European University Institute

DEPARTMENT OF ECONOMICS

Essays in Macroeconomics: Fiscal Policy, Hiring Frictions, Uncertainty, and Risk Sharing

Anna Rogantini Picco

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

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European University Institute
Department of Economics

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Statement of inclusion of previous work (if applicable):

I confirm that chapter 2 was jointly co-authored with Joonseok Oh and I contributed 50% of the work. The chapter was published in the EUI Cadmus Working Paper Series in September 2019.

I confirm that chapter 3 was jointly co-authored with Alessandro Ferrari and I contributed 50% of the work. The chapter was published as ESM Working Paper Series 17/2016 and as ADEMU Working Paper Series 2017/055.

Signature and Date:

Anna Rogantini Picco

October 28, 2019

Abstract

The three chapters of this thesis are inspired by some aspects of the complex world where we live in.

The first chapter uncovers the role of firms' hiring decisions as a key source of state dependence in the fiscal spending multiplier. When the hiring rate is high, a larger share of workers has to be relocated from production to recruitment and training of the new hires. This diversion of resources lowers firms' productivity and reduces the effect of government spending stimulus on output. I establish this result using local projections and I illustrate this mechanism building a non-linear dynamic general equilibrium model.

The second chapter, joint with Joonseok Oh, shows how uninsurable unemployment risk is crucial to qualitatively and quantitatively match macro responses to uncertainty shocks. Empirically, uncertainty shocks i) generate deflationary pressure; ii) have considerably negative consequences on economic activity; iii) produce a drop in aggregate consumption, which is mainly driven by the response of the households in the bottom 60% of the income distribution. Standard representative-agent New Keynesian models have difficulty to deliver these effects. A heterogeneous-agent framework with search and matching frictions and Calvo pricing allows us to jointly attain these results. Uncertainty shocks induce households' precautionary saving and firms' precautionary pricing behaviors, triggering a fall in aggregate demand and supply. These precautionary behaviors increase the unemployment risk of the imperfectly insured households, who strengthen precautionary saving. When the feedback loop between unemployment risk and precautionary saving is strong enough, a rise in uncertainty leads to i) a drop in inflation; ii) amplified negative responses of macro variables; iii) heterogeneous consumption responses of households, which are consistent with the empirical evidence.

The third chapter, joint with Alessandro Ferrari, empirically evaluates whether adopting a common currency has changed the ability of euro area member states to share risk. We

construct a counterfactual dataset of macroeconomic variables through the synthetic control method. We then use the output variance decomposition of Asdrubali, Sorensen and Yosha (1996) on both the actual and the synthetic data to study if there has been a change in risk sharing and through which channels. We find that the euro has reduced consumption smoothing. We further show that this reduction is mainly driven by the periphery countries of the euro area who have experienced a decrease in risk sharing through private credit.

Acknowledgements

I consider this thesis as the end of a wonderful journey and, as importantly, the beginning of a new phase of exciting research and life adventures.

Accomplishing this result has only been possible thanks to the continuous support of my advisors, Evi Pappa and Leonardo Melosi. Evi, who has known me since my very first interview at the EUI, who has warmly made me part of the Pappa family, and who has constantly encouraged and fostered my curiosity, while still keeping me on the right path. Leonardo, who despite having met me at a later stage of my PhD, has been invaluable in shaping my economic thinking and giving me a sense of security and clear view amid the multiple obstacles of research.

I am also deeply indebted to Juan Dolado, whose door has always been open for both intellectual and emotional support, and Joonseok Oh, who has substantially contributed to my improvement as a researcher and as a person.

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Last, but not least, I want to thank Matteo, who has always been by my side along this journey, agile like a feline, sharp like a lynx, and resilient like an oak.

I am well aware of the incredible luck that I have in being surrounded by such people in my daily life. Thus, as my grandmother would tell me: be positive, think deeply, travel the world.

Contents

List of Tables

List of Figures

1 Fiscal Multipliers: a Tale from the Labor Market

Abstract

This chapter uncovers the role of firms' hiring decisions as a key source of state dependence in the fiscal spending multiplier. When the hiring rate is high, a larger share of workers has to be relocated from production to recruitment and training of the new hires. This diversion of resources lowers firms' productivity and reduces the effect of government spending stimulus on output. I establish this result using local projections and I illustrate this mechanism building a non-linear dynamic general equilibrium model.

1.1 Introduction

A key question in macroeconomics is to understand whether and to what extent government spending stimulates the economy. While earlier studies have investigated this issue independently from the state of the economy, the more recent literature started to explore whether the effect of fiscal spending depends on the phase of the business cycle. The underlying intuition rests upon the argument that a fiscal expansion carried out in slack times is less likely to crowd out private consumption and investment and hence stimulates output more.

In the ongoing debate on whether fiscal policy transmission depends on the state of the economy, empirical studies have relied on the labor market condition to identify different phases of the business cycle. The literature proposes multiple summary statistics to measure the state of the labor market. Some are related to the aggregate labor market. The most usual ones are tightness, defined as the ratio between posted vacancies and unemployment, and the unemployment rate. The aggregate labor market affects the transmission of fiscal stimulus due to a labor supply constraint. When tightness is high, firms find it hard to hire workers to fill their vacancies. As fiscal expansions increase tightness, fiscal stimulus that is implemented when tightness is high has a smaller effect on the real activity. Along with these measures of aggregate labor market, the macro labor literature has proposed the hiring rate as a firm-specific measure that captures fluctuations in the labor market (see Merz and Yashiv, 2007). This variable, which is the ratio between new hires and total employees, refers to the hiring decisions internal to firms. Fiscal policy transmission depends on the hiring rate because of a labor demand constraint. Hiring is a costly activity for firms, which have to temporarily relocate some of their employees from production to recruiting and training the new hires. This diversion of resources within firms reduces their ability to produce. As a result, fiscal stimulus that is implemented when firms' hiring rate is high has a lower effect on the real activity.

I contribute to the discussion on how fiscal policy depends on the slack of the economy by showing that the transmission of government spending stimuli is affected by the hiring rate of firms, but not by the aggregate labor market conditions. I empirically test which measures of the labor market affect the transmission of fiscal spending shocks. I use local projections to compute state and sign dependent impulse responses to the fiscal spending shocks. When using aggregate measures of labor market slack, I do not find any significant dependence. By contrast, I do find a stark dependence associated with the hiring rate of firms. I show that expansionary fiscal policy depends on whether the hiring rate is high or low and that fiscal spending stimuli are less effective when the hiring rate is higher. I compute the cumulative multiplier for a fiscal spending expansion over a five-year horizon to be as big as 3.5 when the hiring rate is below trend, and not significantly different from zero when the hiring rate is above trend.

The empirical results that the transmission of government spending stimuli is affected by the hiring rate of firms, but not by the aggregate labor market conditions, have implications for the dynamics of the fiscal multiplier over the business cycle. Figure 1.1 displays the hiring rate and tightness along with NBER recessions.[1]

[1]Both series show a downward sloping trend. Empirical micro literature explores potential reasons for this decline - see e.g. Davis and Haltiwanger (2014). Despite the trend, the cyclical behaviour of the two series is regular. This paper focuses on cyclical fluctuations around the trend.

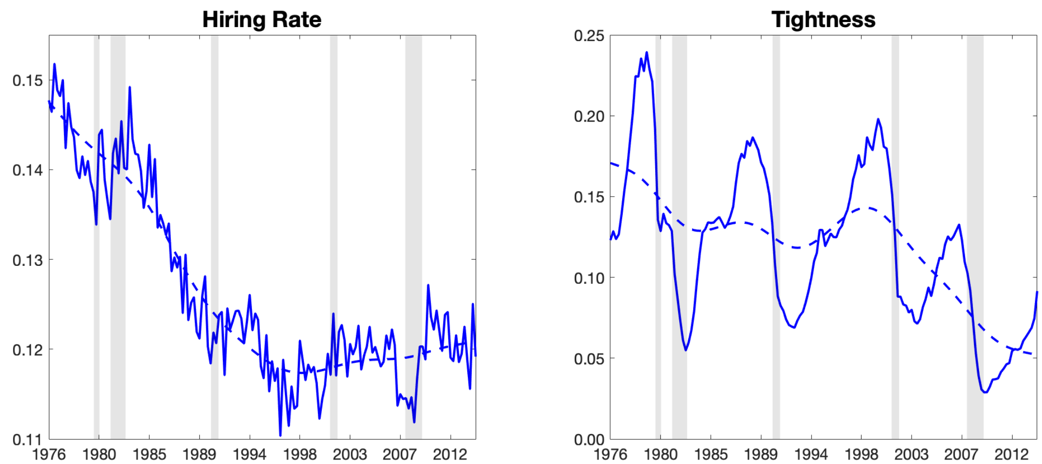


Figure 1.1 – **Measures of labor market slack**

Note: The hiring rate is taken from the Current Population Survey and is defined as the ratio between the number of newly hired employees from unemployment or non-employment and the total number of employees. Tightness is defined as vacancies over unemployed. Vacancies are proxied by the help wanted index of Barnichon (2010). The dashed lines are trends obtained by running a Hodrick-Prescott filter with smoothing parameter 10000. Grey bars indicate NBER recessions.

Recessions are periods in which tightness moves from its peak to its trough. To the contrary, due to anticipatory effects, firms start hiring well before recessions are over. Hence, the hiring rate moves from low to high values over a recessionary period. As I found expansionary spending multipliers to be lower when the hiring rate is higher, this indicates that the end of a recession is not a good time to do fiscal stimulus. A better time would be towards the end of an expansion when the hiring rate is below trend and the multiplier is higher. This implication for the timing of fiscal expansions is different from the conventional idea that fiscal policy is more effective during recessions.

To shed light on the mechanism driving the reduced-form evidence, I build a general equilibrium model with hiring frictions in the labor market and exogenous government expenditure. The dependence of fiscal policy on firms' hiring rate originates from firms' hiring costs being modelled as a function of the hiring rate. This formulation is supported by micro evidence from the literature showing that the biggest component of the hiring cost is not related to vacancy posting, but to training.[2] This assumption

[2]See Manning (2011) for a review of the empirical evidence on hiring costs, and Silva and Toledo (2009) and Faccini and Yashiv (2019) for micro estimates. The functional form is structurally estimated by Yashiv (2000), Merz and Yashiv (2007), and Christiano et al. (2011) and used by Gertler et al. (2008a), Gertler and Trigari (2009).

further translates into modelling hiring costs as forgone output, which is also supported by micro estimates.[3]

Diversion of resources from production to training generates a tradeoff between current and future production. When the value of production is low, it is a good time to hire: diverting employees from production to training is relatively less expensive. On the other hand, when the value of production is high, it is not a good time to hire: the tradeoff between current and future production becomes starker. In short, fluctuations in the value of production generate variations in the marginal cost of hiring. Fiscal stimulus that is implemented when the hiring rate is high, induces firms to expand hiring when it is more costly, as it makes the tradeoff between current and future production more severe. This costly diversion of internal resources temporarily reduces the production efficiency of firms. As a result, a fiscal expansion is less stimulative.

