_t, V_t)}{u_t} = m(1, x_t) = x_t q(x_t) \tag{2.40}$$

The matching function takes the conventional CRS functional form $m_t = m_0 u_t^{\sigma_t^m} V_t^{1-\sigma_t^m}$ where m_0 is a scale-efficiency parameter, and $\sigma_t^m \equiv \sigma^m \exp^{\varrho_t}$ is the time-varying elasticity of the matching function. This elasticity has average value σ^m and is subject to an exogenous disturbance ϱ_t that follows an AR(1) process with autocorrelation ρ_ϱ and white-noise innovations ϵ_t^ϱ with variance σ_ϱ^2. It follows that the job-filling $q(x_t)$ and the job-finding $s(x_t)$ rates are $m_0 x_t^{-\sigma_t^m}$ and $m_0 x_t^{(1-\sigma_t^m)}$, respectively. At the end of each period, a constant proportion of employed workers loses its jobs at the exogenous separation rate $\psi \in (0, 1)$. It follows that the number of productive employed workers in the next period is:

$$ł_{t+1} = (1 - \psi) l_t + h_t = (1 - \psi) l_t + q(x_t) V_t \tag{2.41}$$

Note that this timing implies both the employment level l_t and the pool of unemployed workers u_t are pre-determined variables.

The firm maximizes the present discounted value of its real cash-flows. The firm produces output, post vacancies, and issues new debt. It discounts future cash-flows by $\Lambda_{t,t+s}$ because they are owned by households. In recursive form, the value of the firm at the beginning of the period is:

$$\Omega_t \left(l_t, S_{t-1}\right) = \max_{\{S_t, l_{t+1}, V_t\}} \left\{ S_t + p_t^M y_t - w_t hr_t l_t - \kappa V_t - R_{k,t} S_{t-1} + \Lambda_{t.t+1} \Omega_{t+1} \left(l_{t+1}, S_t\right) \right\} \tag{2.42}$$

where S_{t-1} and l_t are the firm's state variables. Firms and households bargain over the hourly wage rate and the quantity of hours worked,[7] the real cost of debt is determined in the credit market, and the vacancy-filling rate in the labor market. Thus, w_t, hr_t, $R_{k,t}$, and p_t^M are given. Let the multiplier associated with (2.41) be Q_t^l. This can be interpreted as the marginal value of an extra employee to the

[7] Alternatively, I could have assumed the firm chooses the level of hours worked as well. This right-to-manage assumption is present in the literature as an alternative to the efficient-bargaining assumption I use.

firm, or as marginal Q for employment. Combining the first-order conditions with respect to V_t, l_{t+1}, and S_t with the Benveniste-Scheikman conditions yields:

$$Q_t^l = \frac{\kappa}{q_t} \tag{2.43}$$

$$Q_t^l = E_t \left\{ \Lambda_{t,t+1} \left[(p_{t+1}^M A_{t+1} hr_{t+1} - w_{t+1} hr_{t+1}) + (1-\psi) Q_{t+1}^l \right] \right\} \tag{2.44}$$

$$1 = E_t \left[\Lambda_{t,t+1} R_{k,t+1} \right] \tag{2.45}$$

Combining (2.43) and (2.44) I obtain the job-creating condition that replaces the standard labor demand function of neo-classical labor markets.

Firms will post vacancies until the marginal cost of hiring equals the expected marginal benefit. The latter is the sum of the marginal product of labor net of wages next period and the expected savings from current hiring:

$$\frac{\kappa}{q_t} = E_t \left[\Lambda_{t,t+1} \left(p_{t+1}^M A_{t+1} hr_{t+1} - w_{t+1} hr_{t+1} + (1-\psi) \frac{\kappa}{q_{t+1}} \right) \right] \tag{2.46}$$

Since wholesale firms operate in a perfectly competitive market, in each state they make no profit and simply pay out the ex-post return $R_{k,t+1}$ to financial intermediaries:

$$R_{k,t+1} = \frac{(p_{t+1}^M A_{t+1} hr_{t+1} - w_{t+1} hr_{t+1}) + (1-\psi) Q_{t+1}^l}{Q_t^l} \tag{2.47}$$

where the term in brackets is the cash-flow component and $\frac{(1-\psi)Q_{t+1}^l}{Q_t^l}$ is the capital gain on the asset S_t.

Solving equation (2.44) forward and using the law of iterated expectations, I find an expression for the marginal value of employment in terms of discounted expected future marginal products of labor net of marginal hiring costs and wages:

$$Q_t^l = E_t \left[\sum_{s=1}^{\infty} \Lambda_{t,t+s} (1-\psi)^s (p_{t+s}^M A_{t+s} hr_{t+s} - w_{t+s} hr_{t+s}) \right] \tag{2.48}$$

With no hiring costs and a perfectly competitive labor market, workers do not have value above their marginal product and Q_t^l collapses to zero as in the standard neo-classical model. Vacancy costs make the currently employed valuable, and firms can extract a rent from their labor relationships. The value of the firm in fact equals the value of its employed workers at the end of the period $l_{t+1}Q_t^l$ as in Merz and

Yashiv (2007).[8] This resembles the standard result in the neo-classical model with capital in which the value of the firm equals the value of the capital stock it owns. In equilibrium, the total value of the shares the firm issues equals the value of the firm:

$$Q_t S_t = l_{t+1} Q_t^l \tag{2.49}$$

which is to say that the firm uses the borrowed funds to acquire l_{t+1} units of labor each priced at Q_t^l, so that the value of labor acquired equals the value of the claims against this labor. There is an infinite number of pairs $\{Q_t, S_t\}$ that clears the credit market.[9] Since in this framework labor is an asset, the natural normalization is to set the number of shares S_t equal to the units of workers the firm employs l_{t+1}, and the price of each share Q_t equal to the price of labor Q_t^l.

2.3.3.1 The Wage Schedule

The hourly wage rate and hours worked are not determined competitively. I assume that each period the firm and the household bargain over both the amount of hours each employed worker has to supply and the corresponding hourly wage rate. Hours are set efficiently to maximize the joint surplus of the match, while the hourly wage rate is set according to Nash bargaining to split this surplus and plays no allocative role. The solution of this bargaining process is:

$$w_t^{NASH} = \gamma_w \left(p_t^M A_t + x_t \frac{\kappa}{hr_t} \right) + (1 - \gamma_w) \chi c_t \frac{hr_t^{\omega_w}}{1 + \omega_w} \tag{2.50}$$

where $\gamma_w \in (0, 1)$ is a measure of the worker's bargaining power (see Appendix 2.7.1 for the full derivation). This is the hourly wage rate w_t^{NASH} resulting from bargaining when there are no real wage rigidities and wages are fully renegotiated in each period. The equilibrium wage depends on the marginal product per hour worked, the worker's reservation level, and a term depending on current labor market conditions.

As is typical in the search friction literature, I introduce some degree of real wage rigidity.[10] I follow Krause and Lubik (2007) and assume real wages are a

[8] The assumptions of a pre-determined labor stock, and CRS in both the production and vacancy cost functions are crucial for this result.

[9] Let $\tilde{Q}_t = cQ_t$ and $\tilde{S}_t = {}^{S_t}/_{c}$ for $c \subset \mathbb{R}^+$, then $\{\tilde{Q}_t, \tilde{S}_t\}$ also clears the financial market.

[10] Shimer (2005a) has shown that under Nash bargaining, wages are very responsive to TFP shocks and absorb most of the increase in productivity. Firm's profits do not raise much, so firms have little incentive to post more vacancies and the transmission mechanism is very weak.

weighted average between a notional wage and a wage norm. A wage norm restricts the wage adjustment for current employed workers and new hires. I assume the norm to be the steady-state value $\overline{w}^{NASH}$ of the Nash bargaining solution, while the notional wage is simply the Nash bargaining solution w_t^{NASH} found above. Let $\varphi_r \in (0,1)$ be the weight on the Nash bargaining solution, then the real wage follows:

$$w_t = \varphi_r w_t^{NASH} + (1 - \varphi_r)\overline{w}^{NASH} \tag{2.51}$$

When φ_r equals zero, real wages are completely rigid. When φ_r equals one, they are perfectly flexible in a Nash-bargaining sense.

With labor market frictions the real hourly wage does not play an allocative role. There is an infinite number of wage levels that can be sustained in equilibrium, and Nash-bargaining is a mechanism to pick one of these solutions. However, there is an interplay between real wage rigidity and financial frictions. A negative shock requires firms to promise to pay a higher rate of return on lending. Firms optimally choose how to split the extra cost of borrowing between a higher expected cash-flow payment and a higher expected capital gain. The more rigid the real wage is, the less the flow value of a unit of lending can adjust. Hence, the expected capital gain on a unit of labor, which depends on labor market tightness, must increase relatively more, leading to a larger adjustment at the extensive margin.

2.3.3.2 The Intensive Margin Schedule

Hours worked are determined jointly with the real wage to maximize the joint surplus. The marginal benefit of working an extra hour is the resulting marginal product of labor $p_t^M A_t$, while the marginal cost is the marginal disutility of labor for the worker, which decreases the household's surplus. In an efficient allocation, the condition that determines the schedule for hours worked is:

$$p_t^M A_t = \chi c_t hr_t^{\omega_w} \tag{2.52}$$

Hours worked are determined intra-temporally and move in response to exogenous shocks.

2.3.4 Retailers

A continuum of monopolistically competitive firms i on the unit interval transforms the wholesale good y_t into final differentiated goods $y_t(i)$ according to a linear production function. A standard Dixit-Stiglitz bundle aggregates these differentiated goods into a final composite good Y_t:

$$Y_t = \left[\int_0^1 y_t(i)^{\frac{\epsilon_t - 1}{\epsilon_t}} di\right]^{\frac{\epsilon_t}{\epsilon_t - 1}} \tag{2.53}$$

where $\epsilon_t \equiv \epsilon \exp^{\zeta_t}$ is the time-varying elasticity of substitution between final goods. ϵ is the average elasticity of substitution and is subject to a stochastic disturbance ζ_t that follows an AR(1) process with autocorrelation coefficient ρ_ζ and white-noise innovations ϵ_t^ζ with variance σ_ζ^2. Cost minimization delivers the standard downward-sloping demand function:

$$y_t(i) = \left(\frac{p_t(i)}{P_t}\right)^{-\epsilon_t} Y_t \tag{2.54}$$

where $p_t(i)$ is the price charged by firm i, and P_t is the standard Dixit-Stiglitz price aggregator:

$$P_t = \left[\int_0^1 p_t(i)^{1-\epsilon_t} di\right]^{\frac{1}{1-\epsilon_t}} \tag{2.55}$$

I assume Calvo price-setting for final goods producers to introduce nominal price rigidity. Each period, only a fraction $1 - \gamma_p$ of randomly selected final goods producers can reset prices. The remaining final goods producers keep their prices unchanged. Let P_t^* be the new price for a resetting firm at time t. Then, the aggregate price level satisfies:

$$P_t = \left[(1-\gamma_p)(P_t^*)^{1-\epsilon_t} + \gamma_p P_{t-1}^{1-\epsilon_t}\right]^{\frac{1}{1-\epsilon \exp^{\zeta_t}}} \tag{2.56}$$

Final good producers choose the reset price to maximize the discounted sum of expected current and future profits:

$$\max_{P_t^*} \sum_{k=0}^{\infty} \gamma_p^k E_t \left\{\Lambda_{t,t+k} \frac{P_t}{P_{t+k}} (P_t^* - p_{M,t+k}) y_{t+k|t}(i)\right\} \tag{2.57}$$

subject to the sequence of demand constraints (2.54). $y_{t+k|t}(i)$ is the expected demand at time $t+k$ for a firm resetting price at t. The marginal revenue for the firm is the newly set price P_t^*. The nominal marginal cost is simply the price of the intermediate good $p_{M,t+k}$ since it takes one unit of the intermediate good to produce one unit of the final good. The necessary first-order condition for profit-maximization is:

$$E_t\left\{\sum_{k=0}^{\infty}\Lambda_{t,t+k}\frac{P_t}{P_{t+k}}y_{t+k|t}(i)\left(\frac{P_t^*}{P_{t-1}}-\mathcal{M}MC_{t+k|t}\Pi_{t-1,t+k}\right)\right\}=0 \tag{2.58}$$

where $\mathcal{M}\equiv\frac{\epsilon}{\epsilon-1}$ is the gross desired markup, $MC_{t+k|t}=\frac{p_{M,t+k}}{P_{t+k}}$ is the real marginal cost for the final good producer, and $\Pi_{t-1,t+k}$ is the gross inflation rate between $t-1$ and $t+k$.

2.3.5 Government and Market-Clearing

I assume that government expenditure G_t is a constant fraction of output and is financed by lump sum taxes T_t. Thus, the government balances its budget in each period (i.e. $G_t = T_t$). The monetary authority sets the nominal interest rate i_t to react to inflation and a measure of the output gap. For simplicity, following Gertler and Karadi (2011) I use the deviation of the mark-up retailers charge from its optimal level level as a proxy of the output gap. Since the monetary authority also smooths the nominal interest rate over time, i_t follows the rule:

$$i_t=\rho_i i_{t-1}+(1-\rho_i)\left(\kappa_\Pi\Pi_t+\kappa_Y log\left(\frac{p_t^M}{\mathcal{M}}\right)\right)+\varsigma_t \tag{2.59}$$

where $\rho_i\in[0,1)$, κ_Π, and κ_Y are the interest-rate smoothing parameter, the inflation and the output gap coefficients, respectively, while ς_t is a monetary policy disturbance with autocorrelation coefficient ρ_ς and white-noise innovations ϵ_t^ς with variance σ_ς^2. The Fisher relation links the nominal and the real interest rate:

$$1+i_t=R_{t+1}\frac{E_t[P_{t+1}]}{P_t} \tag{2.60}$$

Finally, the aggregate budget constraint is:

$$Y_t=c_t(1+f_B)+G_t+\kappa V_t \tag{2.61}$$

Aggregate output is divided between household consumption, government spending, and the vacancy costs for wholesale producers. Since there is perfect insurance within the household, c_t measures consumption per capita.

2.3.6 Restricted Model

The restricted model is a standard New Keynesian DSGE model with random search frictions in the labor market and no financial frictions. Assume that bankers cannot divert the assets they manage by setting the parameter Θ_t equal to zero for all periods. Equation (2.19) shows that the excess return of the loan over the riskless rate ρ_t is zero, which implies that in expectations the risk-free rate equals the return on bank lending $R_{k,t+1}$:

$$E_t[R_{t+1}] = E_t[R_{k,t+1}] = E_t\left[\frac{(p^M_{t+1}A_{t+1}hr_{t+1} - w_{t+1}hr_{t+1}) + (1-\psi)Q^l_{t+1}}{Q^l_t}\right] \quad (2.62)$$

Equivalently, the Benveniste-Scheinkman condition (2.16) shows that, in a first-order linear solution, the expected marginal value of assets holding net worth constant $g_{s,t}$ must be zero.

If the incentive constraint (2.11) is binding, the value of the intermediary $V(n^j_t, s^j_t)$ is zero as well. Using the linear guess (2.20), this implies that either the net worth n^j_t, or the expected marginal value of net worth holding assets constant $g_{n,t}$, or both are zero. Suppose $g_{n,t}$ were zero, then (2.22) shows that the multiplier η_t on the law of motion for capital would have to be zero as well. From the first-order condition (2.12), it follows that the multiplier λ_t on dividend payments would also be zero. This would violate the set of Kuhn-Tucker conditions necessary to characterize the local optimum. Thus, in equilibrium n^j_t must be zero and $g_{n,t}$ must be strictly positive. Intuitively, if there is no moral hazard bankers do not need to combine their own net worth with deposits from households to finance loans. However, net worth has a strictly positive value because holding higher net worth would enable bankers to provide additional lending to wholesale producers. Besides, since bankers have no net worth, they make no profits and they cannot pay out any dividends, as the law of motion for net worth (2.9) shows when n^j_t and ρ_t are both zero. Finally, since net worth is zero, in this restricted model leverage is an ill-defined concept.

The banking sector is irrelevant because no moral hazard problem limits the ability of bankers to raise deposits from households. The amount of loans depends solely on the amount of household deposit d_t^j. Since there is no interest rate spread, the expected rate of return of intermediary good producers $R_{k,t+1}$ enters directly into the Euler equation for consumption (2.5) and determines the saving behavior of households and the level of deposits. Once we use (2.62) to close the model, all the equations described in Section 2.3.2 are redundant in determining the equilibrium of this economy.

2.4 Empirical Methodology

The empirical strategy is a mixture of Bayesian estimation and calibration of the structural parameters. I estimate the discount factor β, the elasticity of substitution ϵ, the Calvo parameter ξ, the elasticity of of the matching function σ^m, the degree of real wage rigidity φ_r, the coefficients of the Taylor rule κ_π, κ_y and ρ_r, and the variance and autocorrelation coefficient of each shock process. The other structural parameters are calibrated because they are either only weakly identified or unidentifiable. I use Andrle (2010) and Iskrev (2010)'s analysis to determine which parameters to fix in the estimation.

The set of observables used for estimation are the time-series of eight key macroeconomic quarterly US variables: (log) real GDP, (log) real labor productivity per hour, (log) real wage, (log) vacancy stock, (log) real hourly wage, (log) labor market tightness, the unemployment rate, the Federal Funds Rate, and the inflation rate (see Appendix 2.7.2 for a full data description). When the original series are measured monthly, I take quarterly averages. Furthermore, I de-trend all variables with a one-sided HP filter to obtain stationary time-series.

Seven exogenous disturbances drive the behavior of this economy: total factor productivity (ϵ_t^A), net worth (ϵ_t^{NW}), incentive-constraint (ϵ_t^Θ), monetary policy (ϵ_t^ς), preference (ϵ_t^ν), elasticity of demand (ϵ_t^ϱ), and elasticity of the matching function (ϵ_t^ζ). All non-financial shocks are standard disturbances studied in the business cycle literature and can be given a meaningful economic interpretation. In particular, ϵ_t^ν is a preference demand shock affecting the allocation of consumption over time. ϵ_t^ϱ affects the degree of monopolistic competition between final good producers and acts as a mark-up disturbance. ϵ_t^A and ϵ_t^ζ are both supply-side disturbances, with the latter capturing how new matches are responsive to labor market tightness. I am mostly interested in the response of the labor market to credit supply shocks, but I include additional disturbances to expand the information set available for estimation. Since the set of observables exceeds the number of exogenous disturbances, I add measurement error in all the observables, but real labor productivity. This avoids stochastic singularity and also accounts for measurement error incorporated in some of the variables, notably the vacancy stock.[11] I do not include measurement error for real labor productivity because it would be observationally equivalent to the TFP shock.

First, I estimate the mode of the posterior distribution by maximizing the log posterior kernel. The kernel combines the prior information on the parameters with the likelihood of the data. Then, I use the Metropolis-Hastings algorithm to simulate from the posterior distribution and calculate the marginal likelihood of the model. I estimate the model without and with financial frictions to show that adding a banking sector improves the marginal likelihood of the data. The first model has five structural disturbances, while the latter model includes also two financial disturbances.

The model is estimated over the full sample period from 1964:I to 2013:II, with the first 10 years of data (equivalent to 40 observations) used as training period to calculate the marginal likelihood. I create a sample of 1,500,000 observations and discard the first half of the sample. The Hessian matrix evaluated at the posterior mode is used as the variance-covariance matrix of the transition density function generating the new proposed draw. I assess the convergence of the chain using the Brooks and Gelman (1998) test comparing between and within moments of multiple chains, and the multivariate test comparing the difference between

[11] I also estimated a model with only three observables (labor market tightness, the inflation rate, and the nominal interest rate) and no measurement error, but the posterior mode estimation was highly sensitive to the initial values used.

the cumulative mean and the overall mean (Bauwens *et al.*, 2000). According to these statistics, the posterior distributions of all parameters converge to their ergodic distribution (see Appendix 2.7.3).

I use the estimated model to study the economy's response to financial shocks, to conduct a forecasting variance and historical decomposition exercise, and to compare the theoretical cross-correlation coefficients with their empirical counterparts. Furthermore, I am interested in comparing the response of the model with and without a banking sector and focus on the TFP shock to do so.[12] Since the two DSGE models result in slightly different estimations of the posterior distribution, I conduct this assessment calibrating the model at the prior mean.[13]

2.4.1 Prior Distribution

In setting the prior distributions, I follow standard practice as much as possible (see Table 2.1). I assume a strict prior for the discount factor β: a beta distribution with prior mean 0.99 and a standard deviation 0.001. The elasticity of substitution ϵ is assumed to follow a gamma distribution with prior mean 10 and standard deviation 1, implying average profits of 11 percent. The probability of retailers' prices being fixed is assumed to be 0.779 with standard deviation 0.10. The labor market parameters both follow a beta distribution with a rather loose prior. The distribution of the elasticity of the matching function σ^m is centered around 0.5, a typical value in the labor market literature, and has a standard deviation of 0.15. There is less consensus in the literature on the structure of wage rigidity. I center the prior distribution of the real wage rigidity φ_r around 0.5 with a standard deviation of 0.25. This prior mean reflects the calibration in Krause and Lubik (2007), with a loose prior to allow the data to drive the estimation.

The parameters that describe monetary policy are based on a standard Taylor rule. The short-run reaction coefficients on inflation κ_π and the output gap κ_y

[12] I could carry out this analysis with any of the non-financial disturbances, but I focus on the TFP shock because this is the most commonly studied source of business cycle fluctuations in the labor market literature.

[13] Comparing the response of the two estimated models would confound the effects of including a banking sector and the different parameterization resulting from different posterior estimates.

Table 2.1: Prior Distribution of Model Parameters

		Prior Distribution		
		Distribution	*Mean*	*St.Dev.*
	Parameter			
β	Discount factor	Beta	0.99	0.001
ϵ	Elasticity of substitution	Gamma	10	1
ξ	Probability of keeping prices fixed	Beta	0.779	0.10
σ^m	Elasticity of matching function	Beta	0.5	0.15
φ_r	Real wage rigidity	Beta	0.5	0.25
κ_π	Inflation coefficient of the Taylor rule	Gamma	1.1	0.15
κ_y	Output gap coefficient of the Taylor rule	Gamma	0.125	0.10
ρ_r	Smoothing parameter of the Taylor rule	Beta	0.5	0.15
	Standard deviation of structural disturbance			
σ_A	TFP	Inverse Gamma	0.05	0.10
σ_ς	Monetary Policy	Inverse Gamma	0.05	0.10
σ_ϱ	Matching elasticity	Inverse Gamma	0.05	0.10
σ_ν	Preference	Inverse Gamma	0.05	0.10
σ_ζ	Elasticity of demand	Inverse Gamma	0.05	0.10
σ_{NW}	Net worth	Inverse Gamma	0.05	0.10
σ_Θ	Incentive-constraint	Inverse Gamma	0.05	0.10
	AR(1) coefficient of structural disturbance			
ρ_A	TFP	Beta	0.5	0.15
ρ_ς	Monetary policy	Beta	0.5	0.15
ρ_ϱ	Matching elasticity	Beta	0.5	0.15
ρ_ν	Preference	Beta	0.5	0.15
ρ_ζ	Elasticity of demand	Beta	0.5	0.15
ρ_{NW}	Net worth	Beta	0.5	0.15
ρ_Θ	Incentive-constraint	Beta	0.5	0.15
	Standard deviation of measurement error			
σ_e^y	Real output	Inverse Gamma	0.05	0.15
σ_{e^w}	Real hourly wage	Inverse Gamma	0.05	0.15
σ_{e^V}	Vacancy	Inverse Gamma	0.05	0.15
σ_{e^u}	Unemployment rate	Inverse Gamma	0.05	0.15
σ_{e^V}	Labor market tightness	Inverse Gamma	0.05	0.15
σ_{e^π}	Inflation rate	Inverse Gamma	0.05	0.15
σ_{e^i}	Federal Funds Rate	Inverse Gamma	0.05	0.15

follow a gamma distribution with prior means equal to 1.1 and 0.125 and standard deviations of 0.15 and 0.10, respectively. The smoothing parameter follow a beta distribution with prior mean 0.5 and standard deviation equal to 0.15.

I also follow standard conventions in setting the priors on the stochastic processes for both non-financial and financial shocks. I assume the standard deviation of each disturbance to follow an inverse gamma distribution with prior mean equal to 0.05 and standard deviation equal to 0.10. In addition, I assume the autoregressive parameter in the AR(1) process for all disturbances to follow a beta distribution with prior mean equal to 0.5 and standard deviation of 0.15. Finally, the standard deviation of the white noise measurement error processes are assumed to follow an inverse gamma distribution with prior mean equal to 0.05 and standard deviation of 0.15.

The remaining parameters are calibrated as shown in Table 2.2. As typical in the labor market literature, I set the share of the worker's surplus η_w at 50 percent (Blanchard and Galí, 2010; Trigari, 2006), and the separation rate ψ at 8 percent as in Trigari (2006).[14] I set the relative proportion of bankers in the population to 1 percent and the output share of government expenditure to 20 percent. Following Gertler and Karadi (2011), I set the proportional transfer to entering bankers ω to achieve an annual steady-state interest rate spread of 100 basis points, and the average fraction of divertable capital Θ to achieve a steady-state leverage ratio of 4. This results in ω equal to 0.002 percent and Θ equal to 38.5 percent.[15] The scale-efficiency parameter m_0, the vacancy cost κ, the labor elasticity parameter ω_w, and the relative utility weight of labor χ are calibrated to match a 5

[14]Other studies set slightly different values. For instance, Thomas (2011) chooses 60 percent for the share of the worker's surplus.

[15]This is very close to the value of Θ in Gertler and Karadi (38.1 percent). This result is somewhat surprising because the value of the bank's assets depends on a much different productive sector. In their paper, the value of the firm equals the value of its capital stock. Production follows a standard CRS function in capital and labor with a variable utilization rate. Net investment adjustment costs and a competitive labor market complete the model. The model I examine does not have capital, production is linear in labor, and wages are determined in a non-competitive market. This suggests the structure of the goods and labor markets have little effect on the bankers' incentives to divert funds. Since I impose a very specific financial structure, the labor market should have little effect on the moral hazard problem bankers face. In reality, the structure of the labor and financial markets are likely to influence each other.

Table 2.2: Calibrated Parameters

Parameter		*Value*	*Source/Target*
χ	Relative utility weight of labor	1.079	5 percent unemployment rate
ω_w	Inverse Frisch elasticity of labor supply	0.175	0.7 job-filling rate (Shimer, 2005)
m_0	Efficiency of matching function	0.710	1 percent vacancy-cost-to-gdp ratio
κ	Vacancy cost	0.125	Steady-state hours worked of 1
ω	Proportional transfer to entering banks	0.002	100-basis-point interest rate spread on annual basis (GK, 2011)
Θ	Fraction of divertable capital	0.385	Steady-state leverage of 4 (GK, 2011)
ψ	Worker separation rate	0.08	Trigari, 2006; Blanchard & Gali, 2010
γ_w	Share of worker's surplus	0.5	Trigari, 2006; Blanchard & Gali, 2010
f_B	Relative proportion of bankers	0.01	GK, 2011
θ_B	Survival rate for bankers	0.975	Average lifetime of 10 years (GK, 2011)
$\frac{\overline{G}}{\overline{y}}$	Steady-state output share of government expenditure	0.20	Standard value

percent unemployment rate, a 0.7 job-filling rate Shimer (2005b), and vacancy costs equal to 1 percent of GDP (Andolfatto, 1996; Gertler and Trigari, 2009; Blanchard and Galí, 2010; Thomas, 2011). The normalization of steady-state hours worked provides the last necessary restriction.

2.5 Results

I begin the discussion of the empirical results comparing the posterior mode for the models without and with a banking sector. I also assess the relative empirical fit of the full model in explaining the joint distribution of the observables. Then, I discuss in more detail the posterior distribution of the structural parameters for this model in the full sample and over different subsamples. Next, I examine the dynamic response of the economy to credit supply shocks using the full model at the estimated posterior mode. To illustrate the amplification mechanism arising when financial and labor market frictions can interact with one another, I study the response to TFP shocks in the economies with and without a banking sector. I calibrate both models at the prior mean to perform this analysis. Finally, I return to the estimated model to investigate whether the full model can replicate the volatility, persistence, and cross-correlation of the key labor market variables, and to assess the contribution of different structural shocks to these volatilities.

2.5.1 Posterior Distribution

Table 2.3 shows the posterior mode for the restricted and full models along with their respective marginal likelihood. It also shows the posterior mean, the posterior standard deviation, and the 95 percent credibility interval of the full model. First, the marginal likelihood of the full model is higher than the likelihood for the restricted one. The log of the Bayes factor, which is the difference between the marginal likelihood of the full and restricted models (in logs), is 110.[16] Kass and Raftery (1995) suggest a metric to assess whether the log of Bayes factor is large or not. Values above 5 provide very strong evidence in favor of the full model, values between 3 and 5 very strong evidence, values between 1 and 3 positive evidence, and values between 0 and 1 very weak evidence. This criterion suggests that adding a banking sector to a standard New Keynesian DSGE model with random search frictions in the labor market improves the fit of the model with the data. This is particularly remarkable since no financial variables is among the set of observables.

Furthermore, there are some substantial differences between the two models in terms of posterior mode estimates. Relative to the restricted model, the full model estimates a more active monetary authority: the coefficients on both inflation and the output gap are higher, while the importance attached to the lagged interest rate is smaller. In terms of structural disturbances and measurement errors, both models estimate similar values for most of the standard deviations of these exogenous innovations. The autocorrelation coefficients in the AR(1) processes for the structural disturbances, however, differ substantially between the two models. This may reflect the additional two financial disturbances in the model with a banking sector. Apart from the monetary policy shock, all other supply and demand shocks have a lower posterior mode for the autocorrelation coefficient. This

[16] Let $P(Y|M_i)$ and $P(Y|M_j)$ be the value of the marginal likelihood function for models i and j, the Bayes factor BF_{ij} is $P(Y|M_i) - P(Y|M_j)$ and the log of the Bayes factor is $\log(BF_{ij}) = \log\left(\frac{P(Y|M_i)}{P(Y|M_j)}\right)$

Table 2.3: Posterior Distribution of Parameters

	Prior Distribution			Posterior Distribution					
				Restricted Model	*Full Model*				
	Distr.	*Mean*	*St.Dev.*	*Mode*	*Mode*	*Mean*	*St.Dev.*	*5 %*	*95 %*
				Parameter					
β	Beta	0.99	0.001	0.991	0.989	0.989	0.001	0.987	0.991
ϵ	Gamma	10	1	11.356	9.696	9.530	0.478	7.913	11.120
ξ	Beta	0.779	0.10	0.816	0.920	0.950	0.028	0.909	0.992
σ^m	Beta	0.5	0.15	0.485	0.606	0.568	0.086	0.411	0.722
φ_r	Beta	0.5	0.25	0.145	0.599	0.558	0.037	0.476	0.638
κ_π	Gamma	1.1	0.15	0.790	1.063	1.044	0.082	0.810	1.233
κ_y	Gamma	0.125	0.10	0.154	0.989	0.579	0.044	0.345	0.838
ρ_r	Beta	0.5	0.15	0.942	0.247	0.237	0.047	0.102	0.369
			Standard deviation of structural disturbance						
σ_A	Inv. Gamma	0.05	0.10	0.008	0.008	0.008	0.001	0.008	0.009
σ_ς	Inv. Gamma	0.05	0.10	0.006	0.007	0.006	0.001	0.005	0.007
σ_ϱ	Inv. Gamma	0.05	0.10	0.020	0.083	0.095	0.070	0.074	0.116
σ_ν	Inv. Gamma	0.05	0.10	0.017	0.007	0.007	0.001	0.006	0.008
σ_ζ	Inv. Gamma	0.05	0.10	0.018	0.019	0.023	0.002	0.012	0.035
σ_{NW}	Inv. Gamma	0.05	0.10	-	0.013	0.012	0.001	0.010	0.014
σ_Θ	Inv. Gamma	0.05	0.10	-	0.016	0.017	0.002	0.010	0.023
			AR(1) coefficient of structural disturbance						
ρ_A	Beta	0.5	0.15	0.821	0.659	0.654	0.035	0.591	0.712
ρ_ς	Beta	0.5	0.15	0.156	0.564	0.311	0.053	0.117	0.502
ρ_ϱ	Beta	0.5	0.15	0.636	0.859	0.862	0.022	0.822	0.901
ρ_ν	Beta	0.5	0.15	0.976	0.264	0.327	0.034	0.192	0.456
ρ_ζ	Beta	0.5	0.15	0.558	0.336	0.384	0.059	0.175	0.590
ρ_{NW}	Beta	0.5	0.15	-	0.055	0.056	0.008	0.042	0.069
ρ_Θ	Beta	0.5	0.15	-	0.837	0.801	0.074	0.646	0.953
			Standard deviation of measurement error						
σ_{e^y}	Inv. Gamma	0.05	0.15	0.007	0.008	0.008	0.001	0.007	0.009
σ_{e^w}	Inv. Gamma	0.05	0.15	0.012	0.013	0.013	0.001	0.012	0.015
σ_{e^V}	Inv. Gamma	0.05	0.15	0.128	0.138	0.141	0.009	0.128	0.154
σ_{e^u}	Inv. Gamma	0.05	0.15	0.006	0.006	0.005	0.001	0.004	0.005
σ_{e^x}	Inv. Gamma	0.05	0.15	0.025	0.014	0.015	0.003	0.011	0.020
σ_{e^π}	Inv. Gamma	0.05	0.15	0.239	0.247	0.249	0.014	0.226	0.272
σ_{e^i}	Inv. Gamma	0.05	0.15	0.006	0.006	0.005	0.001	0.004	0.005
Marginal likelihood (log)				2,665	2,755				

suggests that other non-financial disturbances may capture some of the persistence that financial shocks generate in the data.

Next, I discuss in more detail the posterior estimates for the model with a banking sector. Figures 2.6 and 2.7 in Appendix 2.7.4 show the posterior distribution of the structural parameters and structural disturbances, respectively. The posterior means of the intertemporal discount rate β and the elasticity of demand ϵ are 0.989 ad 9.530 and close to their prior mean. The data is also informative about the other parameters, and the posterior estimates are measured quite precisely, with small posterior standard deviations. The model estimates a high degree of nominal price rigidity. The posterior mean of the Calvo parameter ξ is 0.950, and the prior mean is outside the 90 percent credibility interval. This implies an average price duration of 5 years, which is higher than usual estimates. For instance, Smets and Wouters (2007) estimate a Calvo parameter of 0.66. The posterior mean of the matching elasticity σ^m is 0.568. This value is extremely close the one found in Trigari (2009), which is 0.55. It is lower than the posterior mean of 0.74 found in Lubik (2009), but in line with the values found in a survey of the matching function in Petrongolo and Pissarides (2001). The posterior mean of σ^m also suggests that new hires are relatively more sensitive to the pool of unemployed workers than the number of available vacancies. Thus, the job-filling rate q_t is relatively more responsive to labor market tightness x_t than the job-finding rate s_t. Furthermore, this implies that asset prices Q_t are quite responsive to labor market conditions. The coefficient of real wage rigidity φ_r has a posterior mean of 0.558 with a 90 percent credibility interval between 0.476 and 0.638. Thus, the equilibrium real hourly wage puts more weight on the Nash bargaining solution than the wage norm. This suggests that the real hourly wage is quite, if not fully, responsive to economic disturbances. Yet, there is sufficient real wage rigidity that non-negligible adjustments in employment are necessary to equilibrate the labor market. This result is consistent with the literature which argues that empirically real wage rigidity helps explain fluctuations in the labor market (Rogerson and Shimer, 2011), though theoretically there is no consensus on which wage structure best microfounds the wage bargaining process. To the extent that the determination of the equilibrium real wage is misspecified, φ_r is best interpreted as a reduced-form coefficient rather than a full structural parameter. Notwithstanding this difficulty, the estimation provides evidence in support of some form of real wage rigidity.

Estimates of the monetary policy function are different from the prior and portray an active monetary authority. Monetary policy is responsive to both inflation and the output gap, with a posterior mean for the coefficients κ_π and κ_y equal to 1.044 and 0.579, respectively. The posterior mean for the interest-rate smoothness coefficient ρ_r is 0.237. This value is lower than typical estimates found in the literature, though its estimates depend upon the exact specification of the monetary policy rule.

The data is also very informative about the structural disturbances. The posterior means of the standard deviations and autocorrelation coefficients of the structural innovations differ substantially from their prior means. Generally, they are also estimated quite precisely. The TFP shock has posterior means for the parameters σ_A and ρ_A equal to 0.008 and 0.654, respectively. Consistent with the literature, TFP shocks are quite persistent. In the case of shocks to the elasticity of the matching function, σ_ϱ and ρ_ϱ have a posterior mean equal to 0.095 and 0.862, respectively. The matching function is subject to large and long-lasting shocks that affect the responsiveness of new matches, the job-finding and the job-filling rates to labor market conditions. In case of the intertemporal preference shock, the posterior mean for σ_ν is 0.007 and the posterior of ρ_ν is 0.264. For the demand elasticity shock, the posterior means for σ_ζ and ρ_ζ are 0.019 and 0.336, respectively.

Credit supply shocks have a large standard deviation, but display different degrees of persistence. In the case of incentive-constraint shocks, the posterior means for σ_Θ and ρ_Θ are 0.017 and 0.801. These shocks are large and persistent. From an economic point of view, this suggests that technological changes, lax regulation, or poor governance structures within banks can allow bank managers to divert funds, in the form of high bonuses and payouts, for prolonged periods. In contrast, net worth shock have a slightly smaller magnitude, but are much less persistent. In fact, the posterior mean of σ_{NW} is 0.012 and that of ρ_{NW} is 0.056. Although the 90 percent credibility interval for ρ_{NW} does not contain zero, this low value suggests that shocks to net worth may best be interpreted as one-off transfers from financial intermediaries to households. In a model without financial frictions, this transfer would have no effect on the economy. When financial frictions are present, however, even small exogenous declines in net worth have large and persistent effects on the economy. The response of the model to net worth shocks in fact shows the model generates a high intrinsic persistence. On the other hand, monetary policy disturbances are much smaller than financial shocks, but somewhat persistent. The posterior means of σ_ς and ρ_ς equal 0.006 and 0.311, respectively.

Finally, measurement error to output, the real wage, the unemployment rate, labor market tightness, and the nominal interest rate are small. In contrast, the vacancy level and, especially, the inflation rate, have much larger measurement error.

2.5.2 Sensitivity Analysis

To assess the stability of the full-sample estimates, I estimate the model over three different subsamples and compare the corresponding estimates which are shown in Table 2.4. The first two subsamples correspond to the Great Inflation and the Great Moderation and cover the 1964:I-1983:IV and the 1984:I-2007:IV periods, respectively. The third subsample covers the pre-Great Recession 1964:I-2007:IV period, so it excludes the recent financial crisis and its aftermath. Comparing this subsample with the full-sample enables me to assess the impact that the Great Recession has on the full-sample estimates. I do not estimate the model over the Great Recession because of its short sample size.

The estimates of the parameters β, ϵ, and σ^m are similar across all samples. In contrast, the weight on the Nash bargaining solution φ_r is 0.599 in the full sample, 0.456 in the Great Inflation and 0.886 in the Great Moderation. This suggests that the real hourly wage has become more flexible over time.[17] The deregulation of the labor market and the weakening of the unions in the 1980s and 1990s might explain this finding. Unsurprisingly, the Great Recession period affects none of these four parameters. On the other hand, it has a strong impact on the estimate of the Calvo parameter ξ, which is 0.920 in the full sample and 0.246 in the pre-Great Recession subsample. This latter value implies an average price duration

[17] The 99 percent credibility intervals constructed around 0.456 and 0.886 do not overlap.

Table 2.4: Posterior Distribution of Parameters in Subsamples

	Sample period							
	Full Sample		*1964:I-83:IV*		*1984:I-2007:IV*		*1964:I-2007:IV*	
	Mode	*St.Dev.*	*Mode*	*St.Dev.*	*Mode*	*St.Dev.*	*Mode*	*St.Dev.*
Parameter								
β	0.989	0.001	0.990	0.001	0.990	0.001	0.990	0.001
ϵ	9.696	0.478	9.685	0.929	9.912	0.913	10.297	0.396
ξ	0.920	0.028	0.230	0.141	0.252	0.046	0.246	0.033
σ^m	0.606	0.086	0.603	0.117	0.661	0.096	0.614	0.061
φ_r	0.599	0.037	0.456	0.060	0.886	0.070	0.627	0.049
κ_π	1.063	0.082	1.205	0.136	1.259	0.095	1.219	0.058
κ_y	0.989	0.044	0.059	0.168	0.054	0.047	0.561	0.019
ρ_r	0.247	0.047	0.556	0.147	0.588	0.083	0.719	0.065
Standard deviation of structural disturbance								
σ_A	0.008	0.001	0.011	0.001	0.008	0.001	0.008	0.001
σ_ς	0.007	0.001	0.012	0.002	0.011	0.002	0.008	0.001
σ_ϱ	0.083	0.070	0.023	0.002	0.021	0.008	0.060	0.016
σ_ν	0.007	0.001	0.012	0.012	0.010	0.001	0.008	0.001
σ_ζ	0.019	0.002	0.019	0.009	0.023	0.005	0.021	0.02
σ_{NW}	0.013	0.001	0.015	0.003	0.017	0.001	0.013	0.001
σ_Θ	0.016	0.002	0.019	0.008	0.017	0.001	0.017	0.003
AR(1) coefficient of structural disturbance								
ρ_A	0.659	0.035	0.635	0.085	0.691	0.058	0.688	0.044
ρ_ς	0.564	0.053	0.269	0.089	0.235	0.071	0.241	0.055
ρ_ϱ	0.859	0.022	0.534	0.152	0.597	0.097	0.842	0.034
ρ_ν	0.264	0.034	0.244	0.097	0.195	0.059	0.179	0.063
ρ_ζ	0.336	0.059	0.480	0.151	0.705	0.107	0.549	0.057
ρ_{NW}	0.055	0.008	0.073	0.018	0.051	0.009	0.056	0.007
ρ_Θ	0.837	0.074	0.591	0.133	0.702	0.119	0.802	0.126
Standard deviation of measurement error								
σ_{e^y}	0.008	0.001	0.011	0.002	0.008	0.001	0.008	0.001
σ_{e^w}	0.013	0.001	0.010	0.001	0.013	0.001	0.012	0.001
σ_{e^V}	0.138	0.009	0.150	0.017	0.112	0.012	0.135	0.008
σ_{e^u}	0.006	0.001	0.009	0.001	0.007	0.001	0.006	0.001
σ_{e^x}	0.014	0.003	0.020	0.009	0.017	0.005	0.015	0.003
σ_{e^π}	0.247	0.014	0.286	0.036	0.167	0.016	0.209	0.014
σ_{e^i}	0.006	0.05	0.008	0.001	0.007	0.001	0.006	0.001

of slightly less than two quarters, which is more in line with microeconometric estimates in Bils and Klenow (2004) who find an average price duration of half a year. Downward nominal price rigidities operating during the Great Recession and preventing prices to adjust downwards might explain why a much higher average price duration is estimated in the full sample.

The Great Recession also has an impact on the estimates of the monetary policy coefficients. Including the post-2007 period lowers the responsiveness of the Fed to inflation κ_π from 1.219 to 1.063, increases the responsiveness to the output gap κ_y from 0.561 to 0.989, and lowers the degree of interest rate smoothness from 0.719 to 0.247. Although I cannot compute credibility intervals around these point estimates because the samples overlap, the Great Recession seems to affect κ_y and ρ_r substantially.

This evidence points to a change in the manner the Fed has managed the economy since 2008. To achieve its dual mandate, and facing the largest output fall since the Great Depression, the Fed became much more responsive to the output gap and placed less weight on deviations of inflation from target. In line with this, the Fed also abandoned its tendency to smooth interest rates in order to respond more strongly to contemporaneous economic conditions. When the Fed smooths interest rates, monetary policy works mostly via the term structure of interest rate. As the Fed lost its ability to influence expectations of future short-term rates during the crisis, its policy became more focused on influencing the current short-term rate. Finally, comparing the point estimates of κ_π and κ_y in the 1964:1983 and 1984-2007 subsamples suggests that the Fed was only marginally more aggressive towards inflation during the Great Moderation than before.

The estimation of the structural shocks is robust across the subsamples. There are little differences between the Great Inflation and Great Moderation subsamples, but they are mostly within the 95 percent credibility intervals. These findings, coupled with the evidence about the changes in the monetary policy rule coefficients, lend support to the *good policy* story about the Great Moderation. Similarly, the Great Recession has a small effect on the properties of the structural shocks apart from the monetary policy disturbance. It is somewhat surprising that the inclusion of the Great Recession period does not affect the volatility of the two financial shocks. The lack of financial variables among the observables may explain this result.

2.5.3 Transmission of Aggregate Shocks

Having shown and discussed the estimates for the full model in detail, I now analyze the response of the economy to different shocks to answer the following questions: can the banking sector be a source of business cycle fluctuations? How are financial shocks originating in the banking sector transmitted to the real economy? Can the banking sector amplify macroeconomic shocks originating elsewhere in the economy?

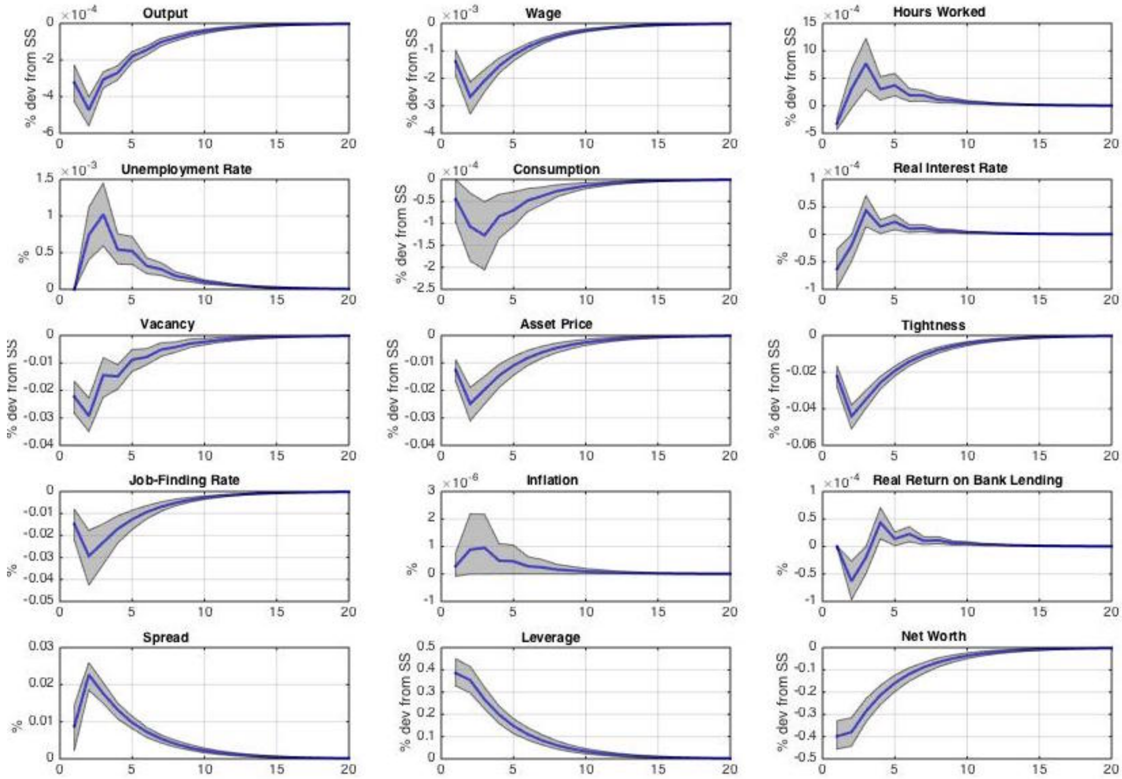
2.5.3.1 Response to Contractionary Credit Market Shocks

To now examine the role of the banking sector as a source of business cycle fluctuations, I study the dynamic response of the model to financial disturbances. This analysis highlights the role the financial sector's net worth plays in the transmission of shocks, and the strong propagation mechanism that financial frictions may generate.

Figure 2.1 shows the estimated impulse response function to a negative net worth shock. This amounts to a transfer from bankers to households at the beginning of the period. This transfer immediately tightens the incentive constraint bankers face. Since bankers can raise fewer funds, in equilibrium more arbitrage opportunities remain unexploited and the interest rate spread rises, increasing borrowing costs for firms. This reduces firms' expected profits and their incentive to create vacancies, decreasing congestion on the demand side of the labor market. Tightness falls, and every individual firm finds it easier to fill up its vacancies. Hence, the expected savings from hiring a worker are lower, reducing the value of an employed worker.

In this economy, there is a one-to-one mapping between the value of employed workers and financial asset prices. As asset prices fall, financial intermediaries experience an unexpected loss in their portfolio. This endogenous effect further tightens the incentive constraint, resulting in an even larger increase in the interest rate spread and borrowing costs for firms. This further squeezes firms' expected

Figure 2.1: Response to a Contractionary Net Worth Shock

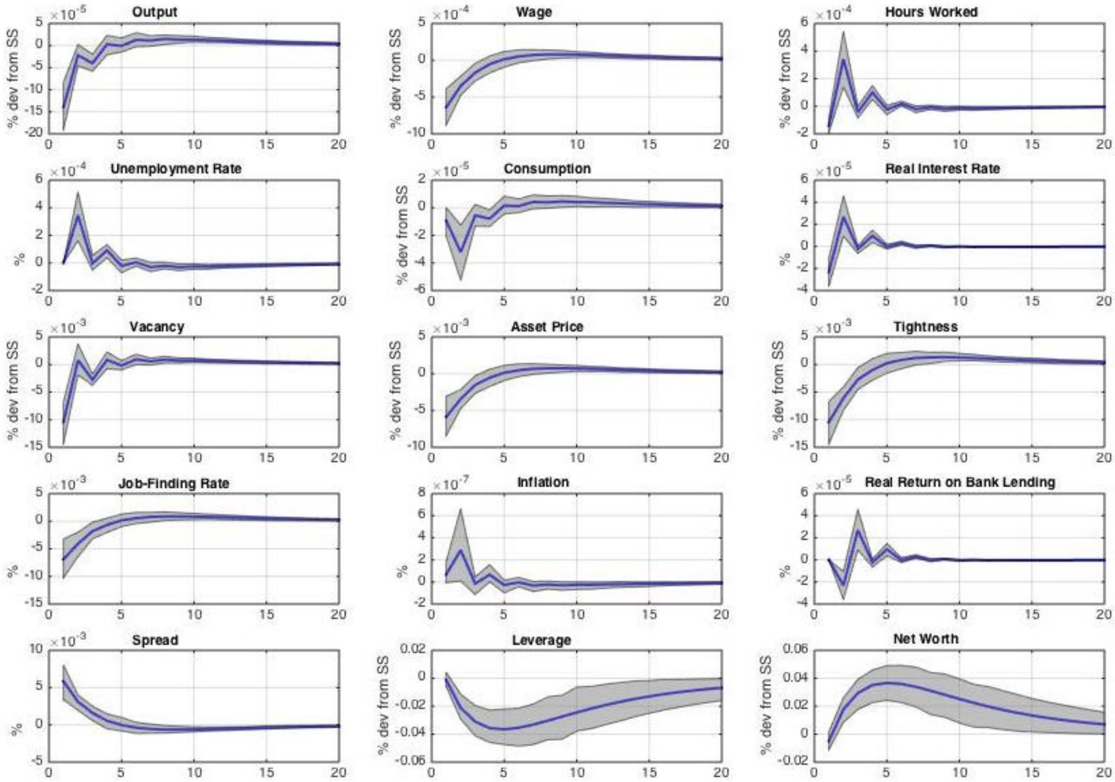


The blue line is the median response. The grey area is the 90 percent credibility interval.

profit and additionally reduces their incentive to post vacancies, leading to a second round of falling asset prices. The increase in unemployment reduces output, the real hourly wage, and consumption. Because the tighter incentive constraint also reduces the incentive for households to save into financial intermediaries, consumption falls relatively less than output, so this negative financial shock is inflationary.

Over time, banks can re-build their net worth through retained earnings and deleverage. As the incentive constraint for banks loosens, borrowing costs fall and profit margins for firms rise, increasing the incentive to post vacancies and hire again. In equilibrium, the initial fall in net worth is much larger than the initial exogenous transfer because of the endogenous fall in asset prices. More strikingly, the model has a strong internal propagation mechanism. With an autocorrelation coefficient of 0.055, the half-life of the exogenous impulse is 0.23 quarters. However, the half-life of net worth is about 5 quarters, and overall it takes about 12 quarters for the

FIGURE 2.2: RESPONSE TO A CONTRACTIONARY INCENTIVE-CONSTRAINT SHOCK



The blue line is the median response. The grey area is the 90 percent credibility interval.

effects of the shock to dissipate. Because it takes time for financial intermediaries to re-build their own net worth, the shock has long-lasting effects on the economy even if it has very little persistence.