Solving the model non-linearly allows me to study the propagation of fiscal shocks across different levels of the hiring rate. I show that when a fiscal expansion is simulated from a state when the hiring rate is high, it generates a wider increase in the value of production. As hiring costs are denominated in terms of the value of production, it becomes more costly for firms to hire. Hence, firms choose to raise hiring by less, which in turn produces a smaller increase in output. These theoretical responses mirror the empirical responses estimated with local projections, showing that my modelling framework is able to generate the asymmetries found in the reduced form evidence.

To check what happens when the state of the labor market is captured by an aggregate measure, I extend the hiring cost function to allow for vacancy posting costs. Following Sala et al. (2013), I assume that the hiring cost is not only a function of the hiring rate, which is a firm-specific object, but also of the vacancy filling rate, which instead reflects the aggregate labor market conditions. This specification reintroduces the more traditional component of vacancy posting costs. With this extended hiring cost function, which allows for both vacancy posting and training costs, I repeat the exercise carried out before to study the propagation of fiscal expansions. However, I now identify the state of the labor market by looking at the level of labor market tightness instead of the hiring rate. I show that allowing for vacancy posting costs results in a much smaller state dependence in the transmission of fiscal expansions. This

[3]See Bartel et al. (2014), Cooper et al. (2015), and Faccini and Yashiv (2019) for micro evidence on the disruption caused by hiring.

is in line with my reduced form evidence, which found no dependence of fiscal policy transmission on the aggregate state of the labor market.

This paper is related to three main streams of literature. First, it is connected to the expanding reduced form literature on state dependent fiscal multipliers. There is an unsettled debate on whether the efficacy of fiscal policy varies across different phases of the business cycle. Barro and Redlick (2011) produce estimates that are not precise enough to conclusively establish whether multipliers have cyclical variation. Owyang et al. (2013) find mixed evidence on the state dependence of fiscal multipliers. They show that multipliers are higher in periods of slack for Canada, but not for the US. Auerbach and Gorodnichenko (2012, 2013) argue that fiscal policy is more effective during recessionary periods. Fazzari et al. (2015)'s empirical findings also support state dependent effects of fiscal policy. Using military spending news, Ramey and Zubairy (2018) contend that this is not the case. Barnichon and Matthes (2019) try to reconcile the two views by arguing that the difference of results lies in the sign dependence of the fiscal shocks and that a contractionary shock generates a multiplier which is much higher than an expansionary shock. Caggiano et al. (2015) show that while the effectiveness of fiscal stimuli does not vary across different phases of the business cycles, it does differ when these phases are extreme in their intensity. Riera-Crichton et al. (2015) analyse state and sign dependent fiscal policy across recessions and expansions and show that multipliers are asymmetric depending on both the sign of the fiscal shock and the state of the business cycle.[4] Often in these studies, the phase of the business cycle is identified with the amount of aggregate slack in the economy. My paper contributes to this stream of the literature by showing that the empirically relevant variable affecting the transmission of fiscal policy is not closely related to the business cycle. In particular, I show that there is no dependence directly deriving from the state of the business cycle or the conditions of the aggregate labor market, which are often used as proxies for the state of the business cycle. Rather, my analysis shows that what affects the transmission of fiscal stimuli is the tradeoff in production that hiring generates.

[4]Other papers focus on different types of state dependence. Examples are Navarro and Ferriere (2018), who study tax regime state dependence, Ilzetzki et al. (2013), who look at different country characteristics, and Roulleau-Pasdeloup (2016) and Ramey and Zubairy (2018) who analyse the effects of government spending at the zero lower bound.

This paper is also related to the growing literature that examines the non-linear effects of fiscal policy using structural models. Various papers study the effects of fiscal expansions over the business cycle, and provide theories for when fiscal policy is more effective. Brinca et al. (2019) show that the fiscal multiplier of government purchases is increasing in the size of the spending shock and argue that this empirical fact can be explained by the response of labor supply across the wealth distribution in a heterogeneous agent model. Hagedorn et al. (2019) carry out a thorough quantitative exercise aiming at gauging the fiscal multiplier in a heterogenous agent context encompassing nominal rigidities. Faria-e Castro (2018) focusses on the US fiscal policy response during the Great Recession, highlighting different channels of transmission of fiscal stimulus in a recessionary period. Sims and Wolff (2018a,b) study the state dependent effects of respectively tax shocks and government spending shocks by showing that fiscal shocks vary across different phases of the business cycle, but the mechanism for why this happens is not fully explored. Canzoneri et al. (2016) propose a model that features costly financial intermediation and countercyclical financial frictions and is able to generate state dependent fiscal multipliers across the business cycle. In this paper, I focus my analysis on the transmission of expansionary fiscal policy depending on the conditions of the labor market. These do not exactly overlap with the states of the business cycle, as often during recessions unemployment goes from its lowest to its highest level. More specifically, I provide a mechanism explaining why the level of the hiring rate is an important factor affecting the transmission of fiscal stimulus. To my knowledge, this is the first paper that uncovers hiring decisions as a source of state dependence in the transmission of fiscal policy. Another paper that studies how labor market tightness affects the transmission of fiscal policy is Michaillat (2014). He studies the interaction between the size of the public sector and the labor market. In his case, an increase in the size of the public sector lowers the number of unemployed people in the labor market, for a given labor force participation. This decrease in unemployment increases labor market tightness for private firms, which have more difficulty to fill their vacancies. This public sector channel could be an alternative channel through which fiscal stimuli and labor market interact. I show that, in the data, I do not find state dependence of fiscal expansions related to aggregate labor market tightness. This evidence points towards my hiring rate friction being the empirically relevant congestion affecting fiscal policy transmission. Another paper studying the interaction between fiscal policy and labor markets is Gomes (2015). He focuses on how public wages should be determined optimally to achieve an efficient allocation of jobs between the private and the public sector. Differently from it, my paper focuses on the effect that government purchases have on the rest of the economy considering hiring frictions in the private sector. Further, Cacciatore et al. (2019) study how employment protection legislation affects the size of fiscal multipliers. While they analyse labor market frictions in the form of firing costs, my main focus is on hiring costs. Our results are consistent with each other and indicate that labor frictions internal to firms lower the size of multipliers.

The third stream of the literature this paper is related to is the one modelling hiring frictions. The standard Diamond-Mortensen-Pissarides (DMP) framework models hiring frictions as a function of the vacancy posting cost denominated in pecuniary terms. Micro evidence shows that the biggest share of the hiring costs borne by firms is related to the effort of bringing the productivity of the new hires to the level of the already experienced employees – see for example Silva and Toledo (2009), Manning (2011), Cooper et al. (2015) and Faccini and Yashiv (2019). These costs are mainly related to training and are a function of the new hires as a share of the existing employees. They are firm-specific and are denominated in terms of foregone output. I contribute to this line of studies by analysing how various types of hiring frictions affect the propagation of fiscal shocks differently. In particular, I show that the hiring frictions generating state dependence in the transmission of fiscal policy are those related to training costs. By constrast, hiring frictions associated to vacancy posting costs are less prominent in affecting the transmission of fiscal spending stimuli.

This paper is organised as follows. Section 1.2 shows the reduced form evidence on expansionary fiscal shocks. Section 1.3 discusses the modelling assumptions of hiring frictions. Section 1.4 describes the model and the theoretical results. Section 1.5 analyses asymmetries in the impulse responses. Section 1.6 studies an extension of the hiring cost function. Section 1.7 concludes.

1.2 Reduced Form Evidence

In this section I estimate fiscal multipliers that are dependent on the state of the labor market and the sign of the fiscal shock. I begin by discussing identification and how I define the labor market.

1.2.1 Fiscal Shocks

To study fiscal shocks, I focus on government purchases (consumption and investment) in the US. Following Auerbach and Gorodnichenko (2012, 2013), I identify unanticipated government spending shocks as the forecast error FE_t for the growth rate of government purchases. The forecast error is defined as the difference between the forecast made at time $t-1$ for government spending growth at t and the actual, first-release government spending growth rate at time t. The underlying idea is that the component of government spending growth, which is not forecasted one period ahead, can be considered as unanticipated by economic agents. Forecasts for government spending are available from the Survey of Professional Forecasters (SPF) since 1982.[5] For the period before that, Greenbook forecasts prepared by the Federal Reserve Board for the Federal Open Market Committee meetings are available from 1966 to 2004. By splicing the Greenbook and the SPF forecasts, Auerbach and Gorodnichenko (2012) compute a forecast error series running from 1966Q3 to 2010Q2.

Other strategies are also used in the literature to identify fiscal shocks. A leading alternative is the narrative series of military spending news constructed by Ramey (2011). What prevents me from using this series is a data restriction. Over the sample period when the hiring rate is available, there are only 27 military spending news, which is not enough to meaningfully compute multipliers in four states, that is the combination of expansionary/contractionary fiscal shocks and high/low hiring rate. Ramey (2011) shows that the forecast error computed by using the SPF forecast has an R-squared of 60 percent for government spending growth for the sample 1968Q4 - 2008Q4, which makes a potentially more powerful indicator of news than the military spending over the sample considered.[6]

[5]The Survey of Professional Forecasters has a quarterly frequency. The forecasters are asked to provide quarterly projections of various macro variables for five quarters (the quarter when the survey takes place and the four following quarters) and annual projections for the current year and the following year. More information can be found at `https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/`

[6]From 1968Q4 to 1981Q2 the SPF predicts nominal defence spending, while from 1981Q3 the SPF predicts total federal spending.

1.2.2 The State of the Labor Market

The theoretical literature on labor market frictions identifies two main measures to describe the state of the labor market: one captures the aggregate labor market conditions, while the other is related to firms' specific conditions. The first is usually referred to as labor market tightness and is the ratio between posted vacancies and unemployment. The second is the hiring rate of firms and is defined as the ratio between new hires and employees. Figure 1.1 shows both the labor market tightness and the hiring rate. Labor market tightness is computed using the help wanted index[7] from Barnichon (2010) and the unemployment series from the FRED Database. The hiring rate is calculated using the series of hires and employment from the Current Population Survey (CPS).[8] Ideally, one would want the flows of new hires to come from both non-employment and employment. Unfortunately, though, the CPS series of hires from employment is only available from 1994. As I need a longer time span to estimate state dependent multipliers, in my baseline analysis I use the series of new hires from non-employment, which is available at quarterly frequency since 1976Q1.[9] The hiring rate series shows a decreasing trend from the seventies to the early nineties. This secular decline is discussed thoroughly in Davis and Haltiwanger (2014), who impute it to a decline in the US labor market fluidity.[10] My analysis does not aim at explaining the secular decline in the trend, rather it focusses on the business cycle component. Labor market tightness and the hiring rate are only mildly correlated. Their correlation is 0.15. This indicates that the aggregate and the firms-specific conditions capture different features of the labor market.

[7]The help wanted index is an 'index that captures the behavior of total – "print" and "online"– help-wanted advertising, by combining the print Help-Wanted Index with the online Help-Wanted Index published by the Conference Board since 2005.', Barnichon (2010).

[8]The CPS is a monthly survey of households conducted by the Bureau of Census for the Bureau of Labor Statistics. It provides a comprehensive body of data on the labor force, employment, unemployment, persons not in the labor force, hours of work, earnings, and other demographic and labor force characteristics.

[9]The Job Openings and Labor Turnover Survey from the Bureau of Labor Statistics provides data on new hires from both non-employment and employment and is available from 2000M12. In Section 1.2.5, I conduct robustness checks using an extended version of this series.

[10]They observe the following: 'An ageing workforce and a secular shift away from younger and smaller employers partly account for the long-term decline in labor market fluidity. These forces are not the main story, however. Instead, we find large declines in the rate at which workers reallocate across employers within cells defined by gender and age and by gender and education. Likewise, there are large declines in the rate at which jobs reallocate across employers within cells defined by industry, employer size and employer age.'

1.2.3 Local Projections

To compute fiscal multipliers, I use local projections, which has been proposed by Jordà (2005) as a more flexible alternative to structural vector autoregressions. Local projections allow for a direct estimation of impulse response functions without imposing any dynamic restriction. Moreover, they are particularly suited to study state dependence as they provide a flexible environment to introduce non-linearities. In its linear version, the local projection that I am interested in is:

$$x_{t+h} = \gamma_h + \phi_h(L)z_t + \beta_h FE_t + \phi_h \text{ trend}_t + \epsilon_{t+h} \qquad h \geq 0, \tag{1.1}$$

where FE_t is the forecast error of government spending growth, x_{t+h} is the logarithm of the variable of which I want to compute the impulse response, z_t is a vector of controls, $\phi_h(L)$ is a lag polynomial of degree L, γ_h is a constant term, and trend_t is a linear time trend. The estimated coefficient β_h is the impulse response of x_{t+h} to an unanticipated government spending shock at t as captured by FE_t. To study sign and state dependence, I need a non-linear version of equation (1.1). Specifically, I introduce the following dummy variables: $\mathbb{1}_t^+ = 1$ when $FE_t > 0$ and $\mathbb{1}_t^+ = 0$ when $FE_t \leq 0$; $\mathbb{1}_t^{Slack} = 1$ when the labor market variable (tightness or the hiring rate) is below trend and $\mathbb{1}_t^{Slack} = 0$ when it is above trend. The non-linear local projection is as follows:

$$\begin{aligned} x_{t+h} =& \mathbb{1}_t^+ \mathbb{1}_{t-1}^{Slack} \left[\gamma_{PS,h} + \phi_{PS,h}(L)z_t + \beta_{PS,h} FE_t\right] \\ &+ \mathbb{1}_t^+ (1 - \mathbb{1}_{t-1}^{Slack}) \left[\gamma_{PT,h} + \phi_{PT,h}(L)z_t + \beta_{PT,h} FE_t\right] \\ &+ (1 - \mathbb{1}_t^+) \mathbb{1}_{t-1}^{Slack} \left[\gamma_{NS,h} + \phi_{NS,h}(L)z_t + \beta_{NS,h} FE_t\right] \\ &+ (1 - \mathbb{1}_t^+)(1 - \mathbb{1}_{t-1}^{Slack}) \left[\gamma_{NT,h} + \phi_{NT,h}(L)z_t + \beta_{NT,h} FE_t\right] \\ &+ \phi_h \text{ trend}_t + \epsilon_{t+h}, \quad h \geq 0. \end{aligned} \tag{1.2}$$

This regression allows me to distinguish among four states: *positive* fiscal shock in a *slack* labor market (PS), *positive* fiscal shock in a *tight* labor market (PT), *negative* fiscal shock in a *slack* labor market (NS), and *negative* fiscal shock in a *tight* labor market (NT). Notice that the dummy variable for the sign of the shock is indexed at time t, while the dummy variable for the state of the labor market is indexed at time $t-1$. This lag is introduced to avoid contemporaneous feedback from policy action into the state of the economy. The coefficients $\beta_{PS,h}$, $\beta_{PT,h}$, $\beta_{NS,h}$, and $\beta_{NT,h}$

are the coefficients of interest and are the impulse responses of variable x_{t+h} at horizon $t+h$ to an unanticipated government spending shock at t. The control variables which I include are: log real output, log real government expenditure, debt-to-GDP, and unemployment rate. The lag L is equal to one. By controlling for lagged output and lagged government expenditure, the forecast error is purified from any component that could have been predicted by professional forecasters the previous period. I control for debt-to-GDP so as to make sure that the state dependence is not imputable to different levels of deficit.[11] In addition, including unemployment rate allows me to control for the phase of the business cycle. The regression is estimated by ordinary least squares. Since standard errors are serially correlated when employing this methodology, I use Newey-West robust standard errors.

Given the impulse responses obtained from equation (1.2), it is possible to compute cumulative fiscal multipliers.[12] This consists of a three-step procedure as follows: first, run equation (1.2) for x_{t+h} equal to log real GDP for $h = 0, ..., H$ and sum all the β_h; second, run equation (1.2) for x_{t+h} equal to log real government expenditure for $h = 0, ..., H$ and sum all the β_h; third, divide the first sum by the second sum to get the elasticity of output to exogenous increases in government expenditure. This three-step procedure is equivalent to using an instrumental variable local projection approach as proposed by Ramey and Zubairy (2018). This method allows me to directly compute the cumulative fiscal multipliers and the associated standard errors. In its linear formulation the regression to estimate is:

$$\sum_{j=0}^{h} y_{t+j} = \gamma_h + \phi_h(L)z_t + m_h \sum_{j=0}^{h} g_{t+j} + \phi_h \text{ trend}_t + \epsilon_{t+h}, \tag{1.3}$$

where $\sum_{j=0}^{h} y_{t+j}$ is the sum of log real output, and $\sum_{j=0}^{h} g_{t+j}$ is the sum of log real

[11] Gali et al. (2007) show that the fiscal multiplier critically depends on how the fiscal expansion is financed. In particular, they argue that it is increasing with the extent of deficit financing.

[12] As argued by Ramey and Zubairy (2018), the policy relevant concept of fiscal multiplier is the *cumulative multiplier*. This is defined as the cumulative GDP response relative to the cumulative government spending response over a given period, as proposed by Mountford and Uhlig (2008), Uhlig (2010), and Fisher and Peters (2010). The cumulative multiplier differs from the concept of *peak multiplier*, defined as the peak of the output response to the initial government spending shock, or the *average multiplier*, defined as the ratio between the average response of output over the horizon of interest and the initial government shock.

government expenditure instrumented by the fiscal shock FE_t. Since g_{t+j} and y_{t+j} are in logs, the coefficient m_h is an elasticity. To convert it to dollar terms, I multiply m_h by the average ratio between real output and real government expenditure over the sample period.[13] Standard errors are also converted by the relevant factor by using the delta method. The non-linear version of equation (1.3) is the following:

$$\begin{aligned}\sum_{j=0}^{h} y_{t+j} = \mathbb{1}_t^{+}\mathbb{1}_{t-1}^{Slack}&\left[\gamma_{PS,h} + \phi_{PS,h}(L)z_t + m_{PS,h}\sum_{j=0}^{h} g_{t+j}\right] \\ +\mathbb{1}_t^{+}(1-\mathbb{1}_{t-1}^{Slack})&\left[\gamma_{PT,h} + \psi_{PT,h}(L)z_t + m_{PT,h}\sum_{j=0}^{h} g_{t+j}\right] \\ +(1-\mathbb{1}_t^{+})\mathbb{1}_{t-1}^{Slack}&\left[\gamma_{NS,h} + \psi_{NS,h}(L)z_t + m_{NS,h}\sum_{j=0}^{h} g_{t+j}\right] \\ +(1-\mathbb{1}_t^{+})(1-\mathbb{1}_{t-1}^{Slack})&\left[\gamma_{NT,h} + \psi_{NT,h}(L)z_t + m_{NT,h}\sum_{j=0}^{h} g_{t+j}\right] \\ &+ \phi_h \text{ trend}_t + \epsilon_{t+h}, \qquad h \geq 0,\end{aligned} \tag{1.4}$$

where again $\sum_{j=0}^{h} g_{t+j}$ is instrumented with the fiscal shock FE_t.

1.2.4 Fiscal Multipliers

Impulse Responses. Figure 1.2 and Figure 1.3 show the impulse response functions of government spending, output, consumption and investment to a positive fiscal shock. Figure 1.2 displays the responses when the hiring rate is used to identify the state of the labor market, while Figure 1.3 exhibits the responses when tightness is used instead.[14] The blue solid line depicts the responses when the series identifying the labor market state is below trend: it corresponds to coefficients $\beta_{PS,h}$ for $h = 1, ..., 20$ in equation (1.2). The red dashed line depicts the responses when the series identifying the labor market state is above trend: it corresponds to the coefficients $\beta_{PT,h}$ for $h = 1, ..., 20$.

[13] The concern raised by Ramey and Zubairy (2018) towards this conversion procedure as responsible for inflating or deflating multipliers does not apply here, as the ratio between output and government expenditure is not very volatile over my sample.

[14] For completeness, Appendix 1.B.1 shows the impulse responses in absence of any state dependence, that is in the linear case.