Figure 2.2 shows how the economy reacts to a different type of financial shock, namely an exogenous increase in the bankers' ability to divert funds. Overall, the response of the goods and labor markets to an incentive-constraint shock are very similar to a negative net worth shock, while the response of financial markets is quite different. The shock immediately tightens the incentive constraint. To raise funds from households, bankers are forced to accumulate net worth and lower their leverage ratio. In contrast to a negative net worth shock, leverage and net worth follow a hump-shaped response since, when the shock dissipates, banks can reduce net worth and raise leverage again. The rise in the interest rate spread reduces firms' expected profits and their incentive to post vacancies, leading to higher unemployment and lower asset prices.

While qualitatively the labor market response is similar for both types of credit supply shocks, the quantitative response is much weaker following a contractionary incentive-constraint shock. The rise in net worth prevents the model from generating the strong propagation effects discussed before. It is the persistence of the exogenous impulse, with a half-life of 3 quarters, that explains the long-lasting effects of the shock. If the original shock had no persistence, its real effects would be much more short-lived.

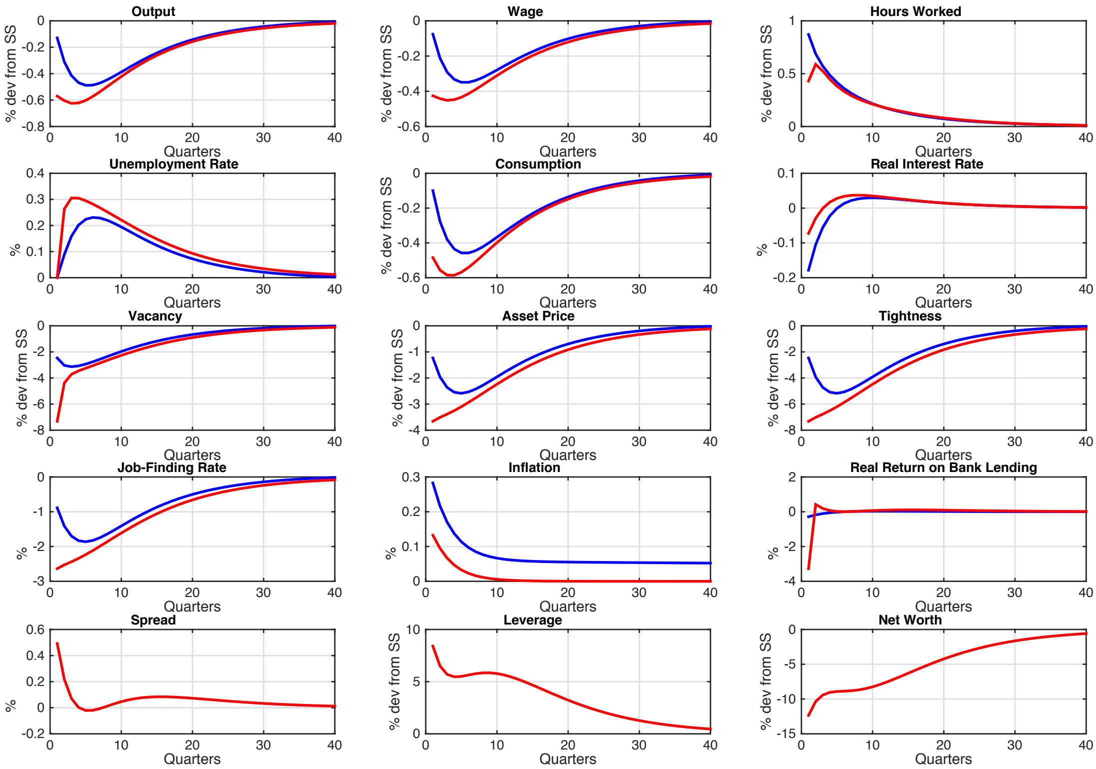
2.5.3.2 Response to a Contractionary TFP shock

In this section I examine how the financial sector amplifies the effect of a shock originating in the real economy. This effect reflects the interaction between vacancy-creation and the process of net worth accumulation, in particular the feedback effect from the financial to the real sector. Figure 2.3 compares the effect of a 1 percent negative TFP shock in the models with and without a banking sector. For this analysis I employ the model calibrated at the prior mean to use the same parameterization. Changes in the dynamic response of the economy are solely due to the presence of financial frictions in the banking sector. The shock is temporary, but persistent, with a quarterly autoregressive coefficient equal to 0.90.[18]

Generally, the economy experiences a sharper response on impact when financial frictions exist. In their absence, the hump-shaped responses are less pronounced. For instance, households are able to achieve a greater degree of consumption smoothing because markets are complete. In the labor market, financial frictions double the impact at the extensive margin and halve the response at the intensive margin, explaining the larger fall in output and consumption. The technological shock is associated with a persistent fall in the marginal product of labor per hour worked. In both models, this reduces firms' profits and their incentive to post vacancies, lowering the job-finding rate for unemployed workers and thus increasing unemployment as a constant flow of workers loses their job. While it is optimal for individual firms to reduce vacancy-creation, this creates an

[18]The size and persistence of the shock are higher than those estimated in the previous section, but are consistent with typical values used in the literature.

Figure 2.3: Response to a Contractionary Technology Shock With and Without Financial Frictions



The blue line is the response in the model without the banking sector. The red line is the response of the model with the banking sector.

externality in the labor market. The fall in labor market tightness makes it easier for all firms to fill up their empty vacancies, reducing the expected savings from hiring a worker and lowering the value of an employed worker. The interaction between the real and the financial sector can indeed explain why the negative shock has a larger impact in the model with financial frictions.

As asset prices fall, financial intermediaries experience an expected loss in their portfolio. This decreases the financial sector's net worth and tightens the incentive-compatibility constraint. As bankers can raise fewer funds from households, their demand for financial assets decreases, causing a further fall in asset prices, and increasing the interest rate spread. Hence, there is a feedback effect from the financial to the productive sector. In order to borrow, firms must promise to repay a larger rate of return above the riskless rate. This further reduces firms' expected profits and their incentive to post vacancies. Vacancy-creation falls further, and so do asset prices. This results in additional unexpected losses in the intermediaries' balance sheet and a tightening of the incentive constraint.

In equilibrium, vacancy-creation falls by 3 percent in the restricted model, and by 7 percent in the full model. The fall in asset prices is almost twice as large in the latter model and corresponds to a 12 percent fall in the financial sector's net worth. Similarly, the unemployment rate peaks at 10.2 percent in the frictionless model and at 10.4 percent when financial intermediaries are constrained. Since job-separation is exogenous, the rise in the unemployment rate is entirely due to the fall in the job-creation rate. Moreover, since the productivity shock lowers the marginal product per hour worked, workers find it optimal to exert more effort at the intensive margin to counteract the negative shock and smooth their consumption. This effect is larger when financial markets are complete. In terms of wage dynamics, workers experience a larger fall in the real wage in the model with financial frictions because the larger drop in the job-finding rate lowers household's bargaining power in the wage negotiation process.

Over time, as the effects of the shock dissipate and workers regain their productivity, banks re-build their net worth through retained earnings. Banks can deleverage and the incentive constraint becomes less tight. As firms experience falling borrowing costs and rising workers' productivity, their expected profits rise. Hence, they start hiring again and unemployment slowly returns to its long-run level.

2.5.4 Applications

Having shown the dynamic response of the model to some exogenous disturbances, and discussed the internal amplification the model generates, I now address a number of key questions about the US labor market: can the model replicate volatility of the unemployment rate, the vacancy level, labor market tightness, real wages, and real output? Can it replicate their cross-correlation? What are the main driving forces of these key labor market variables? To answer these questions I use the estimated model and detrend the endogenous variables using an HP-filter with smoothing parameter equal to 1,600 to treat the model variables as the data.

Moreover, I focus on the volatility, cross-correlation, and forecasting error variance decomposition of the endogenous variables rather than the observables. The endogenous variables with no measurement error are the economic variables of interest because they enter the agents' optimization decisions. In fact, if there were no measurement error, the endogenous and observable variables, and their corresponding moments, would be the same. Since there is measurement error, I am essentially asking what theoretical moments the model generates.

2.5.4.1 How Much Volatility Can the Model Replicate?

Table 2.5 shows the empirical standard deviation, autocorrelation coefficient, and cross-correlation coefficients of the labor market variables of interest along with the corresponding theoretical moments the DSGE model at the posterior mode predicts. Overall, the model generates too little volatility compared with the data. The unemployment rate is half as volatile, while the standard deviation of the vacancy stock is one order of magnitude smaller as in the data. The model also captures 60 percent of the volatility in labor market tightness and 67 percent of the volatility in the real wage, and an even larger proportion of the volatility in real output and productivity. In terms of autocorrelation, the model predicts lower persistence for all labor market variables, particularly for the unemployment rate and the vacancy stock. Lastly,the model predicts the correct sign for all the correlation coefficients between these key labor market variables. The magnitudes, however, often differ substantially. For instance, the model predicts a much flatter Beveridge curve than the one observed in the data.

Compared to other models in the literature, the model I estimate performs relatively less well in replicating the volatility and cross-correlation of labor market variables. Since Shimer (2005a) showed that the standard random search model can only account for 10 percent of the observed business cycle fluctuation in unemployment given labor productivity shocks of plausible magnitude, several

Table 2.5: Descriptive Statistics of Labor Market Variables, US Quarterly Data

	Variable					
	u	V	x	A	w	y
	Panel I: Standard deviation					
Data	0.0081	0.1374	0.2551	0.0114	0.0108	0.0111
Model	0.0040	0.0094	0.1551	0.0092	0.0073	0.0085
	Panel II: AR coefficient					
Data	0.941	0.937	0.944	0.784	0.787	0.773
Model	0.205	0.144	0.706	0.515	0.551	0.452
	Panel III: Cross-correlation coefficients					
	(a) Data					
u	1	-0.914	-0.963	-0.076	-0.048	-0.593
V	-	1	0.983	0.198	0.105	0.565
x	-	-	1	0.148	0.094	0.576
A	-	-	-	1	0.495	0.346
w	-	-	-	-	1	0.374
y	-	-	-	-	-	1
	(b) Model					
u	1	-0.327	-0.549	-0.195	-0.470	-0.330
V	-	1	0.540	0.303	0.543	0.466
x	-	-	1	0.419	0.871	0.631
A	-	-	-	1	0.605	0.722
w	-	-	-	-	1	0.927
y	-	-	-	-	-	1

US data and model theoretical moments are de-trended using an HP-filter with a smoothing parameter equal to 1,600. Model at the estimated posterior mode used to calculate theoretical moments.

mechanisms have been proposed to address this empirical puzzle. While the model I propose performs better than the standard random search model, financial frictions per se are not sufficient to replicate the moments observed in the data. These findings are within the range of results found in the literature on search and matching frictions. Papers that achieve this typically include additional frictions such as habits in consumption or adjustment costs. They also assume a much more detailed vacancy cost structure or wage determination process to make the real wage less sensitive to exogenous disturbances. For instance, Hall and Milgrom (2008) propose an equilibrium wage based on an alternating bargaining offer model to reduce the responsiveness of the wage. Petrosky-Nadeau (2014) uses this mechanism, along with convex vacancy costs, to replicate the volatilities and cross-correlations observed in the data. Since the model I propose does not feature any of the typical bells and whistles used to improve the matching of cross-correlations among labor market variables, the model predictions seem reasonable.

2.5.4.2 What Explains the Volatility of the Labor Market Variables?

In this section I examine the contribution of each structural disturbance to the forecasting variance of the labor market variables. Figure 2.4 shows the forecasting variance decomposition of the unemployment rate, the vacancy level, labor market tightness, real output per worker, and the real hourly wage at the posterior mode shown in Table 2.3 for different forecasting horizons.[19] This is the mean of the FEVD values over all parameter draws.

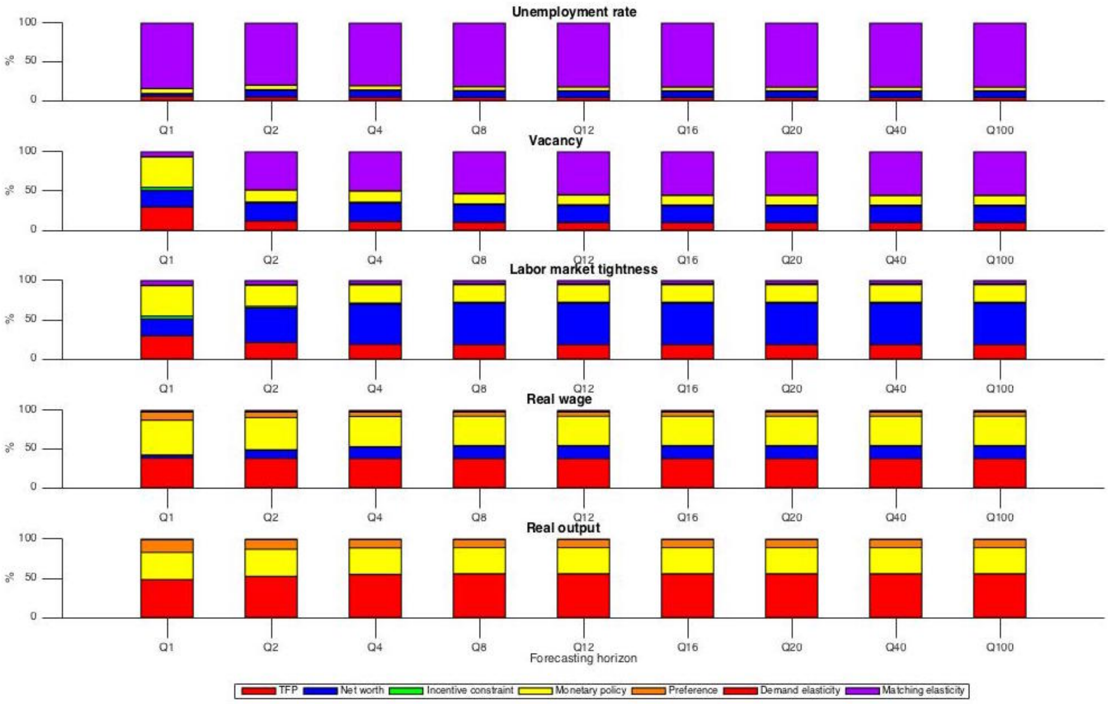
Overall, net worth shocks play an important role in explaining the volatility in u_t, V_t, and x_t, but have little explanatory power for w_t and y_t. Since y_t is real income per capita, other factors entering the production function affect fluctuations in this variable. This explains why net worth shocks play an important role for u_t but not for y_t. On the other hand, the incentive-constraint and the demand elasticity shocks play a negligible role in accounting for labor market fluctuations.

The unemployment rate and the vacancy stock are driven mostly by the matching elasticity shock. This disturbance explains about 80 percent of the volatility in the unemployment rate at all horizons, and about 55 percent of the volatility of the vacancy stock in the medium and long run. The net worth shock plays a marginal role in explaining the volatility of the unemployment rate, about 9 percent, but accounts for more than 20 percent of the volatility in the the vacancy stock at all horizons. Lastly, TFP and monetary shocks account for most of the contemporaneous volatility in the vacancy stock, but their combined contribution falls to a quarter in the medium run and 21 percent at longer horizons.

The net worth shock is the single most important factor for explaining the volatility of labor market tightness. It accounts for 22 percent of the contemporaneous

[19]By construction, productivity is fully explained by the TFP shock.

Figure 2.4: Conditional Forecasting Variance Decomposition of Labor Market Variables



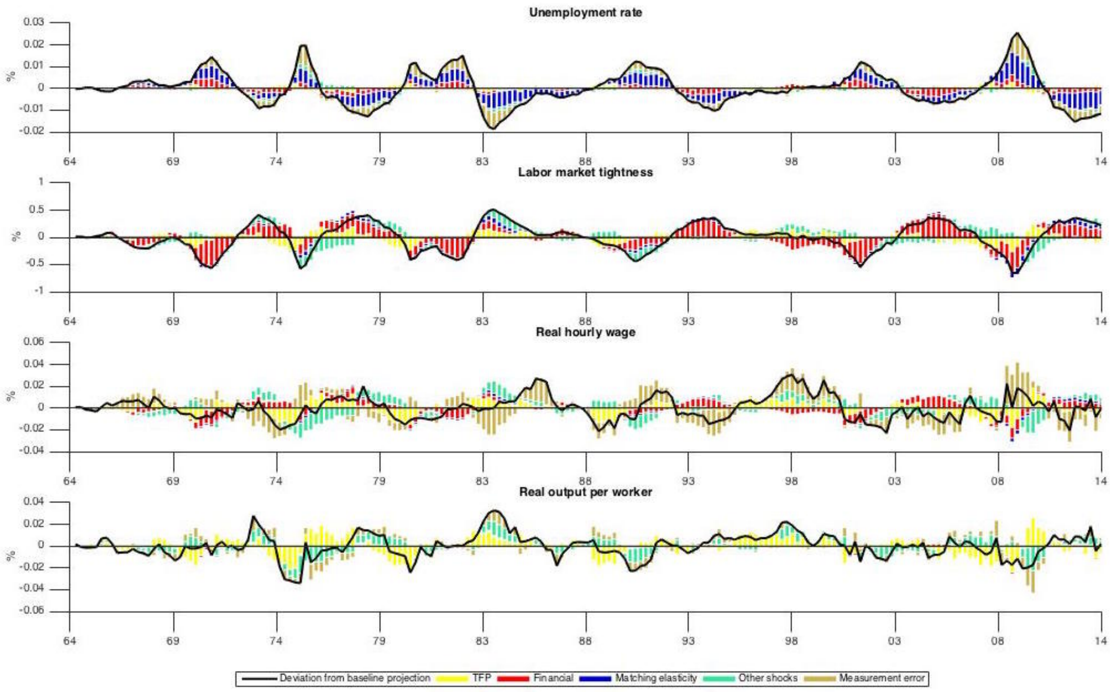
Mean forecasting variance decomposition over all parameter draws and de-trended using an HP-filter with a smoothing parameter of 1,600.

volatility, 44 percent at two quarters, and 51 percent for longer horizons. TFP and monetary policy shocks are important drivers of the volatility in labor market tightness in the short-run, but their role becomes less prominent at longer horizons. TFP and monetary policy shocks also explain most of the volatility in the real hourly wage at all horizons. Net worth shocks play a less important role, but they account for a sizable 17 percent of the volatility of the real wage in the medium and long run. Finally, TFP shocks explain most of the volatility in real output at all horizons. Monetary policy shocks, and to a lesser extent preference shocks, explain the remaining volatility.

2.5.4.3 What Caused Fluctuations in the US Labor Market Between 1964 and 2013?

Figure 2.5 shows the historical contribution of the structural shocks to the observed unemployment rate, labor market tightness, the real hourly wage and real hourly

Figure 2.5: Historical Decomposition: 1964:2013



Historical decomposition calculated at the posterior mode and de-trended using an HP-filter with a smoothing parameter of 1,600.

output in the non-financial sector over the sample period. I do not show the results for the vacancy stock since it is mostly driven by measurement error. To improve readibility, I combine net worth and incentive-constraint shocks into a single "credit supply disturbance". I also combine monetary policy, demand preference, and elasticity of demand shocks into a single "other" disturbance.

This analysis echoes the findings of the previous section. Credit supply shocks have historically played some role in explaining fluctuations in the unemployment rate and the real hourly wage, a major role in determining labor market tightness, and almost no role in accounting for fluctuations in real output per worker. Shocks to the elasticity of the matching function account for most of the rise in the unemployment rate during the past six recessions.

Credit supply shocks generally play a minor role during the first part of the sample, but their relative importance has risen over time. Credit expansion is associated with a fall in the unemployment rate during the mid-1990s and mid-2000s booms and with a rise in the unemployment rate in the late 1990s recession and in the most recent Great Recession. Tighter credit conditions account for most of the reduction in labor market tightness in all recessions since 1964. Similarly, strong credit growth accounts for most of the rise in tightness during economic expansions, particularly the most three recent booms. This suggests the importance of credit supply shocks in determining labor market tightness has increased over time.

2.6 Conclusion

I have built a New Keynesian DSGE model with search frictions in the labor market and moral hazard between financial intermediaries and depositors. This links the hiring decision of non-financial firms to the financial state of the banking sector. A deterioration in the balance sheet of financial intermediaries makes hiring more expensive and reduces employment. This is in contrast with the growing literature on financial and labor market frictions which has exclusively focused on incentive problems and information asymmetries on non-financial corporations, which is on the demand side of the credit market. I have also estimated the model via Bayesian likelihood techniques using US data and a set of labor market variables as observables. I find that including a banking sector in a standard New Keynesian random search model improves the empirical fit with the data.

The model could be extended to allow for the introduction of physical capital or some of these abovementioned frictions to improve the cross-correlation between the model predictions and the data. Furthermore, financial variables such as the banking sector's net worth, its leverage, or the real rate of return on bank lending could be included among the set of observables to improve the precision of the estimates. Finally, the assumption of an exogenous separation rate could also be relaxed. Allowing for endogenous separation rate would help determine whether financial shocks affect the inflow rate into unemployment.

I have shown that the presence of financial frictions amplifies the impact of non-financial shocks. The interaction between vacancy-posting behavior and net worth accumulation is responsible for this effect. Unlike models where firms suffer from incentive problems, shocks are propagated via intermediaries' net worth. A negative shock leads to an unexpected capital loss on the intermediaries' balance sheet, which tightens the incentive constraint and widens the interest rate spread. As borrowing becomes more expensive, firms are forced to cut hiring and reduce employment. The additional fall in asset prices has a feedback effect on intermediaries' net worth, magnifying the impact of the initial shock.

Financial frictions also generate a strong internal propagation mechanism. Any negative shock reduces the net worth of the banking sector. Since it takes time for financial intermediaries to restore their own net worth and loosen the incentive constraint they face, even short-lived shocks have long-lasting effects in the model. For instance, the effects of a one-off reduction in net worth take about twelve quarters to dissipate. This mechanism also operates when other types of exogenous disturbances affect the economy because of the endogenous fall in net worth due to lower asset prices.

The banking sector can also be a source of business cycle fluctuations. Net worth shock can explain 8 percent of the volatility in the unemployment rate, 20 percent of the volatility in the vacancy stock, half of the volatility in labor market tightness, and 17 percent of the volatility in the real hourly wage. Shocks to the elasticity of the matching function explains most of the fluctuations in the unemployment rate and the vacancy stock. TFP and monetary policy shocks can account for the remaining variance in labor market tightness, and they are also the main drivers of the real hourly wage and real output. In contrast, incentive-constraint shocks and shocks to the elasticity of demand play a negligible role in explaining fluctuations in labor market variables. Overall, net worth shocks are an important determinant of the volatility of labor market variables. Thus, the financial state of the banking sector matters for labor market fluctuations.

In terms of volatility, persistence, and cross-correlations of the labor market variables, the model performs less well relative to the data and compared to other models in the literature. The lack of additional frictions, such as consumption habits and adjustment costs, and the simple labor market structure, with linear vacancy costs and rigid wages, may explain these results. Given the absence of all the features typically used to improve the empirical fit of the estimation and the matching of cross-correlations among labor market variables, the model predictions are reasonable and in line with the literature.

2.7 Appendix

2.7.1 Derivation of the Wage Schedule

Formally, in Nash bargaining the hourly wage rate w_t solves the following problem:

$$w_t = \text{ argmax } (\vartheta_t^H)^{\gamma_w} (\vartheta_t^F)^{1-\gamma_w} \tag{2.63}$$

where $\gamma_w \in (0, 1)$ is a measure of the worker's bargaining power, ϑ_t^H is the surplus accruing to the household, and ϑ_t^F is the surplus accruing to the firm. The necessary first-order condition for this problem is:

$$\gamma_w \vartheta_t^F = (1 - \gamma_w)\vartheta_t^H \tag{2.64}$$

Let $\vartheta_t^J \equiv \frac{\partial \Omega_t}{\partial l_t}$ be the value of an existing job and $\vartheta_t^V \equiv \frac{\partial \Omega_t}{\partial V_t}$ the value of a vacancy to the firm. The current flow of an existing job is given by the marginal product of labor $p_t^M A_t hr_t$ net of the real wage $w_t hr_t$. The continuation value is ϑ_{t+1}^J if the job survives, and zero if the match is dissolved. The corresponding Bellman equation is:

$$\vartheta_t^J = p_t^M A_t hr_t - w_t hr_t + E_t \left\{ \Lambda_{t,t+1}(1 - \psi)\vartheta_{t+1}^J \right\} \tag{2.65}$$

The cost of posting an additional vacancy is κ. With probability $q(x_t)$ the vacancy is filled, while with probability $1 - q(x_t)$ it remains vacant:

$$\vartheta_t^V = -\kappa + E_t \left\{ \Lambda_{t,t+1} \left[q_t \vartheta_{t+1}^J + (1 - q_t)\vartheta_{t+1}^V \right] \right\} \tag{2.66}$$

Free-entry ensures that in every period intermediate goods firms will post vacancies until the value of the marginal vacancy is driven to zero. Hence, the marginal cost of an additional hire must equal its expected discounted value:

$$\frac{\kappa}{q_t} = E_t \left[\Lambda_{t,t+1} \vartheta_{t+1}^J \right] \tag{2.67}$$

which simply reformulates the job-creation condition in a slightly different way. Combining (2.65) and (2.67) I can find an expression for the value of the an existing jobs in terms of current variables:

$$\upsilon_t^J = \vartheta_t^F = p_t^M A_t hr_t - w_t hr_t + (1 - \psi)\frac{\kappa}{q_t} \tag{2.68}$$

The value of an existing job is the realized cash flow value plus the capital gain of remaining employed next period. This also equals the surplus from an existing relationship ϑ_t^F to the firm.

The surplus for a household is given by the difference between the marginal value of an employed worker, ϑ_t^W and the marginal value of an unemployed worker ϑ_t^U to the household:

$$\vartheta_t^H \equiv \vartheta_t^W - \vartheta_t^U \tag{2.69}$$

The value of an employed worker for the household is given by the wage net of his marginal disutility from labor plus its expected continuation value. With probability ψ the worker loses his job and with probability $1-\psi$ he retains it:

$$\vartheta_t^W = w_t hr_t - \chi \frac{hr_t^{1+\omega_w}}{1+\omega_w} c_t + E_t \left\{ \Lambda_{t,t+1} \left[(1-\psi) \left(\vartheta_{t+1}^W - \vartheta_{t+1}^U \right) + \vartheta_{t+1}^U \right] \right\} \tag{2.70}$$

The value of an unemployed worker for the household is just the expected discounted gain of remaining unemployed or moving into employment.

$$\vartheta_t^U = E_t \left\{ \Lambda_{t,t+1} \left[s_t \left(\vartheta_{t+1}^W - \vartheta_{t+1}^U \right) + \vartheta_{t+1}^U \right] \right\} \tag{2.71}$$

It follows that the surplus for the household is:

$$\vartheta_t^H = w_t hr_t - \chi \frac{hr_t^{1+\omega_w}}{1+\omega_w} c_t + E_t \left\{ \Lambda_{t,t+1} \left[(1-\psi-s_t) \vartheta_{t+1}^H \right] \right\} \tag{2.72}$$

From the Nash-bargaining optimality condition, I can substitute the household's surplus with the firm's surplus:

$$\gamma_w \upsilon_t^F = (1-\gamma_w) \left(w_t - \chi C_t l_t^{\omega_w} \right) + \gamma_w E_t \left\{ \Lambda_{t,t+1} \left[(1-\psi-s(x_t)) \upsilon_{t+1}^F \right] \right\} \tag{2.73}$$

Using (2.65) and rearranging:

$$w_t^{NASH} \equiv w_t = \gamma_w \left(p_t^M A_t + x_t \frac{\kappa}{hr_t} \right) + (1-\gamma_w) \chi c_t \frac{hr_t^{\omega_w}}{1+\omega_w} \tag{2.74}$$

This is the hourly wage rate w_t^{NASH} resulting from bargaining when there are no real wage rigidities.

2.7.2 Data Description

I primarily use data from the Bureau of Labor Statistics (BLS), including real disposable personal income per capita (series A229RX0Q048SBEA) as a measure of real GDP, real output per hour in the non-financial sector (series PRS88003093) as a measure of productivity, real hourly compensation in the non-financial sector (series PRS88003153) as a measure of real wages, the total non-farm unemployment rate for the 16+ population (series LNS14000000), and the Price All Items Index for All Urban Consumer (series CPIAUCSL) to calculate the inflation rate. I use the Composite Help-Wanted Index as a measure of the vacancy stock (Barchinon, 2010). I also use this series, together with the stock of total non-farm civilian unemployed (series LNS13000000) from the BLS, to calculate labor market tightness. Finally, I use the Federal Funds Rate from the Federal Reserve Board of Governors as a measure of the short-term policy rate.[20]

When the original series are measured monthly, I take quarterly averages. Moreover, I de-trend all variables with a one-sided HP filter to obtain a stationary time-series.[21] The measurement equations of this system are:

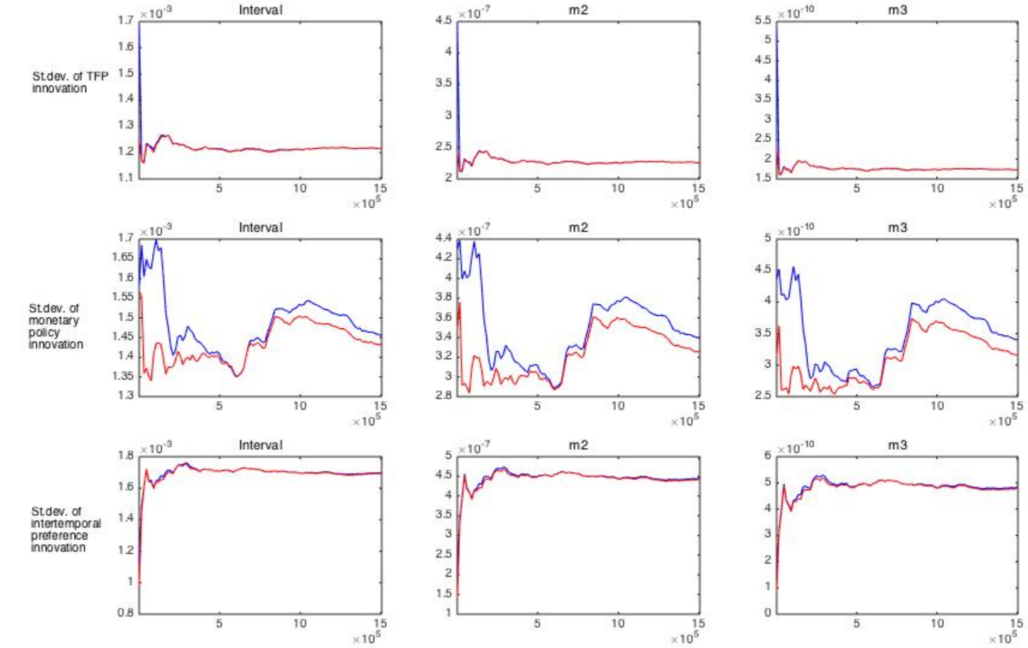
$$Y_t^{OBS} = \begin{bmatrix} log(GDP_t) \\ log(PROD_t) \\ log(WAGE_t) \\ log(VAC_t) \\ log(TIGHT_t) \\ 100 * log(INF_t) \\ 1 + \frac{FEDFUNDS_t}{4} \\ UNEMP_t \end{bmatrix} = \begin{bmatrix} y_t \\ A_t \\ w_t \\ V_t \\ x_t \\ \pi_t \\ i_t \\ u_t \end{bmatrix} + \begin{bmatrix} e_t^y \\ \\ e_t^w \\ e_t^V \\ e_t^x \\ e_t^\pi \\ e_t^i \\ e_t^u \end{bmatrix} \tag{2.75}$$

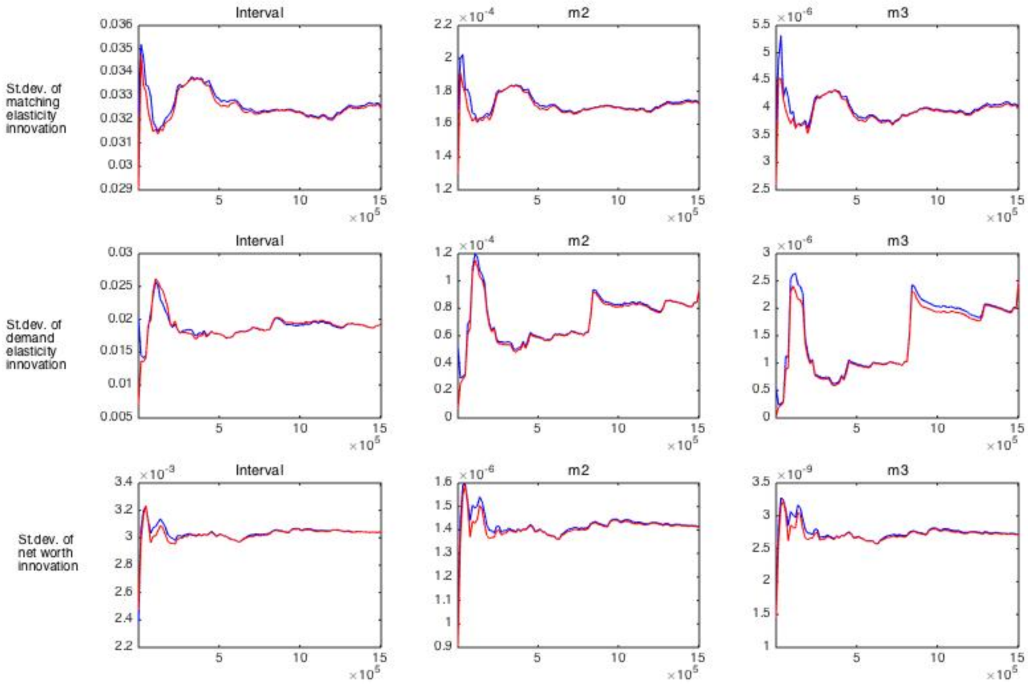
where the second column vector on the right-hand side contains the model's endogenous variables (in deviation from the steady-state), and the second column vector contains white noise measurement errors.

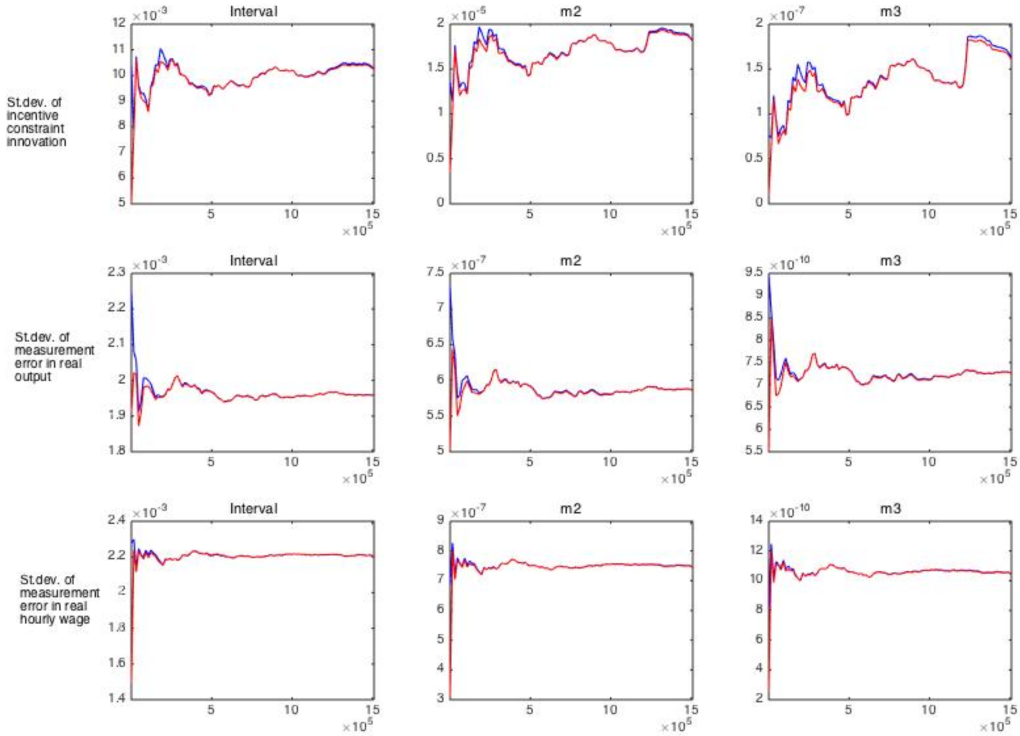
[20]Since December 2008, the Federal Funds Rate is at its effective zero lower bound. This constraint may be problematic during the estimation phase. As a robustness control, I re-estimate the model using data up to 2007:IV to exclude the Great Recession period. The results of this exercise are robust.

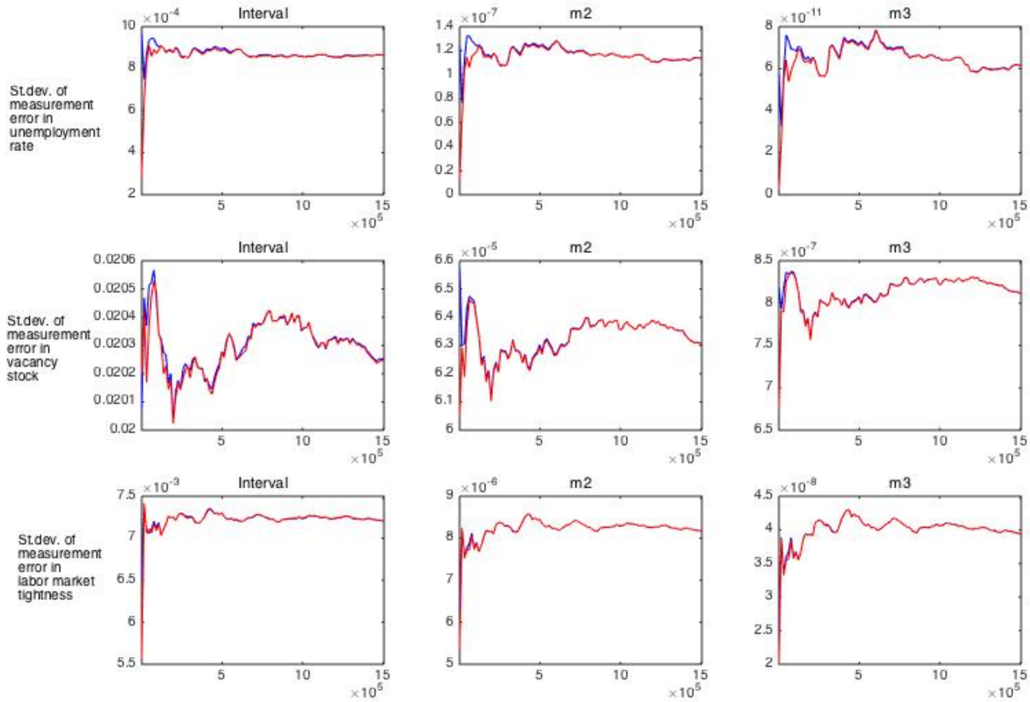
[21]The filtered series is asymptotically zero-meaned. In small samples, the series may have a non-zero mean. Hence, I subtract the sample mean from the filtered series to obtain a zero-meaned series of observables.

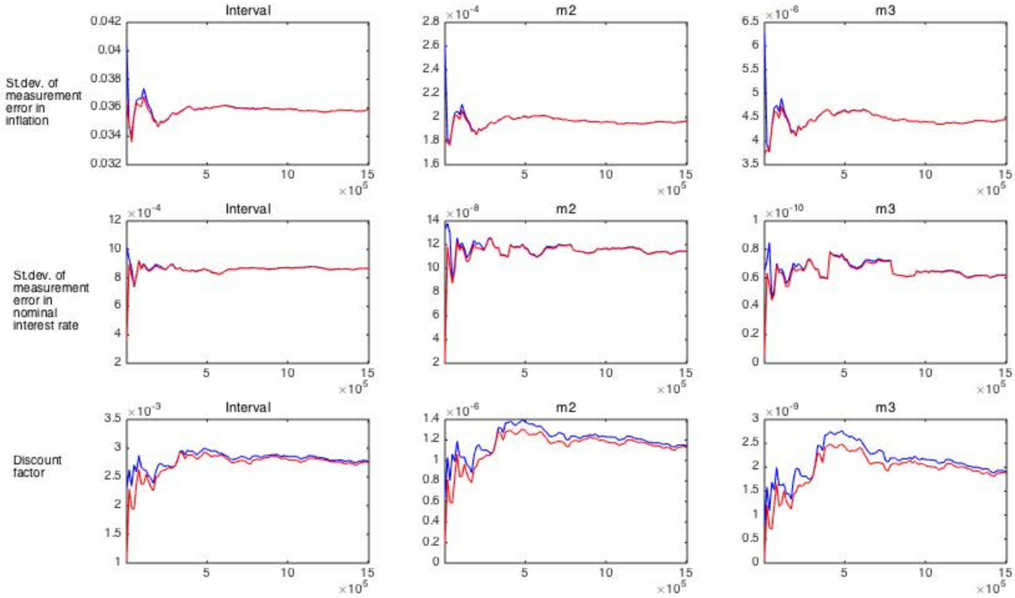
2.7.3 Convergence Diagnostic Statistics

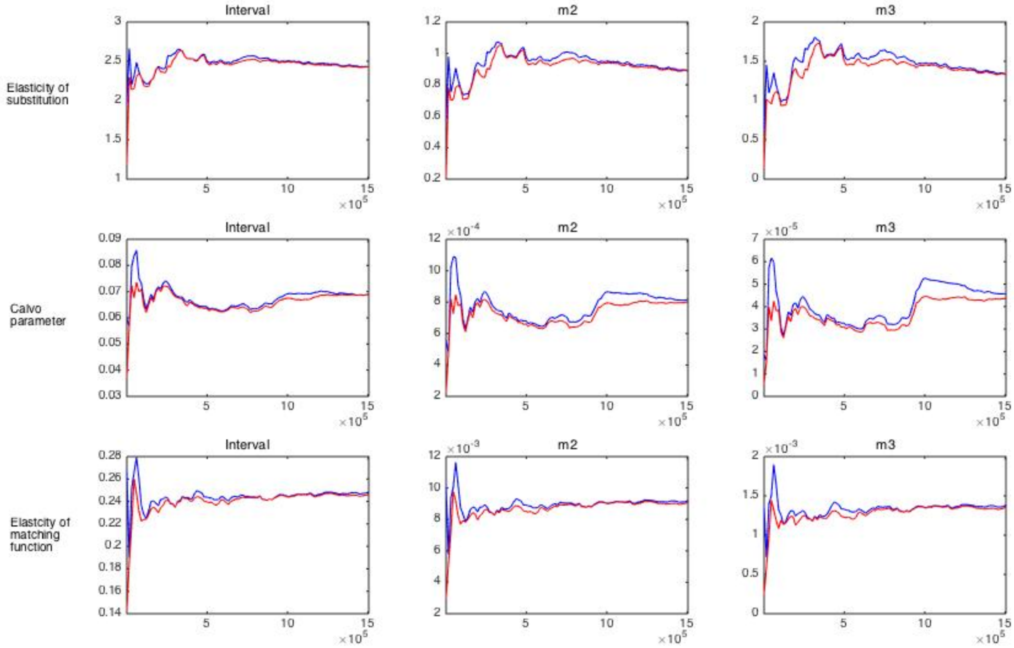


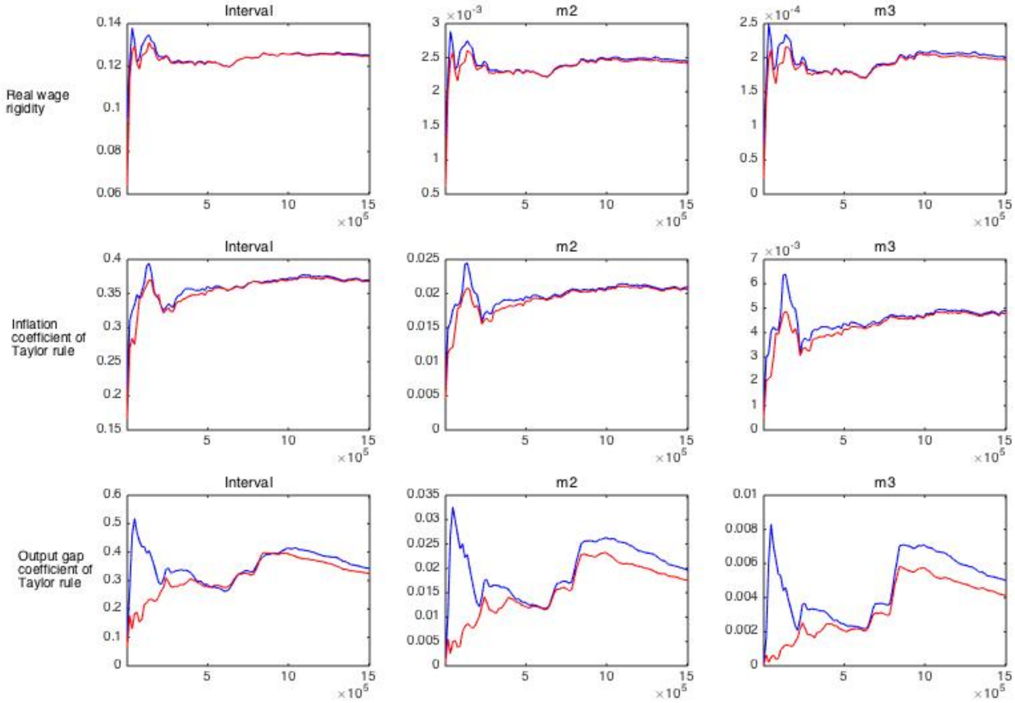


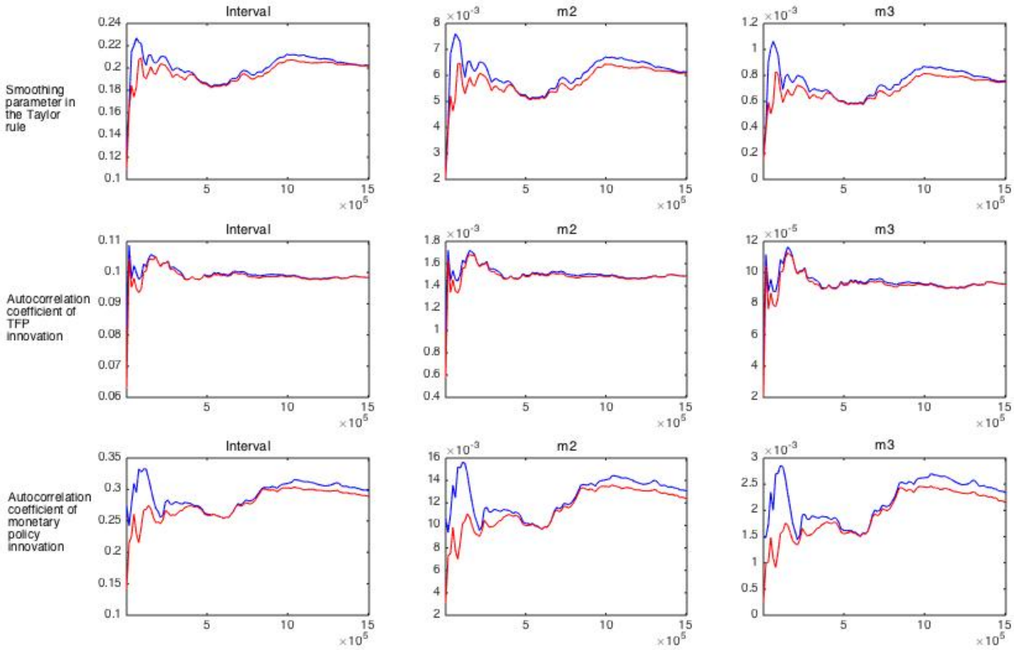

Interval
m2
m3
St.dev. of incentive constraint innovation
St.dev. of measurement error in real output
St.dev. of measurement error in real hourly wage

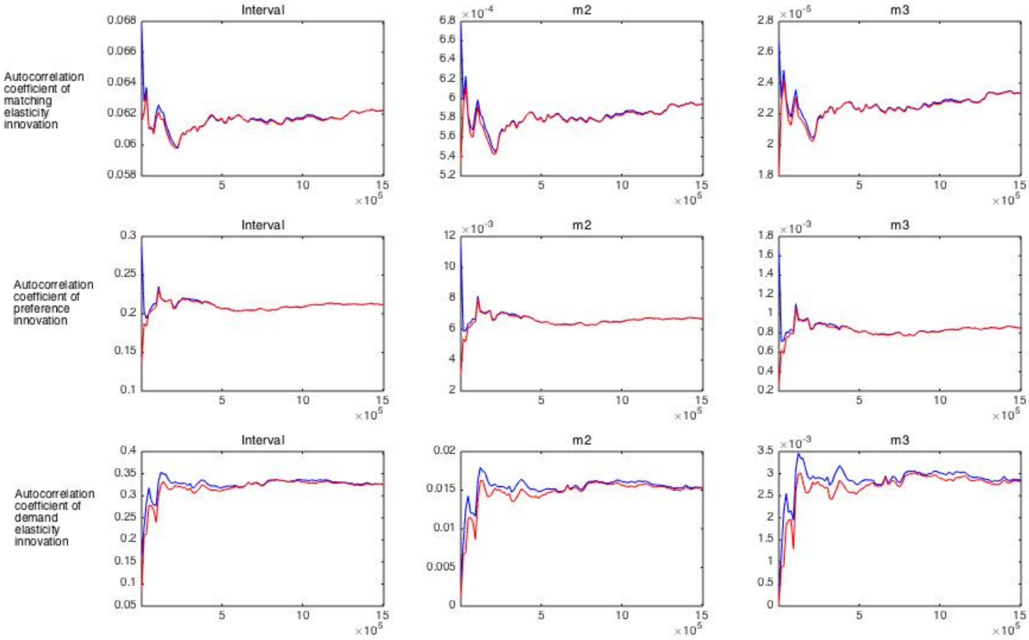

Interval
m2
m3
St.dev. of measurement error in unemployment rate
St.dev. of measurement error in vacancy stock
St.dev. of measurement error in labor market tightness

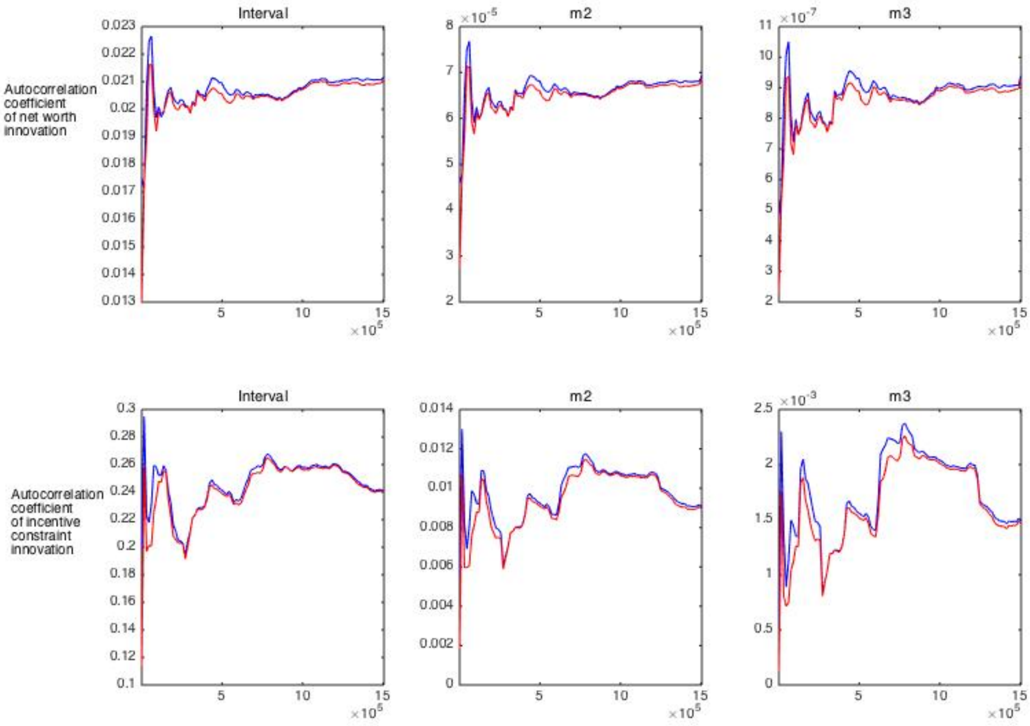

Interval
m2
m3
St.dev. of measurement error in inflation
St.dev. of measurement error in nominal interest rate
Discount factor

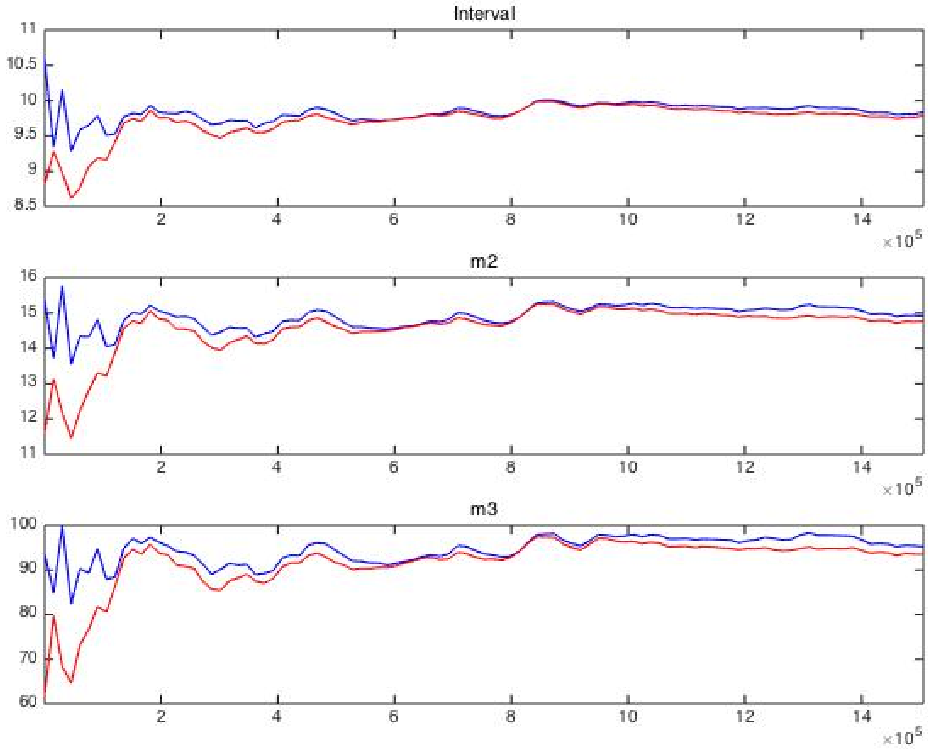

Interval
m2
m3
Elasticity of substitution
Calvo parameter
Elastcity of matching function


Interval
m2
m3
Real wage rigidity
Inflation coefficient of Taylor rule
Output gap coefficient of Taylor rule


Interval
m2
m3
Smoothing parameter in the Taylor rule
Autocorrelation coefficient of TFP innovation
Autocorrelation coefficient of monetary policy innovation


Interval
m2
m3
Autocorrelation coefficient of matching elasticity innovation
Autocorrelation coefficient of preference innovation
Autocorrelation coefficient of demand elasticity innovation

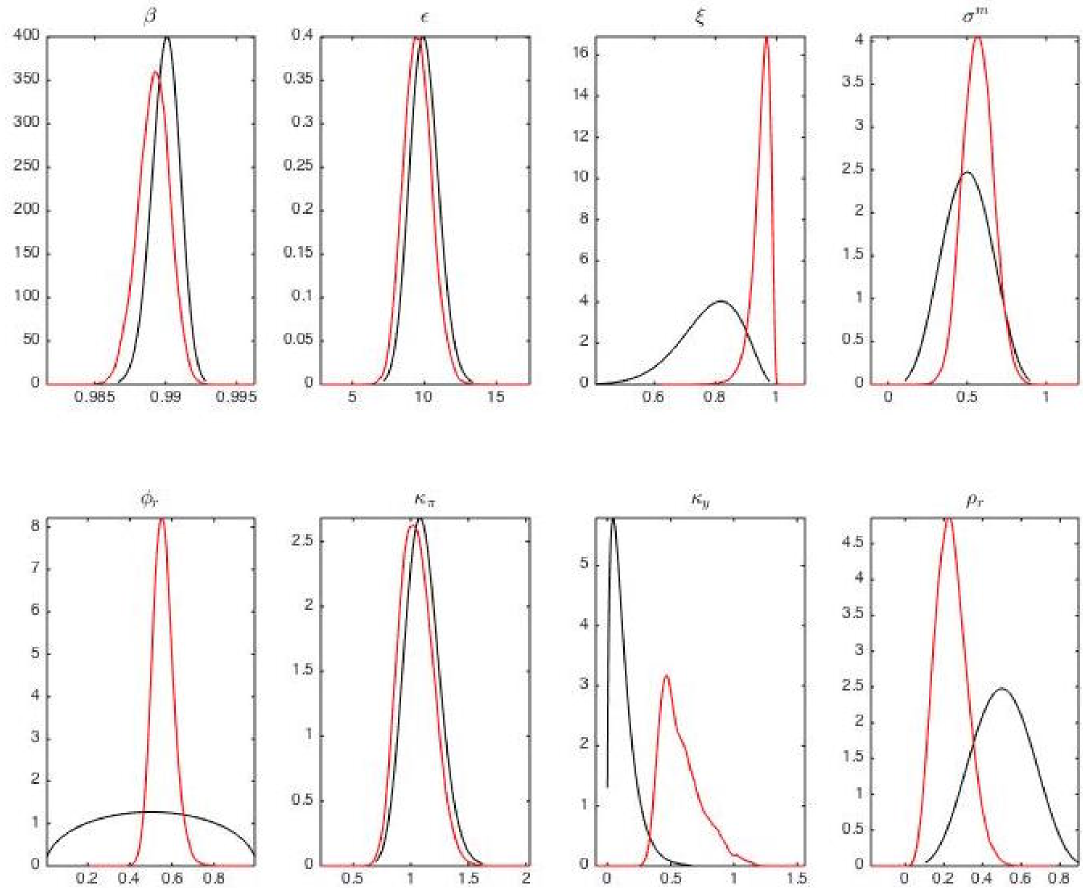

Interval
m2
m3
Autocorrelation coefficient of net worth innovation
Autocorrelation coefficient of incentive constraint innovation



The first column (interval) shows the Brooks and Gelman multivariate convergence diagnostics. The statistic is based on the range of the posterior likelihood function with the posterior kernel used to aggregate the parameters. The blue line is the 80 percent interval based on the pooled draws from all sequences. The red line is the mean interval rage based on the draws of individual sequences. The second (m2) and third (m3) columns shows the same statistic for the second and third central moments. The red and blue lines should flatten out horizontally and be close to each other if convergence is achieved.

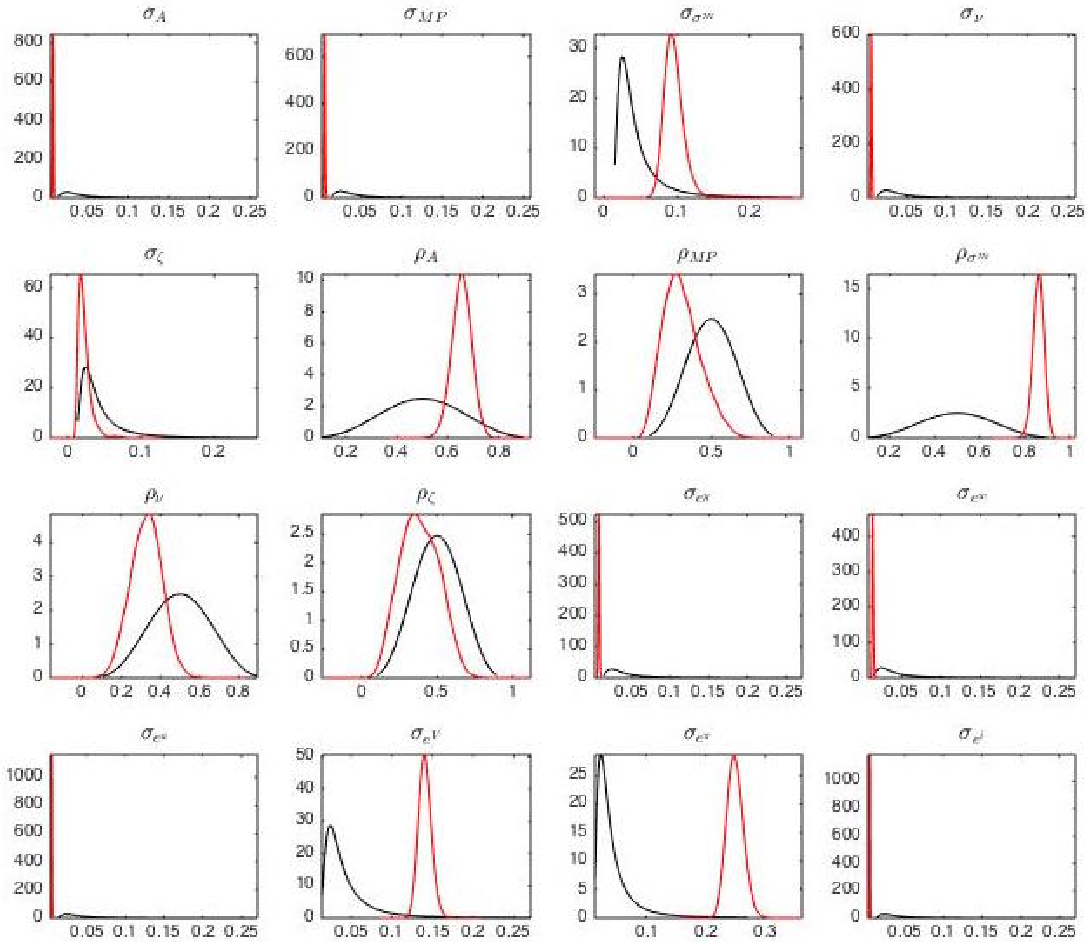
2.7.4 Posterior Distribution

Figure 2.6: Model with Banking Sector: Prior and Posterior Distribution of Model Parameters



The black line is the prior density function. The red line is the posterior density.

Figure 2.7: Model with Banking Sector: Prior and Posterior Distribution of Structural Shocks and Measurement Error



The black line is the prior density function. The red line is the posterior density.

3 How Do Bank Lending Shocks Affect the Labor Market? A SVAR Analysis of the US and UK Credit and Labor Markets*

3.1 Introduction

Since the global financial crisis there has been increased empirical evidence on the macroeconomic importance of credit market shocks and their transmission to the real economy. For instance, Gilchrist *et al.* (2009), Gilchrist and Zakrajšek (2012), and Meeks (2012) estimate the effects of shocks to corporate credit spreads on output fluctuations in the US, whereas Hristov *et al.* (2012), Barnett and Thomas (2013), and Gambetti and Musso (2014) focus on the importance of bank lending shocks to non-financial corporations and households in several countries. The role that credit market shocks have on labor market fluctuations, however, has received less attention. This is despite the severe deterioration of labor market outcomes that many countries around the globe experienced both during and in the aftermath of the financial crisis.

In this chapter we use a structural vector autoregressive (SVAR) framework to estimate the impact of credit market shocks on the UK and US labor markets. We aim to understand their propagation mechanism and to assess their relevance for labor market fluctuations over the business cycle, particularly during the recent financial crisis. In particular, we employ a Bayesian SVAR to estimate corporate loan supply shocks via a mix of sign and short-run exclusion restrictions. Bank lending, or loan supply, shocks can be thought of as unexpected changes in

*This is joint work with Lien Laureys at the Bank of England.

financial intermediaries' willingness to provide credit to non-financial corporations at every level of the lending rate, which moves the loan supply curve. Technological, regulatory, or preference changes may all account for such changes. A positive loan supply shock will lower corporate loan rates and increase credit volumes. Our baseline VAR model includes a set of standard macroeconomic and credit market variables as well as three labor market variables: the unemployment rate, the job-finding rate, and the job-separation rate. In the search theory of the labor market the job-finding and job-separation rates are the key drivers of unemployment dynamics.[1] In an extended specification, we also add an index of vacancies and real wage growth to understand in more detail the transmission mechanism of bank lending shocks to the labor market.

Importantly, we only focus on loan supply shocks to the corporate non-financial sector. Bank lending shocks to the household sector are likely to be important drivers of business cycle fluctuations, particularly over the past twenty years. Nevertheless, the transmission mechanisms of loan supply shocks to the corporate and the household sectors probably differ and have an opposite impact on labor market variables. For instance, a contemporaneous expansion of credit to firms and households is likely to increase firms' demand for labor but decrease households' labor supply due to wealth effects. The overall impact on employment would depend on the size of the two bank lending shocks as well as the relative elasticity of labor demand and labor supply to these shocks. Since this would make the interpretation of impulse response function and the transmission mechanism difficult, we abstract from loan supply shocks to the household sector.

We estimate this model for both the UK and the US. In 2013Q2 UK private non-financial corporations relied on bank loans for 27 percent of their financing needs, down from 38 percent in 2009Q1 (Farrant *et al.*, 2013). In the US, between 2003 and 2013 bank loans accounted on average for less than 10 percent of total credit market instruments, down from approximately 26 percent in the mid-1980s (Contessi *et al.*, 2013). Despite this secular decline in bank lending as a source of

[1]See e.g. Mortensen and Pissarides (1994).

financing for the private non-financial sector as a whole, in both countries bank lending remains the predominant type of funding for small and medium enterprises (SMEs).[2] For instance, in 2013 small business loans (less than 1 million USD) accounted for 51 percent of financing of US SMEs (SBA, 2014).

SMEs are important for employment and job-creation. In the UK, for the past 20 years SMEs have accounted for approximately 63 percent of private sector employment.[3] Between 1997 and 2008,[4] small and medium private enterprises created approximately 65 and 16 percent of all new jobs, and destroyed 50 and 22 percent of the existing ones. On the whole, SMEs contributed to 81 percent of job-creation and 72 percent of job-destruction (Hijzen *et al.*, 2010).[5] Similarly, in the US SMEs have accounted for approximately 50 percent of non-farm employment in the past few years (Kobe, 2012). Between 1990 and 2010 small and medium enterprises created 41 and 32 percent of all new jobs and destroyed 23 and 34 percent of the existing ones. On the net, SMEs contributed positively to job-creation, offsetting the deleterious impact of large firms on the US labor market.[6] Given the importance of SMEs for job-creation and the reliance of SMEs on bank lending, understanding how shocks to the supply of bank loans affect labor market outcomes is important. While business lending is even more important as a source of external finance in the Euro Area (de Fiore and Uhlig, 2011, 2015), we do not include this monetary union in our sample because systematic data on labor market transition rates, necessary to compute job-finding and job-separation probabilities, have

[2] The OECD and the EU define SMEs as firms employing less than 250 employees, but the US define them as having less than 500 employees. Unless stated otherwise, for data comparability we follow the US classification and define small firms as enterprises employing less than 20 employees, and medium firms as establishments employing between 20 and 500 employees.

[3] Statistics from the *Business Population Estimates* released annually by the Office for National Statistics.

[4] Job-creation and job-separation rates are calculated classifying firms on the basis of their initial employment class.

[5] Using the EU classification, UK medium enterprises created 12 percent of all new jobs and destroyed 17 percent of the existing ones.

[6] We calculated these numbers using figures from the US Census Bureau. On average, each year SMEs created 10.1 million jobs and destroyed 9.1 million, while large firms created 6.9 million new jobs but destroyed 7.1 million. This is not the result of job losses during the recent financial crisis.

only been available since 2010.[7]

We contribute to the literature in several ways. Our focus on lending to non-financial private corporations allows us to complement a number of studies that, using firm-level data, show that access to bank lending affects firms' employment decisions. For instance, Chodorow-Reich (2014) estimates that a negative loan supply shock accounts for 20 to 33 percent of the fall in employment in the two months following the Lehman bankruptcy, while Greenstone *et al.* (2014) estimate its impact on total employment to be very small and no larger than 13 percent between 2008 and 2009. On the other hand, our estimate suggests that loan supply shocks were responsible for about half of the deviation of the unemployment rate from its baseline projection in the last quarter of 2008, and they had a cumulative effect of 20 percent in 2009. In contrast to studies based on firm-level data, our VAR analysis does not ignore possible general equilibrium effects. We also do not rely on small samples that may be biased. We use instead aggregate figures that represent the entire labor and non-financial corporate loan markets.

Second, we offer empirical evidence that can inform the development of theoretical labor and financial friction models. Several DSGE models have been proposed to explain how the financial conditions of non-financial firms and the availability of credit affect hiring decisions and, more generally, labor market dynamics (Wasmer and Weil, 2004; Zanetti, 2012; Chugh, 2013; Petrosky-Nadeau and Wasmer, 2013; Petrosky-Nadeau, 2014; Zanetti and Mumtaz, 2016). Each of these models integrates some type of financial friction into a standard random search labor market framework. Although these models typically imply that a worsening of firms' financial conditions reduce labor demand and employment, the underlying transmission mechanisms differ. Our VAR evidence points to the importance of including shocks to supply of loans for explaining labor market fluctuations.

[7] In addition, estimating a VAR for the Euro Area implicitly assumes that EA labor markets are sufficiently homogeneous to treat them as a single market. In chapter 4 I show that labor markets in the EA are heterogeneous along several dimensions. Thus, a single model of the EA would probably suffer from misspecification problems.

Furthermore, understanding the relative importance of bank lending shocks as a source of business cycle fluctuations and their transmission mechanism to the labor market is essential for policymakers. A rise in unemployment due to a decline in lending to non-financial corporations would call for policies strengthening financial intermediaries and their ability to provide credit to the real economy. On the contrary, an increase in unemployment due to weak aggregate demand conditions would require policies supporting real activity.

The main results of this chapter are the following. First, we find that an expansionary bank lending shock increases the job-finding rate and lowers both the job-separation and the unemployment rates. Qualitatively, the responses are similar for both countries in our sample, although the job-finding rate moves more markedly in the UK than in the US. The effects of the shock are also quite persistent, particularly in the UK. This most likely reflects the higher reliance of the British non-financial corporate sector on bank lending as a source of funding. In addition, the extended model for the US economy indicates the following propagation mechanism. Following a positive bank lending shock, firms can secure more and cheaper credit. This increases firms' profits and encourages more vacancy creation. Since the vacancy rate increases, unemployed workers find it easier to find a job and move out of unemployment. At the same time, the rate at which employed workers separate from firms and move into unemployment falls. As the economy grows and unemployment falls, the real wage also increases. This propagation mechanism is consistent with the predictions of the theoretical model discussed in chapter 2.

Second, our evidence indicates that, in response to bank lending shocks, the quantitative response of the job-finding rate is an order of magnitude greater than the response of the job-separation rate. However, since the unemployment rate is a non-linear function of the two transition probabilities, both job-creation and job-destruction are important to explain movements in the unemployment rate. This suggests that theoretical models should endogenize the job-separation rate and make it dependent on some type of financial mechanism.

Furthermore, for the UK we find evidence that bank lending shocks are substantial drivers of labor market fluctuations over the business cycle. Particularly during the recent financial crisis, UK firms experienced a credit crunch that was responsible for most of the rise in the job-separation rate and for a large portion of the fall in the job-finding rate. Strengthening the ability of the banking sector to provide loans to the non-financial corporate sector would have been the appropriate policy response to this credit crunch. In fact, the Bank of England's Funding for Lending Scheme (FLS) launched in July 2013 is coherent with this policy. We find indeed some evidence that bank lending increased after FLS was implemented and counteracted the negative effect of other shocks on the UK economy.

In contrast to the UK, we find that bank lending shocks are less important in explaining fluctuations in the US labor market. Since US firms are on average larger and less reliant on bank credit than their British counterparts, unexpected changes in the cost and volumes of bank lending have a weaker impact on them and their labor demand. Notwithstanding this, loan supply shocks are important drivers of the US business cycle in specific episodes. Both during the mid-1990s expansion and the financial crisis, they have had an important impact on US job-creation and the unemployment rate.

The remainder of this chapter proceeds as follows. Section 3.2 reviews the existing literature. Section 3.3 presents the empirical model. Section 3.4 discusses the data and identification strategy. Section 3.5 presents and discusses the main empirical results, and Section 3.6 some robustness analysis. Section 3.7 concludes.

3.2 Literature Review

This chapter is related to the empirical SVAR literature on loan supply shocks and to theoretical models on labor and financial market frictions. SVAR models have been used to study the effects of bank lending shocks in several countries. In most cases, Bayesian estimation and identification based on either a pure or a mixed sign restriction scheme have been applied. Halvorsen and Jacobsen (2009) and Busch *et al.* (2010) identify loan supply and monetary policy shocks in Norway, the UK, and Germany. They find that bank lending shocks account for a sizeable portion of output fluctuations. Hristov *et al.* (2012) identify aggregate supply, aggregate demand, monetary policy, and loan supply shocks for the Euro Area using a panel VAR. While aggregate demand shocks are the most important drivers of business cycle fluctuations, bank lending shocks played an important role during the financial crisis. Gambetti and Musso (2014) use a time-varying Bayesian SVAR to identify these four shocks in the US, the UK, and the Eurozone. They find loan supply shocks to account for business cycle fluctuations over the past few decades, and not only during the financial crisis. Tamasi and Világi (2011) estimate several credit market shocks for the Hungarian economy, while Helbling *et al.* (2011) identify the effect of global loan supply and productivity shocks for G-7 countries. Lastly, Barnett and Thomas (2013) estimate a VAR for the UK economy and find that loan supply shocks can explain a large proportion of the fall in lending and output during the recent crisis.

SVAR analyses have generally identified an expansionary loan supply shock with a rise in loan volumes and a fall in either default risk (Helbling *et al.*, 2011), or some measures of loan price such as lending rates (Busch *et al.*, 2010; Hristov *et al.*, 2012; Gambetti and Musso, 2014) or credit spreads (Tamasi and Világi, 2011; Barnett and Thomas, 2013). Importantly, identifying truly exogenous movements in loan supply from endogenous responses along the supply curve has been a recurring difficulty. The identification of a large number of structural shocks or the imposition of more restrictions have helped address this issue, but the choice of restrictions is often *ad hoc*.

Structural identification is typically achieved via pure sign restrictions or a mix of sign and exclusion restrictions. Pure exclusion restriction schemes are considered unreasonable due to the fast-moving nature of financial markets; thus, they have not been applied to identify loan supply shocks. Among this empirical SVAR literature, this chapter is closest to Barnett and Thomas (2013) and Gambetti and Musso (2014). We share the identification of four structural shocks and the focus on the UK. There are, however, some substantial differences in terms of identification strategy and data treatment. For instance, we allow loan supply shocks to have contemporaneous effect on real non-labor market variables, and we do not study the impact of total lending to the private non-financial sector. Nonetheless, we complement this empirical literature by studying the impact of loan supply shocks on labor market variables.

Furthermore, we provide some empirical evidence that may potentially help to discriminate between different theoretical models on labor and financial market frictions. The role of the banking sector to explain business cycle fluctuations has been emphasized in Cúrdia and Woodford (2009), Gerali *et al.* (2010), Gertler and Kiyotaki (2010), Gertler and Karadi (2011), and Dib (2010). Newer DSGE models have incorporated non-trivial labor markets into financial friction models. For instance, Zanetti and Mumtaz (2016), Petrosky-Nadeau and Zhang (2013), Chugh (2013), and Petrosky-Nadeau (2014) add a costly state verification mechanism to the standard random search model. Positive financial shocks increase the net worth of non-financial firms and their ability to borrow. Zanetti (2012) studies a model in which firms borrow to finance working capital and financial intermediaries cannot enforce debt contracts. Wasmer and Weil (2004) and Petrosky-Nadeau and Wasmer (2013) propose a model with random search frictions in both credit and labor markets. In general, including financial frictions modifies the cost structure of firms. By affecting firms' real marginal cost, bank lending shocks have an effect on labor demand and labor market dynamics. Moreover, this literature has generally assumed a constant job-separation rate, so changes in the job-finding rate drive unemployment fluctuations. Zanetti (2012), however, finds that exogenous shocks to the separation rate account in fact for most of the variation in the unemployment rate.

3.3 Empirical Model

3.3.1 Estimation

Let y_t be a vector of N covariance stationary processes and μ a $c \times 1$ vector of deterministic terms. The reduced-form VAR(p) model can be written as:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + A_0 \mu + u_t, \quad u_t \sim N(0, \Sigma_{uu}) \tag{3.1}$$

where A_0 is a $N \times c$ matrix, $A_1 \dots A_p$ are $N \times N$ matrices, and u_t is a $N \times 1$ vector of normally distributed reduced-form residuals with variance-covariance matrix $\Sigma_{uu} = E(u_t u_t')$. Let $x_t = [y_{t-1}', \dots, y_{t-p}', \mu']$ be a $1 \times m$ matrix where $m = c + Np$, $X = [x_1', \dots, x_T']'$ a $T \times m$ matrix, $Y = [y_1, \dots, y_T]'$ a $T \times N$ matrix, $A = [A_1, \dots, A_p, A_0]$ be a $N \times m$ matrix, and $U = [u_1', \dots, u_T']$. The simultaneous-equation representation of the VAR system (3.1) is:

$$Y = XA' + U \tag{3.2}$$

Stacking the columns of Y and U into two $TN \times 1$ column vectors y and u and the columns of A' into a $mN \times 1$ column vector α, we can rewrite the system as:

$$y = (I_n \otimes X)\alpha + u \tag{3.3}$$

We cannot use classical estimation methods because of the large number of parameters in α and the relatively small time span T. Thus, we use Bayesian methods to impose more structure on the system and reduce estimation uncertainty via the specification of prior beliefs. We assume a normal inverse Wishart prior for α and Σ_{uu} which can be specified as follows:

$$\alpha | \Sigma_{uu} \sim N(\alpha_0, \Sigma_{uu} \otimes \Omega_0) \tag{3.4}$$

$$\Sigma_{uu} \sim IW(\nu_o, S_0) \tag{3.5}$$

where α_0 and Ω_0 are the prior mean and variance-covariance matrix of VAR coefficients, and S_0 and ν_0 are the prior scale matrix and degrees of freedom of the Wishart distribution.

An advantage of assuming the natural conjugate prior is that we have a functional form for the posterior conditional distribution of α and Σ_{uu} because the prior, the likelihood, and the posterior come from the same family of distributions. The prior beliefs corresponds to the following moments for the VAR coefficients:

$$E[(A_k)_{ij}] = \begin{cases} \chi_i, & j = i, k = 1 \\ 0, & otherwise \end{cases} \qquad Var((A_k)_{ij}) = \varphi \frac{\tau^2}{k^2} \frac{\sigma_i^2}{\sigma_j^2} \tag{3.6}$$

The hyperparameter τ controls the overall tightness of the prior distribution. When τ is zero, the posterior distribution equals the prior distribution. When $\tau \to \infty$, the prior has no weight and the posterior moments collapse to their OLS estimates. The ratio $\frac{1}{k^2}$ is the rate at which increasing lag length decreases the prior variance,[8] the ratio $\frac{\sigma_i^2}{\sigma_j^2}$ controls for different scaling in the data, and the coefficient $\varphi \in [0, 1]$ controls the importance of the lags of other variables relative to own lags.

One shortcoming of the natural conjugate prior is the symmetric treatment of all variables because every equation must include the same set of explanatory variables. Another one is that the prior variances on the coefficients are proportional to each other. These limitations could be relaxed using the extended natural conjugate prior of Kadiyala and Karlsson (1997), but we do not find them too restrictive for our analysis. In fact, we are not assuming any strict exclusion restriction whereby an explanatory variable enters only a subset of equations.[9]

We implement these priors via the dummy variable approach developed in Sims and Zha (1998) as explained in Banbura *et al.* (2010). Setting the hyperparameter φ to 1, we can construct artificial data Y_D and X_D such that the prior moments are functions of this artificial data. In particular, let $\hat{A}' = (X_D' X_D)^{-1}(X_D' Y_D)$, $\alpha_0 = vec(\hat{A}')$, $\Omega_0 = (X_D' X_D)^{-1}$, $S_0 = (Y_D - X_D\hat{A}')'(Y_D - X_D\hat{A}')$, and $\nu_0 = T_D - m$ where T_D is the length of the artificial data. Given this artificial data, the conditional

[8] Other researchers (Kadiyala and Karlsson, 1997) use $\frac{1}{k}$ as the rate at which the prior variance decreases. This implies the prior on further lags is more diffuse around its mean.

[9] For example, under strict monetary neutrality the nominal short-term policy real would not influence real variables.

posterior distribution for the VAR parameters has the analytical form:

$$\alpha|\Sigma_{uu}, Y_t \sim N(vec(\alpha_*), \Sigma_{uu} \otimes (X_*'X_*)^{-1}) \tag{3.7}$$

$$\Sigma_{uu}|\alpha, Y_t \sim IW(\nu_*, S_*) \tag{3.8}$$

where $Y_* = [Y; Y_D]$ and $X_* = [X; X_D]$ are the actual observations appended by the artificial data, T_* denotes the number of rows in Y_*, $\alpha_* = (X_*'X_*)^{-1}(X_*'Y_*)$, and $S_* = (Y_* - X_*\alpha)'(\tilde{Y} - \tilde{X}\alpha)$ are the OLS estimates using the extended data.

Following Banbura *et al.* (2010), we construct the dummy observations in the following way:

$$Y_D = \begin{pmatrix} \frac{diag(\chi_1\sigma_1,\ldots,\chi_N\sigma_N)}{\tau} \\ 0_{N(p-1)\times N} \\ \ldots\ldots\ldots \\ diag(\sigma_1,\ldots,\sigma_N) \\ \ldots\ldots\ldots \\ 0_{c\times N} \end{pmatrix} \tag{3.9}$$

and

$$X_D = \begin{pmatrix} \frac{J_P \otimes diag(\sigma_1,\ldots,\sigma_N)}{\tau} & 0_{Np\times c} \\ 0_{N\times Np} & 0_{N\times c} \\ \ldots\ldots\ldots & \ldots\ldots\ldots \\ 0_{c\times Np} & diag(\epsilon_{\mu 1},\ldots,\epsilon_{\mu c}) \end{pmatrix} \tag{3.10}$$

where J_P is a diagonal matrix with entries $1, \ldots, p$ along the main diagonal, χ_i is the prior mean for the first-order autoregressive coefficient of the dependent variable i, σ_i is the standard deviation of the residuals of a univariate AR(1) OLS regression for the variable i, and $\epsilon_{\mu 1}, \ldots, \epsilon_{\mu c}$ control the tightness on the prior of the deterministic terms. Y_D and X_D are $(m+N) \times N$ and $(m+N) \times m$ matrices, while $\tilde{Y}$ and $\tilde{X}$ have dimensions $(T+m+N) \times N$ and $(T+m+N) \times m$, respectively. We set τ equal to 0.2 as suggested in the RATS manual. Since the processes are mean-reverting, we set the prior for the expected posterior mean χ_i equal to zero. Finally, we assume diffuse priors for the deterministic terms and set very small numbers for ϵ_{μ_i}. Overall, we simulate 25,000 pairs (α, Σ_{uu}) of the posterior distribution of reduced-form coefficients, disregarding the first 5,000 observations.

3.3.2 Identification

The structural representation of (3.1) is:

$$BY_t = B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + B_0 \mu + \epsilon_t, \qquad \epsilon_t \sim N(0, \Sigma_{\epsilon\epsilon}) \tag{3.11}$$

where B is a $N \times N$ matrix of contemporaneous effects, $B_i = BA_i$, $\epsilon_t = Bu_t$ and $\Sigma_{\epsilon\epsilon} = E(\epsilon_t \epsilon_t')$ is the matrix of orthogonal errors in ϵ_t. Let (B, B_+) be the structural parameter space, where $B_+ = \{B_1, \ldots, B_p\}$. Normalizing the structural variances to one, the relationship between the two variance-covariance matrices is $\Sigma_{\epsilon\epsilon} = B\Sigma_{uu}B' = I$, or $\Sigma_{uu} = ZZ'$ where $Z = B^{-1}$. The identification problem arises because for any orthonormal matrix P (i.e $PP' = I$), the matrix $\tilde{Z} = ZP$ is also an admissible matrix since $\tilde{Z}\tilde{Z}' = \Sigma_{uu}$.

We use a mix of sign and short-run exclusion restrictions to identify a set of matrices $\tilde{Z}$ whose impulse response functions satisfy the restrictions we enforce. The sign restrictions are imposed on the standard macro and financial variables and are based on standard New Keynesian DSGE models. The zero restrictions are imposed on the labor market variables. Since we are interested in the response of the labor market to bank lending shocks, we wish to remain as agnostic as possible in this regard. Applying a pure sign restriction scheme that imposes no restriction on the labor market variables is too weak to identify the response of these variables unambiguously;[10] hence, we add these short-run exclusion restrictions. We discuss in more detail the nature and the plausibility of the specific restriction in Section 3.4.3.

We follow Arias *et al.* (2014) to correctly draw from the posterior distribution of structural parameters conditional on the sign and zero restrictions. Past research combining sign and exclusion restrictions had often introduced additional sign restrictions and generated biased impulse responses and artificially narrow confidence intervals. Arias *et al.* (2014)'s algorithm avoids these problems because it samples from the posterior distribution conditional on the zero restrictons.[11]

[10] When the response is ambiguously identified, most of the probability mass of the impulse response functions is consistent with the identified response under a mixed scheme.

[11] In particular, "the set of structural parameters conditional on the zero restrictions will be of measure zero in the set of all structural parameters [...while...] the set of structural parameters conditional on the zero and sign restrictions will be of positive measure in the set of structural parameters conditional on the zero restrictions" (p.13).

The exclusion restrictions impose non-linear constraints on (B, B_+). We first need to transform them into linear restrictions on a transformed parameter space, equivalently on an orthogonal matrix P. The set of restrictions are expressed by a set of $k \times n$ matrices Q_j with $1 \leq j \leq n$ and where k is generally a multiple of n. We order the matrices Q_j to have descending rank. Let $f(B, B_+)$ be the mapping from the original to the transformed space. It must satisfy right-hand multiplication of orthogonal matrices, be continuously differentiable for all points in the original structural parameter space, and its first derivative must be of rank $k \times n$. Then, (B, B_+) satisfies the zero restrictions if and only if $Q_j f(B, B_+)e_j = 0$ where e_j is the j^{th} column of the identity matrix. Because f satisfies right-hand multiplication, for any point in the set of structural parameters we can find an orthogonal matrix P such that $Q_j f(BP, B_+P)e_j = Q_j f(B, B_+)Pe_j = Q_j f(B, B_+)p_j$ for $1 \leq j \leq n$. Thus, the zero restrictions on the IRFs are transformed into restrictions on the columns p_j of P.

We use Rubio-Ramirez *et al.* (2010)'s algorithm for efficient identification to obtain a draw from the posterior distribution of structural parameters. We first take a draw from the posterior distribution of reduced form coefficients (α, Σ_{uu}) and find the Cholesky decomposition of $\Sigma_{uu} = CC'$ where C is a lower triangular short-impact matrix. We then draw an independent standard normal $N \times N$ matrix X and find its unique QR-decomposition. Q is an orthonormal matrix and R an upper triangular matrix such that $X = QR$. We further normalize the diagonal of R to contain only positive elements. We calculate a new draw of the short-run impact matrix as $Z = CQ$. Because we impose restrictions only on the impulse response functions on impact, our mapping f is simply the short-run impact matrix Z.[12] We then find an orthogonal matrix P such that the zero restrictions hold. The matrix $\tilde{Z} \equiv ZP$ constitutes a draw from the posterior distribution conditional on the zero restrictions. We then generate the impulse response functions using the structural matrix $\tilde{Z}$ and verify whether these IRFs are consistent with the sign restrictions imposed on the system. If so, we keep P, $\tilde{Z}$, and the resulting structural parameters.

[12]The function f is a linear projection onto the contemporaneous matrix, so it satisfies right-hand multiplication. Linearity ensures that the function is twice continuously differentiable. Moreover, its derivative has the required rank because it is an onto function.

If not, we disregard this draw and sample another pair (α, Σ_{uu}) from the posterior distribution of reduced-form coefficients. We repeat this 1,000,000 times.

This set identification procedure raises the question of how to present results. Each admissible matrix $\tilde{Z}$ produces a structural model with associated structural equations, shocks, impulse response functions, and other statistics. These models might differ substantially from one another both in quantitative and qualitative terms. When a single shock is identified, it is common to present a credible range of responses, often the 90 or the 64 percentile, along with a measure of central tendency, typically the posterior median, to account for model uncertainty. When multiple shocks are identified, there is no guarantee that the median impulse response functions come from the same underlying model. If this were the case, the shocks might be correlated with one another rather than being structural.

To circumvent this problem we follow Fry and Pagan (2007) and Fry and Pagan (2011)'s median target method and select the model that produces an impulse response function as close as possible to the median response across different shocks. More precisely, we first we find the pointwise posterior median IRFs for each of the four identified shock and endogenous variables for the first 20 quarters following the shock. We choose 20 quarters because we are interested in the impact of structural shocks in the short- and medium-term. We then standardize these IRFs to make them unit-free. Finally, we select the model that minimizes a particular loss function. We choose a quadratic function that minimizes deviations from the median IRF for each identified shock, endogenous variable, and horizon.

3.4 Data

3.4.1 Data Description

In our VAR, we employ US quarterly data from 1984:I until 2014:III and UK quarterly data from 1993:II until 2014:I. This corresponds to 30 years or 123 quarterly observations for the US, and 21 years or 84 quarterly observations for the UK. For the US we possess a full dataset from 1954:I onward, but we choose to focus on the 1984-2014 period to exclude earlier periods marked by structural changes to the US economy (Mcconnell and Perez-Quiros, 2000). For the UK, for most variables we have data spanning a longer period, but the lack of available data to calculate labor market transition probabilities restricts us to using a shorter sample. Nevertheless, the major deregulation of labor and financial markets of the 1980s, and the move to inflation-targeting in 1992 represent structural changes to the UK economy that could have increased the risk of misspecifying the model if included in the sample. Our baseline VAR includes eight endogenous variables grouped in three blocks. For the US, we also estimate an extended VAR with ten endogenous variables. All variables are seasonally adjusted, and we take quarterly averages of monthly series.

3.4.1.1 Standard Macro Variables

The first block of variables includes real output growth, the inflation rate, and a measure of monetary policy. For the US we use the real gross domestic product in billions of chained 2009 dollars (series A191RX1) from the Bureau of Economic Analysis, the Consumer Price All Items Index for All Urban Consumer (CPIAUCSL) from the Bureau of Labor Statistics (with the index equal to 100 for 1982-84), and the nominal yield on the 10-year Treasury constant maturity bond (series DGS10) from the Board of Governors of the Federal Reserve System. For the UK, we use the gross domestic product in chained volumes (series ABMI) and the Consumer Price All Items Index (series DTBT) from the Office of National Statistics (ONS), and the nominal yield on the 10-year zero-coupon government security (series IUQAMNZC) from the Bank of England. The CPI and the interest rate are measured monthly, whereas real output is measured quarterly.

We use a long-term yield, rather than a short-term rate, as a measure of monetary policy stance. The Federal Funds Rate reached its zero lower bound in December 2008 as did the Bank Rate in March 2009. Since they have both remained there ever since, they contain no information on the stance of monetary policy. Moreover, using the short-term nominal interest rate on government bonds would introduce non-linearities into the VAR. Barnett and Thomas (2013) make a similar choice when modeling the UK economy, arguing that long-term rates are a good proxy for the stance of monetary policy. In normal times, adjustments in the short-term rate are transmitted to the long rate via the term structure (Cook and Hahn, 1989; Cohen and Wenninger, 1994; Radecki and Reinhart, 1994). At the zero lower bound, unconventional monetary policy affects long-term rates via portfolio rebalancing and signaling channels in both the US (Gagnon *et al.*, 2011; Bauer and Rudebusch, 2014; Hamilton and Wu, 2012; Neely, 2014) and the UK (Bridges and Thomas, 2012).

Overall, we believe that the yield on the 10-year security is a reasonable, albeit imprecise, proxy for monetary policy. The use of the long-term rate, however, may confound the identification of structural shocks. For instance, if flight-to-quality considerations increased the demand for long-term bonds in the wake of the financial crisis, we might misinterpret a demand-driven fall in the yield as a monetary expansion. To check the robustness of our main results, in Section 3.6.2 we estimate a VAR for the UK economy using a measure of the short-term rate adjusted for the effects of QE, while in Section 3.6.3 we re-estimate the model using the short-term policy rate in lieu of the long-term yield on a sub-sample that excludes the period after 2009. We generally find the results of our baseline specification to be robust.

3.4.1.2 Credit Market Variables

The second block of variables describes conditions in the market for bank loans to private non-financial corporations. We use a measure of loan volumes and one of loan prices. In terms of quantities, we use the Commercial and Industrial Loans by All Commercial Banks monthly series from the Fed (series BUSLOANS) for the US, and the quarterly amount of outstanding monetary financial institutions' net lending (excluding securitization) to private non-financial corporations (series PCTBA).[13] Both series are converted into real volumes using the corresponding CPI series.

We use the corporate bond spread between the average yield on investment-grade company bond and the yield on a government bond of comparable maturity as a measure of the price of loans. Ideally, we would use a measure of the marginal

[13] We use the break-adjusted series which controls for changes in the reporting population, classificatory changes, revaluation effects and write offs.

corporate lending rate, but we only have data on the average loan rate, which is a weighted average of marginal rates on new and existing loans. Since new loans are only a small portion of the loan portfolio of financial intermediaries, the average rate reacts slowly to changed economic conditions, and it may have a low correlation with the current marginal lending rate.[14] To the extent that the corporate bond spread has a higher correlation with the marginal loan rate than the average loan rate, it is a better measure of the marginal bank borrowing cost for non-financial firms.

For the US, the corporate bond spread is calculated as the difference between the Moody's Seasoned Baa corporate bond yield (series BAY10) and the yield on the 10-year constant maturity Treasury yield (series DGS10) from the Fed.[15] Our time series for corporate bond spreads for the UK combines information from two different sources. For the 1993-1996 period, the spread is constructed as the difference between corporate bond yield on investment-grade bonds from the Global Finance Database and the yield on the 10-year zero-coupon government security. For the 1997-2014 period, it is an option-adjusted investment grade spread for all UK companies.[16] This is the spread between bonds with a maturity calculated between 3 and 7 years and gilts with maturity of 5 years.[17]

[14]For the UK, we analyzed the behavior of the corporate loan series. This is a measure of the average corporate loan rate that combines ONS data on interest rate flows and Bank of England data on the debt stock for the pre-1999 period, and data from the Effective Rate Survey (ERS) from 1999 onwards. The ERS interest rate is the weighted average of all interest rates on loans from a sample of UK monetary financial institutions. This series shows a sharp drop after the easing of monetary policy by the BoE in the aftermath of the financial crisis. In a VAR, this would probably be captured as a positive loan supply shock rather than the central bank's reaction to a negative shock. Corporate bond spreads, on the other hand, show a sharp rise. The correlation between average loan rates and corporate bond spreads is -0.69 for the whole sample and 0.03 for the 1993-2007 subsample. For the US, the correlation between the prime rate on commercial loans charged by 25 large banks and the corporate bond spread is 0.30.

[15]Alternatively, the corporate bond spread could be calculated as the difference between the Moody's Seasoned Aaa bond yield (AAY10). The correlation between the two corporate bond yields is 0.86, and the estimation results do not change substantially if we used the alternative series.

[16]The corporate index tracks the performance of sterling-denominated investment grade corporate debt publicly issued in the Eurobond or UK domestic markets. Companies are classified as investment-grade based on an average of Moody's, S&P, and Fitch's ratings. Bonds must have at least one year remaining term to final maturity, at least 18 months to final maturity at the point of issuance, a fixed coupon schedule, and a minimum amount outstanding of GBP 100 million.

[17]For both countries, we also have on the high-yield corporate bond spread. We could have calculated an average bond spread that includes investment-grade and high-yield corporate bonds and used it in our VAR model. We choose not to because the share of high-yield bonds has increased over time. Thus, changes in the spread reflect changes in loan riskiness as well as

3.4.1.3 Labor Market Variables

Finally, the third block of variables describes conditions in the labor market. In our baseline specification, we include the job-finding probability, the job-separation probability, and the unemployment rate. These two probabilities are crucial to understand what drives fluctuations in the unemployment rate. We use the total non-farm civilian unemployment rate for the 16+ population (series LNS14000000) from the Bureau of Labor Statistics (BLS) for the US. For the UK we calculate the unemployment rate for the 16-64 population using data on the stocks of unemployed and economically active people (series LF2I and LF2K) from the ONS. These series are measured at monthly frequency so we take quarterly averages. We use labor stock figures from the BLS, and labor stocks and flows figures from the ONS to calculating the transition probabilities. Due to data availability, however, we take two different approaches to calculating these probabilities.

When constructing transition probabilities, we need to account for inactivity status and time aggregation. We can model individuals to be in one of either two (employment and unemployment) or three (employment, unemployment, and inactivity) states. In a two-state model, only two transitions are possible: from unemployment to employment, and vice versa. The job-finding and job-separation rates measure the corresponding probabilities. In a three-state model, there are six relevant transitions: from unemployment to employment, from unemployment to inactivity, from employment to inactivity, and the three reverse transitions. Thus, the probability of moving out of unemployment (i.e. the gross outflow rate) does not generally equal the job-finding probability because an unemployed worker may move into inactivity. Similarly, the probability of moving into unemployment (i.e. the gross inflow rate) generally differs from the job-separation rate. For both countries, we study a two-state model to ease the interpretability of the results, but the conclusions of the analysis with gross transition probabilities are qualitatively similar to the ones that we present.

portfolio compositional effects. Since we are not interested in the latter effects, we restrict the analysis to investment-grade bonds.

Furthermore, flows in and out each state occur continuously but observations are measured at discrete times. This introduces a time aggregation bias that underestimates the amount of flows taking place in the labor market. Due to data availability, we correct for this bias for the US but not for the UK using Shimer (2012)'s two-state model with homogeneous workers. Suppose data is available only at discrete dates but workers move between the two states continuously. Let t refer to the interval between two measurement dates, and τ be the time elapsed since the last measurement date.

In our analysis, we are interested in measuring the job-finding probability F_t and the job-separation probability S_t during period t. Let $u_{t+\tau}$, $u_t^S(\tau)$, and $e_{t+\tau}$ be the number of unemployed, short-term unemployed, and employed workers at time $t+\tau$. Short-term unemployed workers are individuals who are unemployed at $t+\tau$ but who were were employed at some point between t and $t+\tau$. We assume that a Poisson stochastic process governs the probabilities with which unemployed workers find a job and employed workers lose their job. Specifically, the arrival rates for these two processes are s_t and f_t, which are linked to S_t and F_t via $s_t = -\log(1-S_t)$ and $f_t = -\log(1-F_t)$, respectively.

The change in the number of unemployed workers equals the number of employed workers $e_{t+\tau}$ who lose their job at instantaneous rate s_t minus the number of unemployed workers $u_{t+\tau}$ who find a job at rate f_t:

$$\dot{u}_{t+\tau} = e_{t+\tau}s_t - u_{t+\tau}f_t \tag{3.12}$$

Similarly, the change in the number of short-term unemployed workers equals the number of employed workers losing their job minus the number of short-term unemployed workers finding a job:

$$\dot{u}_t^s(\tau) = e_{t+\tau}s_t - u_t^S(\tau)f_t \tag{3.13}$$

We can combine (3.12) and (3.13) to obtain a differential equation that we can solve for u_{t+1}:[18]

$$u_{t+1} = (1 - F_t)u_t + u_{t+1}^S \tag{3.14}$$

where $u_{t+1}^S \equiv u_t^S(1)$. Solving (3.14) for F_t, we find an expression for the job-finding probability in terms of the number of unemployed and short-term unemployed workers:

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^S}{u_t} \tag{3.15}$$

To retrieve the job-separation probability S_t we can solve (3.12) forwards to obtain an implicit expression for the instantaneous job-separation rate s_t:

$$u_{t+1} = \frac{\left(1 - e^{-(f_t+s_t)}\right) s_t}{f_t + s_t} (e_t + u_t) + e^{-(f_t+s_t)} u_t \tag{3.16}$$

This equation uniquely identifies s_t, and thus the probability of interest, S_t.

For the US we use BLS monthly data, based on the Current Population Survey, on the number of civilian employed people (series LNS12000000), the number of unemployed people (series LNS13000000), and the number of people who have been unemployed for less than five weeks (series LNS13008396) as measures of e_t, u_t, and u_t^S, respectively. There is a known discontinuity in the design of the CPS which affects the measure of short-term unemployment after 1994. We follow Shimer (2005b) and simply multiply this measure by 1.1 to correct for this break.[19] We then take quarterly averages of the transition probabilities.

For the UK, we cannot follow the previous method to calculate the job-separation and job-finding probabilities. This is because the ONS defines as short-term unemployed someone who has not held a job in the past six months. We do have data, however, on flows between different labor market states. Let eu_t be the number of people moving from employment to unemployment during period t and

[18] The differential equation is $(\dot{u}_{t+\tau} - \dot{u}_t^s(\tau)) + \left(u_{t+\tau} - u_t^S(\tau)\right) f_t = 0$. Using the integrating factor $e^{f_t\tau}$, the solution to this equation is $u_{t+\tau} = u_t^S(\tau) - ke^{-f_t\tau}$ where k is a constant of integration. Since $u_t^S(0) = 0$ for all t, we can use this initial condition to find the value of the constant of integration $k = -u_t$. Finally, using a terminal condition and the property that $e^{-f_t} = (1 - F_t)$, we can find $u_{t+1} = (1 - F_t)u_t + u_t^S(1)$.

[19] For a more sophisticated adjustment using CPS data see Shimer (2005b). The two procedures give similar results.

ue_t be the number of people moving from unemployment to employment over the same period. Then, we calculate the transition probabilities as the flow of people moving from one state to another during the period divided by the number of people in the outgoing state at the beginning of the period, that is $F_t = \frac{ue_t}{u_{t-1}}$ and $S_t = \frac{eu_t}{e_{t-1}}$.

Lastly, for the US we also estimate an extended model that includes the real wage and a measure of the vacancy stock. We use real hourly compensation in the non-financial sector (series PRS88003093) from the BLS for the real wage, and the Composite Help-Wanted Index from Barnichon (2010) to measure the vacancy stock. For the UK we do not have sufficiently long data series to estimate the extended model. The ONS has been measuring a series for average weekly earnings (AWE) using household surveys only since January 2000,[20] and a vacancy series based on a representative survey of UK firms only since 2002.[21]

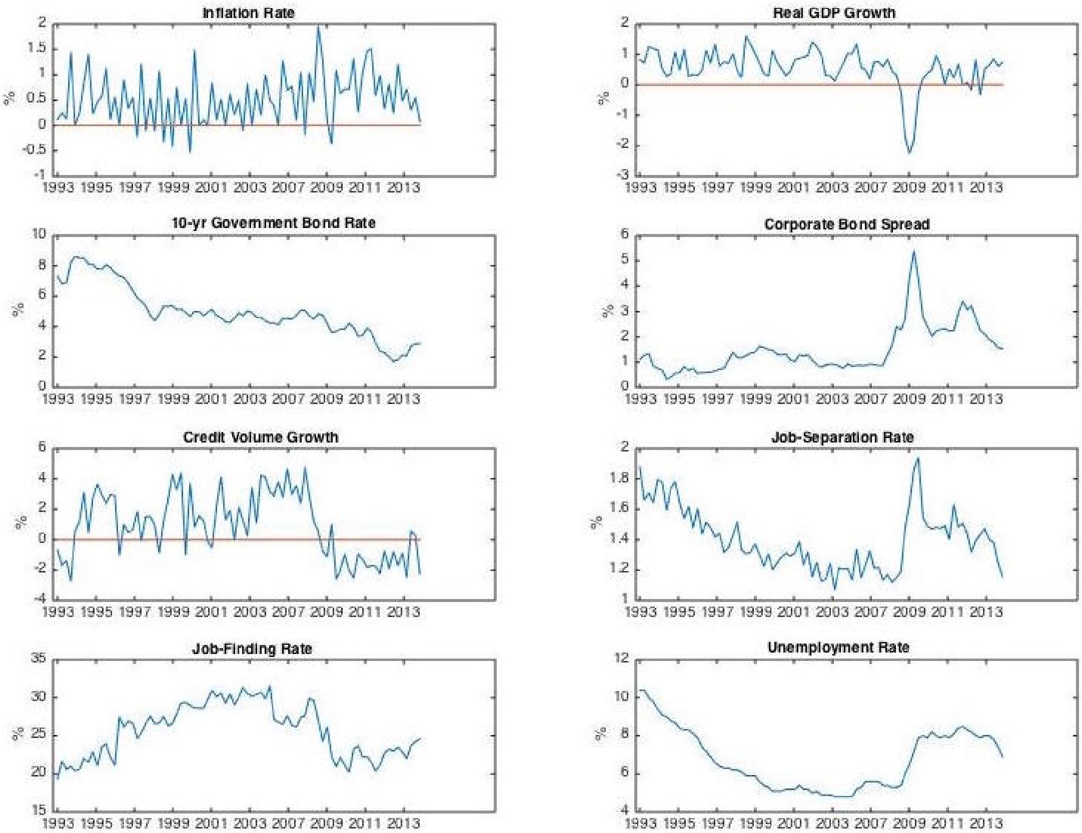
3.4.2 Model Specification

Figures 3.1 and 3.2 plot the time series that enter the two VAR models. To make the model stationary, we take the first-difference of the CPI, real output, the real volume of outstanding loans, and the real wage. For the US job-separation rate, we also remove a quadratic time trend to remove a secular decline and extract the high-frequency component of this variable. If we entered the job-separation rate in levels, we would find this series to be very persistent. The yield on long-term bonds, the corporate bond spread, the unemployment rate, the other probabilities, and the vacancy ratio enter the VAR in levels. Moreover, for the UK, we include a dummy for the 2009-2014 period to control for a possible structural break.

[20] The earlier measure of wage levels in the UK is the average earnings index (AEI) which was discontinued in July 2010. The total pay historic AWE series for the whole economy estimates average earnings using the relationship between AWE and AEI when both series are measured to estimate the pre-2000 AWE series. There are concerns, however, about the reliability of this series, which does not have National Statistics status in the UK.