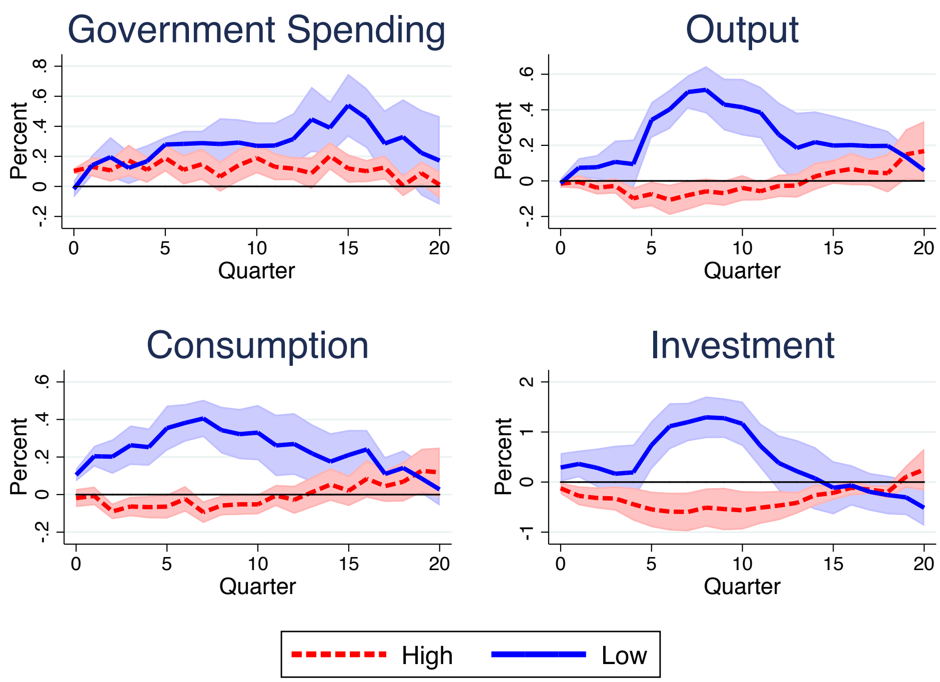


Figure 1.2 – **Empirical responses to a positive government expenditure shock depending on the hiring rate**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate.

As can be observed from Figure 1.2, when the hiring rate is used to identify the labor market state, responses to an expansionary shock are very much state dependent. All variables are more responsive when the hiring rate is below than when it is above trend. Moreover, an expansionary shock when the hiring rate is above trend slightly crowds out private consumption and investment, generating a mild drop in output. To the contrary, the picture is much less clear when tightness is used in place of the hiring rate. As shown by Figure 1.3 , responses of output, consumption, and investment are not statistically different in the two states.

Cumulative Multipliers. From Figure 1.2, it is immediately evident that the peak multiplier is higher when the hiring rate is below trend.[15] However, since the more

[15]The peak multiplier is the ratio between the peak of the output response and the initial government spending shock.

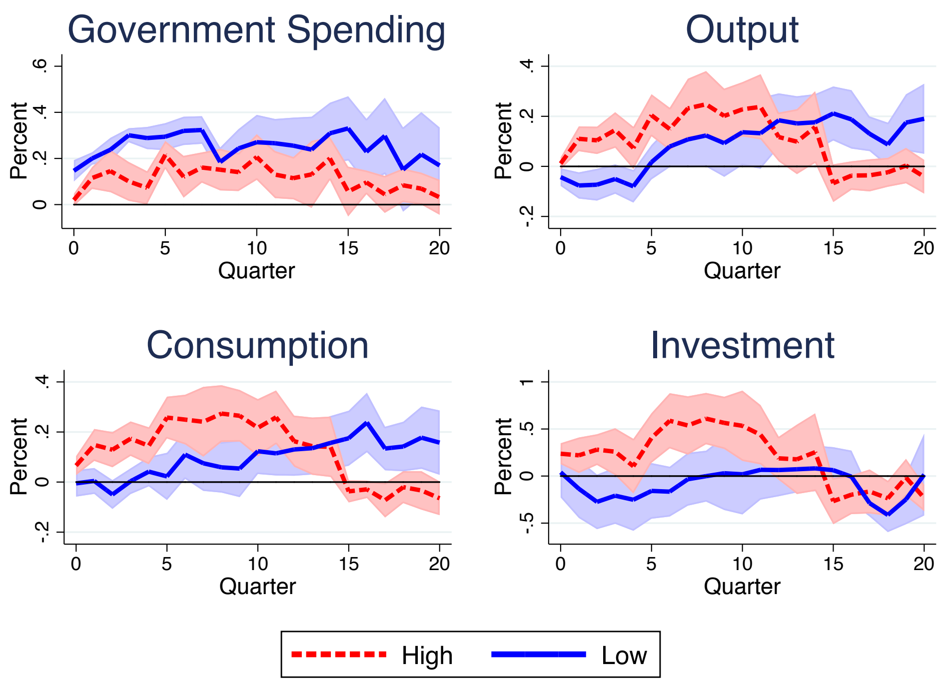


Figure 1.3 – **Empirical responses to a positive government expenditure shock depending on tightness**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) tightness.

policy relevant measure of the fiscal multiplier is the cumulative multiplier defined as the cumulative output response relative to the cumulative government spending response over a given horizion, Table 1.1 reports the cumulative multipliers for a horizon of 20 quarters. These multipliers correspond to the estimated coefficients $m_{PS,h}$ and $m_{PT,h}$ in equation (1.3). To be precise, since these coefficients are elasticities of output to fiscal shocks, they are converted to dollar equivalent by multiplying them by the average output-to-government spending ratio over the sample period. When the hiring rate is used to identify the labor market state, multipliers to an expansionary fiscal shock are as big as 3.58 when the hiring rate is below trend, but they are not significantly different from zero when the hiring rate is above trend. Moreover, the p-value testing whether the multiplier estimates differ across states indicates that the multipliers are statistically different in the two states. On the other hand, when tightness is used to

Table 1.1 – **Cumulative multipliers for a positive shock: baseline**

Labor Market Variable	Horizon	Tight	Slack	p-value
Hiring Rate	5Y	-0.81	3.58	0.005
		(0.59)	(0.31)	
Tightness	5Y	2.52	2.51	0.981
		(0.45)	(0.44)	

Note: Newey-West standard errors in parenthesis. 'p-value' indicates the p-value for the test that the multiplier estimates are different across states. It is based on heteroscedastic- and autocorrelation-consistent standard errors.

identify the labor market state, the five-year cumulative multipliers to an expansionary fiscal shock are not statistically different in the two states of tightness above and below trend.

1.2.5 Robustness Checks

Alternative Measures of Labor Market Tightness

Other measures are used in the literature as proxies for the aggregate state of the labor market. Appendix 1.B.2 shows responses when NAIRU or the unemployment rate trend are used as threshold to identify the state of the aggregate labor market. In the former case, the labor market is defined as tight when the unemployment rate is below the NAIRU and slack otherwise. In the latter case, the labor market is defined as tight when the unemployment rate is below its trend and slack otherwise. In both cases, no state dependence of the impulse responses to an expansionary fiscal shock is evident.

Robustness Checks for the CPS Hiring Rate Series

Appendix 1.B.3 conducts some robustness checks for the local projection results where the labor market state is identified by using the CPS hiring rate series. The first set of robustness checks concerns the specification of the regression model. Results are robust to eliminating the time trend, adding two lags, and changing the control variables to taxes and log employment.

The second set of robustness checks concerns the method applied to detrend the hiring rate. As a matter of fact, the state dependence may be affected by the way the hiring rate series is detrended. Results still hold when changing the HP filter smoothing parameter, as well as when a polynomial trend or a moving average are employed to detrend the series.

An Alternative Measure of the Hiring Rate: JOLTS Extended Series

As an additional robustness check, I use an alternative measure of the hiring rate, which, differently from the CPS series, also includes the new hires from employment. This is the hiring rate series from the Job Openings and Labor Turnover Survey. This series, which starts in 2001, is extended back to 1990 by Davis et al. (2012).[16] To study state dependence, it is important for me to have a long time series. For this reason, I further extend the hiring rate series by Davis et al. (2012) as follows. Over the period 1990-2018, I run the regression:

$$\frac{H_t}{N_t} = \beta_0 + \beta_1 u_t + \beta_2 \Delta \log N_t + \beta_3 t + \epsilon_t, \tag{1.5}$$

where H_t/N_t is the hiring rate series of Davis et al. (2012), u_t is the unemployment rate, $\Delta \log N_t$ is the first difference of log employment, and t is a linear time trend. I can then use the estimated coefficients $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, the unemployment rate, and the employment series to get the fitted values of the hiring rate prior to 1990. Using the fitted hiring rate, I rerun equation (1.2) and equation (1.4). Appendix 1.B.4 shows that results are robust to using this extended hiring rate series to identify the labor market state.

Measures of Recessions vs Expansions

The literature has so far focussed on fiscal spending multipliers dependent on the business cycle. Appendix 1.B.5 illustrates that defining the state of the economy according to the hiring rate is not the same as following the standard definitions of business cycle. In particular, the Appendix shows that expansionary fiscal multipliers are not state dependent when the NBER recessions or Auerbach and Gorodnichenko (2012)'s smooth transition threshold are used to define the state of the economy.

[16] I thank Jason Faberman for sharing this hiring rate series with me.