[21] The ONS has also constructed a historic vacancy series. This combines the more recent series measuring the number of newly created, unoccupied, or soon-to-become vacancies for which employers are taking active recruitment steps (e.g. advertising, approaching, recruiting and interviewing potential candidates), and the older JobcentrePlus vacancy series measuring the number of vacancies registered at employment centers. Estimates suggests that the JobcentrePlus series only captures between one third and one half of total vacancies. Thus, the historic series appears to be a very imprecise measure.

Figure 3.1: UK Data Series



Sample period from 1993Q3 until 2014Q1. All series are seasonally adjusted.

Finally, based on information criteria, we estimate a VAR with two lags. All series are seasonally adjusted.

Before presenting the results of the main analysis, we discuss in more detail the properties of the variables entering the VAR model. For each variable, we conduct an augmented Dickey-Fuller (ADF) test to determine its order of integration. When doing so, we need to pay attention to select the optimal lag length and to include a structural break when appropriate. If the number of lags is too small, serial correlation in the residuals will bias the test for non-stationarity. If it is too large, the test will have low power and the probability of Type II error will increase. We use the standard Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQC) information criteria to determine the correct lag length of each univariate process.[22]

[22]While the AIC is inconsistent, it generally has better small sample properties than the HQC and BIC, which are both consistent. Ventzislav and Kilian (2005) find that for covariance-stationary

Moreover, some of the univariate series appear to have a structural break around the period of the financial crisis. In these circumstances, we may incorrectly fail to reject the null if we did not account for a break (Perron, 1988). We use Zivot and Andrews (1992)'s procedure to test the null hypothesis of a random walk in the presence of a structural break in the mean of the process when the location of the break is unknown.[23,24] Table 3.1 shows the results of conventional ADF tests including up to five lags of the first-difference terms. The underlined value indicates the preferred specification on the basis of the information criteria.

For the UK, we find evidence that real output growth is stationary; nevertheless, using a simple ADF test, we cannot reject the null of a unit root for either the inflation rate or the growth rate of the amount of real outstanding loans. Accounting for the presence of a structural break, however, we find evidence of stationarity for both the inflation rate ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -6.70^{***}$) and the growth rate of real credit volumes ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -7.66^{***}$).[25] For the US, both the price level and real output are $I(1)$ processes, but we cannot reject the null of a unit root for the growth rate of real lending volumes, even if we account for a structural break ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -3.89$). Despite this, graphical inspection of Figure 3.2 suggests that this series is stationary.

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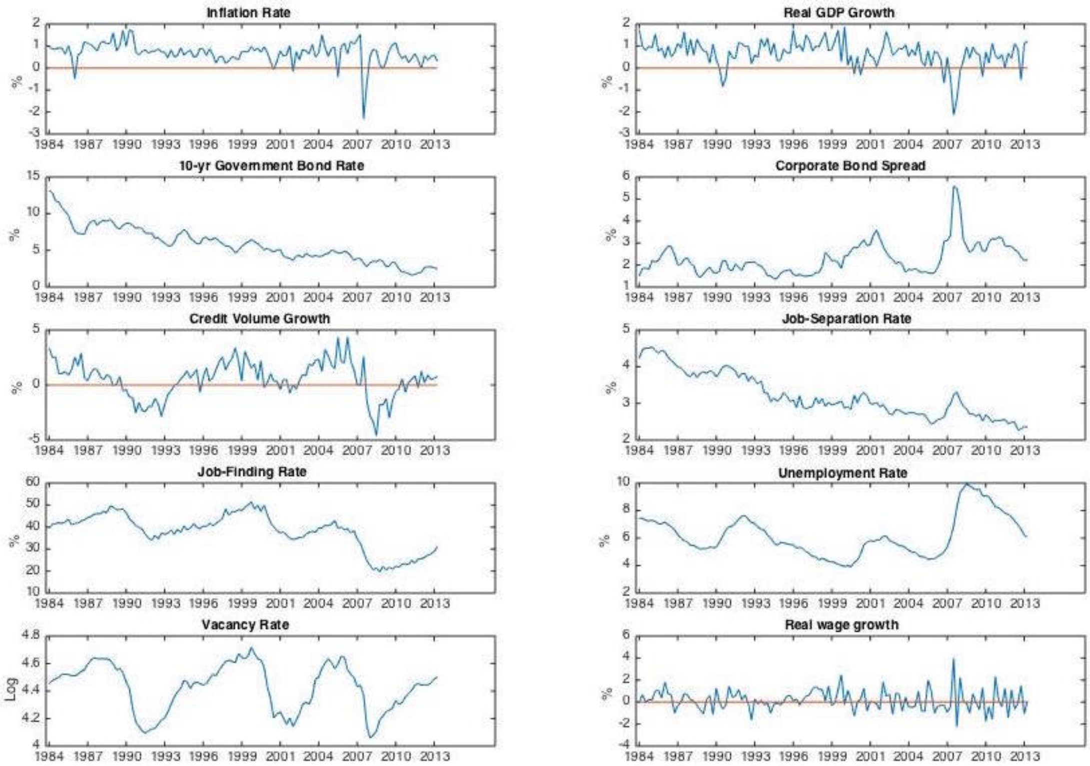
or near-unit root processes, the HQC performs best when using quarterly data. If the information criteria select different lag lengths, we rely on HQC.

[23]Suppose we wish to test the null that the series $\{y_{i,t}\}_1^T$ follows a unit root process with drift and that a structural break occurs at time T_B with $1 < T_B < T$ and location $\lambda = T_B/T$. To test this null hypothesis, we first estimate the regression model $y_{i,t} = \alpha + \theta DU_t + \delta t + \beta y_{i,t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{i,t-j} + e_t$ where α is an intercept, t is a deterministic trend, and $DU_t = 1$ if $t > T_B$ and 0 otherwise. The number k is determined sequentially starting from some $\overline{k}$ until we reject the null that γ_k is zero. We add these extra explanatory variables to reduce autocorrelation in the residuals. Then, we estimate the residuals $\hat{e}_{i,t}$ from this regression, estimate the AR(1) model $\hat{e}_{i,t} = \rho \hat{e}_{i,t-1} + u_{i,t}$, and calculate the t statistic $t_{\hat{\alpha}}(\lambda) = (\hat{\rho} - 1)/se(\hat{\rho})$ where α is the size of the test. Perron (1988) devises a test for a known structural break occurring at time T_B. He shows that the asymptotic distribution of $t_{\hat{\alpha}}(\lambda)$ depends on the location λ of the break and rejects if $t_{\hat{\alpha}}(\lambda) < \kappa_\alpha(t)$ where $\kappa_\alpha(t)$ with size α. Zivot and Andrews (1992) devise a test for an unknown break. This involves running λ over some range Λ and calculating the t statistic $t_{\hat{\alpha}}(\lambda)$ for each value of λ. We then choose λ to minimize the one-sided t statistic, thereby choosing the breakpoint T_B that most likely rejects the null hypothesis: $t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = inf_{\lambda \in \Lambda} t_{\hat{\alpha}}(\lambda)$. Having chosen the location of the break endogenously, we finally rejects the null of non-stationarity if $inf_{\lambda \in \Lambda} t_{\hat{\alpha}}(\lambda) < \kappa_{inf,\alpha}$ where $\kappa_{inf,\alpha}$ is the left-tail critical value with size α from the asymptotic distribution of $inf_{\lambda \in \Lambda} t_{\hat{\alpha}}(\lambda)$. The critical values are -4.93, -4.42, and -4.11 at the 1%, 5%, and 10% level of significance

[24]We could have used Perron (1988)'s original test and reached the same conclusions because Zivot and Andrews (1992)'s test identifies the structural break around 2007-2008.

[25]Using the longer series for the inflation rate starting in 1989Q1, we also fail to reject the null of a random walk ($t = -2.57, p = .103$ with five lags).

Figure 3.2: US Data Series



Sample period from 1983Q2 until 2014Q2. All series are seasonally adjusted.

ADF tests with fewer lags than the optimal level also strongly reject the null; thus, we treat the growth rate of real lending volumes as stationary.[26]

Establishing the stationarity properties of the long-term government bond yield and the corporate bond spread is more complex. While the evidence suggests that the corporate bond spread is stationary in the US, we cannot reject the null of a unit root in the UK series, even if we account for a structural break ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -2.18$). Furthermore, we also fail to reject the null of a random walk for the UK long-term yield either in our sample or in the longer series starting in 1982Q1 ($F = 4.70, p = .165$).[27] For the US, in contrast, we find evidence in favor of trend-stationarity for the long-term yield, but this result reflects the exclusion of the previous three decades of available data. Our sample captures the

[26] The first-difference of this growth rate is stationary ($t = -4.4991, p < .001$ with four lags). If the growth rate were not stationary, this would imply that the real amount of outstanding loans is a $I(2)$ process, which seems unlikely.

[27] We conduct the ADF test with three lags testing against the alternative of trend-stationarity.

Table 3.1: ADF Test for Non-Stationarity

	Number of lags in ADF test[a]					
	0	*1*	*2*	*3*	*4*	*5*
			United Kingdom			
Inflation rate	−11.36***	5.39***	−5.73***	-2.44	−2.95*	−<u>2.06</u>
Real output growth	−3.98***	−3.61***	−<u>4.37</u>***	−3.44**	−3.32**	−2.96**
10-year bond rate[b]	2.43	1.21	1.24	1.23	<u>3.35</u>	3.17
Corporate bond spread	-1.80	−2.81*	−<u>1.94</u>	-2.15	-2.05	-2.01
Real credit volume growth	−4.16***	−2.50	-2.25	-2.20	-1.93	−<u>1.67</u>
Job-separation rate	−<u>3.37</u>**	−2.85*	-2.35	-2.38	-2.16	−2.43
Job-finding rate	−2.36	-2.13	-1.70	-1.79	-1.77	−<u>1.72</u>
Unemployment rate	−2.82*	−2.36	−<u>2.64</u>*	-2.15	-2.10	-1.87
			United States			
Inflation rate	−<u>7.98</u>***	−6.72***	−5.07***	−4.95***	−3.68***	−3.16**
Real output growth	−7.36***	−<u>4.73</u>***	−4.43***	3.73***	−3.50***	−3.59***
10-year bond rate[b]	6.21*	17.18***	14.02***	16.02***	<u>15.32</u>***	13.61***
Corporate bond spread	−2.70*	−<u>3.61</u>***	−3.01**	−3.03**	−2.95**	−2.70*
Real credit volume growth	−4.29***	−3.07**	-2.57	−<u>2.38</u>	-2.16	-2.78
Job-separation rate[b]	4.76	2.74	<u>4.02</u>	4.90	4.42	4.50
Job-finding rate	-1.00	-0.88	−1.76	-2.10	-2.18	−<u>2.51</u>
Unemployment rate	-1.35	-2.47	−<u>3.02</u>**	−3.03**	−2.73*	−2.83*
Vacancy rate	-1.58	−<u>2.67</u>*	−2.78*	−3.40**	−3.69***	−3.67***
Real wage growth	−<u>13.32</u>***	−7.96***	−5.92***	−5.09***	−4.94***	−4.97***

** Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. The critical values (for zero lags) are -2.59, -2.90, and -3.51, respectively.*

For each series, $\{y_{i,t}\}$, the estimated model is $\Delta y_{i,t} = \alpha + \beta y_{i,t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{i,t-j} + \epsilon_{i,t}$ where k is the number of lags in the ADF test. We test the hypothesis that under that the null ($\beta = 0$) the process $\{y_{i,t}\}$ follows a random walk versus the alternative that it does not.

[a] *Underlined values indicate the number of lags information criteria select. When these criteria select different models, the model that the HQC selects is underlined.*

[b] *For the government bond rates and US job-separation rate, we estimate the model $\Delta y_{i,t} = \alpha + \beta y_{i,t-1} + \sum_{j=0}^{k} \gamma_j \Delta y_{i,t-k} + \delta t + \epsilon_{i,t}$ where t is a time-trend. Under the null hypothesis ($\beta = \delta = 0$) this process follows a random walk with drift. Under the alternative, this process is trend-stationary. We compute a F-statistic with non-standard critical values of 8.67, 5.44, and 6.44 at the 1%, 5%, and 10%, respectively.*

slow decline in long-term rates that followed the Volcker disinflation period. In the full period starting from 1953Q2 we cannot reject the null of a random walk ($t = -1.66, p = .446$ with three lags). This result is consistent with early research finding evidence of unit root behavior in real (Rose, 1988) and nominal (Siklos and Wohar, 1997) long-term interest rates. Similar studies on US short-term rates also fail to reject the null of a random walk for post-war data (Galí, 1992; King *et al.*, 1991; Mishkin, 1992; Choi, 1994; Crowder and Hoffman, 1996) even when accounting for the presence of structural breaks (Zivot and Andrews, 1992; Evans and Lewis, 1995; Lumsdaine and Papell, 1997; Nunes *et al.*, 1997; Rapach and Weber, 2004). Only Costantini and Lupi (2007), using panel unit root testing, find evidence for stationarity in short-term nominal interest rates. Similarly, the literature on corporate bond spreads fails to reject the null of a random walk (Morris and Neal, 1998; Collin-Dufresne *et al.*, 2001; Loncarski and Szilagyi, 2012; Neal *et al.*, 2015).

In fact, UK and US long-term nominal interest rates and corporate bond spreads most likely contain no unit roots. Conventional ADF tests, including Perron (1988)'s adjustment for structural breaks, assume that the true data generating process is linear. When the process is non-linear, these tests will have low power and fail to reject the null of a unit root even if the process is stationary (Kruse, 2011). More recent empirical work applying non-linear tests of non-stationarity find that long-term nominal interest rates display mean-reverting behavior (Cerrato *et al.*, 2010; Iskenderoglu, 2011; Van den End, 2011), casting doubts on earlier results based on linear ADF tests.[28] The same criticism applies to the existing empirical literature that attempts to identify the order of integration of the corporate bond spread.[29]

Furthermore, there is a theoretical consensus that in inflation-targeting regimes, such as the US and the UK, the short-term nominal interest rate deviates from its long-run equilibrium value only when the central bank responds to economic shocks (Clarida *et al.*, 1999). Thus, we should expect the nominal short-term rate to be a mean-reverting process. To the extent that long-term rates are a weighted average of current and expected future short-term stationary processes, they will also be mean-reverting.[30] Hence, from a theoretical point of view, treating long-term bond

[28]Interestingly, an ample literature based on linear ADF tests has shown that the short-term interest rate is not inherently a random walk process. Prior to the establishment of the Fed in 1914, it was a $I(0)$ process. Evidence for unit root behavior is only documented after the First World War period (Newbold *et al.*, 2001).

[29]To the best of our knowledge, there is no empirical work studying the stationarity properties of the corporate bond spread using non-linear ADF tests.

[30]The expected theory of the term structure holds that current long-term rates are a weighted average of current and expected future short-term rates plus a liquidity premium. Assuming this theory holds approximately, long-term rates are non-stationary if any of the short-term rates or the liquidity premium contain a unit root. We assume this not to be the case.

rates as unit-root processes is problematic. For these reasons, we treat both the yield on long-term government bonds and the corporate bond spread as stationary.[31]

We also treat the unemployment rate as stationary. For the US, our preferred specification rejects the null of a unit-root, and we also reject if we use the longer series starting in 1948Q1 ($t = -4.44, p < 0.001$ with one lag). For the UK, we find little evidence against non-stationarity, even if we control for a possible structural break in the series ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -1.78$) or use the complete data series starting in 1971Q1 ($t = -2.49, p = 0.112$ with two lags). These results might reflect the low power of conventional (linear) ADF tests in presence of stationary but non-linear processes.[32] Recent work using multivariate unit root test with heterogeneous structural breaks strongly rejects the null of a unit root in the US and in European countries (Song and Wu, 1998; Camarero and Tamarit, 2004; Romero-Ávila and Usabiagat, 2007; Lee *et al.*, 2009; Sephton, 2009; Ener and Arica, 2011). Another approach using non-linear exponential smooth transition autoregressive (ESTAR) models also strongly rejects the null of a unit root in the unemployment rate in OECD countries (Khraief *et al.*, 2015). Having greater statistical power than conventional ADF tests, these approaches can better discern near-unit root behavior from $I(1)$ processes. Thus, based on these findings, we treat the unemployment rate as stationary.

Despite mixed results from non-stationarity tests, we also treat the transition probabilities as stationary. For the UK, we find evidence that the job-separation rate is stationary, but we cannot reject the null of a unit root for the job-finding rate, even when we control for a structural break ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -4.00$).[33] For the US, we fail to reject the null for both transition probabilities. Controlling for

[31] Removing a deterministic trend from the US series of the long-term yield does not affect the quantitative results of our analysis.

[32] Early work on the persistence of the unemployment rate in the US and European countries found little evidence in favour of stationarity (Blanchard and Summers, 1986; Chang *et al.*, 2005) even when controlling for structural breaks (Mitchell, 1993) or using panel data approaches (Leon-Ledesma, 2002; Christopoulos and Leon-Ledesma, 2007). Other works detected stationarity for the US unemployment rate but random walk behaviour for most European countries including the UK (Røed, 1996).

[33] In contrast, if we account for a structural break, we reject the null of non-stationarity for the job-separation rate ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -5.74^{***}$).

Table 3.2: Cointegration Test

Number of cointegrating vectors	*Test statistic*		*Critical values*	
	United Kingdom	*United States*	5%	1%
	Trace test			
0	27.0	29.6	29.8	35.5
1	7.0	15.6	15.5	19.9
2	0.2	5.3	3.8	6.6
	Max-eigenvalue test			
0	19.9	14.0	21.1	25.9
1	6.8	10.4	14.3	18.5
2	0.2	5.3**	3.8	6.6

** Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. In a VECM of k I(1) time series, the trace and max eigenvalue statistics follow a non-standard asymptotic distribution. In both tests, under the null hypothesis the number of cointegrating vectors is r or less. Under the alternative, the number of cointegrating vectors is k in the trace test, and $r+1$ in the maximum eigenvalue test. These are both sequential tests starting with the null of no cointegrating vector.*

a possible break, we also fail to reject the null for both the job-separation rate ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -3.08$) and the job-finding rate ($t_{\hat{\alpha}}[\hat{\lambda}_{inf}] = -1.35$). Using the full sample starting in 1948Q1, we can find evidence in favor of stationarity for the job-finding rate ($t = 3.22^{**}, p = 0.020$ with five lags) but not for the job-separation rate ($t = -2.06, p = .271$ with no lags). Near-unit-root behavior might explain why conventional ADF tests fail to reject the null for these variables. Hence, we treat the UK transition probabilities and the US job-finding rate as stationary. For the US job-separation rate we remove a quadratic trend as in Fujita (2011) to extract its business cycle component. Graphical inspection suggests that, prior to the financial crisis, the job-separation rate was on a slow secular decline. If we used this variable in levels, the model would be stable but display a very high degree of persistence. In fact, removing the low-frequency component of the US job-separation rate improves the estimation of the model.

Furthermore, for the US extended model, we find evidence that the real wage is a $I(1)$ process, since we strongly reject the null that its growth rate has a unit root. In our sample, we cannot reject the null of a random walk for the vacancy rate, but in the full sample starting in 1951Q1 we find evidence for stationarity ($t = -3.17^{**}, p = 0.023$ with one lag). Thus, we enter the real wage in first-differences and the vacancy rate in levels.

Lastly, cointegration may be an issue. If any of the $I(1)$ variables were cointegrated, the VAR would be misspecified and the estimation of the model biased and inconsistent due to the absence of the error correction term. Table 3.2 shows the result of Johansen's testing procedure for the system including the price level, real output, and the volume of real credit. There seems to be little empirical support for cointegration, so we enter these three variables in first-differences.

3.4.3 Sign Restrictions

In our empirical analysis, we identify aggregate supply, aggregate demand, monetary policy, and bank lending shocks. There are a few advantages in identifying several shocks at once. First, aggregate demand and aggregate supply shocks have often been identified as the most important drivers of business cycle fluctuations;[34] thus, controlling for them improves the estimation of our shock of interest. Second, since bank lending and monetary policy shocks originate in financial markets, they might look very similar. Hence, identifying monetary policy shocks explicitly helps separate them from loan supply shocks. Third, the simultaneous identification of several structural shocks facilitates separating truly exogenous movements of the loan supply curve from movements along this curve which are due to other shocks. More generally, Paustian (2007) shows that increasing the number of shocks identified via sign restrictions in a SVAR model helps reveal the correct sign of the impulse response functions of the unrestricted variables.

Nonetheless, we do not identifying as many structural shocks as there are variables. Attaching a structural economic interpretation and finding credible sign restrictions for any additional shocks is a non-trivial task. In particular, we do not identify loan demand shocks because we find it difficult to attach a structural interpretation. Movements in the demand curve for corporate bank loans are likely the endogenous response of firms to some other structural shocks, for

[34]See, for instance, Smets and Wouters (2007).

instance a TFP innovation, rather than truly exogenous changes in the willingness of firms to borrow at any loan rate. Furthermore, by identifying fewer shocks than variables, the unidentified residual components of the vector of structural shocks capture the effect of omitted variables which are then less likely to contaminate the estimation of the shocks of interest.

3.4.3.1 Restrictions on Aggregate Supply, Aggregate Demand and Monetary Policy Shocks

We use conventional short-run restrictions derived from the DSGE literature to identify the three standard macroeconomic shocks.[35] Aggregate supply shocks include oil price, labor supply and TFP shocks, with the exception of innovations to the process of financial intermediation captured instead by loan supply shocks. Aggregate demand shocks encompass consumption, preference, investment, fiscal policy and net export shocks. Expansionary aggregate demand and supply shocks move inflation in opposite directions. A positive aggregate supply shock prompts firms to lower prices, while a positive aggregate demand shock raises inflation. Moreover, while expansionary monetary and aggregate demand shocks are both inflationary, they move the nominal interest rate in opposite directions. An unexpected cut in nominal rates stimulates nominal spending and expands output. On the other hand, a positive demand shock prompts the monetary authority to raise interest rates to counter inflationary pressures. We impose these restrictions only on the matrix of contemporaneous responses.

Furthermore, we assume that these aggregate shocks do not affect labor market variables on impact. We assume instead that the labor market reacts with a lag to economic shocks. For instance, facing temporary declines in sales, there is evidence that firms prefer to hoard labor rather than layoff workers in both the US (Fair, 1985; Fay and Medoff, 1985; Hart and Malley, 1996) and the UK (Larsen *et al.*, 2002; Felices, 2003; Crawford *et al.*, 2013). Maintaining a higher than required employment level may be costly in the short term; however, firms would have to pay hiring and training costs in the medium run if they had to readjust their employment level

[35] See for instance, Smets and Wouters (2007), Dées *et al.* (2010).

after the effects of the shock dissipate. Hoarding is optimal especially if search costs (e.g. advertisement, interviewing, screening costs) are high (Oi, 1962), jobs require very specialized skills, and the shock is short-lived. Similarly, in the case of positive temporary shocks that increase demand and sales, in the short run firms may prefer to adjust the intensive margin of labor rather than varying labor demand. As a result, there is a delay in the transmission of aggregate shocks to the labor market which we model as a short-run exclusion restriction on the unemployment and the transition probabilities. In the extended model, we also impose this short-run exclusion restriction on the vacancy stock and real wage growth. These restrictions help us identify unambiguously the response of labor market variables.[36]

3.4.3.2 Restrictions on Loan Supply Shocks

Loan supply shocks capture technological changes in the process of financial intermediation, changes in financial intermediaries' preference or risk-assessment, and regulatory changes. We do not attempt to identify different types of bank lending shocks. This would require more data and a stronger informational structure. We derive restrictions on the loan supply shocks from both the DSGE literature on financial frictions and the empirical VAR literature on loan supply shocks. Unlike the standard macroeconomic shocks above, there is less consensus on the nature of these restrictions (see Table 3.3).

There is broad agreement that loan supply shocks have opposite effects on the real loan volume and on some measures of the loan price, such as the lending rate, the credit spread, or the default risk. This is consistent with DSGE models incorporating financial frictions (Cúrdia and Woodford, 2009; Gerali *et al.*, 2010; Gertler and Karadi, 2011; Gilchrist *et al.*, 2009; Atta-Mensah and Dib, 2008) that

[36]We also identified a model with a pure sign restriction scheme leaving the contemporaneous response of labor market variables unrestricted. Most of the models in the set of admissible models predict impulse response functions for the labor market variables consistent with our main results; however, there is a non-trivial subset of responses inconsistent with our main results. We found similar results if we added the restriction that the identified model must maximize the contribution of the bank lending shock to the forecasting error variance of the endogenous variables. These results are not surprising because sign identification often relies on identifying restrictions which are too weak. Mumtaz *et al.* (2015) show that this is particularly the case when researchers seek to identify bank lending shocks.

predict expansionary loan supply shocks are associated with higher lending volumes and lower loan rates. On the other hand, there is disagreement on whether short-run exclusion restrictions are reasonable; on the impact of loan supply shocks on inflation and the policy rate; and on the impact of other aggregate shocks on loan volumes and rates. Importantly, we need to take a specific stance on these issues to derive a sufficiently large number of restrictions and identify multiple aggregate shocks.

Different timing assumptions reflect a wide range of beliefs on the nature of the transmission mechanism and the loan supply shock. Barnett and Thomas (2013) assume that financial shocks have an immediate impact on credit markets but no impact on goods markets. These exclusion restrictions allow them to be agnostic on the nature of bank lending shocks, which they find to resemble aggregate supply shocks. A positive loan supply shock is inflationary and increases the policy rate. In contrast, Halvorsen and Jacobsen (2009), Busch *et al.* (2010), and Gambetti and Musso (2014) impose no short-run exclusion restrictions but implicitly assume that loan supply shocks act like aggregate demand shocks: an expansion of credit increases inflation and the policy rate. This is sufficient to distinguish bank lending from aggregate supply and monetary policy shocks. To differentiate expansionary aggregate demand shocks unambiguously from loan supply shocks, Gambetti and Musso (2014) also need to assume that the former increase the lending rate via higher credit demand. This response of inflation and the policy rate is consistent with the predictions of some theoretical models (Cúrdia and Woodford, 2009; Gertler and Karadi, 2011; Gilchrist *et al.*, 2009). Nonetheless, Gerali *et al.* (2010) and Atta-Mensah and Dib (2008) show that expansionary loan supply shocks lower inflation and the policy rate. The theoretical model presented in chapter 2 also predicts that expansionary net worth and incentive-constraint shocks lower the inflation rate because they reduce borrowing costs for firms. Somewhat differently, Hristov *et al.* (2012) make no assumption on the impact of loan supply shocks on inflation and find expansionary shocks to be inflationary. Relaxing this assumption, however, requires that aggregate supply and loan supply shocks move the policy rate in opposite directions. Moreover, they have to assume expansionary aggregate

Table 3.3: Summary of Contemporaneous Theoretical Response of Key Macroeconomic Variables to an Expansionary Loan Supply Shock

Model	*Bank lending shock*	*Real output*	*Inflation rate*	*Policy rate*	*Lending rate*	*Loan volume*
Christiano et al. (2010)	Bank funding technology	+	-	-	-	0
	Bank reserve demand	+	+	uncertain	-	+
Curdia-Woodford (2001)	Bank resource cost function	+	+	+	-	+
	Bank loss rate	+	+	+	-	+
Gerali et al. (2010)	Bank capital	+	-	-	-	+
Gertler-Karadi (2011)	Bank capital quality	+	+	+	-	+
	Bank's net worth	+	+	+	-	+
Chapter 2	Bank's net worth	+	-	-	-	+
	Incentive constraint	+	-	-	-	+

A plus (+)/minus (-) sign indicates a positive/negative contemporaneous response to a positive bank lending shock. A zero indicates no contemporaneous response.

demand shocks raise loan rates via credit demand as in Gambetti and Musso (2014), while expansionary monetary supply shocks lower loan rates because policy movements are transmitted to credit markets.

Identifying multiple shocks requires an assumption about the impact of bank lending shocks on either inflation or the policy rate, and possibly also assumptions on the impact of other macroeconomic shocks on credit market variables. Based on this reading of the literature, in our baseline identification scheme we assume that an expansionary loan supply shock increases real credit growth and lowers the corporate credit spread and inflation. While many theoretical models predict an expansionary bank lending shock to be inflationary, this counters the idea that this shock lowers real marginal costs for firms. For instance, a positive innovation to the process of financial intermediation should be reflected in lower borrowing costs for firms, putting downwards pressures on inflation. This particular assumption on the response of inflation is sufficient to distinguish bank lending from aggregate demand and monetary policy shocks. To differentiate them from aggregate supply shocks, we need to assume the latter are transmitted into the credit market via

Table 3.4: Summary of Identifying Restrictions in Baseline Scheme

Series	*Aggregate Shock*			
	Loan supply (LS)	*Aggregate supply (AS)*	*Aggregate demand (AD)*	*Monetary policy (MP)*
Inflation rate	-	-	+	+
Real output growth	+	+	+	+
Long-term rate			+	-
Corporate bond spread	-	+		
Real loan volume growth	+	+		
Job-separation rate	0	0	0	0
Job-finding rate	0	0	0	0
Unemployment rate	0	0	0	0
Vacancy rate[a]	0	0	0	0
Real wage growth[a]	0	0	0	0

A plus (+)/minus (-) sign indicates a positive/negative response to a positive bank lending shock.
A zero indicates no contemporaneous response.
All the restrictions are only imposed on the matrix of contemporaneous responses.
[a] *Variable entering only the extended VAR model of the US economy.*

demand for loans. Hence, expansionary bank lending and aggregate supply shocks both increase real credit growth but have opposite effects on the corporate credit spread. We impose these restrictions only on the matrix of contemporaneous responses. Furthermore, to improve identification, we also assume that loan supply shocks have no contemporaneous effects on labor market variables. This last assumption is particularly important because pure sign restriction schemes have generally low power to recover loan supply shocks (Mumtaz *et al.*, 2015). Table 3.4 summarizes these restrictions.

Since for some of these restrictions there is little consensus in the literature, we also employ alternative identification schemes as a robustness check. Gambetti and Musso (2014), one of the papers closest to ours, make a diametrically different assumption on the response of inflation to a positive loan supply shock. Since their measure of credit includes loans to the household and the non-financial corporate sectors, they argue that a positive bank lending shock increases household consumption and firms' investment demand, putting upwards pressures on prices. Nonetheless, the consumption channel is completely absent from our analysis,

Table 3.5: Summary of Identifying Restrictions in Alternative Schemes

Series	*Scheme 1*				*Scheme 2*			
	LS	*AS*	*AD*	*MP*	*LS*	*AS*	*AD*	*MP*
Inflation rate	+	-	+	+		-	+	+
Real output growth	+	+	+	+	+	+	+	+
Long-term rate	+		+	-	+		+	-
Corporate bond spread	-		+		-	+	+	
Real loan volume growth	+				+			
Job-separation rate	0	0	0	0	0	0	0	0
Job-finding rate	0	0	0	0	0	0	0	0
Unemployment rate	0	0	0	0	0	0	0	0
Vacancy rate[a]	0	0	0	0	0	0	0	0
Real wage growth[a]	0	0	0	0	0	0	0	0

A plus (+)/minus (-) sign indicates a positive/negative response to a positive bank lending shock. A zero indicates no contemporaneous response.
All the restrictions are only imposed on the matrix of contemporaneous responses.
[a] *Variable entering only the extended VAR model of the US economy.*

and Gambetti and Musso (2014) do not consider that a positive shock lowers borrowing and real marginal costs for firms, putting downwards pressures on prices. We are essentially assuming that at least in the short run this latter channel dominates over the investment effect.

As a robustness exercise, we identify our SVAR model using two alternative schemes. The first one is Gambetti and Musso (2014)'s scheme; hence, we assume that an expansionary loan supply shock raises inflation and the policy rate, while a positive aggregate demand shock increases the lending rate. The rise in the policy rate is necessary to distinguish a bank lending from monetary policy shock. To justify this response, Gambetti and Musso (2014) note that the increase in inflation prompts the monetary authority to raise the nominal rate. The additional restriction on aggregate demand shocks (i.e. the increase in the lending rate) is required to differentiate them from bank lending shocks.

In addition, we examine a second alternative identification scheme in which we do not impose any restrictions on inflation. Under this scheme, we also need to assume that a positive loan supply shock increases the policy rate. This is again necessary to distinguish it from an expansionary monetary policy shock; theoretical models, however, make different predictions about the impact of loan supply shocks on the short-term nominal interest rate. Furthermore, we need to assume that a positive aggregate demand shock increases the corporate bond spread via its effect on credit demand. This is required to differentiate between positive aggregate demand and bank lending shocks. In both of these alternative identification schemes we maintain the additional short-run restrictions on the labor market variables. Table 3.5 summarizes these two identification schemes.

3.5 Results

We now present our main empirical results. We aim to answer the following questions: how are bank lending shocks transmitted to the labor market? Which factors have historically driven business cycle fluctuations in the US and the UK? What explains the volatility of labor market variables? And do bank lending shocks have a role in explaining labor market fluctuations in the US and in the UK?

First, in Section 3.5.1, we show the impulse response functions to one unit-variance positive bank lending shock.[37] We present the 68 percent credibility interval and the response of the median model, which is the structural model closest to the pointwise median effect calculated over the full sample. The labor market response is identified unambiguously for both the UK and the US. Qualitatively, the median response and the 68 percent credibility sets are very similar in the two countries. Like Gambetti and Musso (2014), we also find that the real effects of loan supply shocks are more persistent in the UK than in the US.

Then, in Section 3.5.2, we use the median model to show the temporal evolution of bank lending shocks and the contribution of these shocks to business cycle fluctuations. We find evidence that, especially in the UK, loan supply shocks are important drivers of unemployment and the labor market transition probabilities. A fall in the growth rate of bank lending to non-financial firms has long-lasting effects on labor market variables particularly around the time of significant recessions.

[37]The impulse response functions for aggregate supply, aggregate demand, and monetary policy shocks are shown in *Appendix* 3.8.1.

Lastly, in Section 3.5.3, we examine the average importance of bank lending shocks in explaining deviations of the endogenous variables from their baseline projection. Although most of the variance in the labor market variables remains unexplained, variance decomposition analysis shows that loan supply shocks are the most important factor among the four structural shocks we identify. Generally, bank lending shocks account for a larger proportion of labor market fluctuations in the UK than in the US. We link this finding to the higher reliance of the UK non-financial corporate sector on bank lending as a source of funding.

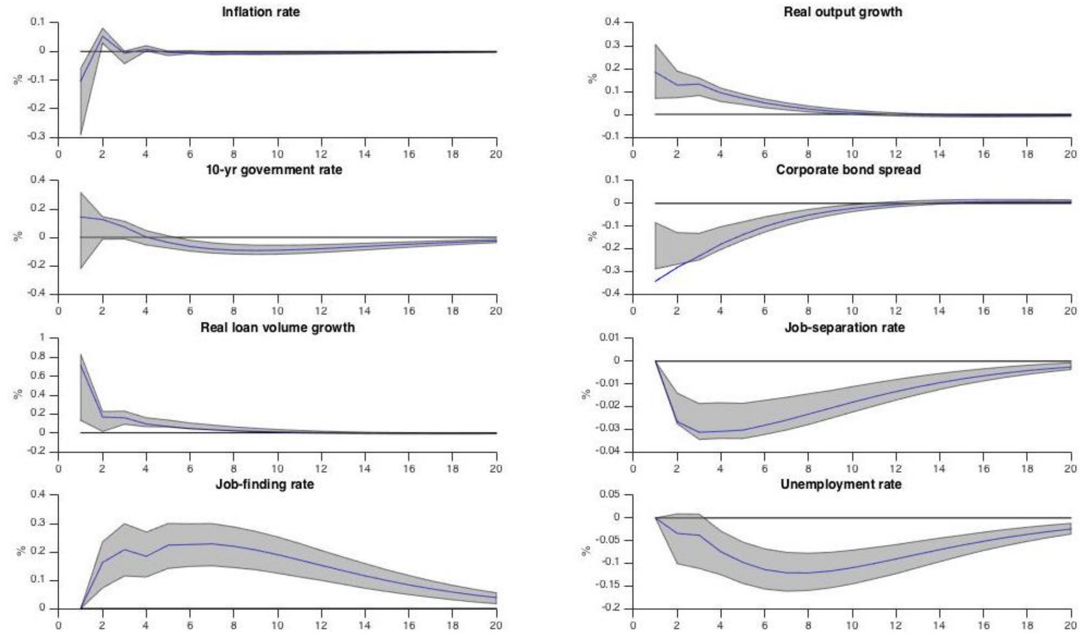
3.5.1 Transmission of Bank Lending Shocks

We now discuss how loan supply shocks are transmitted to the labor market. Figures 3.3 and 3.4 depict the impulse response functions to a positive bank lending shock for the UK and the US, respectively. Consistent with the DSGE literature on financial frictions, we find that a positive shock increases both the growth rate of real credit volumes and the growth rate of real output for several periods. The latter increases by 0.2 percentage points in the first quarter with a cumulative effect of about a percentage point in the first year. This positive effect lasts for two years in the UK and one year in the US. The fall in the corporate bond spread is larger and more persistent in the UK than in the US, with an immediate response of 30 and 20 basis points, respectively.

In both countries, the shock initially lowers inflation, but this effect quickly dissipates. At first, lower borrowing costs reduce real marginal costs for firms and puts downwards pressures on prices. Over time, the expansion in output increases consumption and aggregate demand. This raises the inflation rate and counteracts the initial impact of the shock on prices. The net effect on inflation, however, is quite small, particularly in the US. Moreover, since inflation moves little, the policy rate does not change much in either country.

In terms of labor market dynamics, after an initial sluggish response, the positive bank lending shock increases the job-finding rate and lowers both the job-separation rate and the unemployment rate. Quantitatively, the magnitudes

Figure 3.3: Baseline Model: Response to an Expansionary Loan Supply Shock (UK)

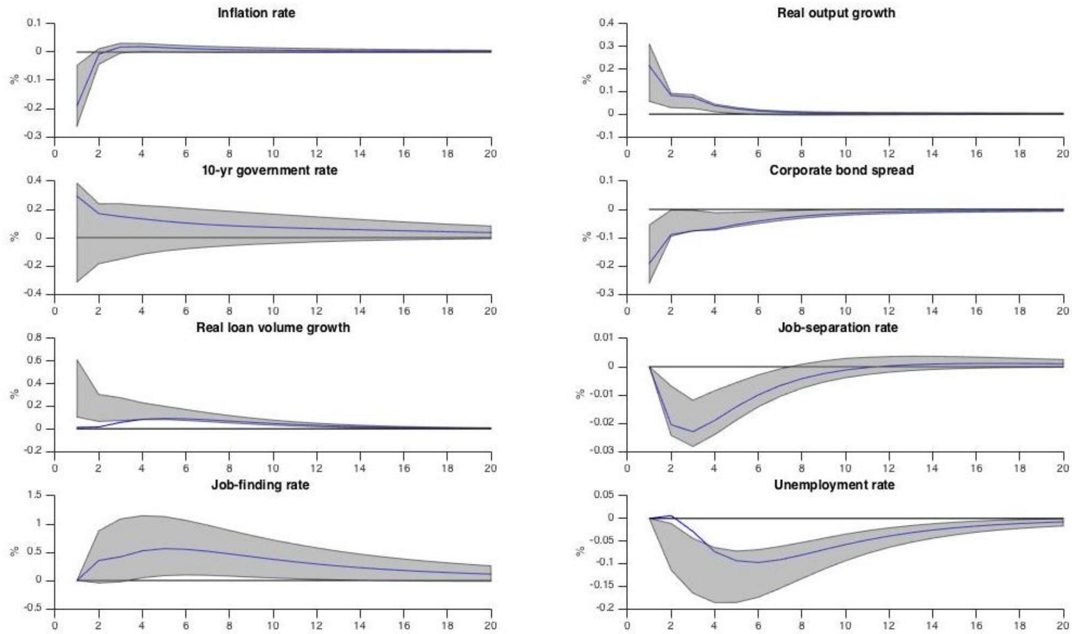


The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

of the median responses are similar in the two countries. Furthermore, all three variables follow hump-shaped responses, with the peak response reached earlier in the US than in the UK. In fact, the unemployment rate starts falling after one quarter in the former, but only after 2-3 quarters in the latter. This slower adjustment process may reflect a higher degree of labor market rigidities in the UK compared to the US that prevent employment levels from adjusting quickly to economic shocks. Moreover, the shock is quite persistent in both countries, particularly in the UK. For instance, the unemployment rate takes about 3 years to return to its initial level in the US and 5 years in the UK. This may reflect the stronger reliance of UK firms on bank lending for their funding as well as higher intrinsic persistence of the UK labor market.

Additionally, while both higher job-creation and lower job-separation contribute to movements in the unemployment rate, the former is quantitatively more important. The median model predicts a peak response of the job-finding rate of 0.2 percentage

Figure 3.4: Baseline Model: Response to an Expansionary Loan Supply Shock (US)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

points in the UK and 0.5 points in the US, but the maximum fall in the the job-separation rate is an order of magnitude smaller at 0.03 and 0.025 percentage points.[38] Overall, the responses of the labor market variables are well-identified and remarkably similar across the two countries.

[38] This, however, does not imply that, following a bank lending shock, changes in job-creation drive movements in the unemployment rate. The actual unemployment rate u_t is well-approximated by the steady-state unemployment rate $\overline{u}$, which is a non-linear function of the two continuous-time transition rates s_t and f_t (Shimer, 2005b, 2012):

$$\overline{u} \equiv \frac{s_t}{s_t + f_t} \approx u_t \tag{3.17}$$

Taking a first-order linear approximation of (3.17) yields:

$$u_t - \overline{u} = \left(\frac{\overline{u}}{\overline{s} + \overline{f}}\right) \left\{ \left(\frac{1-\overline{u}}{\overline{u}}\right) (s_t - \overline{s}) - (f_t - \overline{f}) \right\} \tag{3.18}$$

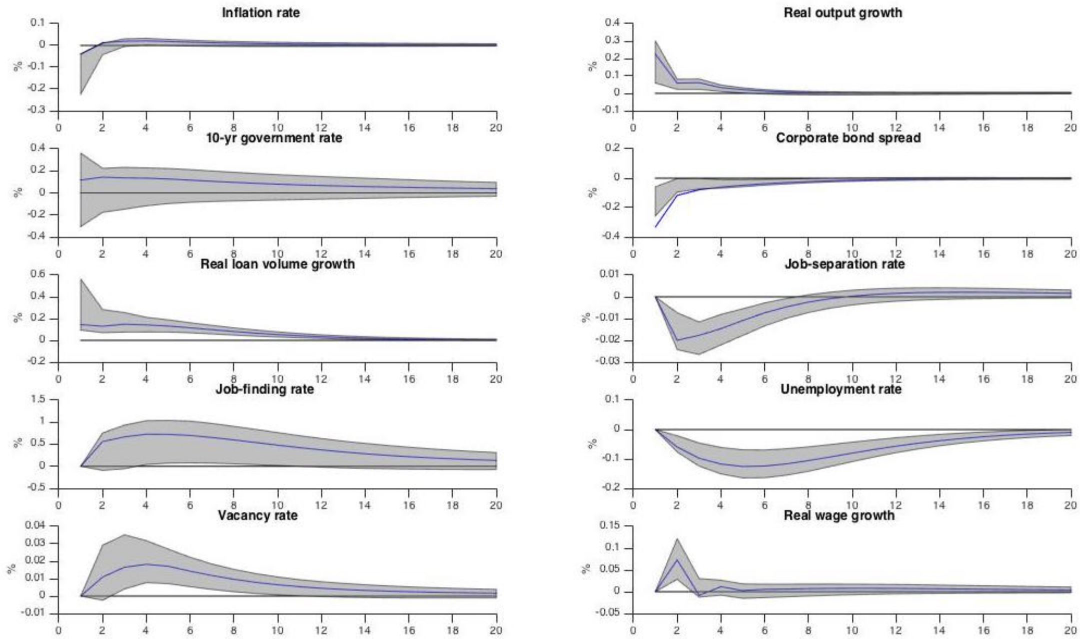
where $\overline{s}$ and $\overline{f}$ are the steady-state job-separation and job-finding transition rates. Using the long-run values of $\overline{u}$, the coefficient $\left(\frac{1-\overline{u}}{\overline{u}}\right)$ equals 13.5 for the UK and 15.6 for the US. Given the size of the responses of two discrete-time transition probabilities, job-destruction has an effect on the unemployment rate in the same order of magnitude of job-creation. Further analysis is required to quantify the relative contribution of these two factors in explaining unemployment rate fluctuations.

To explain in more detail the transmission mechanism of bank lending shocks, Figure 3.5 shows the impulse response function for the extended VAR model of the US economy that includes the vacancy rate and the growth rate in the real wage as additional endogenous variables. The shock has a positive effect on the vacancy rate lasting for approximately two years. By raising the growth rate of real credit volumes and lowering borrowing costs, a positive bank lending shock encourages non-financial firms to post more vacancies. In turn, this makes it easier for unemployed workers to find a job and move out of unemployment, thereby increasing the job-finding rate. As the economy booms, workers also receive faster real wage rises, albeit this effect is short-lived and quantitatively smaller than the rise in real output growth. This suggests that real profit growth outpaces real wage growth.

The results of this analysis are also consistent with the predictions of the theoretical model presented in chapter 2.[39] In the DSGE model, a positive shock to the net worth of financial intermediaries, or a loosening of the incentive constraint that intermediaries face, reduce borrowing costs for firms and increase their profits and their incentive to create vacancies. As a result, labor market tightness increases, raising the job-finding rate and lowering the unemployment rate. The increase in the real wage estimated in the SVAR is also in line with the prediction of the theoretical model. Furthermore, both models emphasize that bank lending shocks have long-lasting effects on the labor market. The theoretical model explains this high persistence as the interaction between intrinsic labor market inertia and a backward-looking accumulation process for the net worth of financial intermediaries.

[39]The directions of the estimated impulse response functions are also consistent with the predictions of a positive financial shock in Zanetti (2012). In this model, firms borrow from financial intermediaries to finance working capital; however, because debt contracts cannot be enforced, firms must pledge their physical capital in order to borrow. If a firm defaults, financial intermediaries can liquidate the collateral and recover some of the nominal debt value. The recovery rate determines the amount of firms' borrowing. A positive financial shock corresponds to an increase in the recovery rate of financial intermediaries. This allows firms to borrow more and finance higher job creation; thus, the vacancy rate and the job-finding rate increase, while the unemployment rate falls. Nevertheless, the effects of the shock are not as persistent as those observed in the data. Other theoretical models with labor and financial market frictions such as Chugh (2013), Petrosky-Nadeau and Wasmer (2013), Petrosky-Nadeau (2014), and Zanetti and Mumtaz (2016) do not study the impact that financial shocks have on the labor market. Comparing their predictions with the SVAR result could help discriminate among competing models.

Figure 3.5: Extended Model: Response to an Expansionary Loan Supply Shock (US)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

On the other hand, the DSGE and the SVAR models differ on the timing of the impact of aggregate shocks on the labor market, and on the response of the job-separation rate. In the theoretical model, firms are forward-looking and adjust their labor demand immediately in response to shocks. In the empirical model, in contrast, we assume that labor market variables react with a delay to aid the identification of structural shocks. Moreover, the model in chapter 2, as in line with most of the theoretical literature on labor and financial market frictions, assumes a constant job-destruction rate. The VAR findings, however, show that the job-separation rate falls persistently following a positive bank lending shock. This suggests that DSGE models should develop endogenous mechanisms that explain movements in the rate at which workers separate from firms. Despite these differences, the DSGE model in chapter 2 is able to capture some of the main responses observed in the data.

3.5.2 Historical Decomposition

In this section we perform a historical decomposition analysis to understand the main factors driving labor market fluctuations over the past few decades. Figures 3.6 and 3.7 show the evolution of the the four structural shocks we identify, with the bottom right panel depicting the bank lending shock.

Negative loan supply shocks tend to anticipate all major recessions over the period. For both countries, in particular for the UK, the largest negative bank lending shocks are associated with the recent 2007-08 financial crisis. We also capture a negative, albeit smaller and less prolonged, series of negative loan supply shocks during the 2000-01 slowdown. In addition, for the US we observe a series of large negative shocks in concurrence with the 1990-91 recession and its associated credit crunch (Bernanke and Lown, 1991; Peek and Rosengren, 1995), while for the UK we pick up a large negative shock in 2011 around the time of the Euro Area debt crisis. UK banks might have been wary to lend to non-financial corporations fearing the repercussions on the UK economy of the recession and the uncertainty in the UK's biggest trading partner. Furthermore, particularly for the US, we identify positive credit expansion during the 1990s and in the period leading up to the Great Recession. Lastly, for the UK, we also observe a series of positive loan supply shocks after the Bank of England launched the Funding for Lending Scheme (FLS) in July 2013.[40] We interpret this as evidence of the positive effects of FLS in the banking sector, consistent with the hypothesis that it helped financial intermediaries reduce financing costs and boast bank lending to firms (Churm *et al.*, 2015).

Figures 3.8 and 3.9 present the historical decomposition for the median model describing the UK economy. Bank lending shocks are important factors driving the evolution of some of the macroeconomic variables we study. Positive loan supply shocks contributed to output expansion during the 1990s and in the period prior to the financial crisis. Similarly, negative bank lending shocks explain most of the output fall during the financial crisis and the slowdown in 2011-12. Interestingly, this

[40]See Churm *et al.* (2012) for a detailed explanation of this scheme. In essence, the Bank of England offered cheap funds to financial intermediaries for a prolonged period of time to ease and promote bank lending to firms and households.

Figure 3.6: Structural Shocks for UK SVAR: 1993-2014

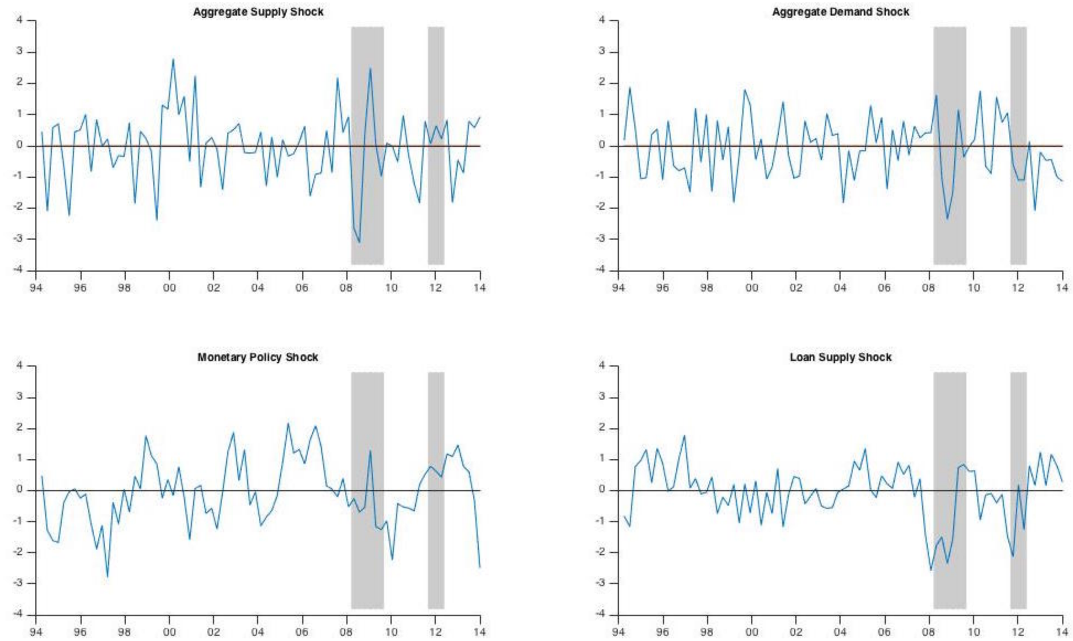
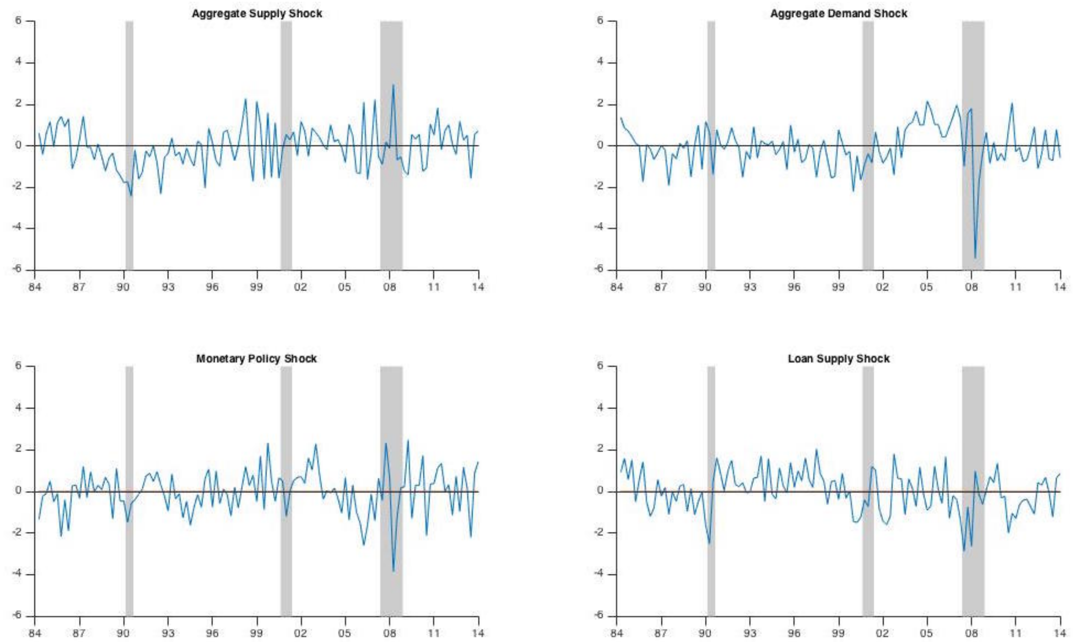


Figure 3.7: Structural Shocks for US SVAR: 1984-2014



These are the structural shocks associated with the median model.
Grey regions indicate recessions.

decomposition suggests that the expansion of credit associated with the launch of FLS has counteracted the effect of other negative shocks on real output growth since 2013. Had FLS not been implemented, real output growth would have been lower.

Moreover, bank lending shocks also explain most of the changes in the corporate bond spread and a great portion of the movement in real credit volume growth. In particular, they are responsible for most of the credit growth in the mid-1990s and for a substantial portion over the 2004-2007 period. Likewise, loan supply shocks explain most of the fluctuations in the corporate bond spread over the past two decades. In contrast, they account for little of the evolution of inflation and the nominal yield on long-term government bonds.

In terms of labor market variables, the residual component of the structural disturbances explains most of the movements in the transition probabilities and the unemployment rate. Nonetheless, bank lending shocks play an important role during specific periods. Credit expansion in the mid-1990s explains much of the rise of the job-finding rate and the fall in the job-separation and the unemployment rates. Similarly, during the financial crisis, negative bank lending shocks are responsible for most of the movements in the transition probabilities and the rise in the unemployment rate. This suggests that in an economy in which firms rely on bank lending to finance themselves, the behavior of the banking sector is important to explain labor market fluctuations not only during large financial crisis, but also in other phases of the business cycle.

The historical decomposition of the US data in Figures 3.10 and 3.11 shows a different pattern. Bank lending shocks are generally less important than in the UK in accounting for labor market fluctuations. Lower reliance of US firms on bank credit most likely explains this. These shocks are responsible for much of the output expansion in the 1990s as well as the fall in output and the rise in the corporate bond spread during the financial crisis. They are also important for explaining labor market fluctuations during the mid-1990s boom and the financial crisis, but they play a limited role outside these two periods.

Figure 3.8: Historical Decomposition for UK SVAR: 1993-2014 (1)

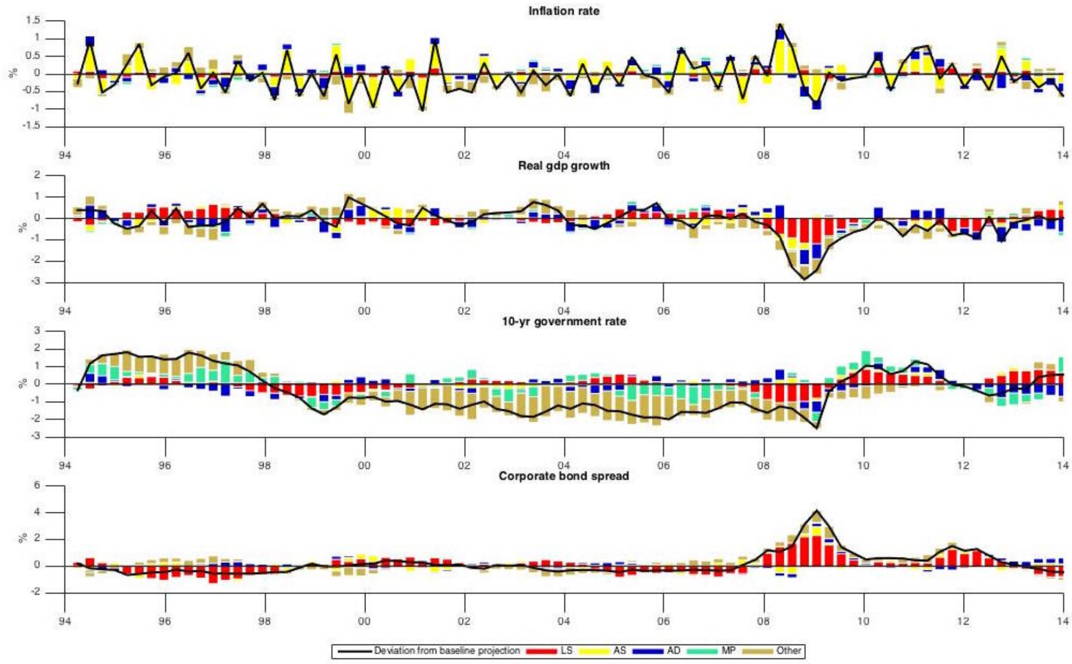
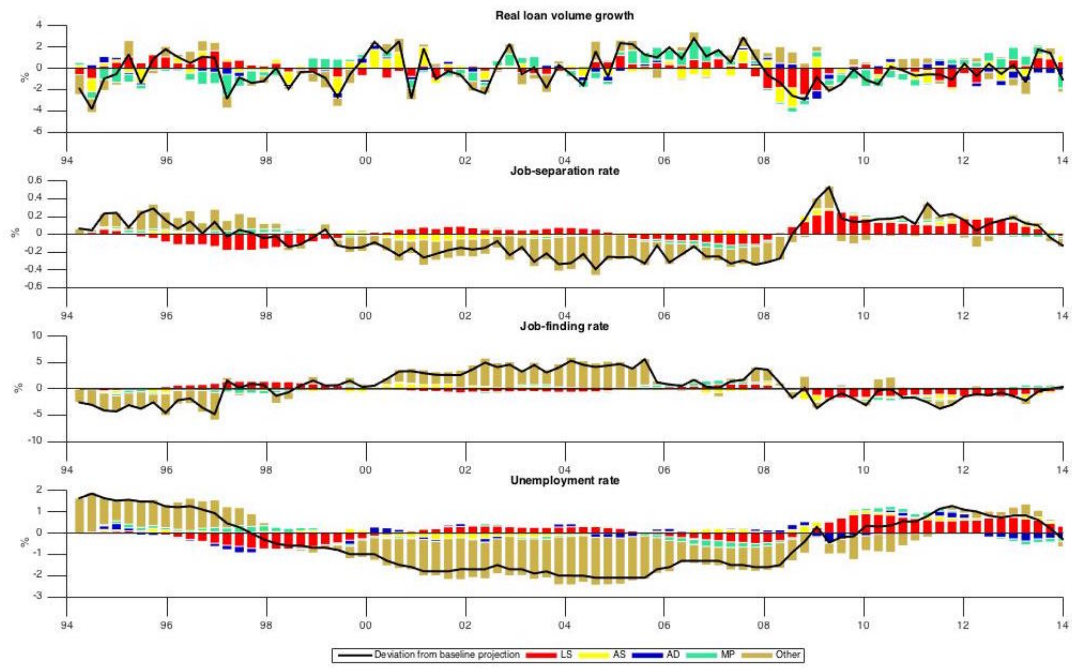


Figure 3.9: Historical Decomposition for UK SVAR: 1993-2014 (2)



This is the historical decomposition of the median model.

In particular, we estimate the effect of negative loan supply shocks on the unemployment rate to be 27 percent for the 2008Q4-2009Q4 period. More precisely, these shocks are responsible for 50 percent of the deviation of the unemployment rate from its baseline projection in the last quarter of 2008, and for 27, 22, 19, and 16 percent of the deviation in each of the four subsequent quarters, with a cumulative effect of 21 percent in 2009. We can compare these estimates with those in the microeconometric literature. Using survey data, Chodorow-Reich (2014) calculates that a negative loan supply shock accounts for 20-33 percent of the fall in aggregate employment in the twelve months following the Lehman bankruptcy. Greenstone *et al.* (2014) estimate this effect to account at most for 13 percent of the fall in total employment between 2008 and 2009.

External validity and general equilibrium effects pose challenges to estimating the effect of bank lending shocks on employment using survey data. First, these datasets are generally unrepresentative of the population of US firms. For instance, before calculating the aggregate effects of the shock, Chodorow-Reich (2014) must rescale the sample to replicate the distribution of firms based on employment size. Second, this effect is calculated as the difference in employment growth rates between firms borrowing from financially constrained banks and those that are borrowing from financially unconstrained ones.[41] In doing this, general equilibrium effects such as the reallocation of labor from constrained to unconstrained firms are ignored.

On the other hand, our SVAR estimates are based on aggregate data on employment and bank lending. Thus, external validity and general equilibrium effects pose less of a concern. The VAR specification and the validity of our identification scheme, however, are crucial for the unbiasedness and the consistency of our estimate of the effects of bank lending shocks on the labor market during the financial crisis.

[41] There is evidence that firm-bank relationships are sticky. Thus, a firm cannot easily switch from a financially constrained bank to an unconstrained one.

Figure 3.10: Historical Decomposition for US SVAR: 1984-2014 (1)

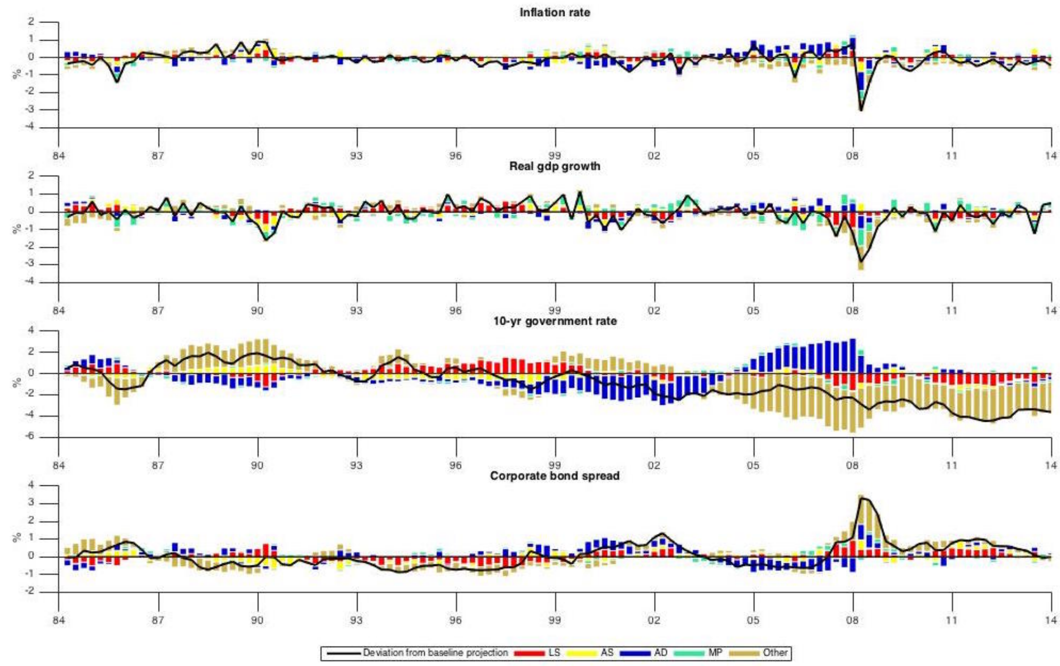
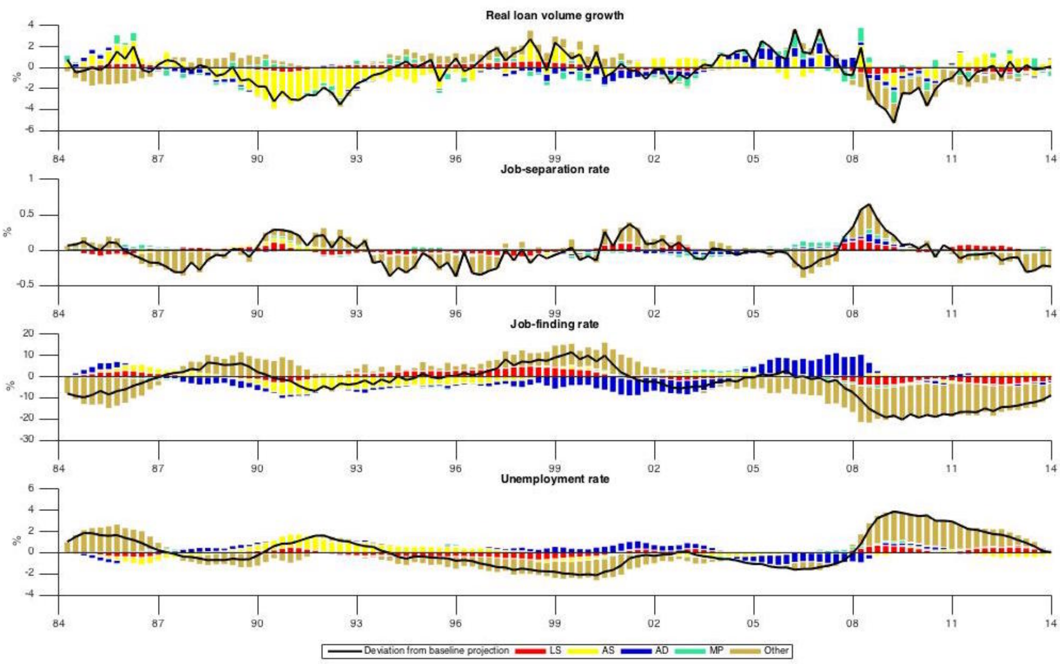


Figure 3.11: Historical Decomposition for US SVAR: 1984-2014 (2)



This is the historical decomposition of the median model.

3.5.3 Forecasting Error Variance Decomposition

Next, we examine how each shock contributes to the volatility of our macroeconomic variables. Tables 3.6 and 3.7 show the forecasting error variance decomposition of the median model at different horizons. For the UK, bank lending shocks account for a significant fraction of real output growth and corporate bond spreads at all horizons. They are also quite important in accounting for the volatility of the growth in real credit volumes, but they are less important for inflation and the yield on long-term government bonds. For the US, with the exception of the growth in real credit volumes, bank lending shocks explain a small fraction of the main real and financial variables.

In terms of labor market variables, most of the variance remains unexplained. Nevertheless, in both countries, bank lending shocks are the most important factor among the structural disturbances we identify. Furthermore, the proportion of variance that loan supply shocks can explain increases over time. For the UK labor market, bank lending shocks can explain 7.2 percent of the job-separation rate volatility at two quarters, 16.1 percent after one year, and more than a quarter for horizons of two years or more. In terms of the job-finding rate, loan supply shocks can account for 3.5, 8.4, and 11.1 percent of its variance at horizons of one, two, and three years, and for 3.5, 10.3, and 14.4 percent of the variance in the unemployment rate at horizons of one, two, and three years. In contrast, for the US, bank lending shocks can account for a negligible fraction of the variance in the job-separation rate, but for about 16 percent of the variance in the job-finding rate at long horizons. Thus, loan supply shocks can explain a growing fraction of the variance in the US unemployment rate, from 1.3 percent after two quarters up to 10.6 percent after 2 years.

3.6 Robustness Analysis

In this section we examine the impact on our main findings of alternative identification schemes and alternative specifications of the mode. First, in Section 3.6.1, we employ the alternative schemes discussed in Section 3.4.3.2 and summarized in Table 3.5

Table 3.6: Forecasting Error Variance Decomposition (UK)

Horizon	*LS*	*AS*	*AD*	*MP*	*Other*	*LS*	*AS*	*AD*	*MP*	*Other*
	Inflation (%)					*Real output (%)*				
1	12.4	1.6	40.5	13.6	31.9	46.2	22.4	7.4	17.8	6.2
2	12.1	4.9	38.2	14.7	30.2	49.6	19.5	7.6	14.9	8.3
4	11.8	5.3	37.8	14.6	30.5	53.8	17.1	7.5	12.1	9.4
8	11.7	5.5	37.5	14.5	30.8	54.2	16.1	8.0	11.2	10.5
12	11.8	5.5	37.4	14.4	30.9	53.6	15.9	8.0	11.1	11.3
16	11.9	5.4	37.3	14.4	30.9	53.4	15.8	8.0	11.1	11.7
20	11.9	5.4	37.3	14.4	30.9	53.4	15.8	8.0	11.0	11.8
40	11.9	5.4	37.3	14.4	30.9	53.4	15.8	8.0	11.0	11.8
	10-year government rate (%)					*Corporate bond spread (%)*				
1	2.1	2.3	57.9	4.5	33.2	29.5	18.1	46.1	1.2	5.1
2	2.1	2.1	51.0	3.7	41.2	40.3	1.8	40.6	0.8	6.4
4	1.8	2.6	39.9	3.0	52.6	48.6	8.4	33.6	0.6	8.7
8	5.6	2.6	30.6	2.6	58.7	50.7	7.4	31.2	0.5	10.2
12	9.5	2.4	27.4	2.3	58.4	50.2	7.3	30.9	0.6	11.1
16	11.2	2.3	26.5	2.3	57.7	49.9	7.3	30.7	0.6	11.5
20	11.7	2.3	26.3	2.2	57.4	49.9	7.3	30.6	0.6	11.7
40	11.8	2.3	26.3	2.2	57.4	49.9	7.2	30.5	0.6	11.8
	Real loan volume growth (%)					*Job-separation rate (%)*				
1	11.2	31.4	0.4	33.7	23.2	0	0	0	0	100
2	11.8	31.3	3.0	30.5	23.4	7.2	0	0	0.2	92.5
4	14.0	31.6	3.7	28.3	22.3	16.1	0.1	0	0.4	83.4
8	15.4	31.2	4.0	27.6	21.8	24.6	0.2	0.3	0.4	74.5
12	15.5	31.1	4.0	27.5	21.9	27.6	0.2	0.6	0.4	71.2
16	15.5	31.1	4.0	27.4	22.0	28.5	0.2	0.7	0.3	70.3
20	15.5	31.1	4.0	27.4	22.0	28.6	0.2	0.8	0.3	70.1
40	15.5	31.1	4.0	27.4	22.0	28.6	0.2	0.8	0.3	70.1
	Job-finding rate (%)					*Unemployment rate (%)*				
1	0	0	0	0	100	0	0	0	0	100
2	0.9	0.3	0.5	0	98.3	1.4	0.1	1.4	0.8	96.3
4	3.5	0.3	1.2	0.2	94.7	3.5	0.8	2.1	1.4	92.3
8	8.4	0.4	1.1	0.3	89.8	10.3	1.0	1.6	1.2	85.9
12	11.1	0.4	1.1	0.3	87.1	14.4	1.0	1.6	1.1	81.9
16	12.1	0.4	1.2	0.3	86.1	15.9	0.9	1.6	1.1	80.4
20	12.3	0.4	1.2	0.3	85.8	16.3	0.9	1.7	1.1	80.0
40	12.3	0.4	1.2	0.3	85.7	16.4	0.9	1.7	1.1	79.9

This is the forecasting variance decomposition of the median model.

Table 3.7: Forecasting Error Variance Decomposition (US)

Horizon	*LS*	*AS*	*AD*	*MP*	*Other*	*LS*	*AS*	*AD*	*MP*	*Other*
	Inflation (%)					*Real output (%)*				
1	14.8	14.7	21.9	6.3	42.3	5.3	3.8	4.2	64.8	21.9
2	13.9	14.1	23.0	6.1	42.9	5.6	3.7	4.1	63.0	23.6
4	14.2	13.8	23.0	6.2	42.8	5.8	3.9	4.1	61.6	24.7
8	14.4	13.5	23.1	6.4	42.7	5.7	3.9	4.4	61.0	25.0
12	14.4	13.3	23.2	6.4	42.6	5.7	3.8	4.5	60.8	25.2
16	14.5	13.3	23.2	6.4	42.6	5.7	3.8	4.6	60.6	25.2
20	14.5	13.2	23.2	6.5	42.6	5.8	3.8	4.6	60.6	25.2
40	14.5	13.2	23.2	6.5	42.6	5.8	3.8	4.6	60.5	25.3
	10-year government rate (%)					*Corporate bond spread (%)*				
1	3.9	1.3	53.7	3.3	37.7	6.4	63.9	4.4	9.9	15.4
2	3.6	1.3	53.4	2.4	39.2	4.7	50.4	6.9	12.3	25.7
4	4.0	1.0	51.4	2.4	41.2	3.9	41.8	7.4	13.3	33.6
8	5.9	0.8	48.1	2.9	42.3	3.7	38.8	7.9	14.0	35.6
12	7.3	0.8	46.4	3.2	42.4	3.7	38.5	8.2	14.0	35.7
16	8.0	0.8	45.5	3.5	42.2	3.7	38.3	8.3	13.9	35.8
20	8.4	0.8	45.0	3.7	42.1	3.7	38.3	8.3	13.9	35.8
40	8.6	0.8	44.7	3.8	42.1	3.7	38.2	8.3	13.9	35.8
	Real loan volume growth (%)					*Job-separation rate (%)*				
1	69.1	11.9	1.9	1.0	16.0	0	0	0	0	100
2	63.7	10.7	1.5	2.7	21.5	0.3	0	0	4.8	94.9
4	54.6	9.3	1.1	5.9	29.1	0.8	0.2	0.4	7.9	90.7
8	48.1	8.5	0.9	9.1	33.4	0.8	0.3	0.9	8.9	89.1
12	47.1	8.4	0.9	9.6	34.0	1.2	0.3	1.2	8.8	88.5
16	47.0	8.4	0.9	9.7	34.0	1.4	0.3	1.4	8.8	88.2
20	47.0	8.4	0.9	9.7	34.0	1.5	0.3	1.4	8.8	88.0
40	47.0	8.4	0.9	9.7	34.0	1.5	0.3	1.5	8.8	87.9
	Job-finding rate (%)					*Unemployment rate (%)*				
1	0	0	0	0	100	0	0	0	0	100
2	4.6	0.2	4.8	1.3	89.1	1.3	0	0	0.3	98.4
4	11.2	0.6	10.2	5.4	72.6	6.7	0.4	0.4	4.1	88.5
8	15.6	1.2	13.1	8.7	61.3	10.3	1.1	0.9	8.8	78.9
12	16.3	1.3	14.2	9.6	58.6	10.6	1.2	1.1	9.8	77.2
16	16.4	1.3	14.7	9.8	57.8	10.6	1.2	1.2	10.0	77.0
20	16.5	1.3	14.9	9.8	57.4	10.6	1.2	1.3	10.0	76.9
40	16.5	1.3	15.1	9.8	57.2	10.6	1.2	1.3	10.0	76.9

This is the forecasting variance decomposition of the median model.

to identify the structural shocks. Then, in Section 3.6.2, we re-estimate the SVAR model for the UK economy using a measure of the short-term policy rate adjusted for the effects of QE instead of the yield on long-term government bonds. Lastly, in Section 3.6.3, we re-estimate the SVAR model using a more conventional measure of monetary policy for a sub-sample that excludes the zero lower bound period from 2009 onwards. The results of this robustness assessment generally support the main findings of the analysis.

3.6.1 Alternative Identification Schemes

In our baseline identification scheme we assume that in the very short run an expansionary bank lending shock lowers inflation. Since firms can borrow more cheaply, real marginal costs and inflation fall. On the other hand, Gambetti and Musso (2014) argue that an expansion of credit to households and firms is inflationary because it increases private consumption and investment demand. In order to identify all four structural shocks, they also need to assume that an expansionary bank lending shock also increases the policy rate. Furthermore, they assume that aggregate demand shocks increase the corporate bond spread, but they can relax the restriction that aggregate supply shock must increase credit demand leading to higher real credit growth and corporate bond spreads.

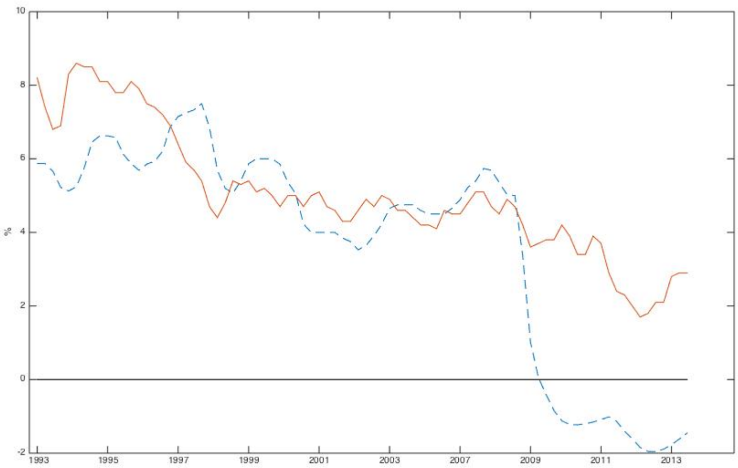
Figures 3.22 and 3.23 in *Appendix* 3.8.2.1 show the impact of a positive bank lending shock on the UK and US economies when we impose this alternative identification scheme. In the US model, the response of the labor market variables to a positive bank lending shock is in line with our main findings. In fact, the response of the job-finding and the unemployment rates are better identified, with narrower credibility intervals. In contrast, in the UK model there are some substantial differences between our preferred baseline scheme and this alternative scheme. In the former, the job-separation rate falls and the job-finding rate rises, leading to an unambiguous and persistent fall in the unemployment rate. In the latter, the responses of the transition probabilities are not well identified. There is a substantial number of models that predicts a fall in the job-finding rate. As a result, the unemployment rate initially rises before falling slightly below its long-run equilibrium value. Thus, the results of this alternative identification schemes are not fully consistent with our main findings. Nonetheless, since our interest is on the impact of loan supply shocks to the corporate sector, as opposed to both the corporate and household sectors as in Gambetti and Musso (2014), we believe that the arguments in favor of an inflationary bank lending shock are less convincing and that our baseline scheme is a more valid identification strategy.

Alternatively, we could leave the response of inflation to a bank lending shock unrestricted but assume instead that the policy rate increases. Under this scheme, we also need to assume that a positive aggregate demand shocks increases the corporate bond spread. Figures 3.24 and 3.25 in *Appendix* 3.8.2.2 show the impact of a positive bank lending shock on the US and UK economies under this alternative identification scheme. Qualitatively, the labor market responses are very similar to those estimated under our baseline scheme. In particular, in the US model, the job-finding and the unemployment rates are better identified, while the job-separation rate moves relatively less. In the UK model, we find a higher degree of labor market inertia. The job-finding rate adjusts more slowly before eventually increasing above its long-run value; thus, compared to our baseline scheme, the unemployment rate falls persistently only after several quarters. Besides, the short-run response of inflation remains indeterminate in both countries. Taken together, the findings of this alternative scheme support our main results.

3.6.2 A QE-Adjusted Measure of the Short-Term Policy Rate for the UK

As a further robustness check, we estimate a SVAR for the UK economy using a different measure of the policy rate. In our main model, we employ the yield on the 10-year government bond as a proxy of the stance of monetary policy because, due to the zero lower bound, the short-term nominal interest rate is uninformative about monetary policy after 2008. The long-term rate interest rate, however, is only an imperfect proxy for the stance of monetary policy. Variations in the long-term yield may capture variations in the term premium as well as movements

Figure 3.12: QE-Adjusted Series
of the Short-Term Policy Rate (UK)



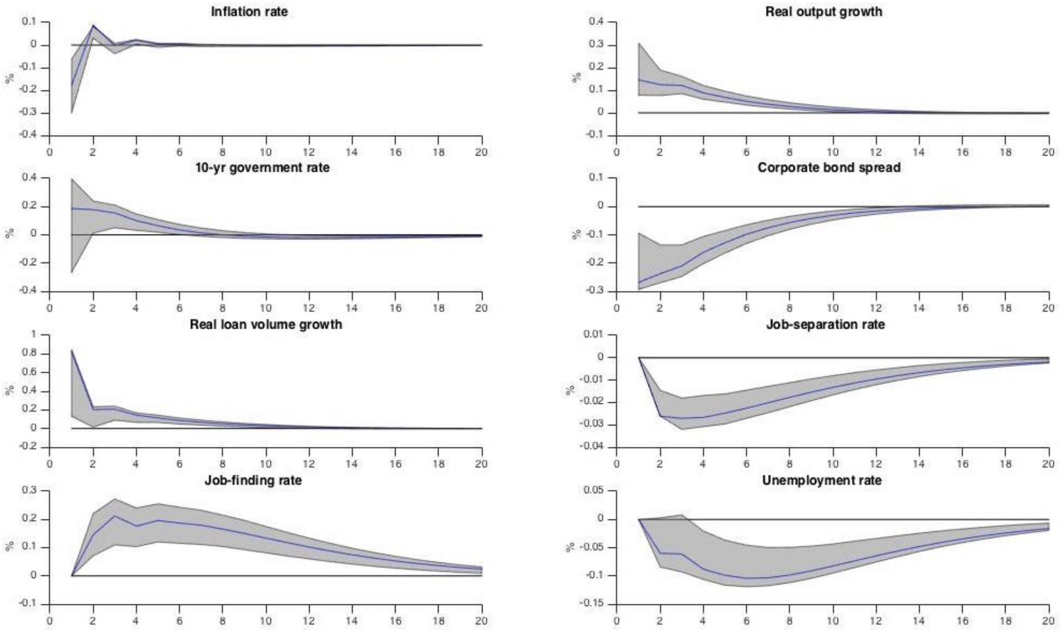
The dashed line is the QE-adjusted short-term rate.
The continuous line is the long-term yield.

in monetary policy. For instance, at times of great economic uncertainty, investors may wish to invest in safe long-term government bonds rather than in equity or corporate bonds of similar maturity. Since changes in the long-term yield may reflect factors other than the stance of monetary policy, in our SVAR model we might have identified a spurious monetary policy shock, with consequences on the identification of the bank lending shock.

In contrast, we now employ a measure of the short-term policy rate which controls for the effects of the Bank of England's asset purchase (QE) facility. Under this policy, the Bank of England has been purchasing government bonds held in the portfolio of private investors to lower yields on these assets and to free up resources for the private sector to invest in other asset classes. To calculate this QE-adjusted interest rate measure, the Bank of England estimated the effects of these asset purchases on the economy and compared them with those of conventional interest rate policy. Using the relative effect, it then estimated the nominal interest rate that would have delivered the same outcomes.

Figure 3.12 plots this series along with the series for the yield of the 10-year

Figure 3.13: Response to an Expansionary Loan Supply Shock Using QE-Adjusted Short-Term Policy Rate (UK)



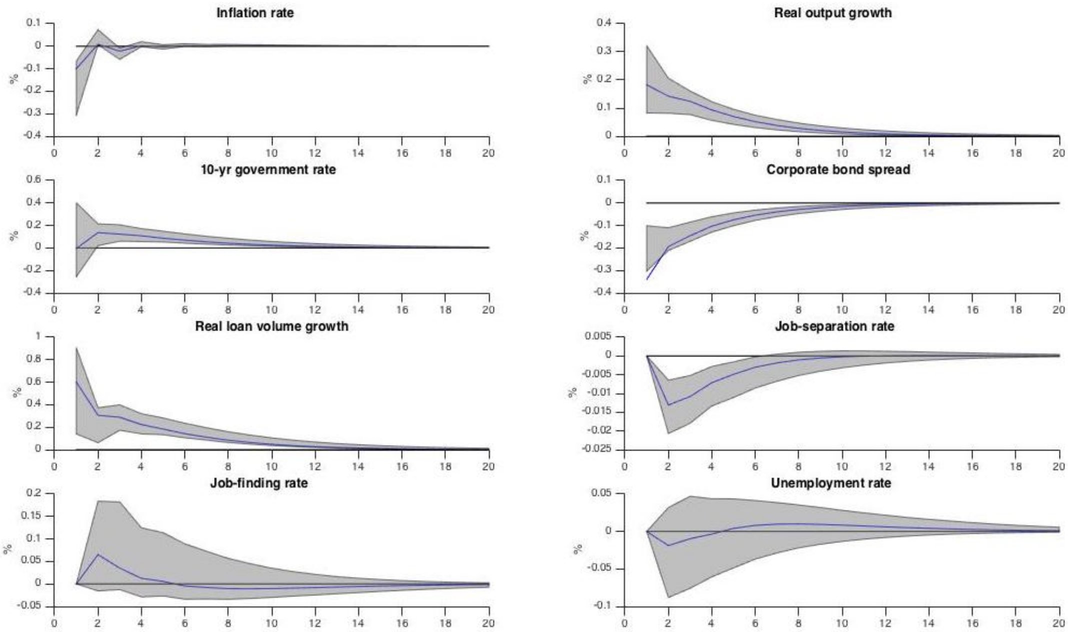
The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

government bond. After 2008, the nominal interest rate falls significantly below zero and reaches -2 percent in 2012. This variable suggests that monetary policy has been much looser than what is implied by the long-term yield. Using this measure in the VAR helps separate monetary policy from bank lending shocks because it captures the fall in the policy rate as the monetary authority's endogenous response to the financial crisis rather than an unexpected cut.[42]

Figure 3.13 shows the impulse response function to a positive bank lending shock. The responses of the two specifications are very similar, both in terms of credibility intervals and median model. A supply-driven expansion of bank credit to firms reduces the job-separation rate and increases the job-finding rate, leading to a persistent fall in the unemployment rate. The historical decomposition analysis shown in Figures 3.27 and 3.28 in *Appendix* 3.8.2.3 reinforces the findings of the main

[42]The correlation between the two series is 0.762 over the full sample.

FIGURE 3.14: RESPONSE TO AN EXPANSIONARY LOAN SUPPLY SHOCK: 1993-2008 (UK)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

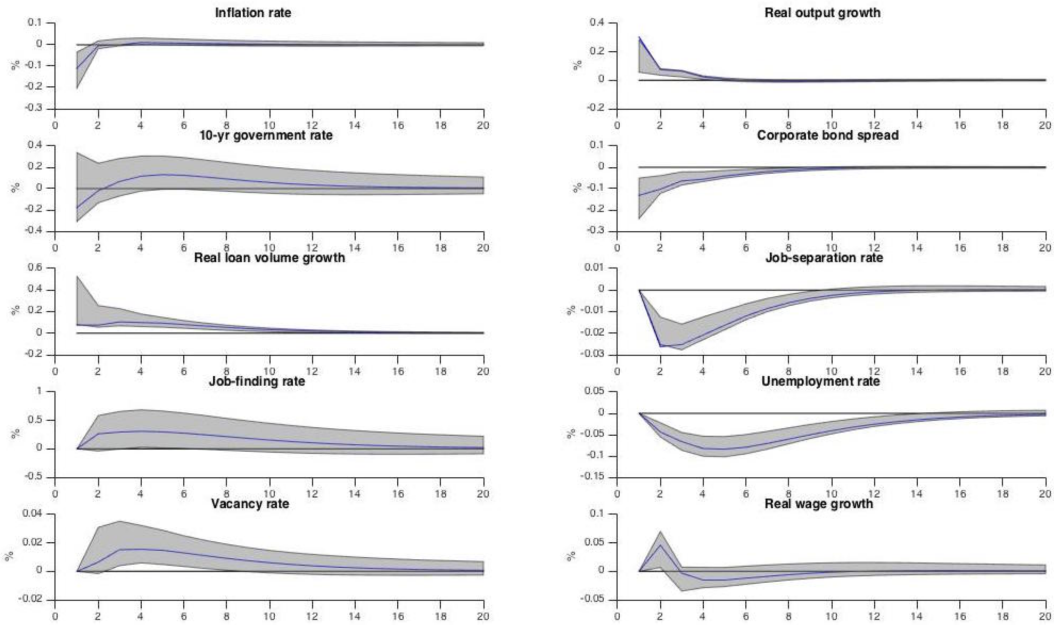
analysis: bank lending shocks are important to explain labor market fluctuations in the UK, particularly during the mid-1990s expansion and the financial crisis.

3.6.3 Bank Lending Shocks in the Great Moderation

As a final robustness check, we re-estimate the model for the sub-sample ending in 2008 which corresponds to the Great Moderation. This excludes the period during which the short-term policy rate hit its zero lower bound, so we can employ it as a measure of monetary policy stance. More precisely, we use the nominal interest rate on the 3-month gilt for the UK (series IUQAGR3M from the Bank of England), and the Federal Funds Rate for the US. We take quarterly averages for both series.

As shown in Figure 3.14, we cannot unambiguously identify the labor market response to a positive bank lending shock. While most models predict the job-finding rate to rise, several models predict a fall; hence, the response of the unemployment rate is undetermined. In contrast, Figure 3.15 shows that the labor market response

Figure 3.15: Response to an Expansionary Loan Supply Shock: 1984-2008 (US)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

for the US economy is both qualitatively and quantitatively similar to the findings of our baseline specification.[43] A positive bank lending shock lowers the job-separation rate and increases both the vacancy ratio and the job-finding rate, leading to a persistent fall in the unemployment rate. The real wage also increases temporarily.

When we remove the period starting in 2009 from the estimation, we are effectively excluding the portion of the sample that is most informative about the labor market impact of bank lending shocks. In addition, we shorten considerably the size of our sample, particularly for the UK, which increases sampling uncertainty. For the US model, the sample is still sufficiently long for us to recover the same bank lending shock and identify its impact on the labor market. However, for the UK model the sub-sample is too short for us to identify unambigously the labor

[43]Estimating the baseline VAR with eight endogenous variables for the 1984-2008 sub-sample and the Federal Funds Rate also shows that the main findings are robust. We present only the results for the extended VAR model to show the robustness of the transmission mechanism.

market impact of loan supply shocks. Thus, at least for the US, there is evidence that the transmission mechanism of bank lending shocks that we identify is robust.

3.7 Conclusion

The global financial crisis has shown the relevance of the banking sector for business cycle fluctuations. Notwithstanding the negative impact of the recession on labor markets across the world, the relationship between financial shocks originating in the banking sector and labor market outcomes has received limited attention in the literature. Understanding how bank lending shocks are transmitted to labor markets is crucial to devise appropriate policy responses as well as to improve our understanding of how labor and financial market frictions interact with each other in determining labor market outcomes.

In this chapter, we estimate a Bayesian structural vector autoregressive model of the UK and the US economies to identify the transmission channel of bank lending shocks to the labor market. We use a scheme based on a mix of short-run sign and exclusion restrictions to identify aggregate supply, aggregate demand, monetary policy, and bank lending shocks. Drawing from the existing literature, we assume that an expansionary bank lending shock increases the growth rate of real credit, reduces the corporate bond spread and the rate of inflation but has no contemporaneous effects on the labor market. After estimating the model, we use impulse response functions to understand the propagation of bank lending shocks to the labor market. We also employ historical and forecasting variance decompositions to assess the contribution of loan supply shocks in explaining labor market fluctuations.

We find that an expansionary bank lending shock increases the job-finding rate and lowers the job-separation rates, leading to a persistent fall in the unemployment rate. In particular, a positive loan supply shock reduces borrowing costs for non-financial firms and encourages them to create more vacancies. As unemployment falls and output rises, the real wage increases as well. These findings are generally robust to alternative identification restrictions and different model specifications.

Moreover, this propagation mechanism is consistent with the predictions of the theoretical model presented in chapter 2. In light of this, we could interpret a positive bank lending shock as an unexpected increase in the net worth of financial intermediaries, or a loosening of the incentive constraint intermediaries face. The SVAR evidence we provide, however, is also consistent with alternative transmission mechanisms such as the one presented in Zanetti (2012). Hence, more work is required to assess which DSGE model with labor and financial frictions provides the most convincing explanation for this propagation mechanism.

Furthermore, we also find that bank lending shocks are important drivers of labor market fluctuations in the UK. At long horizons, loan supply shocks can account for approximately 16 percent of the forecasting variance of the UK unemployment rate. Moreover, they explain most of the fluctuations during the mid-1990s expansion and the recent financial crisis. In contrast, bank lending shock can only account for 11 percent of the forecasting variance of the US unemployment rate. The relatively lower reliance of US firms on bank lending compared to their UK counterparts most likely explains this finding. Nonetheless, loan supply shocks account for about 27 percent of the movement in the unemployment rate between 2008Q4 and 2009Q4. Lastly, we find some evidence suggesting that the Bank of England's Funding for Lending Scheme had a positive effect on the supply of bank credit and counteracted the impact of other negative shocks on labor market outcomes. Helping the financial intermediaries provide loans to the non-financial sector is indeed the appropriate policy response following a severe credit crunch.

In this analysis, we focus on the impact of bank lending shocks on the demand side of the labor market. Further work could examine the impact of these shocks on the labor supply decisions of households. A fully specified model would also investigate the interaction between lending shocks to firms and to households in determining labor market outcomes. In fact, an expansionary loan supply shock may encourage households to work less, counteracting the positive effect on employment of higher labor demand. This household credit channel could be important to explain recent changes in the labor market in both the US (Campbell and Hercowitz, 2011;

Chai *et al.*, 2011) and the UK (Benito and Jumana, 2013). Furthermore, the results of our analysis hinge on the validity of our identification scheme and the specification of the VAR model. Although we have assessed the robustness of our main findings to different identification schemes and measures of the policy rate, alternative identification strategies which are not based on sign restrictions could be employed to provide additional evidence on the transmission mechanism of bank lending shocks. Moreover, we include a structural break into the VAR of the UK economy as an exogenous shifter of the long-run mean of the model. Implicitly we treat this as a temporary shift due to the financial crisis. Nevertheless, if this were a permanent change in the process of the endogenous variables, then we would have greatly underestimated the impact of these shocks on the labor market.

Despite these limitations, we find that shocks to the quantity and price of corporate credit can have important effects on the labor market. Since many firms rely on bank credit to finance their operations, unexpected changes to the availability of credit and their borrowing costs have an impact on labor demand and the job-finding rate for unemployed workers. Thus, more empirical and theoretical work is required to improve our understanding of how bank lending shocks, and financial shocks more generally, affect the labor market.

3.8 Appendix

3.8.1 Impulse Response Functions to Aggregate Shocks

Figure 3.16: Baseline Scheme: Response to an Expansionary Aggregate Supply Shock (UK)

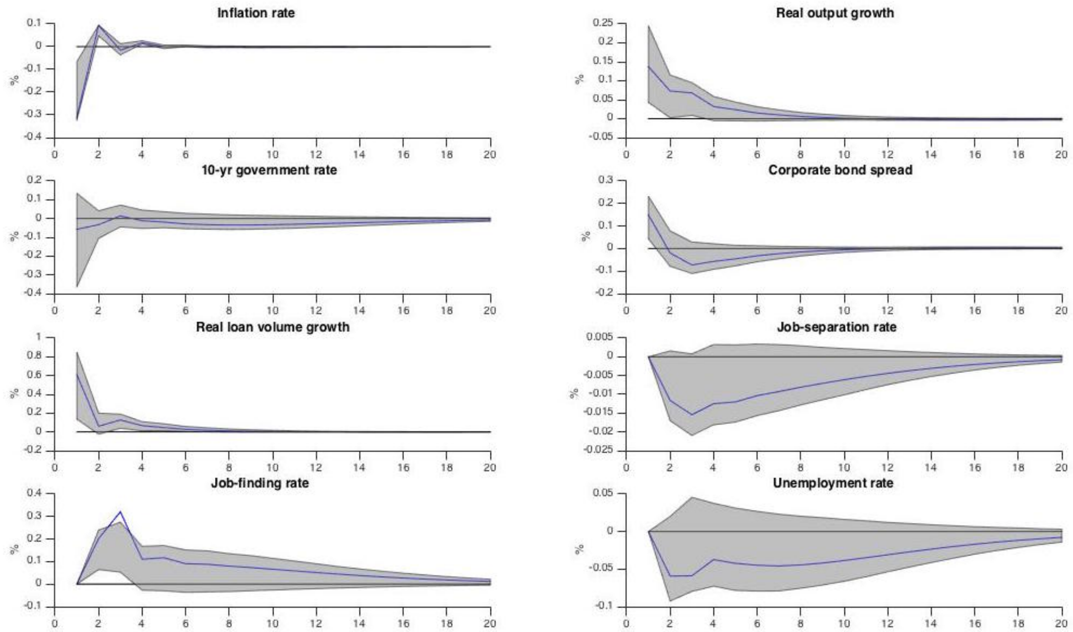
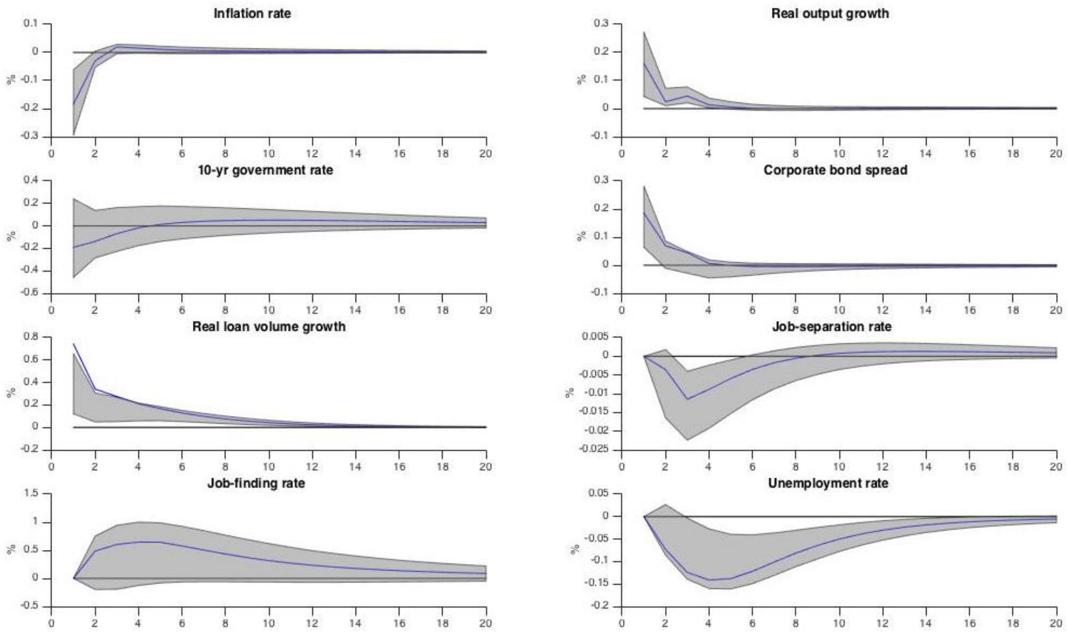


Figure 3.17: Baseline Scheme: Response to an Expansionary Aggregate Supply Shock (US)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

Figure 3.18: Baseline Scheme: Response to an Expansionary Aggregate Demand Shock (UK)

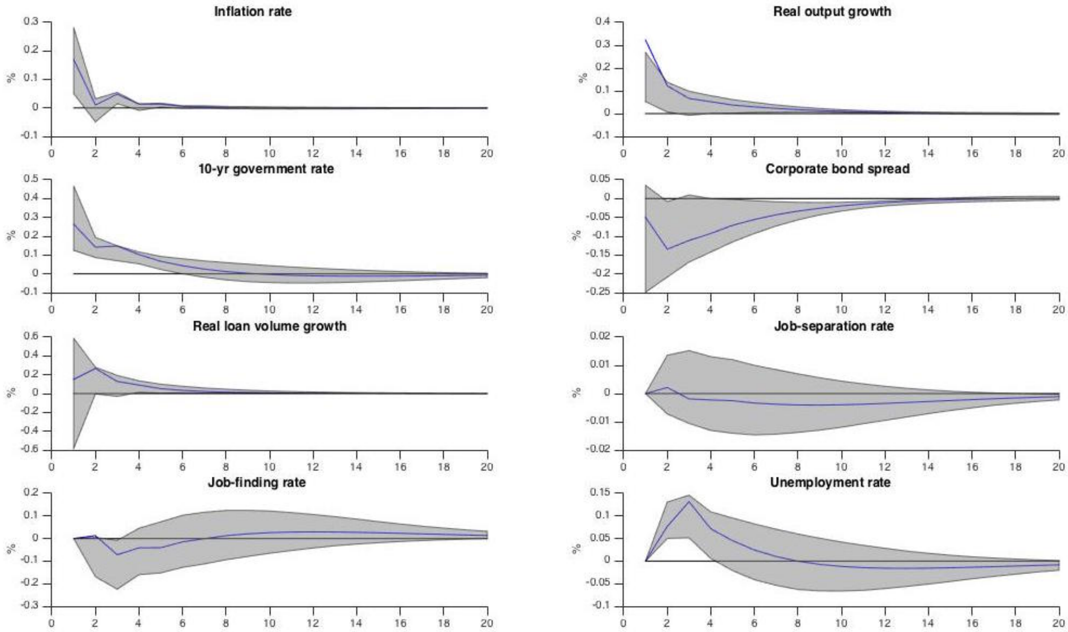
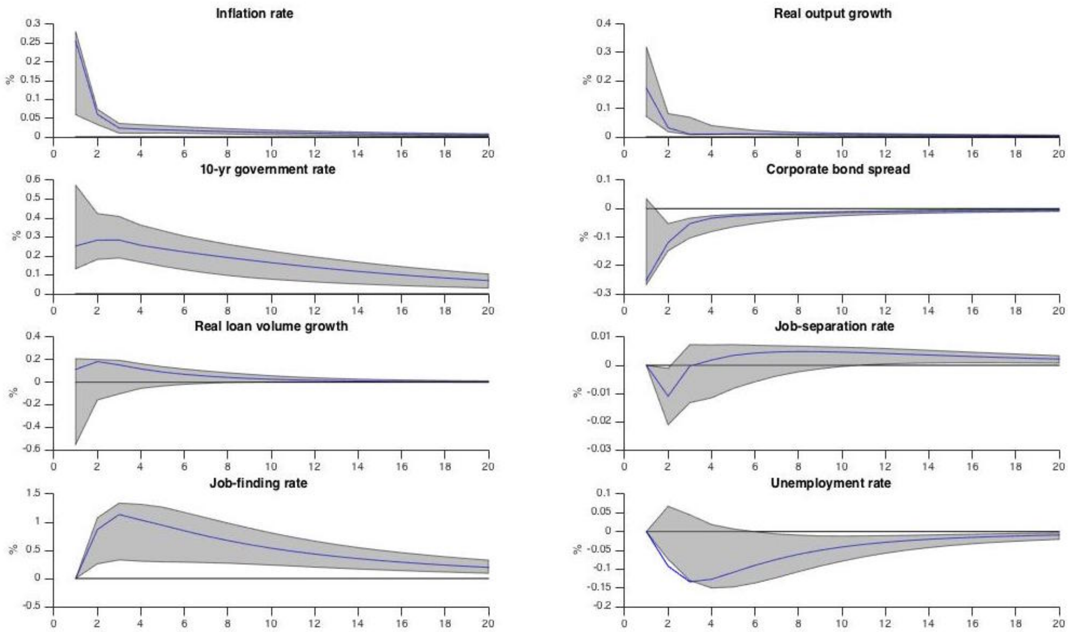


Figure 3.19: Baseline Scheme: Response to an Expansionary Aggregate Demand Shock (US)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

Figure 3.20: Baseline Scheme: Response to an Expansionary Monetary Policy Shock (UK)

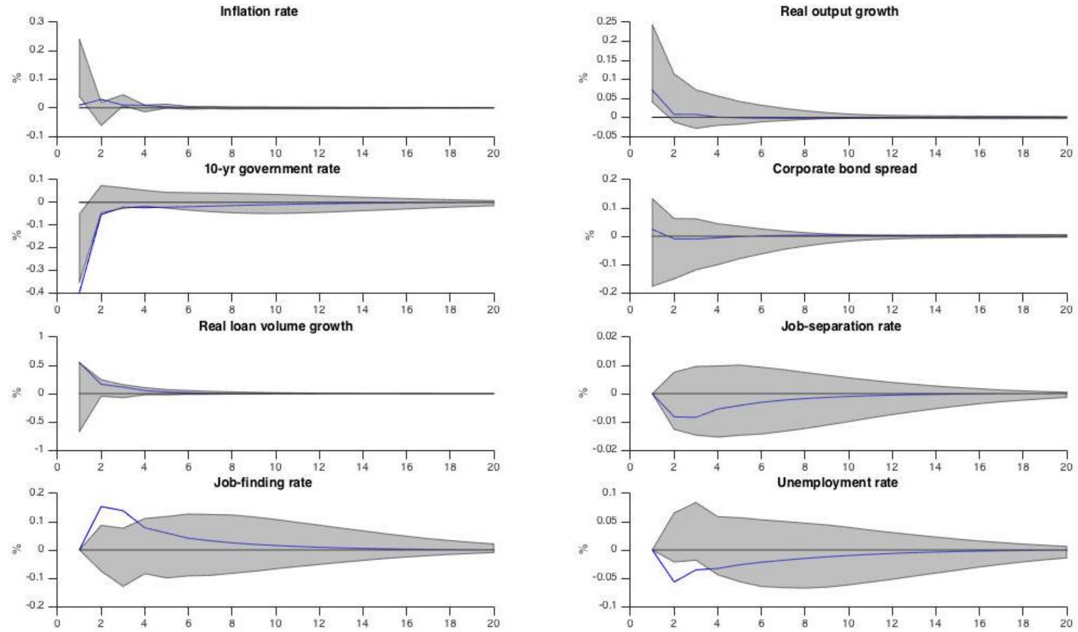
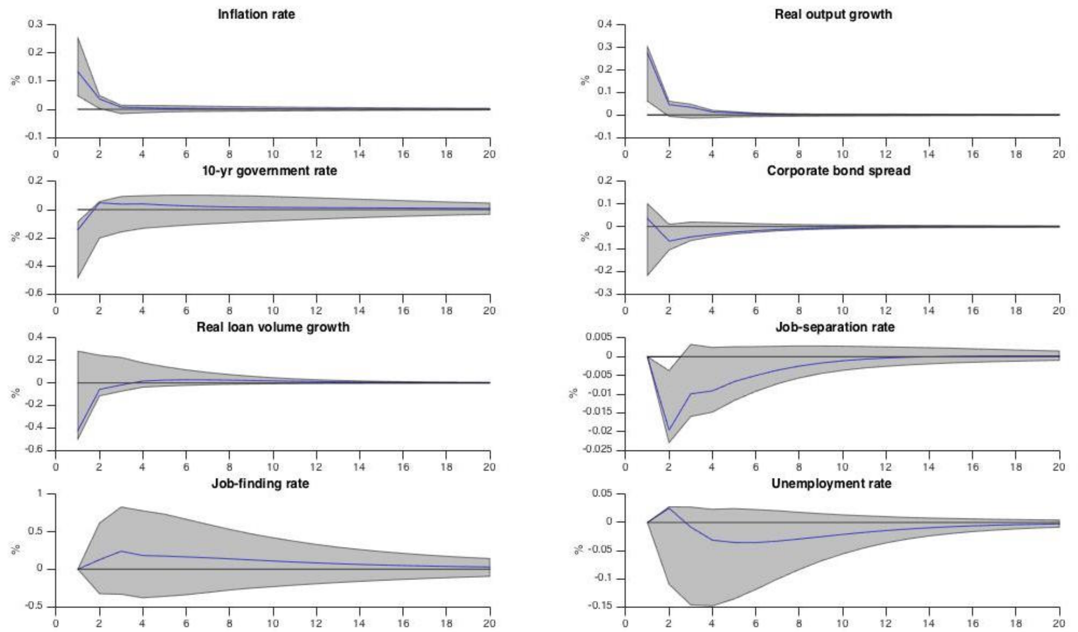