1.3 Modelling Hiring Frictions

In light of the reduced-form evidence provided in Section 1.2, this section discusses how the literature has approached the modelling of hiring frictions and how I tackle it. In the standard DMP framework hiring frictions have two salient features: i) they are modelled as costs of posting new vacancies; ii) they are denominated in terms of the final composite good, i.e. as pecuniary. The first feature implies that the main cost of hiring a worker is borne before the match is created. In particular, it assumes that, once a new worker is hired by a firm, he can start working with the same productivity as the one of experienced workers. The second feature requires the cost of hiring to enter the resource constraint of the economy, thus constituting a share of aggregate demand. Micro-evidence shows that these features are not fully supported by empirical evidence. For this reason, I am modelling hiring frictions as i) mainly post-match and ii) expressed in terms of foregone output. I am going to discuss these two assumptions more in details in the following subsections.[17]

1.3.1 Pre-match versus Post-match Hiring Costs

When hiring a new worker, employers face two types of hiring costs: pre-match costs and post-match costs. Pre-match costs are those related to posting vacancies, head hunting, and interviewing. Post-match costs are those referring to training and all the activities that raise the productivity of a newly employed worker to the level of an already experienced worker. Pre-match costs are also referred to as external costs as they depend on the conditions of the aggregate labor market, which are external to the firm. Post-match costs are also known as internal costs as they depend on the internal conditions of the firm, meaning that they depend on the share of new hires to the already employed workers. While most of the macro literature has focussed on pre-match costs, new micro evidence is showing that the biggest share of the hiring costs borne by firms is actually post-match rather than pre-match. Using German survey data, Faccini and Yashiv (2019) compute that 82.3% of hiring costs are post-

[17] For an overview on hiring frictions and their theoretical and empirical relevance see Manning (2011). Estimates on the magnitude of hiring frictions vary by country, sector, and skill in a range between 2.4% and 11.2% of the wage bill.

match.[18] In the Handbook of Labor Economics, Manning (2011) highlights that the bulk of hiring costs is related to training rather than recruitment. Similarly, Silva and Toledo (2009) review the literature on hiring costs and report that, based on US data, training costs are much more significant than recruiting costs. Muehlemann and Leiser (2018) decompose the cost of hiring into search costs, adaptation costs, and disruption costs and use Swiss administrative establishment-level survey data for 2000, 2004, and 2009 to estimate the cost components. They find that 'The search costs only accounted for 21 percent of the costs incurred to fill a vacancy and most of a firm's hiring expenses occurred after the signing of a contract. Adaptation costs (i.e., training costs and the initially low productivity of a new hire) accounted for 53 percent and disruption costs (i.e., productivity losses because other workers could not perform their regular tasks while providing informal training to new hires) accounted for 26 percent of the total hiring costs.' In parallel to the growing micro evidence, macroeconomic studies started modelling hiring frictions both as pre-match and post-match. Yashiv (2000), Christiano et al. (2011), Furlanetto and Groshenny (2016), and Faccini and Melosi (2019) have specifications of hiring costs which allow for both pre-match and post-match costs. They estimate their models using different datasets[19] and they all find that the biggest share of costs is the post-match one. Given all this micro and macro evidence, in my baseline specification I model hiring costs as post-match following Gertler et al. (2008a), Gertler and Trigari (2009), and Faccini and Yashiv (2019). In particular, the hiring cost function $\tilde{g}_{i,t}$ of firm i that I assume is as follows:

$$\tilde{g}_{i,t} = \frac{e}{2}\left(\frac{H_{i,t}}{N_{i,t}}\right)^2, \tag{1.6}$$

where $H_{i,t}/N_{i,t}$ is the ratio between the new hires and the workforce of firm i, and e is a scale parameter. This formulation assumes that hiring costs are quadratic in the hiring rate. This means that the costs get increasingly more significant with the rise in the hiring rate.[20] Using US data, Merz and Yashiv (2007) structurally estimate the

[18] Namely, they use a survey conducted by the Federal Institute for Vocational Education Training over the years 2012-2013.

[19] Yashiv (2000) uses Israeli data, Christiano et al. (2011) use Swedish data, and Furlanetto and Groshenny (2016) and Faccini and Melosi (2019) use US data.

[20] There could be other forces at play such as economies of scales that would push towards a concave specification. However, structural estimation indicates that these costs are convex in the hiring

functional form of firms' adjustment costs and find strong evidence in favour of their convexity. Since the quadratic specification is the most commonly adopted, I follow the literature in specifying my costs as quadratic. Notice nonetheless that what matters for my results is the convexity of the hiring cost function, not the specific degree of convexity.

1.3.2 Non-pecuniary versus Pecuniary Hiring Costs

In the standard DMP framework, hiring costs are denominated in units of the final good, which is usually the economy numeraire. Yet, micro evidence shows that the most burdensome aspect of hiring a new employee is not the pecuniary costs actually faced. Rather it is the disruption that a new hire causes along two dimensions. First, it takes some time to train the new hires and bring their productivity to the level of already trained employees.[21] Second, unless the training activity is outsourced, internal training generates a disruption in production as some employees have to be diverted from production to the training of the newly hired workers.[22] This cost is quantifiable as foregone production. Faccini and Yashiv (2019) bring micro evidence that these costs represent around 80% of the total hiring cost. Along the same lines, Bartel et al. (2014) find that the arrival of a newly hired nurse in a hospital lowers the productivity of the team when the nurse is hired externally, while Cooper et al. (2015) show that labor adjustment disrupts the production process of manufacturing plants. Given this evidence, I follow Faccini and Yashiv (2019) and Faccini and Melosi (2019) in modelling hiring costs as non-pecuniary. Let's assume that $f_{i,t}$ is the production function of firm i. Having non-pecuniary costs implies forgoing some of the production to actually hire.

rate.

[21] Also anecdotal evidence points towards this being the case. Fastcompany, an American business magazine, writes: 'It can take as long as long as eight months for an employee to become fully productive'. Hundred5, a modern skilled-based hiring platform, notes: 'When you hire someone new, they most likely won't be fully productive their first day of work. In fact, it can take up a few months for them to get comfortable in their new role. As confirmed by research, it will take 8 to 26 weeks for an employee to achieve full productivity. Before this time runs out, you are essentially losing money – the new employee costs more than they are earning for the company. After this period, they provide positive return on investment for your company, i.e. this is the break-even point.'

[22] Harvard Business Review declares that hiring 'disrupts the culture and burdens peers who must help new hires figure out how things work.'

In analytical terms this concept translates into the following equation:

$$Y_{i,t} = f_{i,t}(1 - \tilde{g}_{i,t}). \tag{1.7}$$

In other words, to match demand $Y_{i,t}$ firm i has to produce $f_{i,t}(1 - \tilde{g}_{i,t})$.

1.4 Model

To study the effects of an expansionary fiscal shock across different states of the labor market, I develop a general equilibrium model with hiring frictions and nominal rigidities. I assume that there is a government, which spends wastefully following an exogenous process. Nominal rigidities are needed as the mechanism through which hiring costs affect the propagation of fiscal shocks hinges upon the interaction between these two types of frictions.

The economy is populated by a continuum of households fully sharing risk. Households consume, work, choose whether to join the labor force, invest in capital and one-period bonds. Firms are of two types. Final good firms aggregate intermediate differentiated goods into a homogeneous product. This homogenous good is sold to the households and the government in a perfectly competitive market. Intermediate good firms produce their differentiated good by renting capital and hiring labor from households. They face a quadratic cost of hiring and a quadratic cost of adjusting prices. Labor markets are frictional and wages are set according to Nash bargaining. Real wages are adjusted with some inertia. Monetary policy follows a standard Taylor rule where the interest rate reacts to deviations of inflation and output from their steady state. Wasteful government spending is funded by levying lump-sum taxes on households and issuing one-period bonds. The economy is subject to exogenous shocks in preferences, technology, marginal efficiency of investment, monetary policy and fiscal policy.

1.4.1 Labor Market

There are three different employment states: employed, unemployed but actively looking for a job, and unemployed but inactive. N_t is the number of employed, while U_t is the number of unemployed actively looking for a job. The fraction of people supplying labor, and therefore actively participating in the labor market, is

$$L_t = N_t + U_t. \tag{1.8}$$

The labor market is subject to search and matching frictions. People who are unemployed at the beginning of the period, indicated by $U_{0,t}$, actively look for a job, while firms post vacancies V_t. New hires H_t are created according to a standard Cobb-Douglas function:

$$H_t = mU_{0,t}^l V_t^{1-l}, \tag{1.9}$$

where m is a parameter controlling the matching efficiency and l is the elasticity of hires to beginning-of-period job seekers. The vacancy filling rate and the job finding rate are respectively:

$$q_t = \frac{H_t}{V_t} \quad \text{and} \quad x_t = \frac{H_t}{U_{0,t}}. \tag{1.10}$$

Aggregate employment evolves according to the following law of motion:

$$N_t = (1 - \delta_N)N_{t-1} + H_t, \tag{1.11}$$

where $\delta_N \in (0, 1)$ is the exogenous separation rate between firms and workers.

1.4.2 Household

There is a representative household who gets utility from consuming C_t and get disutility from supplying labor L_t. The period utility function of the household is:

$$\mathcal{U}_t(C_t, L_t) = \frac{\left(\eta_t^p C_t - \frac{\chi}{1+\phi} L_t^{1+\phi}\right)^{1-\sigma}}{1-\sigma}, \tag{1.12}$$

where χ is the parameter that controls the disutility of supplying labor, ϕ is the inverse Frisch elasticity of labor supply, and σ is the intertemporal elasticity of substitution. η_t^p is an exogenous AR(1) process with Gaussian shocks, which will be referred to as preference shocks.

The household can choose to save by investing in capital K_{t+1} or buying zero-coupon government bonds at discounted value $\frac{B_{t+1}}{R_t}$, where R_t is the nominal interest rate set by the monetary policy authority. Capital evolves according to the following law of motion:

$$K_{t+1} = (1-\delta_K)K_t + \eta_t^{Inv}\left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t, \tag{1.13}$$

where I_t are investments, $\delta_K \in (0,1)$ is the capital depreciation rate, and $S\left(\frac{I_t}{I_{t-1}}\right) = \frac{\phi}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2$ are quadratic investment adjustment costs. As in Justiniano et al. (2011), η_t^{Inv} follows an AR(1) process and affects the marginal efficiency of investment.

The household gets a return R_t^K on capital rented to firms and earns nominal wage W_t from working. Moreover, he gets dividends Θ_t from owning firms and pays lump-sum taxes Θ_t. The budget constraint of the household is:

$$P_tC_t + P_tI_t + \frac{B_{t+1}}{R_t} = R_t^K K_t + W_tN_t + B_t + \Theta_t - T_t, \tag{1.14}$$

where P_t is the price of the final composite good in which both consumption and investment are denominated.

Given the initial value of bonds B_0 and the discount factor β, the household chooses state-contingent sequences $\{C_t, L_t, N_t, K_{t+1}, I_t, B_{t+1}\}_{t=0}^{\infty}$ to maximise the discounted present value of utility:

$$\max_{\{C_t,L_t,N_t,K_{t+1},I_t,B_{t+1}\}} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \mathcal{U}_t(C_t, L_t) \tag{1.15}$$

subject to the labor supply constraint (1.8), the employment law of motion (1.11), the capital law of motion (1.13), and the budget constraint (1.14).

1.4.3 Firms

There are two types of firms of measure one: perfectly competitive final good producers and monopolistically competitive intermediate good producers.

1.4.4 Final Good Producers

Final good producers buy differentiated goods from intermediate producers, aggregate them into a final homogeneous good, and sell it to the households and the government in a perfectly competitive market. To aggregate intermediate goods, final producers use a Dixit-Stiglitz aggregator:

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1.16}$$

where ϵ indicates the elasticity of substitution between different varieties of intermediate good. Cost minimisation gives the demand function for the intermediate good:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\epsilon} Y_t, \tag{1.17}$$

where $P_t = \left(\int_0^1 P_{i,t}^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}}$ is the price index for the final good.

1.4.5 Intermediate Good Producers

Each intermediate good producer i produces a differentiated good by using capital $K_{i,t}$, and labor $N_{i,t}$. These factors of production are combined into $f_{i,t}$ according to the Cobb-Douglas function:

$$f_{i,t} = (A_t N_{i,t})^{\alpha} K_{i,t}^{1-\alpha}, \tag{1.18}$$

where α is the labor share in the inputs of production and A_t is a labor-augmenting technology, which follows an AR(1) process. Intermediate good producers rent capital from households at nominal rate R_t^K and hire labor in a frictional labor market.

Hiring frictions

Hiring costs as training. When hiring workers, intermediate good firms face hiring frictions. As discussed in Section 1.3.1, these costs are modelled as post-match and mainly refer to training and all the activities required to bring the productivity of a newly hired worker to the level of an already experienced one. Following Gertler et al. (2008a), Gertler and Trigari (2009), and Faccini and Yashiv (2019), the hiring cost function $\tilde{g}_{i,t}$ of firm i is:

$$\tilde{g}_{i,t} = \frac{e}{2}\left(\frac{H_{i,t}}{N_{i,t}}\right)^2, \tag{1.19}$$

where $H_{i,t}/N_{i,t}$ is the ratio between the new hires and the workforce of firm i, and e is a scale parameter.[23]

Hiring costs as foregone output. As documented in Faccini and Yashiv (2019) by using micro data, the biggest component of hiring costs is not borne in pecuniary terms, but in terms of disruption to production. Therefore, as discussed in Section 1.3.2 and following Faccini and Yashiv (2019), I choose to model hiring costs as a fraction of foregone output. This modelling assumption captures the idea that hiring is internally costly as it requires firms to divert part of their workforce from production to hiring activities. The net output of intermediate firm i is then given by:[24]

$$Y_{i,t} = f_{i,t}(1 - \tilde{g}_{i,t}). \tag{1.20}$$

For notational convenience, I define $g_{i,t} \equiv \tilde{g}_{i,t} f_{i,t}$.

Problem of the Intermediate Good Producers

Intermediate good producers set their price monopolistically and are subject to quadratic price adjustment costs à la Rotemberg (1982).

They solve the following problem:

$$\max_{\{P_{i,t} H_{i,t}, N_{i,t}, K_{i,t}\}} \mathbb{E}_t \sum_{t=0}^{\infty} \Lambda_{t,t+1} \left\{ \frac{P_{i,t}}{P_t} Y_{i,t} - \frac{W_t}{P_t} N_{i,t} - \frac{R_t^K}{P_t} K_{i,t} - \frac{\zeta}{2}\left(\frac{P_{it}}{P_{i,t-1}\bar{\Pi}} - 1\right)^2 Y_t \right\} \tag{1.21}$$

subject to the employment law of motion (1.11), the demand function (2.23), and the constraint requiring demand to be fully satisfied by production net of hiring costs (1.20).

[23] In this model, workers' skills are homogeneous. Therefore, there is no heterogeneity in hiring costs arising from workers' skill heterogeneity. In fact, it could be that hiring more skilled workers is more costly. This margin is left to further explorations.

[24] Alternatively, I could assume that the hiring cost is not directly proportional to output, but only indirectly through hiring. This specification would impy: $Y_{i,t} = f_{i,t} - \tilde{g}_{i,t}$. I have run the model with this alternative formulation and verified that it gives rise to the same mechanism and model dynamics. Results are available upon request.

ζ is the parameter that controls price rigidities, $\bar{\Pi}$ is the steady-state gross inflation rate, while $\Lambda_{t,t+1}$ is the household's stochastic discount factor.

1.4.6 Wage Bargaining

Once a match is created between a firm and a worker, wage is bargained according to a standard Nash bargaining process. The Nash wage W_t^{NASH}/P_t maximises the geometric average of the household's and firm's surplus weighted by the the parameter γ, indicating the bargaining power of the household:

$$\frac{W_t^{NASH}}{P_t} = \arg\max\left\{\left(\mathcal{V}_t^N\right)^{\gamma}\left(Q_t^N\right)^{1-\gamma}\right\}. \tag{1.22}$$

$\mathcal{V}_t^N$ and Q_t^N are the marginal values of a job for the household and the intermediate firm i and correspond to the Lagrange multipliers of the labor law of motions in the respective maximisation problems.

I assume that there is real wage inertia as in Hall (2005):

$$\frac{W_t}{P_t} = \left(\frac{W_{t-1}}{P_{t-1}}\right)^{\omega}\left(\frac{W_t}{P_t}^{NASH}\right)^{1-\omega},$$

where ω controls the degree of wage rigidity.

1.4.7 Fiscal and Monetary Policies and Market Clearing

Fiscal authority. The government spends G_t wastefully.[25] This expenditure is financed through a lump-sum tax T_t on the household and a zero-coupon bond issued at the discounted value $\frac{B_{t+1}}{R_t}$. The government's budget constraint is:

$$P_tG_t - T_t = \frac{B_{t+1}}{R_t} - B_t. \tag{1.23}$$

[25] I could alternatively assume that government spending is not wasteful. For example, I could suppose that it enters the utility function of the household as a complement to the private consumption good. In this case, I would get an even stronger state dependence of expansionary fiscal shocks than in the case of wasteful expenditure. Results are available upon request.

Government spending obeys the following AR(1) process:

$$\ln G_t = (1-\rho_G)\ln \bar{G} + \rho_G G_{t-1} + \epsilon_{G,t}, \tag{1.24}$$

where $\bar{G}$ is the steady state value of government spending, ρ_G is the autoregressive parameter, and $\epsilon_{G,t}$ is an i.i.d. shock.

Monetary authority. Monetary policy is set according to a standard Taylor rule:

$$\frac{R_t}{\bar{R}} = \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{r_\pi} \left(\frac{Y_t}{\bar{Y}}\right)^{r_y} \epsilon_t^R, \tag{1.25}$$

where barred variables indicate steady state values, r_π and r_y control the response of monetary policy to inflation and output deviations from their steady state values, and ϵ_t^R is an i.i.d. monetary policy shock.

Market Clearing. Consolidating the household's and government's budget constraint, imposing a symmetric equilibrium across firms, and substituting for the intermediate firms' profits yields the following resource constraint:

$$\left[1 - \frac{\zeta}{2}\left(\frac{\Pi_t}{\bar{\Pi}} - 1\right)^2\right] Y_t = C_t + I_t + G_t, \tag{1.26}$$

where $Y_t = f_t(1-\tilde{g}_t)$, that is Y_t indicates aggregate output net of aggregate hiring costs, and $\bar{\Pi}$ is the steady state inflation.

1.4.8 The Employment and Hiring Decisions

The employment decision. The marginal value of a job to the household is given by the first order condition (FOC) of the household's problem with respect to N_t:

$$\mathcal{V}_t^N = \frac{\Phi_t}{\lambda_t P_t} + \frac{W_t}{P_t} + (1-\delta_N)E_t\Lambda_{t,t+1}\mathcal{V}_{t+1}^N, \tag{1.27}$$

where $\mathcal{V}_t^N$ is the Lagrange multiplier associated with the employment law of motion and Φ_t is the Lagrange multiplier associated to the labor supply constraint.[26] In particular,

[26]See Appendix 1.D for the Lagrangian of the household's problem and the FOCs.

$\frac{\Phi_t}{\lambda_t P_t}$ is the marginal rate of substitution between consumption and leisure. Hence, the marginal value of a job is equal to the sum of the marginal rate of substitution between consumption and leisure, the real wage, and the continuation value.

Imposing symmetry across firms, the marginal value of a job to firms is given by the FOC of the firm's problem with respect to N_t:

$$\mathcal{Q}_t^N = \xi_t(f_{N,t} - g_{N,t}) - \frac{W_t}{P_t} + (1-\delta_N)E_t\Lambda_{t,t+1}\mathcal{Q}_{t+1}^N, \tag{1.28}$$

where $\mathcal{Q}_t^N$ is the Lagrange multiplier associated with the employment law of motion (1.11), ξ_t is the Lagrange multiplier associated with the demand function (2.23), while $f_{N,t}$ and $g_{N,t}$ are the derivatives of the production and the hiring cost function with respect to N_t. In particular, the marginal value of a job for the firm is equal to the marginal revenue obtained with an additional employee net of the real wage plus a continuation value.

The hiring decision. The FOC of the firm with respect to H_t is:

$$Q_t^N = \xi_t g_{H,t}. \tag{1.29}$$

This condition equates the marginal value of a job to the marginal cost of a hire. It is important to notice that the marginal cost of a hire depends on ξ_t, which can be interpreted as the shadow value of output. Fluctuations in the shadow value of output generate fluctuations in the marginal value of a job and, hence, in the hiring decisions of firms. This is because hiring costs are modelled as non pecuniary in nature, meaning that hiring activities require diverting employees from production to recruitment activities. This feature plays an important role in the propagation of a fiscal shock as is going to be explained in Section 1.4.12.

1.4.9 Exploring the Main Mechanism

Intuition: Because of search and matching frictions in the labor market, hiring can be thought of as an investment activity in workers - as a matter of fact, employment N is a state variable. The decision of investing in workers, i.e. hiring, is therefore going to depend on the future value of workers. When the hiring rate is high today, the value of workers is already high and it is not expected to further increase very significantly. A smaller expected change in the value of workers implies a higher output shadow value today. As hiring costs are denominated in terms of output shadow value, this results in a more costly hiring activity. On the contrary, if the hiring rate is not as high today, the value of workers is expected to increase much more. The expected increase in the value of workers is going to lower the output shadow value, thus making investment in employment more valuable.