Figure 3.21: Baseline Scheme: Response to an Expansionary Monetary Policy Shock (US)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

3.8.2 Robustness Analysis

3.8.2.1 Impulse Response Analysis Under Alternative Identification Scheme 1

Figure 3.22: Alternative Scheme (1): Response to an Inflationary Loan Supply Shock (UK)

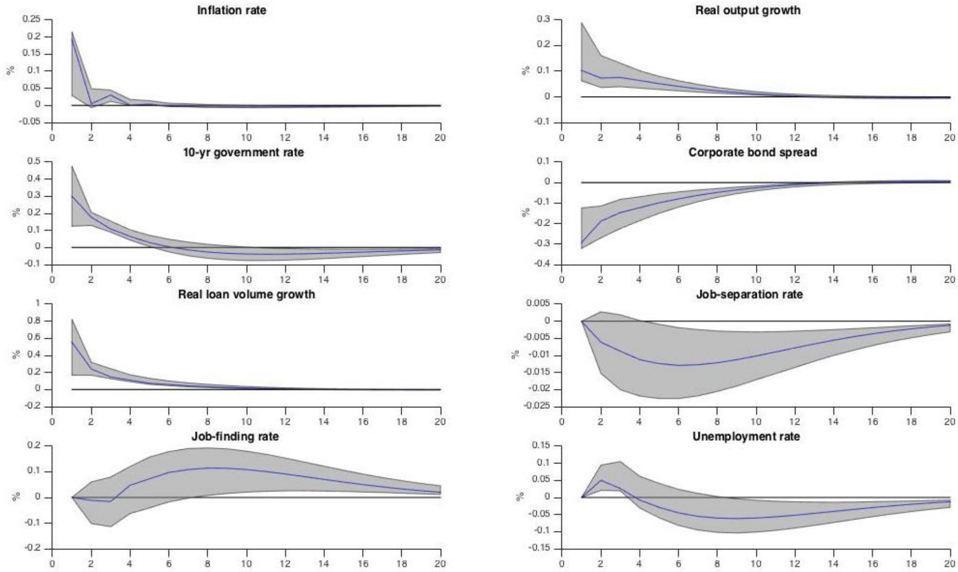
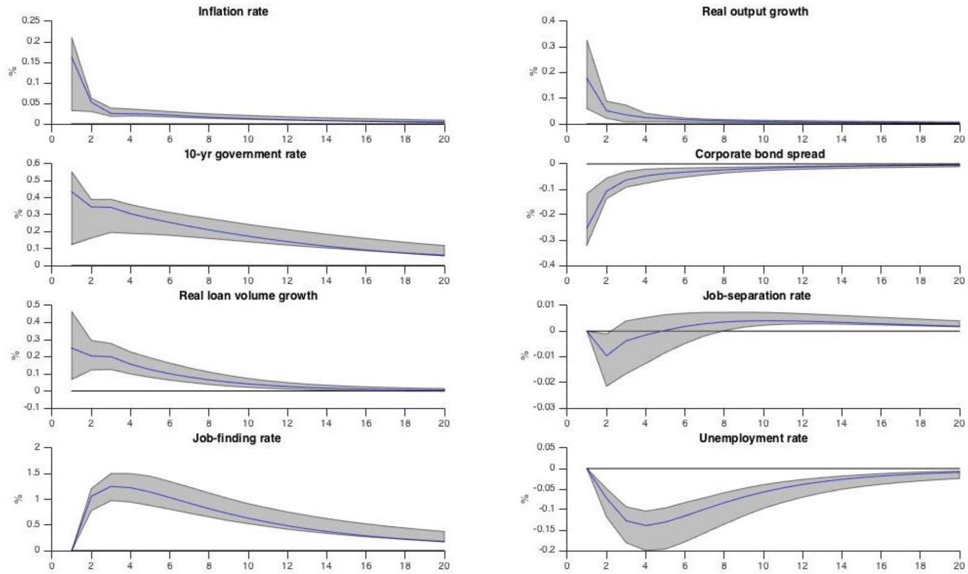


Figure 3.23: Alternative Scheme (1): Response to an Inflationary Loan Supply Shock (US)



The grey area is the 68 percent credibility region. The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

3.8.2.2 Impulse Response Analysis Under Alternative Identification Scheme 2

Figure 3.24: Alternative Scheme (2): Response to an Expansionary Loan Supply Shock with no Restriction on Inflation (UK)

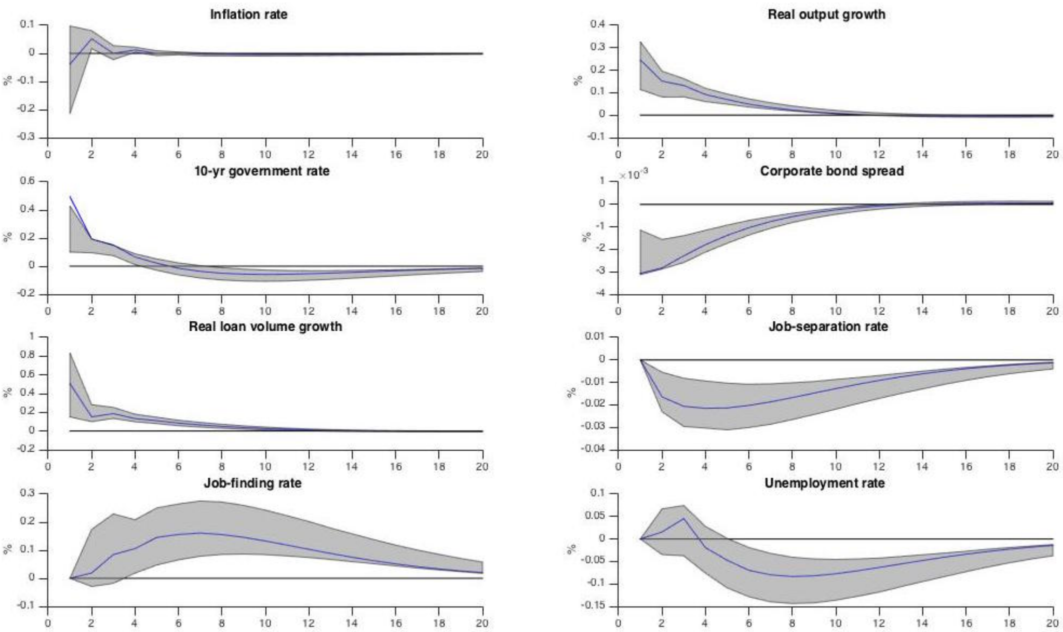
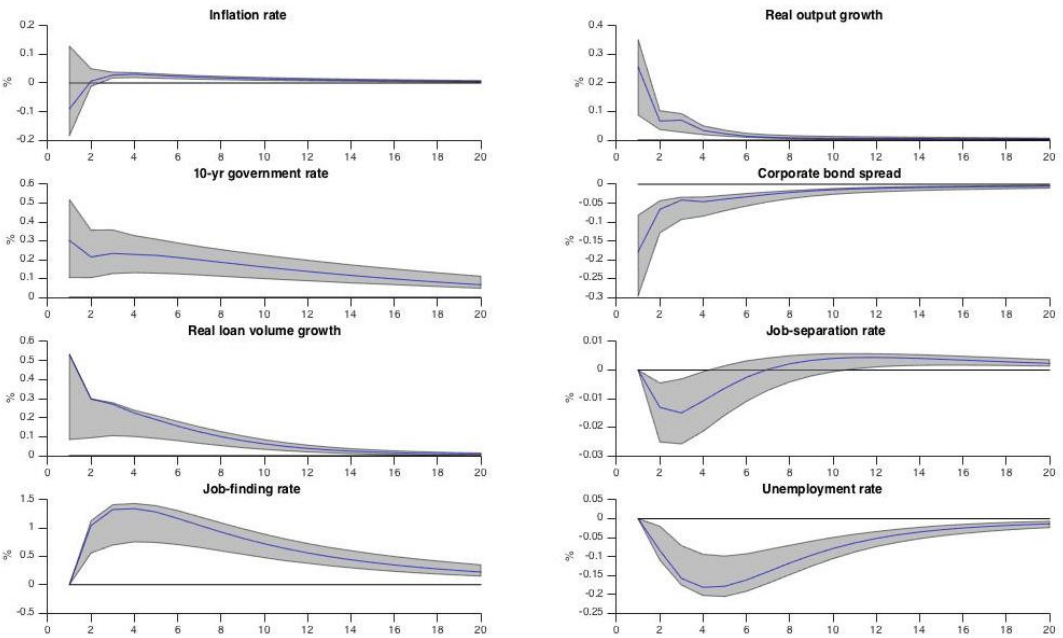


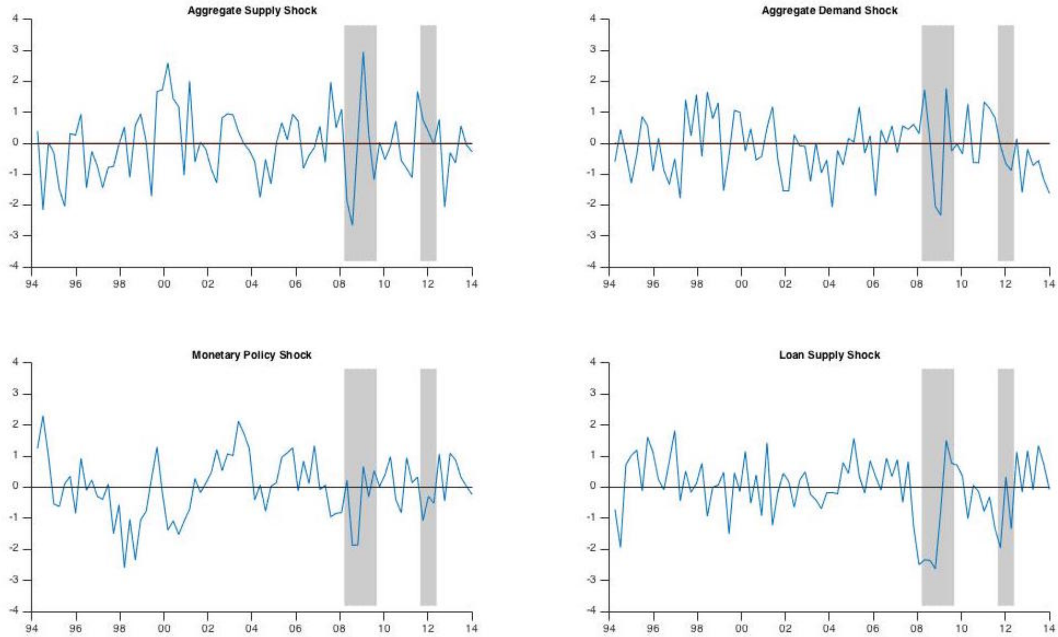
Figure 3.25: Alternative Scheme (2): Response to an Expansionary Loan Supply Shock with no Restriction on Inflation (US)



The grey area is the 68 percent credibility region.The blue line is the impulse response function of the median model. Occasionally, the response of the median model may fall outside the credibility region.

3.8.2.3 Historic Decomposition Analysis Using QE-Adjusted Short-Term Policy Rate (UK)

FIGURE 3.26: STRUCTURAL SHOCKS FOR UK SVAR USING QE-ADJUSTED SHORT-TERM POLICY RATE: 1993-2014 (UK)



These are the structural shocks associated with the median model.
Grey regions indicate recessions.

Figure 3.27: Historical Decomposition for UK SVAR Using QE-Adjusted Short-Term Policy Rate: 1993-2014 (1)

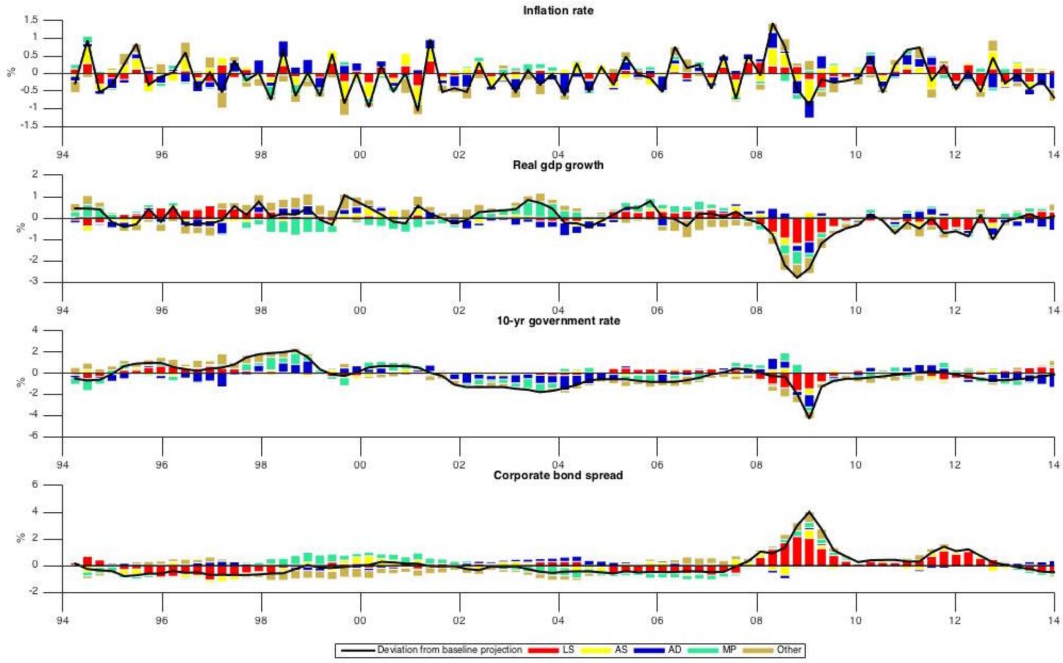
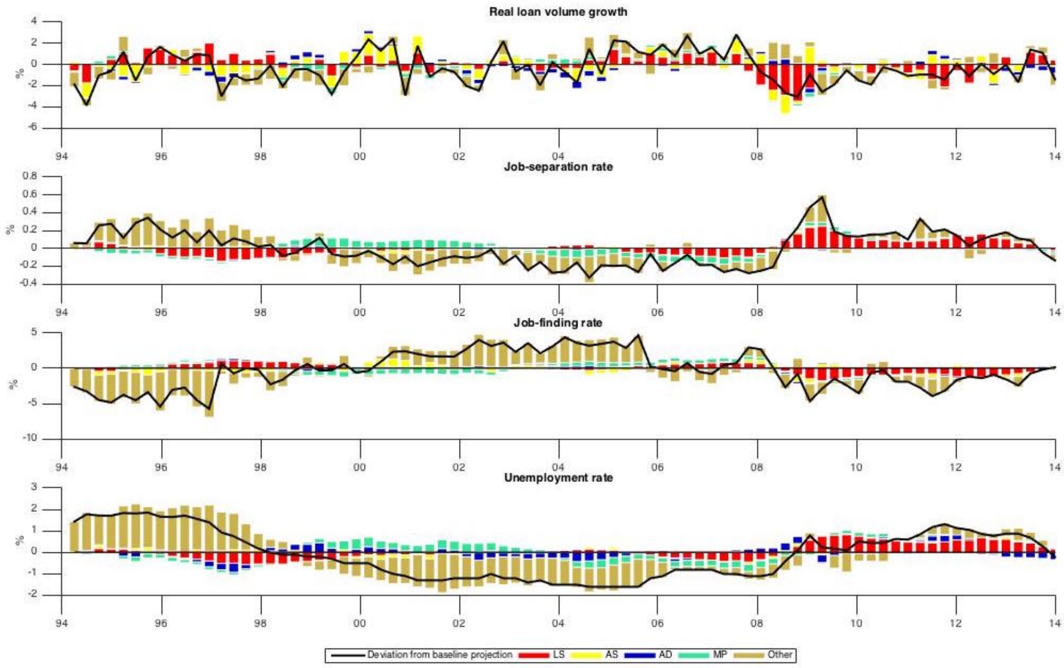


Figure 3.28: Historical Decomposition for UK SVAR Using QE-Adjusted Short-Term Policy Rate: 1993-2014 (2)



This is the historical decomposition of the median model.

4 What Are the Stabilization and Convergence Properties of European Unemployment Insurance? A DSGE Assessment

4.1 Introduction

Several prominent economists, policy-makers and politicians have recently proposed the creation of European Unemployment Insurance (EUI). They argue that a common unemployment benefit scheme could act as an automatic counter-cyclical stabilization mechanism for the Euro Area (EA) and help achieve convergence between heterogeneous labor markets (Dullien, 2007, 2013; Allard *et al.*, 2013; Claeys *et al.*, 2014). According to this view, EUI would reduce the aggregate volatility of unemployment and inflation in the EA (i.e. *stabilization*), as well as the volatilities of the inflation and unemployment differentials between regions of the currency union (i.e. *convergence*). These desirable properties would materialize not only when asymmetric shocks hit the currency union, but also when symmetric shocks have asymmetric effects because of regional heterogeneity in economic structure and institutions. Lastly, EUI proponents argue that it could play an important role for business cycle stabilization, especially when the short-term policy rate is at its lower bound, and/or long-term debt sustainability concerns force discretionary fiscal policy to be contractionary.

Despite these potential benefits, the macroeconomic properties of EUI have not been studied in a general equilibrium framework. Given the political and technical effort that would be required to establish EUI, examining and assessing its quantitative impact is important. *Can EUI smooth the business cycle and* *improve the efficiency of the adjustment process in the Euro Area as its proponents argue? In which ways does it affect the regional and aggregate volatilities of inflation and unemployment in the single-currency area? Does EUI decrease the volatilities of the inflation and unemployment differentials among different regions, or do trade-offs exist? Do its stabilization properties depend on the source of disturbance affecting the economy?* To answer these questions, I calibrate a DSGE model of a two-region currency union featuring either EUI or independent unemployment insurance (UI) schemes to EA12 data.

Then, I compute the regional and aggregate volatilities of inflation and unemployment, as well as the volatilities of the inflation and unemployment differential, for aggregate and idiosyncratic TFP, preference, and cost-push shocks. I use the volatility in the specification with EUI relative to the volatility in the specification with independent UI schemes as a quantitative measure of the *aggregate properties* of EUI. In particular, I distinguish between its *stabilization* properties, captured by the relative aggregate and regional volatilities of inflation and unemployment, and its *convergence* properties, measured by the relative volatilities of the inflation and unemployment differentials.

Proponents of EUI highlight its potential nature as shock absorber for both symmetric and asymmetric shock (Allard *et al.*, 2013; Dullien, 2013). This is particularly relevant for a currency union in which wage and price adjustment, factor mobility, and fiscal policy, rather than monetary policy, bear the burden of adjustment to shocks with asymmetric effects on the union (Mundell, 1961; McKinnon, 1963). EUI could play the role of an automatic fiscal counter-cyclical stabilizer that transfers resources from areas with relatively low unemployment to areas with relatively high unemployment rates. Moving away from a system of independent insurance schemes would improve risk-sharing across the currency union and help the ECB achieve its inflation target, particularly in an environment with a lack of coordinated national discretionary fiscal policies, limited fiscal space available to high-debt countries to counteract recessions, and low internal labor mobility.

The US federal unemployment insurance scheme is often cited as a positive example to argue in favor of EUI (Dullien, 2007). Nevertheless, higher internal labor market mobility, more homogeneous labor market institutions and similar unemployment insurance schemes (in terms of benefit duration, coverage, and eligibility criteria) distinguish the US experience from EA labor markets. Thus, EUI proposals must be evaluated on their own merits. Existing studies assessing these proposals use econometric simulations based on microeconomic data and partial equilibrium frameworks (Beblavý and Maselli, 2014; Brandolini *et al.*, 2014). These analyses support the creation of EUI and cite moral hazard problems and administrative difficulties as the main challenges to its implementation.

These studies, however, abstract from general equilibrium effects arising from the interaction of EUI, other labor market institutions, monetary policy, and rational forward-looking agents. For instance, using a standard random search model, Hagedorn *et al.* (2013) show that unemployment benefits affect firms' demand for labor and the job-finding rate for unemployed workers. Unemployment benefits raise workers' outside option and equilibrium wages, reducing labor demand and resulting in higher unemployment. Using a fully-fledged DSGE model to study the aggregate properties of EUI circumvents these issues. To the best of my knowledge, this is the first attempt to study the business cycle stabilization properties of EUI from a macroeconomic perspective using a dynamic general equilibrium model.

Ignoring general equilibrium effects may have important implications on the assessment of EUI's stabilization and convergence properties. Since risk-sharing increases business cycle synchronization between different regions of the monetary union, EUI may reduce the volatility of unemployment in each region, meanwhile raising the overall volatility in the currency union. For the same reason, a fall in the volatility of the unemployment differential, necessary to achieve convergence, may be accompanied by a rise in the aggregate volatility. To make these points more explicitly, consider a currency union made of n blocks of equal size each with unemployment volatility $\sigma^2_{u_i}$. The volatility $\sigma^2_{u^U}$ of the overall unemployment rate u_t^U in the currency union is:

$$\sigma^2_{u^U} = \frac{1}{n^2}\sum_{i=0}^{n}\sigma^2_{u_i} + \frac{1}{n}\sum_{i=0, i\neq j}^{n}\sum_{j=1}^{n} cov(u_i, u_j) \tag{4.1}$$

whereas the volatility of the unemployment differential Δu_{ij} between regions i and j is:

$$\sigma^2_{\Delta u_{ij}} = \sigma^2_{u_i} + \sigma^2_{u_j} - 2cov(u_i, u_j) \tag{4.2}$$

Suppose that EUI decreases unemployment volatility $\sigma^2_{u_i}$ in each individual region. To the extent that EUI acts like a risk-sharing mechanism, it also induces higher business cycle synchronization, increasing the covariance terms $cov(u_i, u_j)$. In (4.1), if the change in the covariance terms is large enough, it will offset the impact of lower regional volatilities $\sigma^2_{u_i}$ on $\sigma^2_{u^U}$ and in fact drive up unemployment volatility in the currency union. On the other hand, lower regional volatilities and a higher covariance term decrease unambiguously the volatility of the unemployment differential $\sigma^2_{\Delta u_{ij}}$ in (4.2). If EUI did not decrease all regional volatilities, its qualitative effects on $\sigma^2_{u^U}$ and $\sigma^2_{\Delta u_{ij}}$ would be even more ambiguous. The same argument applies to the volatility of the overall inflation rate $\sigma^2_{\Pi^U}$ and the volatility of the inflation rate differential $\sigma^2_{\Delta \Pi_{ij}}$. Furthermore, if EUI limits the degree to which employment adjusts to exogenous disturbances, real wages and inflation will have to absorb the impact of the shock. This is particularly important when labor market rigidities magnify the effect of shocks on the economy. Thus, EUI may reduce the size of unemployment fluctuations but increase the volatility of inflation, creating a tension between these two stabilization goals

This simple analysis suggests the existence of two potential trade-offs. First, EUI may not achieve contemporaneously the business cycle stabilization and convergence objectives its proponents claim. This is because reducing the volatility of inflation or unemployment differential between different regions of the currency union may increase the aggregate volatility. Second, particularly in the presence of significant labor market rigidities, there could be a potential tension between unemployment and inflation volatility: reducing one increases the other. If EUI lowers aggregate unemployment volatility at the expense of higher inflation volatility, it will be also more difficult for the ECB to achieve its inflation target. This creates a conflict between monetary policy and automatic fiscal stabilizers. Hence, a general equilibrium assessment, rather than a partial equilibrium analysis, is required to understand and quantify these potential trade-offs between stabilization and convergence objectives that EUI may create.

To this end, I calibrate a two-region currency union model based on Mueller and Abbritti (2013). Building on the seminal small open economy framework of Galí and Monacelli (2005), they build a DSGE model featuring hiring frictions *à* la Blanchard and Galí (2010), heterogeneous labor market structures, and nominal price rigidities.[1] They show that in flexible labor markets with high employment flows, employment bears the burden of adjustment to economic shocks. In contrast, the real wage and inflation must adjust in sclerotic labor markets with low employment flows. They also show that the volatilities of the inflation and unemployment differentials are increasing in the degree of labor market heterogeneity between the two regions.

I extend this model to include unemployment insurance. The baseline specification features two independent UI schemes in which benefits are financed through local taxation. In the alternative specification, there is EUI whereby residents in one of the two regions partially finance benefits to residents in the other region. Deviations of the unemployment rate from its efficient level determine the proportion of benefits paid by residents of the other region. This effectively amounts to a fiscal transfer of resources between the two regions. If both unemployment rates deviate from their efficient level, there will be a cross-transfer of resources. As long as the magnitude of these deviations differ, there will be a net transfer from one region to the other which enables partial risk-sharing.

[1] Campolmi and Faia (2011) propose another currency union model with nominal price rigidities and random search frictions in the labor market. They show that inflation differentials in the EA may arise as a result of heterogeneous replacement ratios in unemployment insurance between EA countries. A higher replacement ratio reduces average firm's profits but makes labor demand more sensitive to economic shocks. Thus, real wages and inflation respond relatively less when replacement ratios are high. This is not the only explanation for inflation differentials. Price convergence processes due to productivity catching-up (i.e. Balassa-Samuelson effect), income level convergence (Rogers, 2007), and heterogeneous degree of of competition (Andres *et al.*, 2008) may also account for its existence.

Furthermore, I calibrate the model differently from Mueller and Abbritti (2013). First, the parameterization of the model relies more heavily on EA12 data. For instance, I calculate the average job-finding rates using data on employment flows and stocks. Second, I use factor analysis to divide the EA12 into two regions with similar labor market institutions. Countries in the *Southern* region (Belgium, France, Greece, Italy, Portugal, and Spain) have rigid markets with generally high average unemployment rates, low job-finding rates, and low replacement ratios. Countries in the *Northern* region (Austria, Finland, Germany, Ireland, Luxembourg, and the Netherlands) have flexible markets with generally low average unemployment rates, high job-finding rates, and high replacement ratios.

Then, I study the impact of aggregate and idiosyncratic TFP, preference, and cost-push shocks on the volatilities of interest. I calculate the regional and union-wide volatilities of inflation and unemployment, and the volatilities of the regional differentials, in the two specifications. I use the relative volatilities as measures of the quantitative macroeconomic impact of EUI. More precisely, regional and aggregate relative volatilities capture the stabilization properties of EUI, whereas the relative volatilities of the differentials measure its convergence properties. This disaggregated analysis provides a nuanced and multifaceted picture of the effects of EUI. I do not compute a single metric because it requires stronger assumptions, such as the frequency with which different shocks affect the economy.

The main findings of this simulation exercise are as follows. First, EUI has a very limited impact when aggregate shocks hit the currency union. These shocks have asymmetric effects because heterogeneity in labor market institutions make the unemployment rate in each region deviate from its efficient level by a different amount. However, this difference is small, so the fiscal transfer between the two regions is too modest to have a significant effect on regional and aggregate volatilities. In terms of convergence properties, EUI lowers the volatility of the inflation differential but at the expense of higher volatility in the unemployment differential. Second, in case of idiosyncratic shocks, the nature of the shock matters for determining the qualitative and quantitative implications of EUI. In case of TFP shocks, EUI helps stabilize regional and aggregate unemployment rates as well as achieve convergence between regional unemployment rates. EUI also lowers the volatility of the inflation differential; nevertheless, there is a trade-off between regional inflation volatilities which, coupled with higher business cycle synchronization, in fact increases the overall volatility of inflation in the currency union. In case of preference shocks, EUI helps achieve convergence in both the unemployment and inflation rates; nevertheless, it does not unambiguously stabilize the economy. EUI acts like a risk-sharing mechanism because the volatilities of inflation and unemployment fall in the region directly hit by the shock but increase in the other region. Nonetheless, at the aggregate level, while unemployment volatility falls, inflation volatility raises. In case of idiosyncratic cost-push shocks, the effects are also ambiguous, generating several trade-offs, but they are also quantitatively small. Third, there are strong non-linearities in the relationship between the strength of EUI and the volatilities of interest. The stabilization and convergence effects of EUI, when present, exist even for fiscal transfers of small magnitude.

The main conclusion of this analysis is that EUI cannot contemporaneously stabilize the monetary union and achieve convergence in unemployment and inflation rates as its proponents argue. Important trade-offs between aggregate volatilities and the volatility of the inflation or unemployment differentials, and between inflation and unemployment volatilities, exist. The impact of EUI is also highly dependent on both the nature of the shock and whether the shock affects one or all regions of the currency union. Intuitively, this is because EUI is essentially a fiscal transfer and operates via income effects. To achieve the constrained efficient allocation, changes in relative prices, namely the real interest rate and the real exchange rate, are required, but EUI has only an indirect effect on them. Besides, the existence of unemployment insurance per se is a source of inefficiency because it creates a wedge between the social marginal rates of substitution and transformation between consumption and labor which EUI cannot eliminate.

This chapter proceeds as follows. Section 4.2 discusses the heterogeneity of labor market institutions in the Euro Area and identifies two regional country blocks based on these institutions. Section 4.3 presents a general equilibrium model of a currency union. Section 4.4 discusses the calibration of the model based on the two country blocks identified earlier. Section 4.5 presents the main results of the simulation exercise. Section 4.6 concludes.

4.2 Asymmetric Labor Markets in the Euro Area

I calibrate a two-region model of a currency area to represent the EA12. With the exception of Greece joining in 2001, the other countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain) are the original 1999 Euro-adopters. I focus on these countries for several reasons. First, they have been part of a currency union for over a decade and have had time to adjust and adapt to its dynamics. Second, notwithstanding their cross-country differences, they are relatively more homogeneous with respect to the late Euro adopters in Central and Eastern Europe. The latter have been transitioning towards fully-fledged market economies for the past two decades, but large differences persist with their Western European counterparts. Third, data on the late Euro-adopters is scarcer, making it more challenging to calibrate the model. Despite this, the EA12 countries account for no less than 97 percent of the current Euro Area (EA19) nominal gross domestic product measured in purchasing power standards.[2].

I divide this monetary union into two regions based on their labor market institutions. As shown in Tables 4.1 and 4.2, European labor markets differ widely in terms of average equilibrium unemployment rates, employment protection legislation, long-term unemployment, and other labor market characteristics. I use factor analysis to identify two groups of countries with a broadly similar set of labor market institutions based on the following variables: the average unemployment rate, the youth unemployment rate (aged 25 years of less), the inactivity rate, the proportion of long-term unemployed, the change in unemployment rate between

[2]Using alternative measures such as nominal GDP, or real GDP also shows that the EA12 accounts for at least 97-98 percent of the EA or the EA19 GDP over the past two decades

Table 4.1: Labor Market Statistics (A)

Country	*Unemployment rate (%)*			*Change in unemployment (%) between 2007Q4-2014Q4*	*Job-finding [a] rate (%)*	*Job-separation [b] rate (%)*
	1998-2014	*1998-2007*	*2008-2014*		*2010-2014*	*2010-2014*
Northern Block [c]	*7.3*	*8.0*	*6.3*	*-1.4*	*21.3*	*1.4*
Austria	4.8	4.7	5.0	1.1	28.7	1.3
Finland	8.6	9.0	7.9	2.4	25.9	1.8
Germany	8.0	9.2	6.2	-3.3	-	-
Ireland	7.9	4.9	12.3	5.5	11.1	1.6
Luxembourg	4.1	3.4	5.2	2.0	-	-
Netherlands	4.9	4.5	5.5	3.3	22.1	1.3
Southern Block [c]	*10.8*	*9.3*	*12.9*	*7.7*	*16.0*	*2.5*
Belgium	7.9	8.0	7.9	1.4	-	-
France	9.1	9.0	9.3	3.0	21.4	1.9
Greece	13.5	10.3	18.1	17.8	4.1	1.9
Italy	9.1	8.7	9.5	6.5	14.9	1.6
Portugal	9.4	7.0	12.9	4.6	17.0	2.7
Spain	15.2	11.2	20.8	15.1	15.9	4.5
EA12 [c]	*9.4*	*8.8*	*10.3*	*4.1*	*16.4*	*2.3*

Source: The unemployment rate series is from the Adjusted labor Force Survey (Eurostat). The job-finding and job-separation rate series are calculated using flow data from the LFS longitudinal series and stock data from the Adjusted labor Force Survey (Eurostat).

[a] *I calculate the job-finding rate as the ratio between the flow of people moving from unemployment into employment during a quarter and the stock of unemployed workers in the previous quarter.*

[b] *I calculate the job-separation rate as the ratio between the flow of people moving from employment into unemployment during a quarter and the stock of employed workers in the previous quarter.*

[c] *Regional statistics are my own calculations. The average quarterly job-finding and job-separation rates exclude Belgium, Germany, and Luxembourg due to data availability.*

Table 4.2: Labor Market Statistics (B)

Country	*Youth unemployment (%)*	*Long-term unemployment (% of unemployed)*	*Inactivity rate (%)*	*Discouraged workers (% of inactive)*	*Strictness of employment protection* [a]	
					Permanent employment (0-6)	*Temporary employment (0-6)*
	1998-2014	*1998-2014*	*1998-2014*	*2005-2014*	*1998-2013*	*1998-2013*
Northern Area						
Austria	8.5	26.3	27.2	0.8	2.71	1.31
Finland	20.2	25.2	24.4	6.8	2.08	1.56
Germany	10.3	50.1	25.7	1.6	2.95	1.35
Ireland	15.4	41.4	30.8	3.4	1.87	0.48
Luxembourg [b]	13.4	27.8	33.5	1.2	2.71	3.75
Netherlands	10.2	33.5	22.8	5.9	2.90	0.96
Southern Area						
Belgium	20.4	49.7	34.1	4.4	2.83	2.38
France	20.9	39.1	30.3	2.9	2.68	3.63
Greece	33.2	53.5	34.1	1.6	2.84	3.42
Italy	27.5	54.2	38.1	13.9	3.14	2.38
Portugal	22.7	45.9	27.2	12.1	3.79	2.41
Spain	31.6	35.6	30.1	7.1	2.72	3.07

Source: The youth, inactivity, and long-term unemployment rate series are from the Adjusted labor Force Survey, the proportion of discouraged workers series is from the detailed annual survey series (Eurostat), and the employment protection regulation indicators from the OECD annual series.

[a] *All indicators are expressed on a 0-6 scale (6=maximum protection, 0=minimum protection). The EPL for permanent employment includes eight indicators concerning the regulation for individual dismissals (accounting for 5/7 of the weight) and four indicators concerning additional provisions for collective dismissals. The EPL for temporary employment includes six indicators.*

[b] *Data on EPR available only from 2008 onwards.*

2007Q4 and 2014Q4, the proportion of inactive respondents citing "no work is available" as the main reason for their labor market status[3], the strictness of employment protection regulation (EPR) for individual and collective dismissals (regular contracts), and for temporary employment. I compute quarterly averages when data is available (unemployment rate and youth unemployment rate) and annual averages when quarterly data is either missing for some countries and some quarters (inactivity rate, long-term unemployment rate, and proportion of discouraged workers) or only available at annual frequencies (strictness of labor protection). The two measures of employment protection are indices measured over the 1995-2013 period that the OECD constructs using a large number of other variables. All other variables are from the Labor Force Surveys and available on Eurostat. I focus on the 1998-2014 period due to data availability.

These variables should be related to the flexibility of labor market institutions and their efficacy in matching workers with suitable jobs. A labor market with less significant search frictions or other rigidities should be associated with a small proportion of long-term unemployment, low youth unemployment, and a low proportion of discouraged workers (gauged by the proportion citing "no work is available" as a reason for their inactivity). In the same vein, a more efficient labor market should have relatively low employment regulations. The change in the unemployment rate between 2014Q4 and 2007Q4 is a simple measure of the labor market's capacity to reabsorb those who lost their jobs after a severe contraction.

Factor analysis identifies two country blocks that roughly correspond to a *Northern region* made of Austria, Finland, Germany, Ireland, Luxembourg, and the Netherlands, and a *Southern region* made of Belgium, France, Greece, Italy, Portugal, and Spain (detailed results are in *Appendix* 4.7.1). Based on the number of eigenvalues greater than unity, the analysis suggests that two factors are enough to explain the variation in the data sufficiently well. Despite this, I use only the

[3]The LFS contains a supplementary variable measuring the proportion of respondents available to work but not seeking a job. This may be a better measure of discouraged workers but it is only measured from 2005 onward. The correlation between this variable and the proportion of inactive people citing 'no work is available' as the main reason for their inactivity is 63 percent. The results of the factor analysis are unchanged using either variable

first factor because I wish to categorize countries on a univariate scale. This factor accounts for 52 percent of the variation in the data; moreover, the factor loadings are high for almost all the variables used in the analysis and consistent with labor market rigidity. Hence, retaining only one factor seems a sensible choice. Higher unemployment rates, more rigid labor market structures, and higher employment protection are instead generally associated with countries in the Southern region. Lower unemployment rates, flexible labor markets, and low employment protection usually characterize countries in the Northern region.[4]

These results are robust to the inclusion of only a sub-set of variables, and a non-orthogonal rotation of the correlation matrix. The two country blocks are also approximately similar in terms of economic activity.[5] This justifies modelling the currency union as being composed of two regions of equal size.[6] Nevertheless, lumping together diverse countries into two different regional areas based on their labor market characteristics raises the question of whether countries within a block are sufficiently homogeneous on other economically relevant dimensions to be considered a single entity. On one important aspect, namely the transmission mechanism of monetary policy, the empirical evidence suggests that common monetary policy shocks have similar effects on output across Euro Area countries.[7]

Table 4.2 also reports the average job-finding and job-separation rates. These figures are based on 2010Q2-2014Q4 quarterly averages. To calculate quarterly figures for the EA12 and both regional country blocks, I add the number of unemployed workers transitioning from unemployment into employment during a quarter across the relevant region and divide it by the total region-wide stock of unemployed workers in the previous quarter. I do not use data for Belgium, Germany, and Luxembourg which is unavailable. Compared to the US, Euro Area

[4]Because there is wide heterogeneity across European labor markets, a country may have a relatively high unemployment rate but relatively low employment protection.

[5]The Southern region accounts for about 57 percent of nominal GDP, 59 percent of nominal GDP adjust for purchasing power, and 57 percent of real GDP over the 1995-2014 period.

[6]Relaxing this assumption is straightforward but has no substantial impact on the main conclusions of the analysis given that the gap in economic activity between the two regions is quite small.

[7]See Peersman (2004) for a discussion of the debate and an empirical analysis.

countries have smaller flows in and out of unemployment. In the terminology of Blanchard and Galí (2010), the US has a fluid labor market with high flows and a low unemployment rate, whereas Europe has a sclerotic labor market with low flows and a high unemployment rate. These disaggregated figures depict a more nuanced picture of Euro Area countries that does not reflect fully the terminology Blanchard and Galí (2010) use. In fact, countries in the Northern region tend to have a higher job-finding rate but lower job-separation rate than countries in the Southern region.

4.3 Model

The model is essentially the currency union model developed in Mueller and Abbritti (2013). The monetary union is composed of two regions of equal size populated by identical infinitely-lived households that provide labor to wholesale firms and purchase goods produced domestically and in the other region of the currency union. Labor is immobile and cannot migrate across the two regions. Moreover, the government issues a risk-free short-term bond that households can freely trade across the union because capital markets are complete. Each region produces a different bundles of differentiated goods. The productive sector is made of competitive wholesale firms producing a homogeneous intermediate good and retailers repackaging this input into differentiated final goods.[8] There is no physical capital, so labor is the sole input of production. Calvo pricing prevents final good producers to adjust nominal prices in every period.

To introduce equilibrium unemployment, I assume that wholesale firms must pay a hiring cost to change their employment level because of labor market frictions. As in Blanchard and Galí (2010), the marginal hiring cost depends on the aggregate level of labor market tightness. Since hiring a new worker increases labor market tightness and hiring costs for competing firms, there are congestion externalities, and the decentralized competitive equilibrium is generally inefficient. A new match avoids the firm paying more hiring costs in the future; thus, there is a surplus associated with the marginal employed worker. Because a set of real wages is compatible with

[8] This standard modeling device separates the production from the pricing decision.

equilibrium, firms and households bargain over the real wage. The existence of real wage rigidities, however, prevents the wage to respond fully to economic shocks.[9] In Mueller and Abbritti (2013), the marginal rate of substitution between leisure and consumption determines the reservation wage for unemployed workers.

In this model, I add unemployment benefits financed through general taxation. UI creates a wedge between the social marginal rate of substitution and the social marginal rate of transformation which leads to an inefficient labor allocation. In the baseline specification of the model, residents in one region of the currency union finance unemployment benefits for unemployed workers in the same region. In the version with EUI, residents in one region may finance benefits for unemployed workers in the other region. Deviations of the unemployment rate from its efficient level determine the proportion of benefits financed by residents in the other region.

The two regions are entirely symmetric apart from labor market institutions. More specifically, the Home region has a more rigid labor market with a high average unemployment rate and a low job-finding rate for unemployed workers. The Foreign region has a more flexible labor market with a low average unemployment rate and a high job-finding rate for unemployed workers. Hence, the Home region corresponds to the Southern country block, and the Foreign region to the Northern one. Next, I discuss in turn households, wholesale firms, retailers, and government. I describe the efficient allocation at the end of this section.

4.3.1 Households

Each region of the currency union is populated by a continuum of households j on the unit interval. Each household produces a differentiated good also labeled by j. The representative household in region i ($i = H$ or F) maximizes a standard

[9] If real wages were fully flexible, they would absorb the impact of shocks and firms would have few incentives to adjust their labor demand. In response to economic disturbances, employment would fluctuate too little. Real wage rigidity is a standard device to increase employment volatility used in Blanchard and Galí (2010) and Mueller and Abbritti (2013) among others.

expected lifetime utility function:

$$E_t \sum_{s=0}^{\infty} \beta_i \Omega_{t+s} \left(\frac{C_{t+s}^{1-\sigma}}{1-\sigma} - \chi \frac{(N_{t+s}^H)^{1+\phi}}{1+\phi} \right), E_t \sum_{s=0}^{\infty} \beta_i \Omega_{t+s}^* \left(\frac{(C_{t+s}^*)^{1-\sigma}}{1-\sigma} - \chi^* \frac{(N_{t+s}^F)^{1+\phi}}{1+\phi} \right) \tag{4.3}$$

where C_t and C_t^* are the consumption indices for home and foreign households, N_t^i is the number of employed people in the representative household in region i, Ω_t and Ω_t^* are region-specific preference shocks to the intertemporal discount rate β, σ is the elasticity of intertemporal substitution, ϕ is the inverse of the Frisch elasticity of labor, and χ^i is the weight associated with the disutility of working. C_t and C_t are defined as:

$$C_t \equiv \frac{(C_{H,t})^{1-\alpha}(C_{F,t})^{\alpha}}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}}, C_t^* \equiv \frac{\left(C_{F,t}^*\right)^{1-\alpha^*}\left(C_{H,t}^*\right)^{\alpha^*}}{\left(1-\alpha^*\right)^{1-\alpha^*}\alpha^{\alpha^*}} \tag{4.4}$$

$C_{H,t}$ and $C_{F,t}$ are the bundles of home-produced and imported goods that residents in the Home region consume, $C_{H,t}^*$ and $C_{F,t}^*$ are the bundles of imports and domestically produced goods that residents in the Foreign region consume, and α and α^* are the share of imports in each consumption bundle.

These bundles are standard Dixit-Stiglitz aggregators for the continuum of goods $c_{H,t}(j)$ and $c_{F,t}(j)$ that households in the two regions produce. For the Home region they take the form $C_{H,t} \equiv \left[\int_0^1 c_{H,t}(j)^{\frac{\epsilon-1}{\epsilon}} dj\right]^{\frac{\epsilon}{\epsilon-1}}$, and $C_{F,t} \equiv \left[\int_0^1 c_{F,t}(j)^{\frac{\epsilon-1}{\epsilon}} dj\right]^{\frac{\epsilon}{\epsilon-1}}$, where ϵ is the standard constant elasticity of substitution between varieties. Letting the nominal prices of the differentiated goods be $p_{i,t}(j)$ if sold in the Home region and $p_{i,t}^*$ if sold in the Foreign region, the price indexes for the consumption bundles are $P_{H,t} = \left(\int_0^1 p_{H,t}(j)^{1-\epsilon} dj\right)^{\frac{1}{1-\epsilon}}$, and $P_{F,t} = \left(\int_0^1 p_{F,t}(j)^{1-\epsilon} dj\right)^{\frac{1}{1-\epsilon}}$.The optimal allocation of goods in the bundles leads to the isoelastic demand functions:

$$c_{H,t}(j) = \left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon} C_{H,t}, \qquad c_{F,t}(j) = \left(\frac{p_{F,t}(j)}{P_{F,t}}\right)^{-\epsilon} C_{F,t} \tag{4.5}$$

while the optimal allocation between the bundles of domestically-produced and imported goods is $C_{H,t} = (1-\alpha)Z_t/P_{H,t}$ and $C_{F,t} = \alpha Z_t/P_{F,t}$, where $Z_t \equiv C_t P_t$ is the total nominal consumption expenditures and $P_t = P_{H,t}^{1-\alpha} P_{F,t}^{\alpha}$ is the Consumer Price Index (CPI) in the Home region. Foreign residents have similar demand functions for the individual goods and for domestically-produced and import bundles, in particular $C^*_{H,t} = \alpha^* Z^*_t / P^*_{H,t}$, and $C^*_{F,t} = (1-\alpha^*) Z^*_t / P^*_{F,t}$, where $P^*_t = P^{\alpha^*}_{H,t} P^{1-\alpha^*}_{F,t}$ is the CPI and $Z^*_t = C^*_t P^*_t$ total nominal consumption expenditure in the Foreign region.

I define the bilateral terms of trade S_t between the Home and the Foreign region as the relative price of imports in terms of domestically produced goods $P_{F,t}/P_{H,t}$, and the real exchange rate ε_t as the ratio between foreign and home CPIs P^*_t/P_t. I also assume that the law of one price holds, so each good j costs the same across the currency union (i.e. $p_{H,t}(j) = p^*_{H,t}(j)$ and $p_{F,t}(j) = p^*_{F,t}(j)\ \forall j$) This implies the price aggregators for goods produced in the Home and Foreign region are the same across the monetary union (i.e. $P_{H,t} = P^*_{H,t}$ and $P_{F,t} = P^*_{F,t}$). Thus, the Home CPI can be re-written as $P_t = P_{H,t} S^{\alpha}_t$, the Foreign CPI as $P^*_t = P_{F,t} S^{-\alpha^*}_t$, and the real exchange rate as $\varepsilon_t = S^{1-\alpha-\alpha^*}_t$.

Home bias in consumption allows the real exchange rate to deviate from its long-run equilibrium level. If there were no bias, the real exchange rate would not respond to shocks. In the long-run, purchasing power parity will only hold if the consumers have the same preferences, and average aggregate hiring cost relative to GDP and the steady-state unemployment rates in the two countries are the same.[10] However, since I assume the Home region to have a lower average unemployment rate than the Foreign region, the average real exchange rate is less than unity. Intuitively, since output in the Home region is less than in the Foreign region, goods produced in the Home region must be more expensive.

Domestic households have access to a safe asset common across the currency union with nominal payoff i_{t+1}, they receive nominal wage income $W^H_t(j)$ from workers $N_t(j)^H$ employed in firm j, unemployment benefits ub_t (expressed in units of domestic goods), and profit revenues (net of taxes) T^H_t from the firms they own.

[10]Using the international risk-sharing condition (4.11), the goods market equilibrium relationships (4.29) and (4.30), and the production functions, the long-run equilibrium value of the terms of trade S must satisfy: $\frac{(1-cy^*)(1-u^*)}{(1-cy)(1-u)}\left(1-\alpha+\alpha^* S^{(1-\alpha-\alpha^*)\left(1-\frac{1}{\sigma}\right)}\right) = S^{-(1-\alpha-\alpha^*)\frac{1}{\sigma}-\alpha-\alpha^*}\left(1-\alpha^*+\alpha S^{-(1-\alpha-\alpha^*)\left(1-\frac{1}{\sigma}\right)}\right)$ where cy and cy^* are the aggregate hiring cost to GDP ratios and u and u^* are the steady-state levels of unemployment in the Home and Foreign regions, respectively.

Thus, the face an intertemporal period budget constraint:

$$\begin{aligned}\int_0^1 c_{H,t}(j)p_{H,t}(j)dj + \int_0^1 c_{F,t}(j)p_{F,t}(j)dj + D_t \leq \\ (1+i_t)D_{t-1} + \int_0^1 W_t^H(j)N_t^H(j)dj + ub_t P_{H,t}(1-N_t^H) + T_t^H \end{aligned} \tag{4.6}$$

where D_t is the nominal stock of bonds, and $N_t^H \equiv \int_0^1 N_t^H(j)dj$. Using the properties of the CES aggregators,[11] I can express the budget in real terms as:

$$C_t + d_t \leq \frac{(1+i_t)}{\Pi_t}d_{t-1} + \int_0^1 w_{H,t}(j)N_t^H(j)dj + ub_t S_t^{-\alpha}(1-N_t^H) + \frac{T_t^H}{P_t} \tag{4.7}$$

where d_t is the real stock of bonds, $w_{H,t}(j)$ the real wage rate, and Π_t is the CPI inflation rate in the Home region. Since wholesale producers are all alike, they pay the same real wage $w_{H,t}$, so the term $\int_0^1 w_{H,t}(j)N_t^H(j)dj$ simplifies to $w_{H,t}N_t^H$.

Households choose the optimal path of consumption, bond purchases, and labor supply $\{C_t, d_t, L_t\}_{t=0}^{\infty}$ to maximize (4.3) subject to (4.7) and $N_t^H \leq 1$. Letting $\Lambda_{t,t+i}^H \equiv \beta^i \frac{\Omega_{t+i}}{\Omega_t}\left(\frac{C_{t+i}}{C_t}\right)^{-\sigma}\frac{P_t}{P_{t+1}}$ be the discount factor of the household in the Home region, the necessary first-order condition are:

$$1 = E_t\left[\Lambda_{t,t+1}^H(1+i_{t+1})\right] \tag{4.8}$$

$$w_{H,t} \geq \chi(N_t^H)^{\phi}C_t^{\sigma} + ub_t S_t^{-\alpha}, \quad N_t^H \leq 1 \tag{4.9}$$

(4.8) is the standard Euler equation for consumption, while (4.9) is the intra-temporal labor supply equation. In presence of labor market frictions, unemployment arises in equilibrium so this condition is a strict inequality. An Euler equation analogous to (4.8) also holds for the Foreign region. Combing the two Euler equations for consumption yields the international risk-sharing condition:

$$\varepsilon_t = S_t^{1-\alpha-\alpha^*} = \vartheta\frac{\Omega_t^*}{\Omega_t}\left(\frac{C_t^*}{C_t}\right)^{-\sigma} \tag{4.10}$$

which describes how the two regions experience different consumption growth rates due to movements in the real exchange rate, equivalently in the terms of trade. The constant ϑ depends on the two regions' initial net asset conditions. Assuming

[11] $\int_0^1 c_{H,t}(j)p_{H,t}(j)dj = P_{H,t}C_{H,t}$ and $\int_0^1 c_{F,t}(j)p_{F,t}(j)dj = P_{F,t}C_{F,t}$. Similarly, $P_{H,t}C_{H,t} + P_{F,t}C_{F,t} = P_tC_t$. Thus, the intertemporal allocation between differentied domestically-produced and foreign goods reduces to choosing the aggregate bundle C_t

that both regions have zero initial net assets, ϑ equals unity. Solving for C_t^*, I can find an expression for aggregate consumption in the Foreign region in terms of consumption in the Home region:

$$C_t^* = S_t^{-(1-\alpha-\alpha^*)\frac{1}{\sigma}} \left(\frac{\Omega_t}{\Omega_t^*}\right)^{-\frac{1}{\sigma}} C_t \tag{4.11}$$

4.3.2 Wholesale Producers

Each region has a retail and a wholesale sector. The wholesector produces a single homogeneous intermediate good sold in a competitive markets to retailers that repackage it into final differentiated goods. Each intermediate firm j in region i produces the good $X_t^i(j)$ according to a linear production function:

$$X_t^i(j) = A_t^i N_t^i(j) \tag{4.12}$$

where A_t^i is a region-specific level of technology common to all firms in region i, and $N_t^i(j)$ is the quantity of labor employed. At the beginning of each period an exogenous fraction δ^i of employed workers loses its job and becomes unemployed. Then, each firm j chooses how much new labor to hire. It must pay a hiring cost per new worker $G^i(\theta_t^i)$ which depends on the regional labor market tightness θ_t^i. New hires $h_t^i(j)$ join the firm and become immediately productive. Thus, employment in firm j evolves according to:

$$N_t^i(j) = (1-\delta^i)N_{t-1}^i(j) + h_t^i(j) \tag{4.13}$$

Defining the regional employment level $N_t^i \equiv \int_0^1 N_t^i(j)dj$ and the regional number of new hires $h_t^i \equiv \int_0^1 h_t^i(j)dj$, total employment in region i evolves according to:

$$N_t^i = (1-\delta^i)N_{t-1}^i + h_t^i \tag{4.14}$$

At the beginning of each period, the number of unemployed workers who, in each region, are searching for a job equals $U_t^i = 1-(1-\delta^i)N_t^i$. Labor market tightness θ_t^i in region i equals the ratio of total hires to the number of searching individuals $\theta_t^i \equiv h_t^i/U_t^i$. Unit recruitment costs, expressed in units of aggregate output, are a convex increasing function of labor market tightness:

$$G_t^i(\theta_t^i) = A_t^i B^i \left(\theta_t^i\right)^{\varphi} \tag{4.15}$$

where B^i is is a positive constant measuring the efficiency of the hiring process, and $\varphi > 0$ measures the elasticity of the hiring cost function to labor market tightness.