Analytically: To better understand the hiring decision of the firm, it is useful to rearrange equation (1.28) as follows:

$$\xi_t = \frac{\frac{W_t}{P_t}}{f_{N,t} - g_{N,t}} + \frac{\mathcal{Q}_t^N - (1-\delta_N)E_t\Lambda_{t,t+1}\mathcal{Q}_{t+1}^N}{f_{N,t} - g_{N,t}}, \tag{1.30}$$

which allows me to decompose the output shadow value ξ_t in two components. The first term is the ratio of the real wage to the marginal productivity of labor and represents the real unit labor cost. The second term arises in the presence of hiring frictions and is a correction for the marginal value of employment relative to the *expected* marginal value of employment, that is the expected change in the value of employment. Differently from a standard search and matching model with pecuniary costs of posting vacancies, in this model the marginal value of a job $\mathcal{Q}_t^N$ is a function of the marginal hiring cost $g_{H,t}$ evaluated at the output shadow value ξ_t, as can be seen from equation (1.29). Fluctuations in the output shadow value are going to affect firms' hiring decisions. Hence, to better identify the determinants of the output shadow value, I substitute equation (1.29) into equation (1.30) to get:

$$\xi_t = \frac{\frac{W_t}{P_t} - (1-\delta_N)E_t\Lambda_{t,t+1}\xi_{t+1}g_{H,t+1}}{f_{N,t} - g_{N,t} - g_{H,t}}. \tag{1.31}$$

Equation (1.31) shows that the current output shadow value is a function of multiple objects: the difference between the real wage and the continuation value of a job; the difference between the marginal productivity of labor and the marginal hiring cost. Being a general equilibrium model, all these variables are endogenous. Nonetheless, the following observations can be made from equation (1.31). Because of the convexity of the hiring cost function g_t, when the hiring rate increases the marginal hiring cost $g_{H,t}$

rises, resulting in a higher output shadow value. As hiring costs are denominated in terms of output shadow value, an increase in the latter raises the cost of hiring. As for the numerator of equation (1.31), it depends on the expected value of next period output shadow value ξ_{t+1} and next period marginal hiring cost $g_{H,t+1}$. The former implies that when the output shadow value is expected to increase in the next period, it gets relatively cheaper for firms to front-load hiring today. The latter has the following implication. A higher expected hiring rate increases the expected marginal hiring cost $g_{H,t+1}$. This makes it relatively more convenient for firms to hire today as it lowers the current output shadow value. If a fiscal expansion hits the economy in a state of already high hiring rate, the expectation that this hiring rate is going to increase even further, thus increasing the expected value of workers, is much lower than if the fiscal expansion hits the economy in a normal labor market condition.

These reasonings carry two implications. First, the output shadow value is going to be higher if the fiscal expansion happens when the hiring rate is already high. Second, the output shadow value can decrease following an expansionary fiscal shock. In fact, differently from models with competitive labor markets where the output shadow value is simply given by the real unit labor cost, in the presence of hiring frictions there is an additional adjustment term. This term captures the fluctuations in the expected value of employment. If the value of employment is expected to increase enough to compensate the increase in the real unit labor cost, the output shadow value will decrease following an expansionary fiscal shock. As hiring costs in this model are denominated in terms of output, when the shadow value of output decreases hiring costs also decline.

1.4.10 Solution Method and Calibration

To study state dependence, the model is solved via a third order perturbation method around the steady state. This allows me to take non-linear effects into account.[27]

Table 1.2 reports the parameters of the model. The discount factor is calibrated to 0.99 to target a quarterly interest rate of 1%, while the inverse Frisch elasticity of labor supply is set to the standard value of 2. The intertemporal elasticity of substitution is set to 2.7, which is within the range entertained by the literature. The capital

[27] To analyse state dependence, an alternative strategy would be to simulate the model under perfect foresight as in Michaillat (2014). Third-order perturbation does not force me to assume that agents have perfect foresight.

depreciation rate targets a quarterly investment rate of 2.5%, while the investment adjustment cost is set to 5. The Rotemberg adjustment cost parameter maps into a five-quarter price stickiness with Calvo type price rigidities. The elasticity of substitution between varieties is calibrated to 11, implying a steady state price markup of 10%. The elasticity of output to labor is set to the standard 0.66.

Moving to parameters related to the labor market, the unemployment rate is calibrated to the US average of 6% over the period 1976Q1-2019Q2. Following Faccini and Melosi (2019), who target an average quarterly hiring rate of 12.76%, the separation rate is calibrated to 0.126. Also the steady state labor supply, the vacancy filling rates, and the elasticity of hires to the beginning of period unemployment are set following Faccini and Melosi (2019). Wage stickiness is calibrated to 0.87 to match the persistence of the US wages as in Faccini and Yashiv (2019). The scale parameter e in the hiring cost function is set to the value estimated by Faccini and Melosi (2019).

The Taylor rule coefficients on inflation and output are set to the standard 2 and 0.125, while the output share of public spending is calibrated to the US average of 20%. Since three steady state variables are calibrated (unemployment rate, vacancy filling rate and labor supply), this leaves three parameters to be determined in steady state: the workers' bargaining power γ, the matching efficiency parameter m, and the disutility of supplying labor χ.

Persistence and standard deviations of the exogenous processes are parametrised following the estimated values of Faccini and Melosi (2019).

1.4.11 State dependent responses

Impulse responses in non-linear models. There are two main features that differentiate impulse responses of non-linear models from those of linear (or linearised) ones. First, while in linear models the path of variables in response to a shock does not depend on the initial state of the simulation, in non-linear models impulse responses do depend on the initial state. Second, in linear models there is a natural benchmark against which to compare impulse responses. This benchmark is the behavior of the model absent the shock, that is the deterministic steady state. In non-linear models, instead, identifying this benchmark is less straightforward. As a matter of fact, the model reacts differently depending on the initial state and the sequence of shocks, so

Table 1.2 – **Parameter values**

Parameter	**Description**	**Value**	**Target/Source**
		Standard Parameters	
β	Discount factor	0.99	quarterly interest rate of 1%
φ	Inverse Frisch elasticity	2	standard
σ	Intertemporal elasticity of substitution	2.5	in standard range
δ_K	Capital depreciation rate	0.024	quarterly investment rate of 2.5%
ϕ	Investment adjustment cost	5	in standard range
ζ	Rotemberg adj. cost parameter	140	reset prices every five quarters
ϵ	Elasticity of substitution	11	steady state mark up of 10%
α	Elasticity of output to labor	0.66	standard
		Labor Market Parameters	
u_{rate}	Unemployment rate	0.06	US average
δ_N	Separation rate	0.126	average quarterly hiring rate 12.76%
$\bar{L}$	Steady state labor supply	0.65	US average
l	Elasticity of hires to U_0	0.597	Faccini and Melosi (2019)
q	Vacancy filling rate	0.7	Faccini and Melosi (2019)
ω	Wage stickiness	0.87	match persistence of the US real wage
e	Hiring friction parameter	4.17	Faccini and Melosi (2019)
γ	Household's bargaining power	0.305	match u_{rate}
χ	Disutility of labor supply	3.709	match $\bar{L}$
m	Matching efficiency	0.704	match q
		Policy parameters	
r_π	Taylor rule coefficient on inflation	2	standard
r_y	Taylor rule coefficient on output	0.125	standard
s_G	Output share of public spending	0.2	US average
		Exogenous Processes	
ρ_G	Persistence of G	0.90	Faccini and Melosi (2019)
σ_G	Volatility of G shock	0.009	Faccini and Melosi (2019)
ρ_A	Persistence of TFP	0.98	Faccini and Melosi (2019)
σ_A	Volatility of TFP	0.003	Faccini and Melosi (2019)
ρ_p	Persistence of preference shock	0.45	Faccini and Melosi (2019)
σ_p	Volatility of preference shock	0.004	Faccini and Melosi (2019)
ρ_I	Persistence of investment shock	0.81	Faccini and Melosi (2019)
σ_I	Volatility of investment shock	0.008	Faccini and Melosi (2019)

even in absence of a contemporaneous shock, the model may behave differently due to a different history of shocks. In the coming analysis, I will be specific on the initial state of the simulation and the benchmark against which to compare impulse responses.[28]

My exercise. My goal is to study how differently an expansionary fiscal shock propagates throughout the economy depending on the hiring rate level when the shock hits. In brief, I first obtain a distribution for the hiring rate. Then, I study the responses to an expansionary fiscal shock simulated from an economy with different hiring rate levels. More specifically, I proceed as follows. First, I compute the stochastic steady state, that is the steady state to which the model converges when it is not subject to shocks. Second, starting from the stochastic steady state, I simulate the model for one period and repeat this simulation for 100 000 times.[29] By doing so, I obtain a distribution for the hiring rate. I take the simulation in which the hiring rate corresponds to the 90^{th} percentile of its distribution. Then, I simulate an expansionary fiscal shock starting from the state corresponding to the 90^{th} percentile of the hiring rate distribution and from the stochastic steady state. As benchmark against which to compare the model subject to the fiscal shock, I take the model absent the fiscal shock. Therefore, I subtract the path of the variables when the model receives a fiscal shock at time $t = 0$, ${Z_t}^{\text{shock}}$, with the path of the same variables when the model does not receive any fiscal shock at time $t = 0$, ${Z_t}^{\text{no shock}}$. Finally, since the path of the variables converges to the stochastic steady state, I standardise the responses by the latter, $Z^{\text{stoch. SS}}$. In short, for each variable Z_t and time $t = 0, ..., T$, the impulse

[28] A non-linear state space representation of the model is as follows:

$$s_t = \Phi_{s,0} + As_{t-1} + B\epsilon_t + \frac{1}{2}\Phi_{s,1}(s_{t-1} \otimes s_{t-1}) + \frac{1}{2}\Phi_{s,2}(\epsilon_t \otimes \epsilon_t) + \Phi_{s,3}(s_{t-1} \otimes \epsilon_t) + h.o.t.$$
$$x_t = \Phi_{x,0} + Cs_{t-1} + D\epsilon_t + \frac{1}{2}\Phi_{x,1}(s_{t-1} \otimes s_{t-1}) + \frac{1}{2}\Phi_{x,2}(\epsilon_t \otimes \epsilon_t) + \Phi_{x,3}(s_{t-1} \otimes \epsilon_t) + h.o.t.,$$

where s_t and x_t are the vectors of state and non-state variables respectively, ϵ_t is the vector of shocks, capital letters indicate matrices of coefficients, and *h.o.t.* refers to higher order terms. From this representation it is clear that, since the vector of shocks interacts with the state vector, the response of the system depends on the part of the state space where the economy is when the shock hits.

[29] Another possibility is to simulate the model for 100 000 times starting from the stochastic steady state, and then compute the distribution of labor market tightness. Results hold also with this type of simulation.

response that I plot is:

$$IRF(Z_t|s_0) = \frac{(Z_t^{\text{shock}}|s_0) - (Z_t^{\text{no shock}}|s_0)}{Z^{\text{stoch. SS}}}, \tag{1.32}$$

where s_0 is the initial state of the simulation. Because of higher order approximation, $IRF(Z_t|s_0)$ will depend on s_0. In particular, $IRF(Z_t|s_0)$ will be different when the initial state s_0 corresponds to the 90^{th} percentile of the hiring rate distribution or to the stochastic steady state.