The representative firm j in the Home region maximizes its profit subject to the production function (4.12) and the law of motion for employment (4.13) and taking as given the nominal price of intermediate good $P_{X,t}$, the price of domestic production price index $P_{H,t}$, the nominal wage $W_{H,t}$, and unit hiring costs (4.15). Households in the Home region own firms. Thus, firm j discounts nominal payoffs using the household's discount factor and maximizes its nominal profit function:

$$\max \sum_{s=0}^{\infty} E_t \left\{ \Lambda_{t,t+s}^H \left[P_{X,t+s}^H X_{t+s}^H(j) - W_{H,t+s} N_t^H(j) - P_{H,t+s} G_{t+s}^H(\theta_{t+s}^H) h_{t+s}^H(j) \right] \right\} \tag{4.16}$$

The firm's labor demand function is:

$$\frac{P_{X,t}}{P_{H,t}} A_t^H = w_{H,t} S_t^{\alpha} + G_t^H(\theta_t^H) - (1-\delta^H) E_t \left[\beta_{t,t+1}^H G_{t+1}^H(\theta_{t+1}^H) \right] \tag{4.17}$$

where $\beta_{t,t+i}^H \equiv \Lambda_{t,t+i}^H \left(\frac{S_t}{S_{t+i}}\right)^{\alpha}$ is an adjusted stochastic discount factor that takes into account that firms and households face different prices.

The equilibrium real wage $w_{H,t}$ is determined as the weighted average between the Nash bargained wage $w_{H,t}^N$ and the wage w_H prevailing in steady-state:

$$w_{H,t} = \left(w_{H,t}^N\right)^{\gamma_w} (w_H)^{1-\gamma_w} \tag{4.18}$$

where $\gamma_w \in [0,1]$ is an index of real wage rigidity in the Home region. The steady-state real wage can be thought of as a wage norm determined by social conventions.[12] The Nash bargained wage splits the surplus of a worker-firm relation

[12]Introducing real wage rigidity allows employment to respond to economic disturbances. Otherwise, the real wage would fully absorb the impact of the shock with little change in firms' profit. Thus, firms would have few incentives to change their labor demand, and employment would respond little. Since a set of wages consistent with equilibrium exists, small deviations from the Nash bargained wage remain in the bargaining set and are privately efficiently.

between the household and the firm. Letting $\upsilon^W_{H,t}$, $\upsilon^U_{H,t}$, and $\upsilon^J_{H,t}$ be the value of an employed worker, of an unemployed worker, and of a job to the firm in the Home region (all expressed in units of the consumption index):

$$\begin{aligned}
\upsilon^W_{H,t} &= w_{H,t} - \chi(N^H_t)^{\phi} C^{\sigma}_t + \\
&\quad + E_t\left\{\Lambda_{t,t+1}\left[\left(1-\delta^H(1-\theta^H_{t+1})\right)\upsilon^W_{H,t+1} + \delta^H(1-\theta^H_{t+1})\upsilon^U_{H,t+1}\right]\right\} \qquad (4.19)\\
\upsilon^U_{H,t} &= ub_t S^{-\alpha}_t + E_t\left\{\Lambda_{t,t+1}\left[\theta^H_{t+1}\upsilon^W_{H,t+1} + (1-\theta^H_{t+1})\upsilon^U_{H,t+1}\right]\right\} \qquad (4.20)\\
\upsilon^J_{H,t} &= G^H_t(\theta^H_t)S^{-\alpha}_t \qquad (4.21)
\end{aligned}$$

Nash bargaining requires that the split between households and firms satisfies $\left(\upsilon^W_{H,t} - \upsilon^U_{H,t}\right) = \gamma\upsilon^J_{H,t}$ where γ is the relative weight of workers in the bargaining game. Using (4.19), (4.20), and (4.21), the Nash bargained wage is:

$$\begin{aligned}
w^N_{H,t}S^{\alpha}_t &= \chi(N^H_t)^{\phi}C^{\sigma}_t S^{\alpha}_t + ub_t + \\
&\quad + \gamma\left\{G^H_t(\theta^H_t) - (1-\delta^H)E_t\left[\beta_{t,t+1}(1-\theta^H_{t+1})G^H_{t+1}(\theta^H_{t+1})\right]\right\} \qquad (4.22)
\end{aligned}$$

where the first two terms on the RHS represent workers' reservation wage, and the remaining term is the share of the surplus accruing to workers.

The corresponding labor demand function and wage equations for the Foreign regions are:

$$\begin{aligned}
\frac{P^*_{X,t}}{P^*_{F,t}}A^F_t A^U_t &= w^F_t S^{-\alpha^*}_t + G^F_t(\theta^F_t) - (1-\delta^F)E_t\left[\beta^*_{t,t+1}G^F_{t+1}(\theta^F_{t+1})\right] \qquad (4.23)\\
w^N_{F,t}S^{-\alpha^*}_t &= \chi^*(N^F_t)^{\phi}(C^*_t)^{\sigma}S^{-\alpha^*}_t + ub^*_t + \\
&\quad + \gamma\left\{G^F_t(\theta^F_t) - (1-\delta^F)E_t\left[\beta^*_{t,t+1}(1-\theta^F_{t+1})G^F_{t+1}(\theta^F_{t+1})\right]\right\} \qquad (4.24)\\
w_{F,t} &= \left(w^N_{F,t}\right)^{\gamma^*_w}(w_F)^{1-\gamma^*_w} \qquad (4.25)
\end{aligned}$$

where $\beta^*_{t,t+i} \equiv \Lambda^F_{t,t+i}\left(\frac{S_t}{S_{t+i}}\right)^{-\alpha^*}$ is the adjusted stochastic discount rate for firms in the Foreign region, $w_{F,t} \equiv \frac{W_{F,t}}{P_t*}$ is the real wage expressed in units of the consumption basket in the Foreign region, and $\gamma^*_w \in [0,1]$ is an index of real wage rigidity in the Foreign region.

The unemployment benefit ub_t for workers in the Home region is partly financed in the Home region and partly financed in the Foreign region. Let $ub_{H,t}$ and and

$ub_{F,t}$ be the real value of the unemployed benefit produced in the Home and Foreign regions accruing to unemployed residents of the Home region. Then, the real value, in domestic produced prices, of the unemployment benefit in the Home region is:

$$ub_t = ub_{H,t} + u_{F,t}S_t \tag{4.26}$$

Let b^H be the replacement ratio in the home region, so that $ub_t = bw_{H,t}S^{\alpha}$. I define $\sigma_{H,t} \equiv \frac{ub_{H,t}S_t^{-\alpha}}{b^H w_{H,t}}$ and $\sigma_{F,t} \equiv \frac{ub_{F,t}S_t^{1-\alpha}}{b^H w_{H,t}}$ as the shares of the Home region unemployment benefit financed domestically and abroad. In the baseline specification with no EUI, I set $\sigma_{F,t}$ equal to zero because there is no transfer of resources between the two regions. Unemployment benefits in the Home region are fully financed through taxation of residents of that region. In the specification with EUI, a reaction function determines the value of this proportion. After determining a rule for $\sigma_{F,t}$ which I discuss in Section 4.3.5, it follows that $ub_{H,t} = (1-\sigma_{F,t})b^H w_{H,t}S_t^{\alpha}$ and $ub_{F,t} = \sigma_{F,t}b^H w_{H,t}S_t^{\alpha-1}$.

Similarly, the unemployment benefit for workers in the Foreign region is $ub_t^* = ub_{H,t}^* S_t^{-1} + ub_{F,t}*$. Defining the ratios $\sigma_{H,t}^* \equiv \frac{ub_{H,t}^*}{S_t b^F w_{F,t}}$ and $\sigma_{F,t}* \equiv \frac{ub_{F,t}^*}{b^F w_{F,t}}$, it follows that $ub_{H,t}^* = \sigma_{H,t}^* b^F w_{F,t} S_t^{1-\alpha^*}$ and $ub_{F,t}^* = (1-\sigma_{H,t}^*)b^F w_{F,t}S_t^{-\alpha^*}$ where b^F is the replacement ratio in the Foreign region. In the baseline specification, $\sigma_{H,t}^*$ is set to zero, whereas in the specification with EUI a reaction function determines its value.

4.3.3 Retailers

Retailers transform intermediate goods into final differentiated final goods and are subject to Calvo pricing. In every period, they can reset their price with probability $1-\xi^i$. Letting $p_{H,t}(j)^*$ be the optimal price of a resetting firm j in the Home region, $p_{H,t+i}(j) = p_{H,t}^*$ with probability ξ^i. Firm j, owned by households in the Home region, discounts profits using the rate $\Lambda_{t,t+i}$ and maximizes the discounted expected stream of nominal profits subject to a sequence of demand constraint:

$$\max_{p_{H,t}^*} E_t\left[\sum_{s=0}^{\infty} \xi^i \Lambda_{t,t+s} y_{t+s}(j)\left(p_{H,t}^* - P_{X,t+s}\right)\right] \tag{4.27}$$

$$s.t. \qquad y_{t+s}(j) \leq \left(\frac{p_{H,t}^*(j)}{P_{H,t}}\right)^{-\epsilon}\left(c_{H,t+s}(j) + c_{H,t+s}^*(j)\right) \equiv y_{t+s|p_{H,t}^*}(j)$$

where $P_{X,t+i}$ represents nominal marginal costs, and $y_{t+i|p^*_{H,t}}(j)$ is the demand for good j at time $t+i$ conditional on the price $p^*_{H,t}(j)$ fixed at time t. The first-order condition to this maximization problem is:

$$E_t\left[\sum_{s=0}^{\infty}\xi^i\Lambda_{t,t+s}y_{t+s|p^*_{H,t}}(j)\left(p^*_{H,t}(j)-\frac{\epsilon}{\epsilon-1}P_{X,t+s}\right)\right]=0 \qquad (4.28)$$

A similar optimal pricing condition applies to final goods producers in the Foreign region. Letting $\Pi_{H,t}$ and $\Pi_{F,t}$ be producer price inflation in the two regions, the CPI inflation rates in the Home and Foreign regions equal $\Pi_t = \Pi_{H,t}\Delta S_t^{\alpha}\varsigma_t$ and $\Pi^*_t = \Pi_{F,t}\Delta S_t^{-\alpha^*}\varsigma^*_t$, where ς_t and ς^*_t are cost-push shocks.

4.3.4 Market-Clearing

In equilibrium, aggregate supply (measured in domestic producer prices) net of hiring cost and unemployment benefit transfers equals aggregate demand:

$$Y_t - G^H_t h^H_t + NUB_t = \int_0^1 y_t(j)dj = \int_0^1\left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}\varpi_t S_t^{\alpha}C_t dj = Z_t\varpi_t S_t^{\alpha}C_t \qquad (4.29)$$

where $Z_t \equiv \int_0^1\left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}dj$ is a measure of price dispersion, $NUB_t \equiv ub_{F,t}S_t - ub^*_{H,t}$ is the net unemployment benefit transfer to the Home region measured in Home producer prices, and $\varpi_t \equiv \left[(1-\alpha)+\alpha^*\varepsilon_t^{\left(1-\frac{1}{\sigma}\right)}\left(\frac{\Omega_t}{\Omega^*_t}\right)^{-\frac{1}{\sigma}}\right]$. Similarly, for the Foreign region equilibrium in the goods market requires:

$$Y^*_t - G^F_t h^F_t - \frac{NUB_t}{S_t} = \int_0^1 y^*_t(j)dj = \int_0^1\left(\frac{p_{F,t}(j)}{P_{F,t}}\right)^{-\epsilon}\varpi^*_t S_t^{-\alpha^*}C_t dj = Z_t\varpi^*_t S_t^{-\alpha^*}C_t \qquad (4.30)$$

where $\varpi^*_t \equiv \left(\alpha\varepsilon_t^{-\left(1-\frac{1}{\sigma}\right)}\left(\frac{\Omega_t}{\Omega^*_t}\right)^{\frac{1}{\sigma}}+(1-\alpha^*)\right)$. Total output Y^U_t in the currency union (measured in domestic CPI) is $(Y_t + Y^*_t S_t)S_t^{-\alpha}$, while total unemployment u^{UNION}_t is the simple arithmetic average of the unemployment rates in the two regions because of equal population size. I also define the unemployment differential Δu_t as the difference between the unemployment rate u_t in the Home region and the corresponding rate u^*_t in the Foreign region.

4.3.5 Government

Policy-makers in the currency union are responsible for setting monetary policy and the shares of unemployed benefit financed across the two regions. The monetary authority sets the short-term nominal rate i_t following a standard Taylor rule with interest-rate smoothing:

$$(1+i_t) = \rho_r(1+i_{t-1}) + (1-\rho_r)\left(\phi_\Pi log(\Pi_t^U) + \phi_y(y_t^U - \tilde{y}_t^U)\right) \tag{4.31}$$

where ρ_r is the weight assigned to the lagged nominal rate i_{t-1}, ϕ_Π is the responsiveness to deviation of union-wide inflation Π_t^U, ϕ_y is the responsiveness to deviation of union-wide output y_t^U to the corresponding efficient level $\tilde{y}_t^U$. Under a strict interpretation, price stability is the only statuary objective of the ECB's mandate. However, empirical evidence based on reduced-form single-equation estimation suggests that that the ECB also responds to fluctuations in output (Sauer and Sturm, 2007; Gorter *et al.*, 2008; Sturm and De Hann, 2011; Belke and Klose, 2011).[13,14] Thus, I assume a monetary authority with a dual mandate.

Lastly, I assume that in the model with EUI the shares of unemployment benefits financed in the other region of the currency union follow the rules:

$$\sigma_{F,t} = \nu^H(u_t^H - \tilde{u}_t^H), \qquad \sigma_{H,t} = \nu^F(u_t^F - \tilde{u}_t^F) \tag{4.32}$$

where $\tilde{u}_t^H$ and $\tilde{u}_t^F$ are the efficient levels of the unemployment rate. Under this specification, on average there is no transfer of real resources across the currency union. If there were, the model would imply a permanent transfer of resources from one region to the other akin to the structural Cohesion Policy of the European Union rather than the stabilization tool EUI proponents argue for. Furthermore, under this policy rule the steady-state of the model is unchanged. This implies

[13] I am ignoring the literature estimating the reaction function of a hypothetical ECB or the Bundesbank in for the pre-1999 period. Similarly, the empirical literature estimating the reaction of the ECB using a short time period has been superseded and is not very informative.

[14] Structural DSGE estimation (Christoffel *et al.*, 2009; Christiano *et al.*, 2008; Sahuc and Smets, 2008; Smets and Wouters, 2003; Adjemian *et al.*, 2007) also provides evidence in favor of a policy reaction akin to a Taylor rule. However, the sample used in estimation usually starts from the 1970s or 1980s, implicitly assuming the existence of a hypothetical ECB with a single reaction function responding to union-wide economic conditions.

that both the model dynamics and the degree of inefficiency due to unemployment benefits is unaffected by the existence of EUI.

4.3.6 Efficient Equilibrium

Following Blanchard and Galí (2010), I derive the constrained efficient allocation as the equilibrium that would arise if the social planner maximized the welfare of the currency union. The social planner cannot eliminate hiring frictions in the labor market but takes into account the congestion externalities that variations in the level of employment in an individual firm have on the marginal hiring costs other firms face. The efficient equilibrium requires four conditions to hold: i) a production subsidy eliminating distortions in the goods market due to monopolistic competition, ii) fully flexible real wages ($\gamma_w^i = 1$), iii) the bargaining power of workers γ^i in the Nash bargaining solution equaling the elasticity of the hiring cost function φ^i,[15] and iv) zero replacement ratio b for unemployment benefits (see *Appendix* 4.7.4 for the full derivation).

To highlight the implications that UI has on the equilibrium of the model, consider a specification of the model in which conditions i)-iii) hold. In such an economy, unemployment benefits are the only source of inefficiency because they create a wedge between the social marginal rate of substitution and the social marginal rate of transformation between consumption and labor. Combining equations (4.17), (4.18), and (4.22) yields:

$$\chi(N_t^H)^\phi C_t^\sigma S_t^\alpha = \left\{A_t - (1+\varphi^H)G_t^H + (1-\delta^H)E_t\left[\beta_{t,t+1}G_{t+1}^H\left(1+\varphi^H(1-\theta_{t+1})\right)\right]\right\} - b^H w_{H,t} S_t^\alpha \tag{4.33}$$

The LHS is the social marginal rate of substitution between consumption and labor. The first term on the RHS is the social marginal rate of transformation which includes the current marginal product of labor net of hiring cost and the expected marginal savings due to lower hiring needs in the next period. The second term on the RHS is the wedge due to unemployment benefits. Intuitively, these benefits raise

[15] This is akin to the *Hosios* condition that characterizes the efficient allocation in a model with random search frictions in the labor market

the value of the outside option of unemployed workers and their reservation wage. As households demand a higher real wage for every level of labor market tightness, in equilibrium, for a given labor demand curve, the real wage will be higher, but labor market tightness and employment will be lower, than under the efficient allocation.

4.4 Calibration

I calibrate the model at quarterly frequency. Since I am interested in matching EA data as accurately as possible, I choose a parameterization that differs from the one in Mueller and Abbritti (2013) in several respects. I set labor market parameters for the Home and Foreign regions to match labor market statistics for the Southern and Northern EA country blocks. The data covers the 1998Q1:2014Q4 period. Although the Euro became the EA official unit of account on 1 January 1999 and entered in circulation as a physical currency only two years later, convergence in national nominal interest rates had been achieved by 1998 (Rabanal, 2009). Moreover, there is evidence of convergence in the policy reaction function of national central banks in the major EU countries during the 1988-1997 Exchange Rate Mechanism period (Angeloni and Dedola, 1999).[16] For the remaining preference, technology, and structural shock parameters I rely, whenever possible, on values estimated in structural models of the EA, otherwise I use standard values found in the New Keynesian literature. All parameters are summarized in Table 4.3.

4.4.1 Preferences

I set the discount rate β to 0.992, which implies an annual return on the riskless bond of approximately 3.3 percent. I assume logarithmic preferences in the consumption of the aggregate bundle and set the intertemporal elasticity of substitution of consumption σ equal to unity. I also set the elasticity of labor supply ϕ equal to

[16] These authors test for homogeneity of the reaction function coefficients of an augmented Taylor rule for France, Italy, the Netherlands, Spain, and the UK vis-*à*-vis Germany. Apart from the UK, the homogeneity restrictions are generally accepted, providing evidence for an ongoing, albeit incomplete, process of convergence. This would have the potential of combining different national policy frameworks into a single coherent monetary policy. The authors, however, also find that national policy put little emphasis on area-wide measures of inflation and output gap when conducting national monetary policy.

TABLE 4.3: CALIBRATION

Parameter	*Value* Southern (Home)	Northern (Foreign)	*Source/Target*
Household preferences			
Discount rate β	0.992		Annual rate of 3.3 percent
Elasticity of intertemporal substitution σ	1		Log utility
Labor supply elasticity ϕ	0		Mueller and Abbritti (2013)
Share of imported goods α, α^*	0.25		Andres *et al.* (2008)
Wholesale producers and retailers			
Elasticity of hiring cost function φ^i	1		Blanchard and Galí (2010)
Demand elasticity of substitution ϵ	6		Average profit of 20 percent
Price rigidity ξ	0.75		Altissimo *et al.* (2006)
Labor market			
Real wage rigidity γ_w	0.5		Blanchard and Galí (2010)
Worker's bargaining weight γ^i	0.5		Blanchard and Galí (2010)
Job-finding rate θ^i	18%	22%	Eurostat
Unemployment rate u^i	11%	7%	Eurostat
Aggregate hiring cost G^ih^i	$0.005Y^i$		Blanchard and Galí (2010)
Replacement ratio	40%	50%	Cesifo
Policy			
Response to inflation ϕ_Π	1.5		Smets and Wouters (2003)
Response to output gap ϕ_y	0.125		Christiano *et al.* (2008)
Interest-rate smoothing ρ_r	0.85		Rabanal and Rubio-Ramirez (2008)
Responsiveness of UB share ν^i	1		
Shocks			
St.dev. of TFP process σ_{A^i}	0.624		Smets and Wouters (2003)
St.dev. of preference process σ_{Ω^i}	1.624		Smets and Wouters (2003)
St.dev. of cost-push innovations σ_{ς^i}	1.624		Smets and Wouters (2003)
Autocorrelation coefficient of TFP innovations ρ_{A^i}	0.815		Smets and Wouters (2003)
Autocorrelation coefficient of preference innovations ρ_{Ω^i}	0.850		Smets and Wouters (2003)

zero for both regions, and the shares of imports α and α^* equal to 0.25, compatible with average data for European countries (Andres *et al.*, 2008).

4.4.2 Technology

Following Blanchard and Galí (2010), I set the parameter φ^i in the hiring cost function to unity. This is similar to assuming an elasticity of 0.5 in the matching function of a random search model of the labor market, which is a value in line with the available evidence.[17] As in Campolmi and Faia (2011) and Gerali *et al.*

[17] Assuming the CRS function $m_t = m_0 U_t^{\sigma_m} V_t^{1-\sigma_m}$, the expected cost per hire in the steady-state is proportional to the expected vacancy duration which is $\frac{V}{H} = m_0^{\frac{1}{\sigma_m - 1}} \left(\frac{H}{U}\right)^{\frac{\sigma_m}{1-\sigma_m}}$ where V_t is the number of vacancies. This results in the mapping $\varphi^i = \frac{\sigma_m}{1-\sigma_m}$.

(2010), I set the elasticity of substitution ϵ across different varieties to 6, implying an average mark-up of 20 percent. As in Christoffel *et al.* (2009), I set the Calvo parameter ξ equal to 0.75 to match the available micro-evidence on average consumer price lasting for 4-5 quarters[18] in the EA (Altissimo *et al.*, 2006; Álvarez *et al.*, 2006; Dhyne *et al.*, 2006).[19]

4.4.3 Labor Market

I set the steady-state unemployment rates for the Home and Foreign region to 11 and 7 percent to match the average unemployment rates in the Southern and Northern EA country blocks over the 1998-2014 period. The calibration of the quarterly steady-state job-finding rate is trickier. Blanchard and Galí (2010) set it to 25 percent for the whole Euro Area, which turns out to be consistent with LFS data for the 2005-2008 period.[20] More recent evidence shows that between 2010 and 2014 the average quarterly rate fell to 16 percent.[21] This evidence also indicates no systematic North-South divide in terms of job-finding rates before 2010 (Anderton *et al.*, 2015). The rate was around 35 and 33 percent in Spain and Austria, around 24 percent in France and Finland, and around 22 percent in Ireland, the Netherlands, and Italy. Greece was the only country with a substantially lower average rate equaling 10.5 percent. In most recent years the average job-finding rate in the Northern and Southern regions was 21.3 and 16.0 percent. Thus, I set

[18]Campolmi and Faia (2011) and Mueller and Abbritti (2013) set ξ equal to 0.66. In structural DSGE models, Christiano *et al.* (2008) estimate a value of ξ equal to 0.81, consistent with the upper range of the micro-evidence on price changes. In constrast, Smets and Wouters (2003), Thomas and Zanetti (2009), and Sahuc and Smets (2008) estimate a larger degree of price stickiness, amounting to 0.908, 0.912, and 0.88, respectively. Smets and Wouters (2003) explain that the flat real marginal cost curve typical of New Keynesian DSGE model leads to an upward bias in the estimation of the Calvo parameter. Assuming a concave production function in labor, Rabanal (2009) obtains an upward-sloping marginal cost curve and estimates ξ consistent with an average price duration of 2.06 quarters.

[19]They find that the median firm changes prices less than once a year, and that industrial prices in the EA are changed slightly more frequently than consumer prices. Moreover, they find a considerable degree of heterogeneity within and across product categories. This heterogeneity is also more important than cross-country average price duration.

[20]Belgium and Germany are excluded from this calculation due to data availability.

[21]Mueller and Abbritti (2013) set the average job-finding rate equal to 0.45 consistent with a monthly rate of 0.18. However, it is unclear on which evidence this figure is based.

the steady-state quarterly job-finding rate to 18 percent for the Home region and to 22 percent for the Foreign region to match all the available evidence.[22]

Lastly, I use figures on average net unemployment benefit replacement rates from 2001 until 2010 elaborated by the Cesifo on OECD data to set the replacement ratio b^i.[23] I use the share of a country's GDP to weight national replacement ratios and compute the average replacement ratio for each one of the two country blocks. Thus, I obtain 50 and 40 percent for the Northern and Southern regions, respectively.

The other labor market parameters are common to both regional blocks. Following Blanchard and Galí (2010), Mueller and Abbritti (2013) and much of the literature, I set the bargaining power of workers γ to 0.5, and the weight of the Nash bargaining solution in determining the equilibrium real wage ρ_w equal to 0.5 (in the midpoint of the available evidence). I also set hiring cost in the steady-state equal to 0.5 percent of aggregate output. Lacking direct empirical evidence, this is the mid-point in the range of plausible values. Some authors, among others Blanchard and Galí (2010) and Mueller and Abbritti (2013) use the upper value of 1 percent, while others use lower values (for instance, the calibration in Christoffel *et al.* (2009) implies that vacancy costs account for 0.23 percent of quarterly GDP).

Given the values used to match the average job-finding and unemployment rates, the quarterly separation rate δ^i equals $\theta^i u^i / ((1-u^i)(1-\theta^i))$. This equals 2.7 percent for the Southern region and 2.1 percent for the Northern region, which are only slightly higher than the empirical average separation rates of 2.5 and 1.4 percent.[24] These estimates are based on 2010Q2-2014Q4 data using the

[22]The main results of the calibration exercise are robust to setting this parameter in a wider range of values consistent with the evidence discussed above.

[23]This is defined as the average unemployment benefit replacement rate (excluding social assistance) for two earning levels (67 and 100 percent of an adult full-time worker earning the average wage in the corresponding industry sector), three family situations (single, one-earner married couple, and two-earner married couple) and a 60-month spell of unemployment (with replacement rates equally weighted over the course of five years). The average wage for adult full-time workers usually covers sectors B to N of the Revision 4 of the International Standard Classification of All Economic Activities.

[24]For the currency union, setting an average unemployment rate of 9.5 percent implies a separation rate of 2.6 percent, which is only slightly above the empirical rate of 2.3 percent

adjusted LFS series.[25,26]

Similarly, matching the job-finding rate, the unemployment rate, and aggregate hiring cost relative to output determines the scale parameter B^i in the hiring cost function as $(gh/y)/((\theta^i)^{\varphi^i}\delta^i)$. Under this calibration, B equals 1.02 for the Home region, and 1.07 for the Foreign region. This captures the intuitive idea that a more dynamic labor market with a higher job-finding rate and a lower unemployment rate creates new jobs more efficiently. Lastly, steady-state relationships determine the relative weight of labor disutility in the utility function χ which determines the marginal rate of substitution and the worker's reservation wage.

4.4.4 Policy

In setting the monetary policy parameters ϕ_Π, ϕ_y, and ρ_r I choose values consistent with the empirical literature and set them to 1.5, 0.125, and 0.85. Using EA data between 1980 and 2003, Smets and Wouters (2003) estimate them to equal 1.684, 0.099, and 0.961. With a slightly longer samples, Rabanal and Rubio-Ramirez (2008) estimate values of 1.38, 0.13, and 0.66 (1980-2003), while Christiano *et al.* (2008) estimate values of 1.58, 0.19, and 0.8 (1983-2006). Lastly, over an even longer horizon (1973-2004), Adjemian *et al.* (2007) estimate these coefficients to equal 1.576, 0.097, and 0.961.

Moreover, I assume EUI to be a symmetric policy and set the responsiveness of the unemployment benefit rule ν^i equal to zero in the specification without EUI and to unity in the specification with EUI. The latter implies that when the unemployment rate in one country deviates from its efficient level by 1 percent, the share of unemployment benefits paid for by residents in the other region of the currency union rises by 1 percent. While this parameterization may seem too conservative, I examine the impact of different values of ν^i in Section 4.5.3.

[25] The average job-separation rates exclude Belgium, Germany, and Luxembourg, for which data is unavailable.

[26] The total exit rate from employment is 4.8 percent for the EA12, 5.0 percent for the Southern block, and 4.1 percent for the Northern block. This probability, however, overstates the degree of job-destruction because it includes not only discouraged workers who do not look for a new job after losing one, but also recent retirees or other individuals who willingly exit the labor force.

4.4.5 Shocks

The parameters for TFP, preference, and cost-push shocks are based on the Bayesian estimation in Smets and Wouters (2003). I assume that the log-level of technology follows an AR(1) process with autoregressive parameter ρ_{A^i} and subject to innovation $\epsilon_t^{A_i} + \epsilon_t^{A_U}$, where $\epsilon_t^{A_i}$ is an idiosyncratic shock specific to region i and $\epsilon_t^{A_U}$ is a union-wide aggregate shock. I set the standard deviation σ_{A^i} equal to 0.624, and the persistence ρ_{A^i} equal to 0.815.[27] Similarly, I assume that the log-level of the preference process follows an AR(1) process with autoregressive parameter ρ_{Ω^i} and subject to innovation $\epsilon_t^{\Omega_i} + \epsilon_t^{\Omega_U}$, where $\epsilon_t^{\Omega_i}$ is an idiosyncratic shock specific to region i and $\epsilon_t^{\Omega_U}$ is a union-wide aggregate shock. I assume the standard deviation σ_{Ω^i} to be equal to 0.258. Furthermore, I assume the (log-level) of the cost-push shocks ς_t^i to be a white-noise process with idiosyncratic and union-wide components each with standard deviation σ_{ς^i} equal to 0.164.

4.5 Results

I now discuss the main results of this chapter. First, in Section 4.5.1 I present the impact of EUI on the relative volatilities of interest. Then, in Section 4.5.2, I show the impulse response functions for the specifications with and without EUI to explain the functioning of EUI in more detail. Lastly, in Section 4.5.3 I conduct sensitivity analysis and discuss how the main results of the analysis change over a range of values for the responsiveness parameter ν^i.

4.5.1 Effects of EUI on Relative Inflation and Unemployment Volatilities

Table 4.4 reports the aggregate volatilities of the unemployment and inflation rates in the EA12, and the volatilities of the inflation and unemployment differentials between the Southern and the Northern regions. The inflation rate is based on the Harmonised Index of Consumer Prices (HICP). All volatilities are computed

[27]In similar Bayesian exercises, Sahuc and Smets (2008) estimate σ_A equal to 0.503 and ρ_A equal to 0.962. Christoffel *et al.* (2009) estimate lower values at 0.39 and 0.64, while Rabanal (2009) finds 0.54 and 0.94.

Table 4.4: Business Cycle Properties in EA12

	Data	*Model*	
		Union-wide shocks	*Idiosyncratic shocks*
Unemployment rate	0.247	0.092	0.057
Unemployment differential	0.241	0.002	0.239
Inflation rate	0.122	0.117	0.075
Inflation differential	0.132	0.002	0.117

All volatilities are computed detrending the inflation and unemployment series with a HP filter with smoothing parameter equal to 1,600.

detrending the series with a HP filter with smoothing parameter equal to 1,600. Table 4.4 also reports the unconditional volatilities that the model predicts either under aggregate or idiosyncratic shocks.

The third column shows that aggregate shocks can replicate 37 percent of the unemployment rate volatility, and almost of the inflation rate volatility. Aggregate shocks, however, cannot account for the volatility of the regional differentials. A symmetric shock to the monetary union can lead to inflation and unemployment differentials only if the two regions differ on some economically relevant dimensions. In this case, diverse labor market institutions generate heterogeneous effects even for aggregate shocks, but the magnitude of these effects is too small to replicate the volatility of the inflation and unemployment differentials between the Southern and the Northern regions of the EA.

The fourth column shows that idiosyncratic shocks generate lower volatility in the aggregate variables than aggregate shocks but they perform better in terms of volatilitities of the regional differentials. Compared to the data, idiosyncratic shocks can generate approximately a quarter of the unemployment rate volatility, and 61 percent of the inflation rate volatility. However, idiosyncratic shocks can essentially replicate the volatility of the inflation and unemployment differentials. Overall, some combination of aggregate and idiosyncratic shocks should be able to replicate reasonably well the aggregate volatilities of inflation and unemployment in the EA12, and the volatilities of the differentials between the Southern and

Table 4.5: Effect of European Unemployment Insurance

	Unconditional [a]	*Conditional* [b]		
		TFP	*Preference*	*Cost-push*
		Panel I: Aggregate Shocks		
(a) Unemployment rate				
EA12	1.000	1.000	1.002	1.002
South	1.014	1.014	1.028	1.015
North	0.984	0.982	0.972	0.986
Differential	1.086	1.052	1.334	1.174
Differential (eff.)	1.084	1.052	1.314	1.174
(b) Inflation rate				
EA12	0.997	0.997	0.994	1.002
Southern	1.001	1.000	1.014	0.995
Northern	0.992	0.986	0.993	1.007
Differential	0.858	0.758	0.870	0.832
	Panel II: Idiosyncratic Shocks			
(a) Unemployment rate				
EA12	1.008	0.850	0.822	1.002
South	0.651	0.500	0.512	1.015
North	0.655	0.342	92.2	0.986
Differential	0.317	0.345	0.280	1.174
Differential (eff.)	0.325	0.345	0.361	1.174
(b) Inflation rate				
EA12	0.987	1.106	1.025	1.002
Southern	0.949	0.761	0.712	0.998
Northern	0.861	2.649	2.333	0.987
Differential	0.666	0.402	0.276	0.995

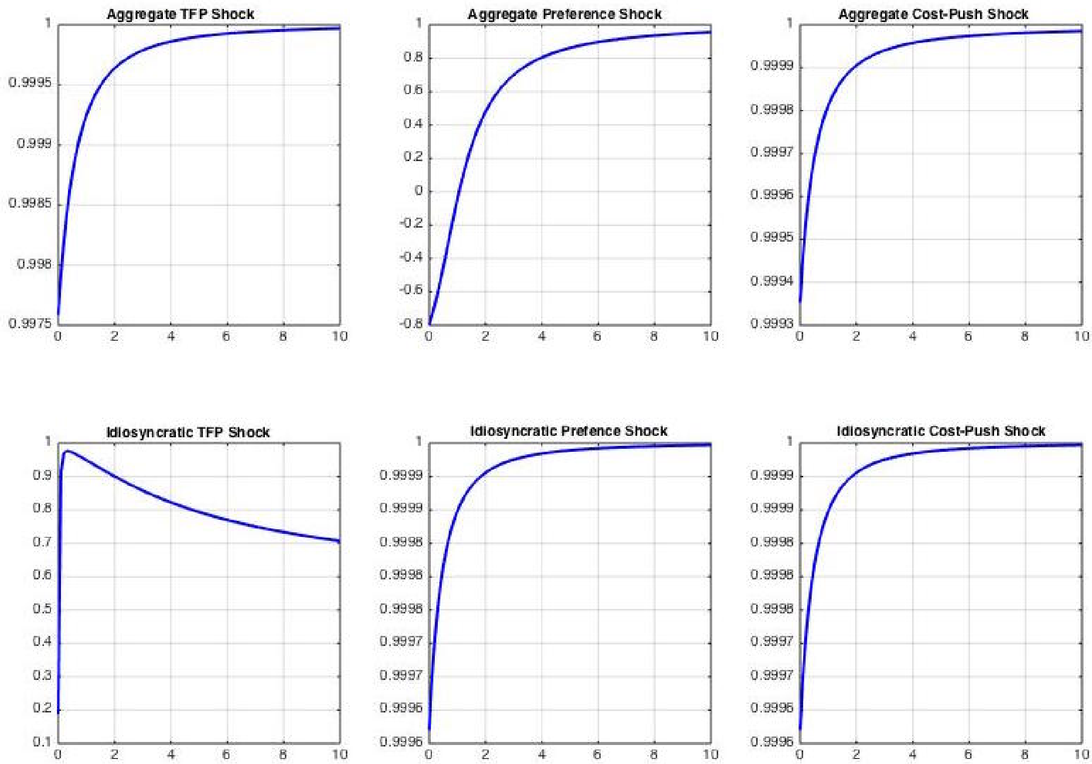
Each entry represents the ratio between the volatility in the specification with EUI (with ν^i equal to 1) and the model with two independent unemployment insurance schemes.
[a] *Unconditional volatilities are computed in a simulation in which all shocks affect the economy.*
[b] *Conditional volatilities are computed in a simulation in which only a shock affects the economy.*

Northern regions.[28] Thus, the model is able to capture the main business cycle properties of the Euro Area.

Table 4.5 reports the main results of the simulation exercise. Each figure is the ratio between the volatility in the specification with EUI and the same

[28] Mueller and Abbritti (2013) mention that their baseline specification calibrated to EA average data can replicate well the volatility of output, inflation, and unemployment. This specification, however, would be unable to replicate the volatility of the regional differentials because it features two symmetric regions with no labor market asymmetries. They do not discuss whether their calibration with asymmetric labor markets would replicate the volatility observed in the data.

Figure 4.1: Business Cycle Synchronization: Impact of EUI on the Correlation Between Regional Unemployment Rates



The horizontal axis shows different values for the reaction coefficients ν^H and ν^F. The vertical axis displays the volatility of the variable of interest relative to the baseline model with $\nu^H = \nu^F = 0$.

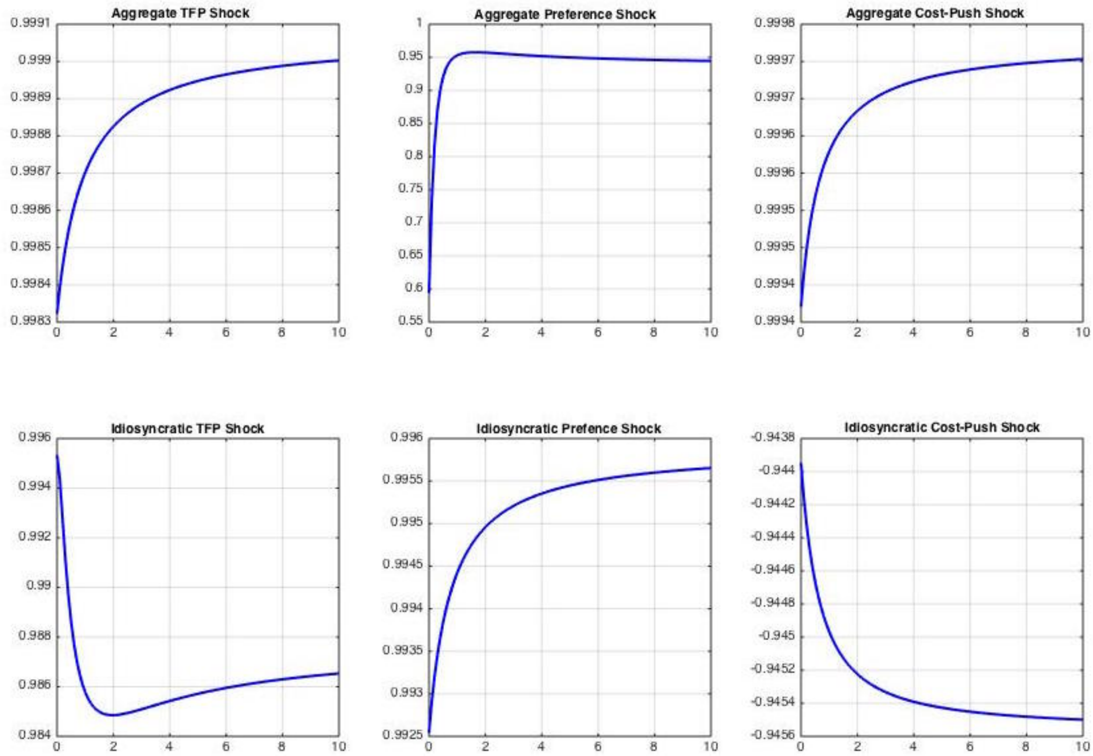
volatility in the baseline specification with two independent regional unemployment insurance schemes. I compute relative volatilities for the regional and the aggregate unemployment and inflation rates as a measure of the stabilization properties of EUI. Moreover, I also compute relative volatilities for the unemployment and inflation differentials between the two regions as a measure of the EUI's convergence properties. Since the efficient level of unemployment may be time-varying, I also compute the relative volatility of the differential between the overall unemployment rate and its efficient level.[29] The table reports the predicted unconditional relative volatilities, when all shocks hit the economy, and conditional ones. In the latter case, I simulate the impact of a single shock hitting the Southern region of the currency union.

[29]That is, $\Delta u_t = (u_t^H - \tilde{u}_t^H) - (u_t^F - \tilde{u}_t^F)$ where $\tilde{u}_t^i$ is the efficient level of unemployment in region i. I do not calculate the relative volatility of the overall efficient level of unemployment because EUI does not affect this level.

In response to aggregate shocks, EUI has only a marginal impact on the aggregate and regional volatilities of unemployment and inflation. Regardless of the nature of the shock, there is a trade-off between regional volatilities: reducing inflation or unemployment volatility in one region of the currency union increases it in the other one. In particular, EUI generally reduces volatilities in the Northern region with a more flexible labor market. The magnitude of these effects, however, is small. Furthermore, the aggregate inflation and unemployment volatilities are essentially unchanged; thus, EUI only redistributes the impact of aggregate shocks between the two regions with few, if any, aggregate stabilizing effects. EUI also increases the correlation between regional inflation and unemployment rates (see Figures 4.1 and 4.2). In terms of convergence properties, EUI can lower the volatility of the inflation differential but at the expense of a higher volatility in the unemployment differential. In particular, the former drops by 13, 17, and 25 percent for preference, cost-push, and TFP shocks, while changes in the latter range from 5 percent for TFP shocks to 31 percent for preference shocks.

In the case of idiosyncratic shocks affecting the Southern region, the impact of EUI varies depending on the nature of the shock. Only for TFP and preferences does EUI have a strong quantitative impact on the relative volatilities. The case of idiosyncratic cost-push shocks is similar to aggregate shocks, whereby EUI affects only the magnitude of the volatility of the differential from the efficient level. In case of TFP shocks, EUI strengthens the correlation between the regional unemployment rates but weakens the correlation between the two regional inflation rates (see Figures 4.1 and 4.2). EUI also reduces the volatilities of the regional unemployment rates, whereas it moves the volatilities of the regional inflation rates in opposite directions. The volatilities of the unemployment and inflation differentials are both substantially lower than under independent UI schemes. They are indeed 34 and 40 percent of the original volatility. Nevertheless, while the volatility of the aggregate unemployment rate is lower, the volatility of aggregate inflation is higher. On balance, for idiosyncratic TFP shocks, EUI helps achieve

FIGURE 4.2: BUSINESS CYCLE SYNCHRONIZATION: IMPACT OF EUI ON THE CORRELATION BETWEEN REGIONAL INFLATION RATES



The horizontal axis shows different values for the reaction coefficients ν^H and ν^F. The vertical axis displays the volatility of the variable of interest relative to the baseline model with $\nu^H = \nu^F = 0$.

convergence in unemployment and inflation rates, but its stabilization outcomes are more ambiguous.

In the case of idiosyncratic preference shocks, EUI creates trade-offs between the regional volatility of both unemployment and inflation. In the absence of EUI, the Northern region would be insulated from the impact of the shock to the Southern region, and it would experience little employment and inflation fluctuations. EUI acts as a proper risk-sharing mechanism, transferring resources from the Northern to the Southern region. This reduces inflation and unemployment volatility in the latter at the expense of higher volatility in the former. As a result, there is a higher degree of business cycle synchronization. The combined effect is to lower the aggregate unemployment volatility, the volatility of the unemployment differential, and the volatility of the unemployment differential from its efficient level. These effects are all quantitatively relevant.

EUI has also a substantial impact on the volatility of the inflation differential, which falls by 72 percent, but it also slightly increases aggregate inflation volatility. Overall, in case of idiosyncratic preference shocks, EUI has significant convergence properties. It also has substantial stabilization properties, although stabilization of the unemployment rate in the currency union is at the expense of more volatility in the region not directly affected by the shock.

4.5.2 Impulse Response Analysis

To gain some intuition about the functioning of EUI, I now present and discuss impulse response functions for idiosyncratic TFP and preference shocks to the Southern region. In both cases EUI has a substantial impact on the volatilities of interest. Yet, there are also trade-offs between inflation and unemployment volatility at either the aggregate or regional level that are important to understand in more detail.

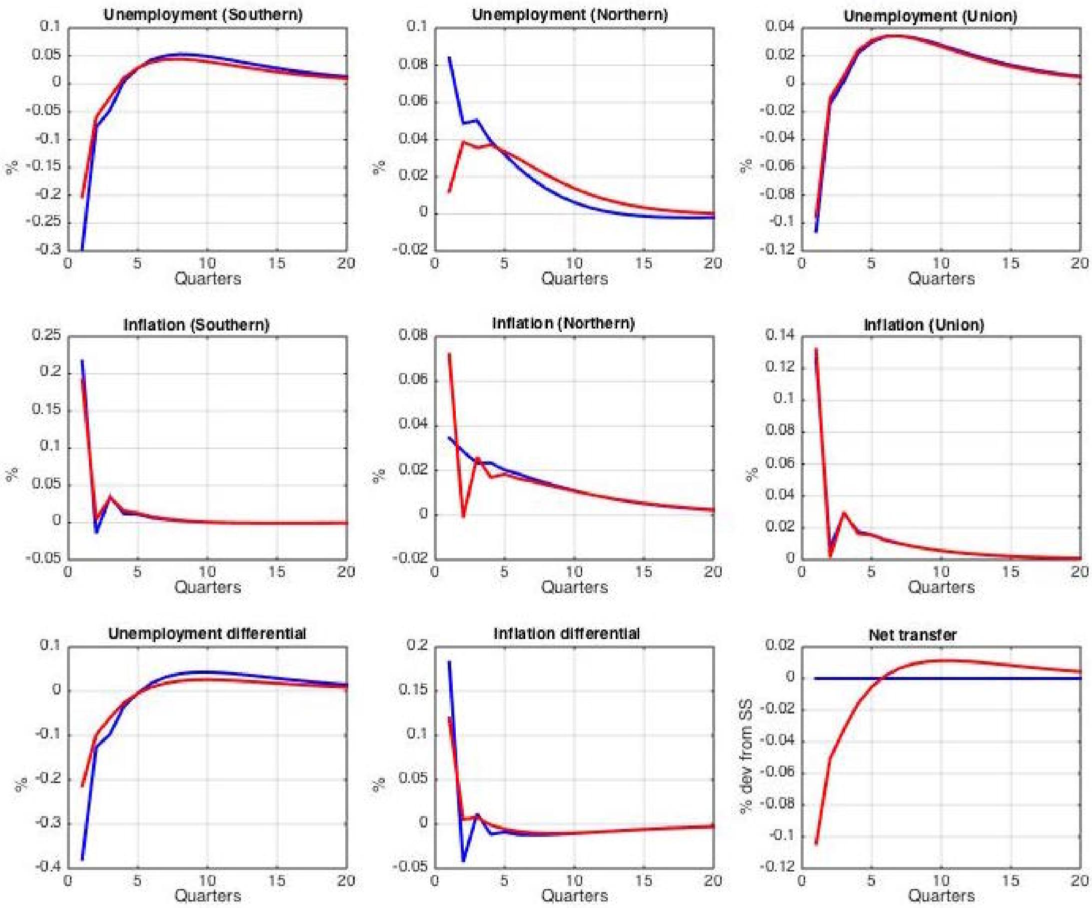
4.5.2.1 Impulse Response Analysis to a Negative Idiosyncratic TFP Shock in the Southern Region

Figure 4.3 shows the impact of a negative TFP shock to the Southern region. In this model, the efficient level of labor market tightness, and so the efficient unemployment rate, is invariant to productivity shocks.[30] If prices were fully flexible, goods produced in the Southern region would become more expensive, lowering demand for these goods. In equilibrium, the real interest rate would rise to decrease Southern residents' aggregate consumption, while the real exchange rate would appreciate to shift consumption towards goods produced in the Northern region. Since unemployment is invariant to TFP shocks, under flexible prices output would fall in the Southern region exclusively because of lower productivity, whereas there would be no change in output in the Northern region.

With nominal price rigidities, neither the real interest rate nor the real exchange rate adjust sufficiently to achieve the flexible-price allocation. As a result, Southern

[30] See Blanchard and Galí (2010) for an explanation.

Figure 4.3: Impulse Response to a Negative Idiosyncratic TFP Shock in the Southern Region



The blue line is the impulse response in the baseline specification, while the red line is the impulse response in the specification with EUI.

residents' consumption demand does not fall enough, and there is an insufficient substitution towards goods produced in the Northern region. Given home bias in consumption, demand for goods produced in the Southern region is higher than it would have been under flexible prices. Since workers have become less productive, more workers are necessary to satisfy demand for goods produced in the Southern region, so the unemployment rate falls.[31] In contrast, the incomplete substitution effect results in lower demand for goods produced in the Northern region, so the unemployment rate in this region rises. As prices and the real exchange rate adjust

[31] A negative correlation between productivity and employment has been reported in Galí (1999), Galí and Rabanal (2004), and Francis and Ramey (2005), though others such as Christiano *et al.* (2003) challenge this finding.

over time, the unemployment rate in the Southern region gradually rises above the steady-state, whereas unemployment in the Northern region falls.

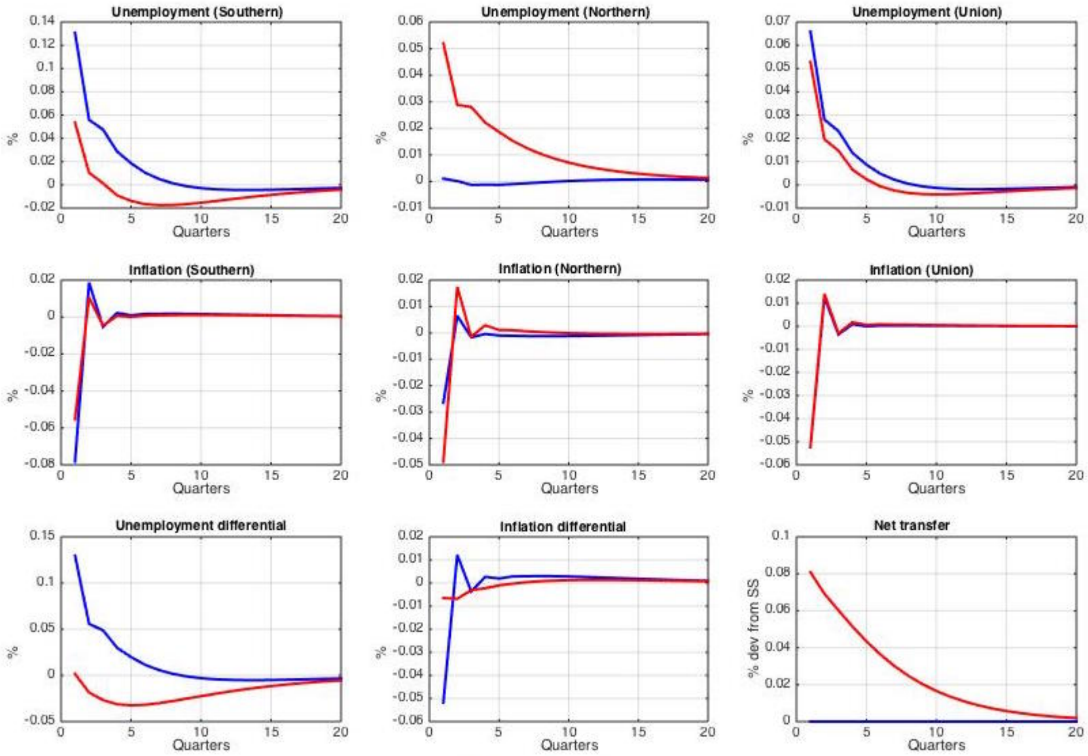
EUI moves the economy towards the efficient employment allocation. The fiscal transfer acts like an income tax on Southern residents, reducing their consumption, and as a subsidy for Northern residents, increasing their consumption. Despite the incomplete price adjustment, Southern residents reduce their consumption demand because of lower income. Because of home bias in consumption, this effect is particularly strong for goods produced in the Southern region; hence, EUI reduces the employment adjustment necessary for equilibrium in the labor market, bringing the unemployment rate closer to its efficient level. This also reduces inflation pressures in this region. On the contrary, the transfer makes residents in the Northern region increase their consumption demand, particularly for Northern goods, partially offsetting the impact of the incomplete real exchange rate adjustment. This results in a smaller rise in the unemployment rate, but higher inflationary pressures, in this region.

Overall, the aggregate unemployment rate falls only slightly but the regional unemployment differential halves. In contrast, the aggregate inflation rate rises slightly, while the differential falls. Over time, as prices adjust and the negative TFP shock dissipates, increasing the unemployment rate in the Southern region increases above its steady-state level, the fiscal transfer moves resources from the Northern to the Southern region. In this case, the effects of EUI are reversed. In particular, the unemployment rate in the Northern region is slightly above its equilibrium level under independent UI schemes. The sharp initial reduction, however, more than compensate for this smaller rise; thus, EUI reduces unemployment volatility in the Northern region substantially.

4.5.2.2 Impulse Response Analysis to a Negative Idiosyncratic Preference Shock in the Southern Region

Following a negative preference shock in the Southern region, demand for goods produced in both regions of the currency union falls. If prices were fully flexible, they would also fall to counteract the impact of the shock, with a larger fall in

Figure 4.4: Impulse Response to a Negative Idiosyncratic Preference Shock in the Southern Region



The blue line is the impulse response in the baseline specification, while the red line is the impulse response in the specification with EUI.

the Southern region due of home bias. This would lead to both a lower real interest rate and a real exchange rate depreciation. Unlike TFP shocks, preference shocks lead to movements in the efficient level of labor market tightness and the unemployment rate. With sticky prices, neither the real interest rate nor the real exchange rate adjust sufficiently to achieve the flexible-price equilibrium. Hence, the unemployment rate rises in both regions, although the employment adjustment in the Northern region is very small because of home bias.

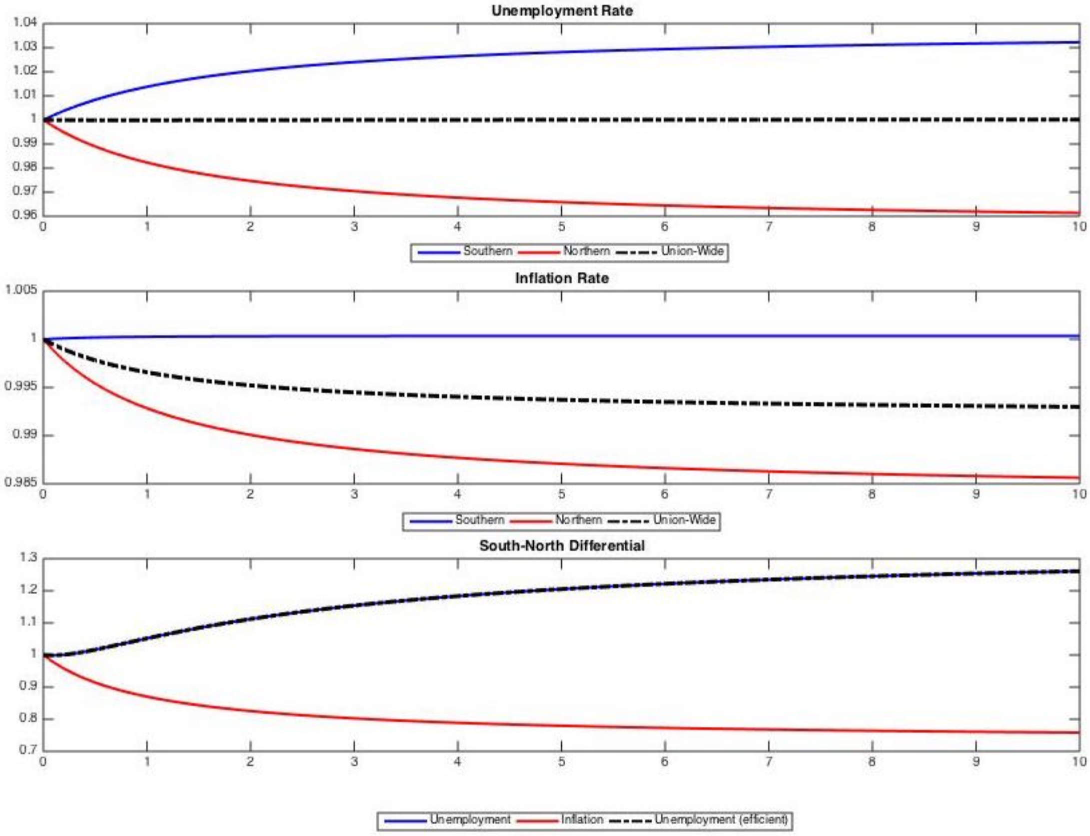
EUI transfers resources from the Northern to the Southern region. Residents of the Northern region reduce their demand for goods, so that labor demand falls by more than in the absence of EUI. Since in the baseline specification the adjustment is close to zero, in relative terms the unemployment rate rises substantially. This explains why the relative unemployment volatility in the Northern region is very large. On the other hand, the fiscal transfer increases income and consumption demand in the Southern region. This counteracts the impact of the shock on the regional unemployment and inflation rates, whose adjustments are smaller than in the baseline specification. EUI clearly acts like a risk-sharing mechanism. In the absence of EUI the Northern region would essentially be isolated from the impact of the preference shock affecting the Southern region. EUI, on the other hand, reduces inflation and unemployment fluctuations in the Southern region at the expense of higher fluctuations in the Northern region. As a result the business cycles in the two countries become more correlated with each other, and the unemployment and inflation differentials fall. At the aggregate level, EUI reduces the unemployment rate but increases the inflation rate.

4.5.3 Sensitivity Analysis

The results presented so far depend on the choice of the reaction coefficients ν^H and ν^F in the policy rules for the share of unemployment benefits. Calibrating these parameters equal to 1 is entirely arbitrary, so I now discuss how the main results change over a range of values for ν^H and ν^F. I maintain the assumption that the responsiveness to a deviation of the unemployment rate from its efficient level is the same in the two regions. To illustrate this analysis, Figures 4.5 and 4.6 show the results for aggregate and idiosyncratic TFP shocks, respectively (the figures for preference and cost-push shocks are in *Appendix* 4.7.5).

First, for aggregate shocks and idiosyncratic cost-push shocks, EUI has a quantitatively substantial impact only on the magnitude of the relative volatility of the unemployment and inflation differentials. When EUI lowers the volatility of the inflation differential, however, the volatility of the unemployment differential rises, so there is an important trade-off along this dimension. The effect of EUI on the regional and aggregate volatilities of unemployment and inflation is close to zero. These results do not change over the range of parameter values for ν^i. Second, for idiosyncratic TFP and preference shocks, EUI reduces substantially the volatilities of the inflation and unemployment differentials as well as the regional and aggregate volatilities across the range of values for ν^i. Nevertheless, some

Figure 4.5: Negative Aggregate TFP Shock: Relative Volatility

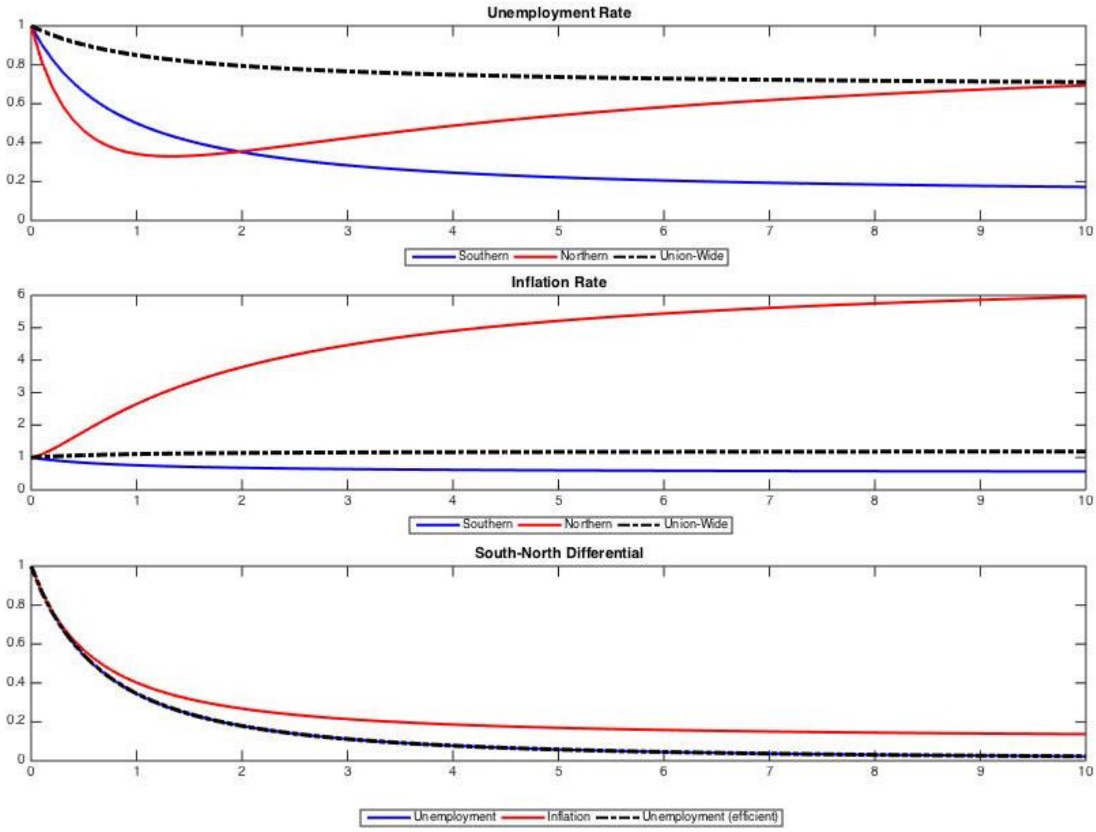


The horizontal axis shows different values for the reaction coefficients ν^H and ν^F. The vertical axis displays the volatility of the variable of interest relative to the baseline model with $\nu^H = \nu^F = 0$.

trade-offs between regional volatilities, or between the volatilities of inflation and of unemployment, persist at all levels of ν^i. Third, the policy displays strong non-linearities. The marginal impact of increasing the reaction parameters on the relative volatility decreases rapidly as the policy reacts more and more to deviations of unemployment. This implies that small fiscal transfers are sufficient to achieve the long-term properties of EUI. Fourth, in some cases the impact of a stronger reaction function on the relative volatility is non-monotonic. For instance, for low positive values of ν^i, the relative volatility of unemployment in the Northern region in response to idiosyncratic shocks is decreasing in ν^i, but for larger values this relative volatility is rising.

This analysis also highlights the following important point. Unemployment benefit schemes financed across a monetary union may help achieve risk-sharing

Figure 4.6: Negative Idiosyncratic TFP Shock to Southern Region: Relative Volatility



The horizontal axis shows different values for the reaction coefficients ν^H *and* ν^F*. The vertical axis displays the volatility of the variable of interest relative to the baseline model with* $\nu^H = \nu^F = 0$.

across the union and reduce the volatility of inflation and unemployment differentials. However, they do not possess full stabilization properties because they operate mainly through income effects. To achieve the constrained efficient allocation, the real interest rate and the real exchange rate must adjust to replicate the flexible-price equilibrium, but fiscal transfers have only second-order effects on these relative prices. Moreover, the existence of unemployment benefits is a source of inefficiency. Thus, EUI could never fully achieve the constrained efficient allocation.

4.6 Conclusion

European unemployment insurance (EUI) has been proposed as a stabilization tool to help the Euro Area adjust to shocks with asymmetric effects as well as a tool to achieve convergence among heterogeneous labor markets. Its proponents argue that EUI can act as a counter-cyclical automatic fiscal transfer smoothing business cycle fluctuations and lowering inflation and unemployment differentials between different regions of the currency union. While the scheme's benefits are mainly macroeconomic in nature, the existing literature has only assessed its stabilization and convergence properties via microeconomic simulations in a partial equilibrium setting. To provide a macroeconomic assessment of EUI, I examine the macroeconomic properties of EUI in a dynamic general equilibrium framework.

More precisely, I calibrate a DSGE model of a two-region monetary union with sticky prices and labor market frictions to the EA12. I develop a baseline specification with independent unemployment insurance schemes, and one with EUI. First, using factor analysis, I identify two country blocks in the Euro Area with similar labor market institutions: a Southern region with generally rigid labor markets, high average unemployment rates, low job-finding rates and low unemployment benefit replacement ratios, and a Northern region with more flexible labor markets.

After calibrating the model to these two areas, I simulate the impact of aggregate and idiosyncratic TFP, preference, and cost-push shocks on the regional and aggregate volatilities of inflation and unemployment, as well as on the volatilities of the inflation and unemployment differentials. I use the relative volatility in the two specifications of the model, with and without EUI, as a metric of the macroeconomic impact of EUI. In particular, I regard the relative regional and aggregate volatilities as measures of the stabilization properties of EUI, and the relative volatilities of the regional differentials as measures of its convergence properties.

First, for aggregate shocks, EUI has only a marginal stabilization effect. This is because the degree of labor market heterogeneity is insufficient for aggregate shocks to create large inflation and unemployment differentials. EUI helps reduce the volatility of the inflation differential, but at the cost of higher volatility of the unemployment differential. Second, in the case of idiosyncratic TFP and preference shocks, EUI may help to significantly reduce unemployment volatility at both the regional and currency union level. Yet, the volatility of inflation might increase in the region that the shock does not hit directly, increasing the overall volatility of inflation in the currency union.

This is because EUI acts like a fiscal transfer that affects the consumption decisions of households through an income effect, but it is unable to achieve the constrained efficient equilibrium. The efficient response to economic disturbances requires changes in relative prices, but EUI influences the real interest rate and the real exchange rate only indirectly and generally not by the level required for the efficient allocation. In particular, the rise of inflation volatility signals that household's consumption allocation remains inefficient due to incomplete substitution effects between goods produced in different regions of the currency union. Third, this policy displays strong non-linearities. Small fiscal transfers are sufficient to achieve the long-term properties of EUI, and the marginal impact on the relative volatility falls rapidly as the size of the fiscal transfer increases.

This analysis could be enriched in several dimensions. First, I present no welfare calculations. In several cases, there are clear trade-offs between inflation and unemployment; nevertheless, without a proper welfare analysis, it is unclear whether EUI would be welfare-improving at the currency union level. This would also entail solving for the optimal responsiveness coefficients in the unemployment benefit rules. Second, I assume shocks to be small enough so that the economy remains in the neighborhood of the steady-state. In these circumstances, EUI has a substantial effect on the aggregate and regional volatilities of inflation and unemployment only for idiosyncratic TFP and preference shocks. For aggregate shocks, the scheme is only relevant in terms of convergence properties. Nonetheless, when large and persistent negative demand shocks move the economy away from the steady-state and monetary policy becomes ineffective due to the zero lower bound constraint, EUI may have relevant stabilization properties also for aggregate shocks. Thus, the analysis can be extended to analyze the stabilization role of EUI at the zero lower bound. Third, the full interaction between monetary policy and EUI could be studied in more detail. For instance, by reducing the volatility of the union-wide inflation rate, EUI helps the monetary authority achieve its inflation objective. Fourth, I assumed a very simple structure for EUI. Several schemes have been proposed, each with different characteristics. The structure of EUI could be modified to assess the stabilization and convergence properties of different variants. For instance, some proposals allow for fiscal transfers only when the unemployment rate surpasses some threshold. Modeling this specific proposal would require solving a non-linear model.

In conclusion, this analysis has shown that the stabilization and convergence properties of EUI are more ambiguous than its proponents contend. These properties are highly dependent on the nature of the shock hitting the economy. Moreover, important general equilibrium effects and the inability of EUI to mimic the constrained efficient allocation generate several trade-offs that policymakers should take into account if designing EUI.

4.7 Appendix

4.7.1 Factor Analysis

Table 4.6: Factors

Factor	*Eigenvalue*	*Difference*	*Proportion (%)*	*Cumulative proportion (%)*
Factor 1	3.610	2.277	51.9	51.9
Factor 2	1.333	0.363	19.2	71.0
Factor 3	0.970	0.420	13.9	85.0
Factor 4	0.650	0.237	9.4	94.3
Factor 5	0.414	0.295	5.9	102.7
Factor 6	0.119	0.151	1.7	102.0
Factor 7	-0.032	0.073	-0.01	101.5
Factor 8	-0.1058		-0.02	100

LR test: independent vs. saturated: $\chi^2 = 64.26^{***}$.

Table 4.7: Factor Loadings and Unique Variances

Variable	*Factor 1*	*Factor 2*	*Factor 3*	*Factor 4*	*Factor 5*	*Factor 6*	*Uniqueness*
Unemployment rate	0.807	-0.295	-0.368	-0.002	-0.196	-0.150	0.065
Change in unemp. (2008-14)	0.784	-0.383	-0.166	0.061	-0.053	0.267	0.132
Youth unemp.	0.973	-0.145	-0.133	0.056	0.083	-0.054	0.001
Long-term unemp.	0.586	0.428	0.070	-0.507	-0.251	-0.033	0.147
Inactivity rate	0.624	0.024	0.486	-0.334	0.305	0.042	0.168
Discouraged workers	0.419	0.568	-0.441	0.130	0.385	-0.026	0.142
EPL (regular)	0.327	0.748	0.112	0.304	-0.248	0.090	0.159
EPL (temporary)	0.617	-0.112	0.585	0.407	-0.006	-0.099	0.089

Table 4.8: Predicted Values

Country	*Predicted value*
Netherlands	-1.21
Austria	-1.19
Germany	-0.92
Ireland	-0.71
Luxembourg	-0.66
Finland	-0.35
France	0.09
Belgium	0.37
Portugal	0.56
Italy	1.09
Spain	1.13
Greece	1.80

4.7.2 Firm's Maximization Problem

The first-order condition to this maximization problem is:

$$E_t\left[\sum_{i=0}^{\infty}\xi^i\Lambda_{t,t+i}y_{t+i|p^*_{H,t}}(j)\left(p^*_{H,t}(j)-\frac{\epsilon}{\epsilon-1}P_{X,t+i}\right)\right]=0 \tag{4.34}$$

Demand can be re-written as:

$$\begin{aligned}
y_{t+i|p^*_{H,t}}(j) &= \left(\frac{p^*_{H,t}(j)}{P_{H,t+i}}\right)^{-\epsilon}\left(c_{H,t+i}(j)+c^*_{H,t+i}(j)\right)= \\
&= \left(\frac{p^*_{H,t}(j)}{P_{H,t+i}}\right)^{-\epsilon}\left[(1-\alpha)+\alpha^*S_{t+i}^{(1-\alpha-\alpha^*)\left(1-\frac{1}{\sigma}\right)}\left(\frac{\Omega_{t+i}}{\Omega^*_{t+i}}\right)^{-\frac{1}{\sigma}}\right]S^{\alpha}_{t+i}C_{t+i}= \\
&= \left(\frac{p^*_{H,t}(j)}{P_{H,t+i}}\right)^{-\epsilon}\varpi_{t+i}S^{\alpha}_{t+i}C_{t+i}
\end{aligned} \tag{4.35}$$

where $\varpi_t \equiv \left[(1-\alpha)+\alpha^*\varepsilon_t^{\left(1-\frac{1}{\sigma}\right)}\left(\frac{\Omega_t}{\Omega^*_t}\right)^{-\frac{1}{\sigma}}\right]$. Substituting (4.35) and the definition of stochastic discount rate into (4.34):

$$E_t\sum_{i=0}^{\infty}(\xi\beta)^i\left(\frac{C_{t+i}}{C_t}\right)^{-\sigma}\frac{\Omega_{t+i}}{\Omega_t}\frac{P_t}{P_{t+i}}\left(\frac{p^*_{H,t}(j)}{P_{H,t+i}}\right)^{-\epsilon}\varpi_tS^{\alpha}_{t+i}C_{t+i}\times \left(p^*_{H,t}(j)-\frac{\epsilon}{\epsilon-1}P_{X,t+i}\right)=0$$

$$E_t\sum_{i=0}^{\infty}(\xi\beta)^iC^{1-\sigma}_{t+i}\Omega_{t+i}\frac{P_{H,t+i}}{P_{t+i}}\left(\frac{p^*_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}\left(\frac{P_{H,t}}{P_{H,t+i}}\right)^{-\epsilon}\varpi_tS^{\alpha}_{t+i}\times \left(\frac{p^*_{H,t}(j)}{P_{H,t+i}}-\frac{\epsilon}{\epsilon-1}\frac{P_{X,t+i}}{P_{H,t+i}}\right)=0$$

$$E_t\sum_{i=0}^{\infty}(\xi\beta)^iC^{1-\sigma}_{t+i}\Omega_{t+i}\Pi^{\epsilon-1}_{H,t+i}\varpi_t\left(\frac{p^*_{H,t}(j)}{P_{H,t}}-\frac{\epsilon}{\epsilon-1}\left(\frac{P_{X,t+i}}{P_{H,t+i}}\right)\Pi_{H,t+i}\right)=0 \tag{4.36}$$

In recursive form this condition may be re-written as:

$$\left(\frac{p^*_{H,t}(j)}{P_{H,t+i}}\right)=\frac{J_t}{H_t} \tag{4.37}$$

where the auxiliary variables J_t and H_t are defined as:

$$H_t \equiv C_t^{1-\sigma}\Omega_t\varpi_t+\xi\beta\Pi^{\epsilon-1}_{H,t+1}H_{t+1} \tag{4.38}$$

$$J_t \equiv \left(\frac{\epsilon-1}{\epsilon}\right)C_t^{1-\sigma}\Omega_t\varpi_t\left(\frac{P_{X,t}}{P_{H,t}}\right)+\xi\beta\Pi^{\epsilon}_{H,t+1}J_{t+1} \tag{4.39}$$

Thus, the dynamics of domestic good inflation are captured by the equation:

$$1=(1-\xi)\left(\frac{J_t}{H_t}\right)^{1-\epsilon}+\xi\Pi^{\epsilon-1}_{H,t} \tag{4.40}$$

Similarly, the corresponding equations for the Foreign region are:

$$\left(\frac{p^*_{F,t}(j)}{P_{F,t+i}}\right) = \frac{J^*_t}{H^*_t} \tag{4.41}$$

$$H^*_t \equiv (C^*_t)^{1-\sigma}\Omega^*_t\varpi^*_t + \xi\beta\Pi^{\epsilon-1}_{F,t+1}H^*_{t+1} \tag{4.42}$$

$$J^*_t \equiv \left(\frac{\epsilon-1}{\epsilon}\right)(C^*_t)^{1-\sigma}\Omega^*_t\varpi^*_t\left(\frac{P^*_{X,t}}{P_{F,t}}\right) + \xi\beta\Pi^{\epsilon}_{F,t+1}J^*_{t+1} \tag{4.43}$$

$$1 = (1-\xi)\left(\frac{J^*_t}{H^*_t}\right)^{1-\epsilon} + \xi\Pi^{\epsilon-1}_{F,t} \tag{4.44}$$

where $\varpi^*_t \equiv \left(\alpha\varepsilon_t^{-\left(1-\frac{1}{\sigma}\right)}\left(\frac{\Omega_t}{\Omega^*_t}\right)^{\frac{1}{\sigma}} + (1-\alpha^*)\right)$. Thus, CPI inflation in the Home and Foreign regions are $\Pi_t = \Pi_{H,t}\Delta S^{\alpha}_t\varsigma_t$ and $\Pi^*_t = \Pi_{F,t}\Delta S^{-\alpha^*}_t\varsigma^*_t$, where ς_t and ς^*_t are cost-push shocks.

4.7.3 Market-Clearing

Aggregate demand $y_t j$ for good j produced in the Home region equals domestic and foreign demands (4.5):

$$\begin{aligned} y_t(j) = C_{H,t}(j) + C^*_{H,t}(j) = \left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}C_{H,t} + \left(\frac{p^*_{H,t}(j)}{P^*_{H,t}}\right)^{-\epsilon}C^*_{H,t} = \\ = \left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}\left(C_{H,t}+C^*_{H,t}\right) = \left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}\left((1-\alpha)\frac{Z_t}{P_{H,t}} + \alpha\frac{Z^*_t}{P^*_{H,t}}\right) \end{aligned} \tag{4.45}$$

Using $Z_t = P_tC_t$ and $Z^*_t = P^*_tC^*_t$, the risk-sharing condition (4.11) and the definition of terms of trade, we can re-write total demand for good j as:

$$y_t(j) = \left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}\varpi_tS^{\alpha}_tC_t \tag{4.46}$$

In equilibrium, aggregate supply (measured in domestic producer prices) net of hiring cost and unemployment benefit transfers equals aggregate demand:

$$Y_t - G^H_th^H_t + NUB_t = \int_0^1 y_t(j)dj = \int_0^1\left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}\varpi_tS^{\alpha}_tC_tdj = Z_t\varpi_tS^{\alpha}_tC_t \tag{4.47}$$

where $Z_t \equiv \int_0^1\left(\frac{p_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon}dj$ is a measure of price dispersion, and $NUB_t \equiv ub_{F,t}S_t - ub^*_{H,t}$ is the unemployment benefit transfer to the Home region measured in

Home producer prices. Similarly, for the Foreign region equilibrium in the goods market requires:

$$Y_t^* - G_t^F h_t^F - \frac{NUB_t}{S_t} = \int_0^1 y_t^*(j)dj = \int_0^1 \left(\frac{p_{F,t}(j)}{P_{F,t}}\right)^{-\epsilon} \varpi_t^* S_t^{-\alpha^*} C_t dj = Z_t \varpi_t^* S_t^{-\alpha^*} C_t \tag{4.48}$$

4.7.4 Constrained Efficient Equilibrium

The social planner maximizes the welfare of the currency subject to the technology and hiring constraints in the economy. Since the two regions are of equal size, welfare is the simple sum of the utility functions in (4.3). Symmetry in individual preferences and technology in the two regions means that the social planner chooses a symmetric allocation across goods produced in the Home and Foreign regions. The social planner's Lagrangean function is:

$$L = E_0 \sum_{t=0}^{\infty} \beta_i \left\{ \Omega_{t+i} \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \chi \frac{(N_t^H)^{1+\phi}}{1+\phi} \right) + \Omega_{t+i}^* \left(\frac{(C_t^*)^{1-\sigma}}{1-\sigma} - \chi * \frac{(N_t^F)^{1+\phi}}{1+\phi} \right) \right\} \tag{4.49}$$

$$-E_0 \left\{ \sum_{i=0}^{\infty} \beta^i \left[\mu_{0,t} \left((1-\delta^H) N_{t-1}^H + h_t^H - N_t^H \right) + \mu_{0,t}^* \left((1-\delta^F) N_{t-1}^F + h_t^F - N_t^F \right) \right] \right\}$$

$$-E_0 \left\{ \sum_{t=0}^{\infty} \beta^i \left[\mu_{1,t} \left(C_{H,t} + C_{H,t}^* + A_t^H B^H (\theta_t^H)^{\varphi^H} h_t^H - A_t^H N_t^H) \right) \right] \right\} +$$

$$- E_0 \left\{ \sum_{t=0}^{\infty} \beta^i \left[\mu_{1,t}^* \left(C_{F,t} + C_{F,t}^* + A_t^F B^F (\theta_t^F)^{\varphi^F} h_t^F - A_t^F N_t^F \right) \right] \right\} +$$

$$-E_0 \left\{ \sum_{t=0}^{\infty} \beta^i \left[\mu_{2,t} \left(C_t - \frac{(C_{H,t})^{1-\alpha} (C_{F,t})^{\alpha}}{(1-\alpha)^{1-\alpha} \alpha^{\alpha}} \right) + \mu_{2,t}^* \left(C_t^* - \frac{\left(C_{F,t}^*\right)^{1-\alpha^*} \left(C_{H,t}^*\right)^{\alpha^*}}{(1-\alpha^*)^{1-\alpha^*} \alpha^{\alpha^*}} \right) \right] \right\} +$$

$$-E_0 \left\{ \sum_{t=0}^{\infty} \beta^i \left[\mu_{3,t} \left(\frac{h_t^H}{1-(1-\delta^H) N_{t-1}^H} - \theta_t^H \right) + \mu_{3,t}^* \left(\frac{h_t^F}{1-(1-\delta^F) N_{t-1}^F} - \theta_t^F \right) \right] \right\}$$

The first-order conditions with respect to $C_t, C_t^*, C_{H,t}, C_{H,t}^*, C_{F,t}$, and $C_{F,t}^*$ are:

$$\mu_{2,t} = \Omega_t C_t^{-\sigma} \tag{4.50}$$

$$\mu_{2,t}^* = \Omega_t^* (C_t^*)^{-\sigma} \tag{4.51}$$

$$\mu_{1,t} = \mu_{2,t} \frac{(1-\alpha)C_t}{C_{H,t}} \tag{4.52}$$

$$\mu_{1,t} = \mu_{2,t}^* \frac{\alpha^* C_t^*}{C_{H,t}^*} \tag{4.53}$$

$$\mu_{1,t}^* = \mu_{2,t} \frac{\alpha C_t}{C_{F,t}} \tag{4.54}$$

$$\mu_{1,t}^* = \mu_{2,t}^* \frac{(1-\alpha^*)C_t^*}{C_{F,t}^*} \tag{4.55}$$

$$\tag{4.56}$$

Combining (4.50), (4.51), (4.52), and (4.53) yields:

$$\frac{1-\alpha}{\alpha^*} = \frac{\Omega_t^*}{\Omega_t} \left(\frac{C_t^*}{C_t} \right)^{1-\sigma} \frac{C_{H,t}}{C_{H,t}^*} \tag{4.57}$$

while combining (4.50), (4.51), (4.54), and (4.55) yields:

$$\frac{1-\alpha^*}{\alpha} = \frac{\Omega_t}{\Omega_t^*} \left(\frac{C_t}{C_t^*} \right)^{1-\sigma} \frac{C_{F,t}^*}{C_{F,t}} \tag{4.58}$$

Alternatively, the optimal consumption allocation can be expressed as:

$$\frac{\mu_{1,t}^*}{\mu_{1,t}} = \frac{\alpha}{1-\alpha} \frac{C_{H,t}}{C_{F,t}} = \frac{1-\alpha^*}{\alpha^*} \frac{C_{H,t}^*}{C_{F,t}^*} \tag{4.59}$$

Moreover, equations (4.50) and (4.52), together with the optimal demand function $C_{H,t} = (1-\alpha)Z_t/P_{H,t}$ shows that the marginal value of hiring $\mu_{1,t}$ equals $\Omega_t C_t^{-\sigma} S_t^{-\alpha}$. Similarly, the marginal value of the of hiring in the Foreign region is $\mu_{1,t}^* = \Omega_t^* (C_t^*)^{-\sigma} S_t^{\alpha^*}$. The first-order conditions with respect to $N_t^H, h_t^H, \theta_t^H, N_t^F, h_t^F$, and θ_t^F

are:

$$\chi(N_t^H)^{\varphi}\Omega_t \leq \mu_{1,t}A_t^H + \mu_{0,t} - \beta(1-\delta^H)E_0\left[\mu_{0,t+1} + \mu_{3,t+1}\frac{\theta_{t+1}^H}{U_{t+1}^H}\right] \tag{4.60}$$

$$\mu_{0,t} = -\mu_{1,t}A_t^H B^H(\theta_t^H)^{\varphi^H} - \frac{\mu_{3,t}}{U_t^H} \tag{4.61}$$

$$\mu_{3,t} = \mu_{1,t}\varphi^H A_t^H B^H(\theta_t^H)^{\varphi^H} U_t^H \tag{4.62}$$

$$\chi(N_t^F)^{\varphi}\Omega_t^* \leq \mu_{1,t}^* A_t^F + \mu_{00}^* - \beta(1-\delta^F)E_0\left[\mu_{0,t+1}^* + \mu_{3,t+1}^*\frac{\theta_{t+1}^F}{U_t^F}\right] \tag{4.63}$$

$$\mu_{0,t}^* = -\mu_{1,t}^* A_t^F B^F(\theta_t^F)^{\varphi^F} - \frac{\mu_{30}^*}{U_{t+1}^F} \tag{4.64}$$

$$\mu_{3,t}^* = \mu_{1,t}^*\varphi^F A_t^F B^F(\theta_t^F)^{\varphi^F} U_t^F \tag{4.65}$$

Combining conditions (4.60), (4.61), and (4.62), I obtain the optimality condition for the constrained efficient allocation:

$$\frac{\chi(N_t^H)^{\phi}C_t^{\sigma}S_t^{\alpha}}{A_t} \leq 1 - (1+\varphi^H)B^H(\theta_t^H)^{\varphi^H} +$$
$$+(1-\delta_t^H)E_t\left\{\beta_{t,t+1}\frac{A_{t+1}^H}{A_t^H}B^H\left[(\theta_{t+1}^H)^{\varphi^H} + \varphi^H(\theta_{t+1}^H)^{\varphi^H}\left(1-\theta_{t+1}^H\right)\right]\right\} \tag{4.66}$$

with a strict equality with $N_t^H < 1$. From the decentralized equilibrium, setting the degree of real wage rigidity γ_w in (4.18) equal to one, and combining the labor demand equation (4.17) with the Nash wage equation (4.22) yields the equilibrium equation for labor in the Home region:

$$\frac{\chi(N_t^H)^{\phi}C_t^{\sigma}S_t^{\alpha}}{(1-b^H)A_t} = \frac{P_{X,t}}{P_{M,t}} - \left(1+\frac{\gamma}{1-b}\right)B^H(\theta_t^H)^{\varphi^H} +$$
$$+(1-\delta^H)E_t\left\{\beta_{t,t+1}\frac{A_{t+1}^H}{A_t^H}B^H\left[(\theta_{t+1}^H)^{\varphi^H} + \frac{\gamma}{1-b^H}(\theta_{t+1}^H)^{\varphi^H}\left(1-\theta_{t+1}^H\right)\right]\right\} \tag{4.67}$$

Analogously for the Foreign region, combining (4.63), (4.64), and (4.65), I obtain the optimality condition for the constrained efficient allocation:

$$\frac{\chi(N_t^F)^{\phi}(C_t^*)^{\sigma}S_t^{-\alpha^*}}{A_t^*} \leq 1 - (1+\varphi^F)B^F(\theta_t^F)^{\varphi^F} +$$
$$+(1-\delta_t^F)E_t\left\{\beta_{t,t+1}^*\frac{A_{t+1}^F}{A_t^F}B^F\left[(\theta_{t+1}^F)^{\varphi^F} + \varphi^F(\theta_{t+1}^F)^{\varphi^F}\left(1-\theta_{t+1}^F\right)\right]\right\} \tag{4.68}$$

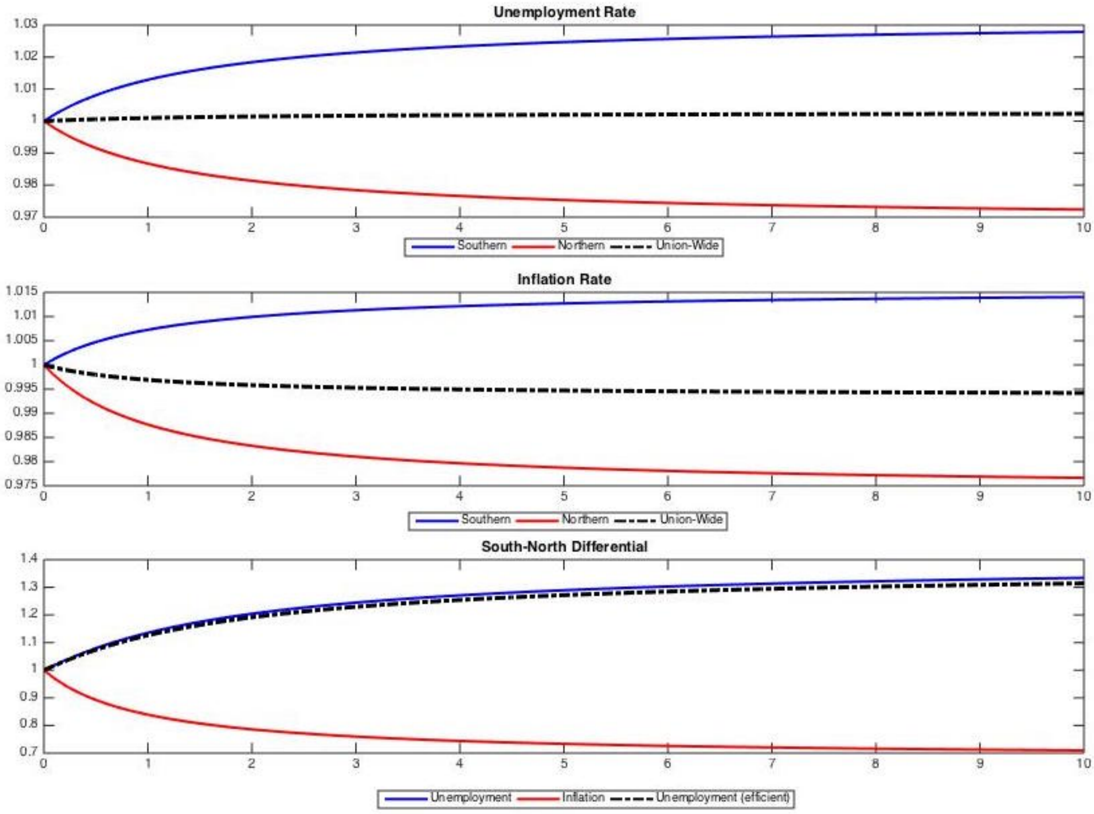
with a strict equality with $N_t^F < 1$. From the decentralized equilbrium, setting $\gamma_w^* = 1$ and combining (4.23) with (4.24) yields the equilibrium equation for labor in the Foreign region:

$$\frac{\chi(N_t^F)^{\phi}(C_t^*)^{\sigma}S_t^{-\alpha^*}}{(1-b^*)A_t^F} = \frac{P_{X,t}^*}{P_{M,t}^*} - \left(1+\frac{\gamma}{1-b^F}\right)B^F(\theta_t^F)^{\varphi^F} +$$
$$+(1-\delta^F)E_t\left\{\beta_{t,t+1}^*\frac{A_{t+1}^F}{A_t^F}B^F\left[(\theta_{t+1}^F)^{\varphi^F}+\frac{\gamma}{1-b^F}(\theta_{t+1}^F)^{\varphi^F}\left(1-\theta_{t+1}^F\right)\right]\right\} \qquad (4.69)$$

Comparing (4.66) with (4.67) and (4.69) with (4.24) shows that the decentralized equilibrium is constrained efficient when, in both regions of the currency union, the replacement ratio b^i is set to zero, the barganing power of the worker γ equals the elasticity of the hiring cost function φ^H, and a production subsidy eliminates the price-markup that final producers charge over the intermediate good price such that $\left(\frac{P_{X,t}}{P_{M,t}}\right)$ equals one.

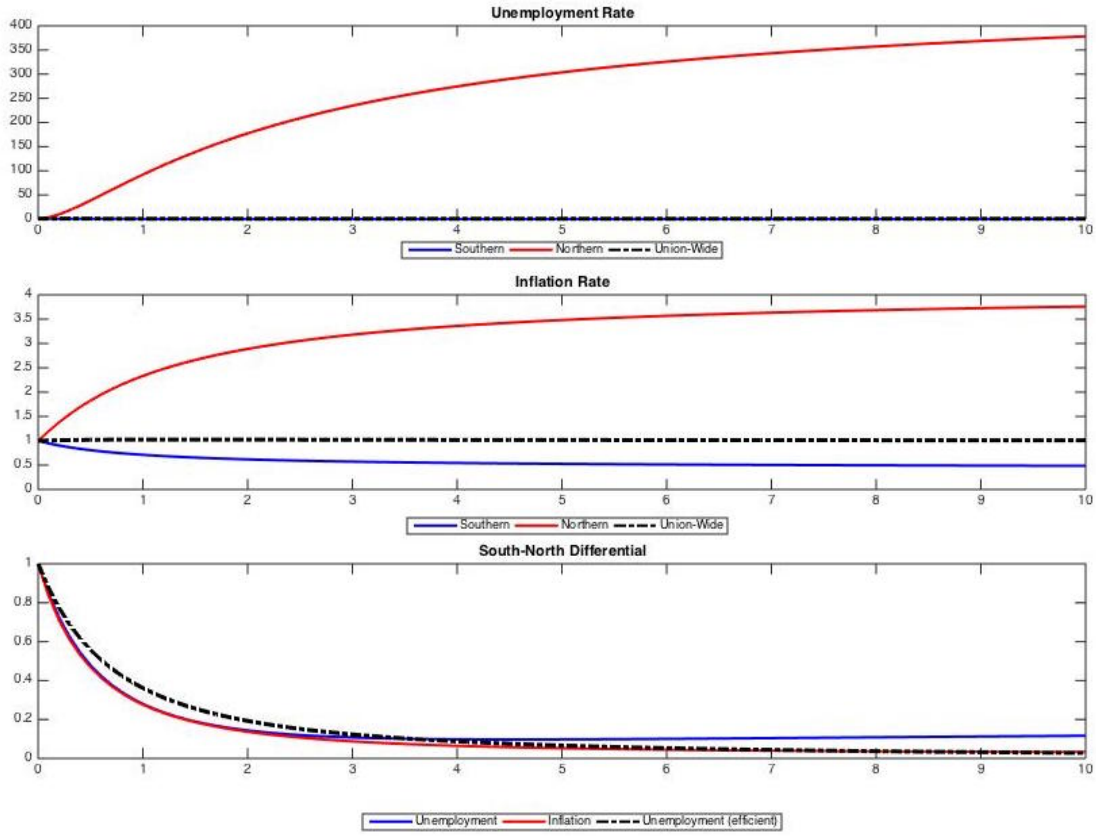
4.7.5 Sensitivity Analysis

Figure 4.7: Negative Aggregate Preference Shock: Relative Volatility



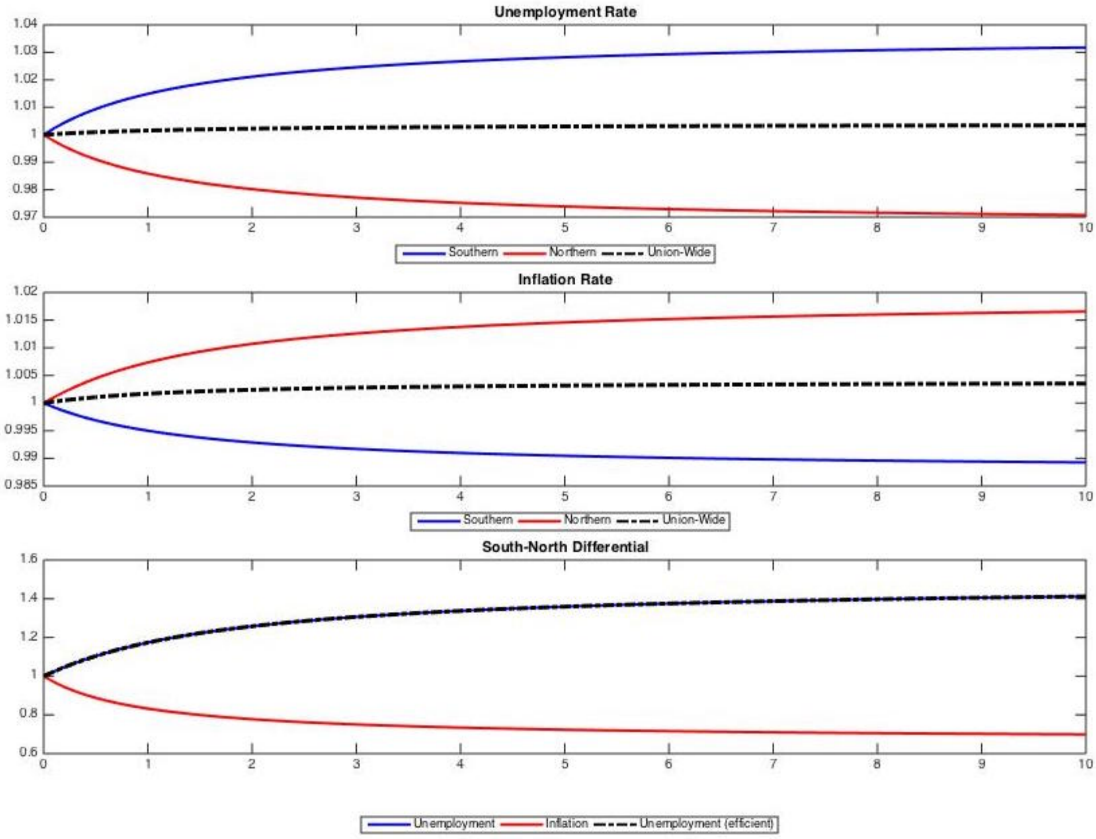
The horizontal axis shows different values for the reaction coefficients ν^H and ν^F. The vertical axis displays the volatility of the variable of interest relative to the baseline model with $\nu^H = \nu^F = 0$.

Figure 4.8: Negative Idiosyncratic Preference Shock to Southern Region: Relative Volatility



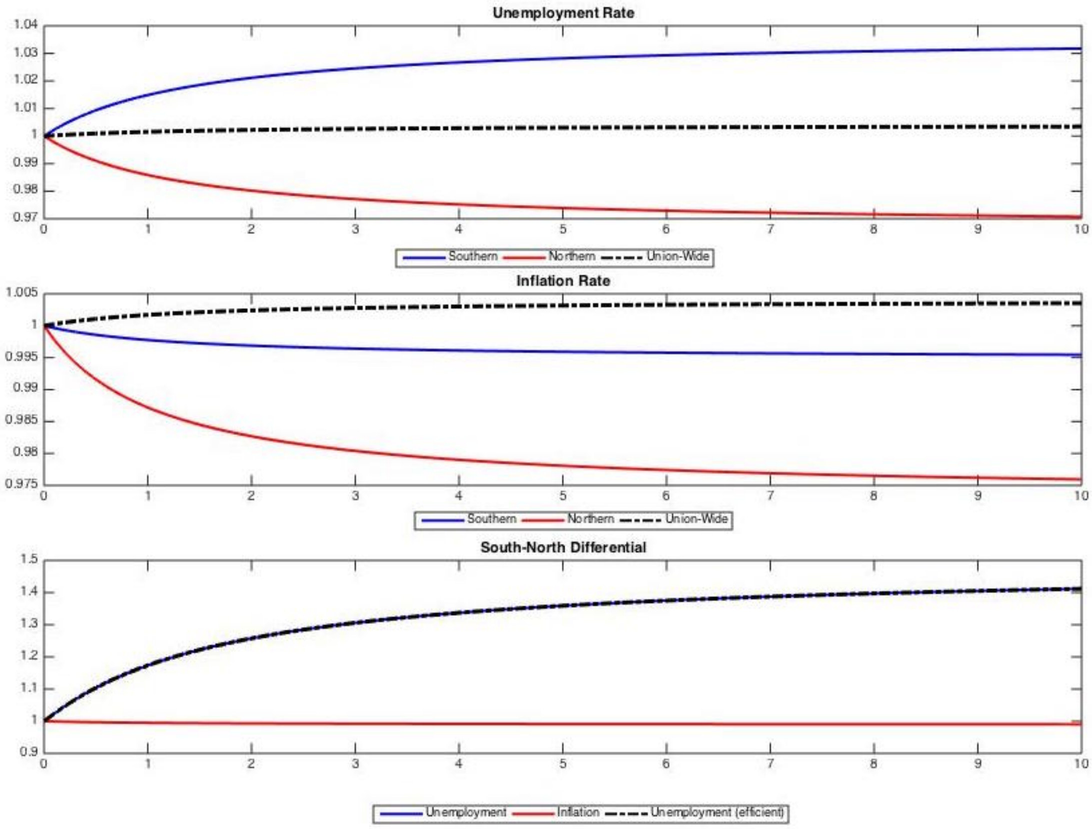
The horizontal axis shows different values for the reaction coefficients ν^H and ν^F. The vertical axis displays the volatility of the variable of interest relative to the baseline model with $\nu^H = \nu^F = 0$.

Figure 4.9: Negative Aggregate Cost-Push Shock: Relative Volatility



The horizontal axis shows different values for the reaction coefficients ν^H and ν^F. The vertical axis displays the volatility of the variable of interest relative to the baseline model with $\nu^H = \nu^F = 0$.

Figure 4.10: Negative Idiosyncratic Cost-Push Shock to Southern Region: Relative Volatility



The horizontal axis shows different values for the reaction coefficients ν^H and ν^F. The vertical axis displays the volatility of the variable of interest relative to the baseline model with $\nu^H = \nu^F = 0$.

5 | Conclusion

This thesis sheds light on the functioning of labor markets in advanced economies. First, I study the transmission mechanism of bank lending shocks to the labor market and quantify the contribution of these shocks for explaining labor market fluctuations in the US and the UK. Then, I evaluate the merits of European Unemployment Insurance, a policy that has been put forward to help the Euro Area adjust to economic shocks. From a macroeconomic perspective, both topics are relevant to improving our understanding of how labor markets work and how to respond to economics shocks.

In Chapter 2 I build and estimate a New Keynesian DSGE model that describes the role that the banking sector plays in determining labor market outcomes. Bankers provide loans to firms that are used to finance vacancy-posting and job-creation. When a negative aggregate shock directly or indirectly deteriorates the balance sheet of financial intermediaries, compromising their ability to raise funds and provide lending, firms experience a credit crunch and reduce job-creation. This increases the unemployment rate and generates a recession. I estimate the model using US data and show that the full model with a banking sector explains the time-series properties of the joint distribution of key labor market variables better than a restricted model with no financial frictions. In fact, the banking sector is a quantitatively important source of business cycle fluctuations, and the status of financial intermediaries has substantial implications for the behavior of labor market variables. Credit supply frictions also amplify the impact of aggregate shocks. Furthermore, I find that the model has a strong internal propagation mechanism. An exogenous reduction in the net worth of financial intermediaries has long-lasting effects on the labor market because it takes time for banks to rebuild their own net worth and deleverage.

In Chapter 3 I estimate a SVAR model of the US and UK economies to provide further evidence on the nature of the transmission mechanism of bank lending shocks to the labor market. I use a mix of sign and short-run exclusion restrictions to identify credit supply and other aggregate shocks. Consistent with the theoretical DSGE model, I find that a contractionary loan supply shock reduces job-creation and increases job-destruction, leading to a persistently higher unemployment rate and lower wages. For both the US and the UK, I find that bank lending shocks are, among the structural shocks that I identify, the most important drivers of labor market fluctuations. In particular, loan supply shocks explain the mid-1990s expansion and the severe contraction occurring during the financial crisis. For instance, they account for over a quarter of the deviation of the US unemployment rate from its baseline projection between 2008 and 2009. Quantitatively, credit supply shocks are relatively more important in the UK than the US, most likely reflecting the higher reliance of UK firms on bank lending as a source of finance.

In Chapter 4 I shift the focus of my analysis to the Euro Area and quantify the macroeconomic convergence and stabilization properties of European Unemployment Insurance. This is the first general equilibrium assessment of EUI. I divide the Euro Area into two regions: a Northern region with a flexible labor market and a generous unemployment insurance, and a Southern region with a more rigid labor market and less generous benefits. Then, I calibrate a two-region currency union DSGE model and simulate the impact of several aggregate and idiosyncratic shocks on the relative volatilities of inflation and unemployment, and the volatilities of the inflation and unemployment differentials. In case of idiosyncratic TFP and preference shocks, EUI has the greatest impact, and it can achieve some of its stabilization and convergence objectives. However, since it works through income effects rather than relative prices, it cannot reach the constrained efficient allocation. Thus, there exist several trade-offs between inflation and unemployment volatilities, and between regional and aggregate volatilities.

In conclusion, this thesis contributes to the debate about the impact of the banking sector on the labor market. It shows empirically that credit supply shocks have very persistent effects on the labor market. It also offers an explanation for why, several years after the financial crisis, unemployment remains above its pre-crisis level and labor markets are still disrupted. The net worth of the banking sector plays a crucial role for the allocation of credit and the determination of labor market outcomes. Restoring the balance sheet of financial intermediaries to a healthy level after a severe shock is a slow process. This generates a high degree of persistence which is transmitted to the labor market. Finally, this thesis provides a first quantitative evaluation of European Unemployment Insurance. The main message of this analysis is that automatic fiscal transfers within a currency union with heterogeneous labor markets cannot simultaneously stabilize aggregate and regional economies. Taken together, these findings move forward our theoretical and empirical understanding of how labor markets in advanced economies operate.

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