1.4.12 Fiscal Shocks

Figure 1.4 plots the impulse responses to a one standard deviation increase in public spending. The blue solid line shows $IRF(Z_t|s_0 = \text{stochastic SS})$, the response of variable Z_t at quarterly horizon $t = 0, ..., 10$ when the shock is simulated from the stochastic steady state. The red dashed line displays $IRF(Z_t|s_0 = 90^{th}\text{ percentile})$, the response of variable Z_t at quarterly horizon $t = 0, ..., 10$ when the shock is simulated from the state corresponding to the 90^{th} percentile of the hiring rate distribution.

Because of price rigidities, a rise in the fiscal expenditure makes the shadow value of output ξ_t fluctuate. In particular, while the shadow value of output increases on impact following a fiscal shock simulated from a high hiring rate (90^{th} percentile of its distribution), it decreases when starting from the stochastic steady state.[30] The different response in the shadow value of output triggers a different behaviour of the marginal value of a job, as given by equation 1.29. Hiring costs are non-pecuniary and hiring is an activity that implies forgoing current production. Hence, the higher the value of output gets, the more costly it is to engage in hiring as this activity requires diverting some resources from production to recruiting and training. As a consequence, hires rise less when the fiscal expansion is simulated from the state corresponding to the 90^{th} percentile of the hiring rate distribution than from the stochastic steady state. Given that the separation rate is exogenous and constant, a lower increase in hires translates into a lower rise in employment.

Moving to output and its subcomponents, consumption and investment drop on im-

[30] As explained in Section 1.4.9, the shadow value of output can decrease following a fiscal expansion. This happens when the expected value of employment increases more than the real unit labor cost.

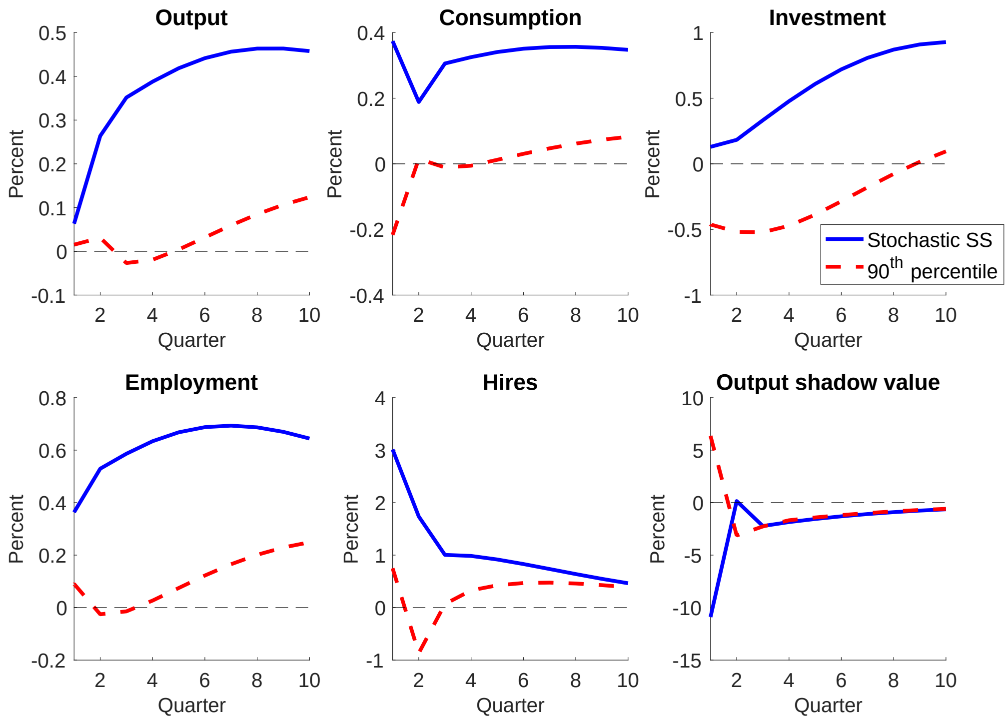


Figure 1.4 – **Impulse responses to a one-standard deviation positive government expenditure shock depending on the hiring rate**

Note: Responses are in deviation from their stochastic steady state. The figure shows responses to an expansionary fiscal shock simulated from two states: the stochastic steady state (solid blue line) and the state corresponding to the 90^{th} percentile of the hiring rate distribution (red dashed line).

pact following the fiscal shock simulated from the 90^{th} percentile of the hiring rate distribution. After the initial drop, they start rising again. To the contrary, both consumption and investment increase when the fiscal expansion is simulated starting from the stochastic steady state. Because of the combined effect of the fiscal expansion on employment, consumption, and investment, output increases more when the fiscal expansion is simulated from the stochastic steady state. Notice that these theoretical impulse responses are broadly in line with the empirical impulse responses computed through the local projections and displayed in Figure 1.2.

1.5 Asymmetries

Figure 1.5 shows a quadratic hiring cost function. The convexity of the function creates asymmetries in the strength of the friction. In particular, it shows that the hiring cost

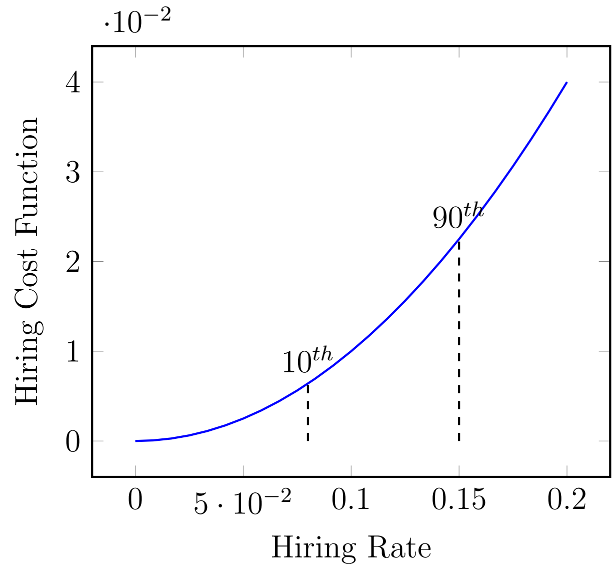


Figure 1.5 – **Hiring cost function**

Note: The figure shows that the hiring cost is increasingly bigger in the hiring rate. 10^{th} and 90^{th} indicate respectively the 10^{th} and 90^{th} percentiles of the hiring rate distribution.

is increasingly bigger in the hiring rate. This has at least two implications. First, a positive government spending shock carried out when the hiring rate is higher is less expansionary than when the hiring rate is lower because the hiring cost gets increasingly more significant.[31] Second, the effects of positive and negative spending shocks are more asymmetric when carried out from a higher hiring rate. These points are better illustrated by Figure 1.6 and Figure 1.7. They compare responses to a positive and negative spending shock of the same size carried out from the states corresponding to the 10^{th} and the 90^{th} percentile of the hiring rate distribution (for the sake of comparison, responses to a contractionary shock are multiplied by -1). When the positive and negative shocks are implemented from the 90^{th} percentile, the difference between the responses is more marked than when implemented from the 10^{th} percentile. This is

[31] As indicated by equation 1.29, the convexity of the hiring cost function is not the only reason why hiring costs are increasing in the hiring rate. Fluctuations in the output shadow value also play a key role in determining how hiring costs depend on the hiring rate.

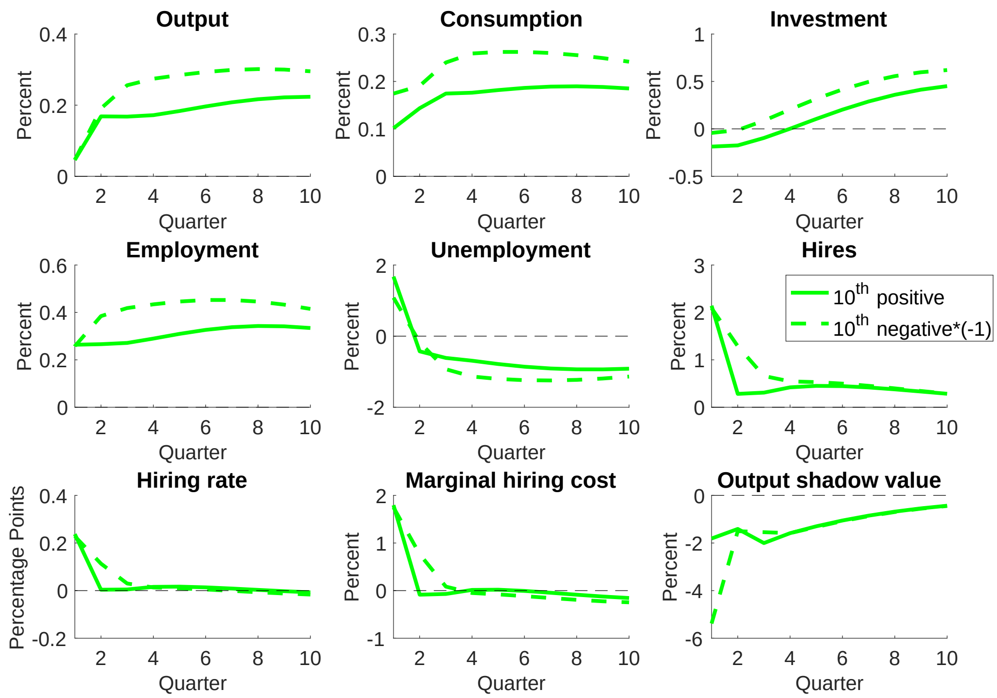


Figure 1.6 – **Impulse responses to a one-standard deviation positive and negative government expenditure shock:** 10^{th} **percentile**

Note: The figure compares impulse responses to a positive and negative fiscal shock of the same magnitude (one standard deviation) simulated from the state corresponding to the 10^{th} percentile of the hiring rate distribution. For the sake of comparison, impulse responses to a negative shock are multiplied by -1.

because at the 90^{th} percentile, the hiring friction is more severe: a positive shock is much less expansionary on output as the hiring friction gets increasingly bigger. Instead, at the 10^{th} percentile, the asymmetry between a positive and a negative shock is less severe as the convexity is milder.

The state dependence of responses is due to two features: the convexity of the hiring cost function and the behaviour of the output shadow value. Figure 1.6 and Figure 1.7 illustrate how much of the state dependence has to be imputed to the convexity of the hiring cost function. The remaining difference between the positive and the negative response is to be attributed to the state dependent dynamics of the output shadow value.

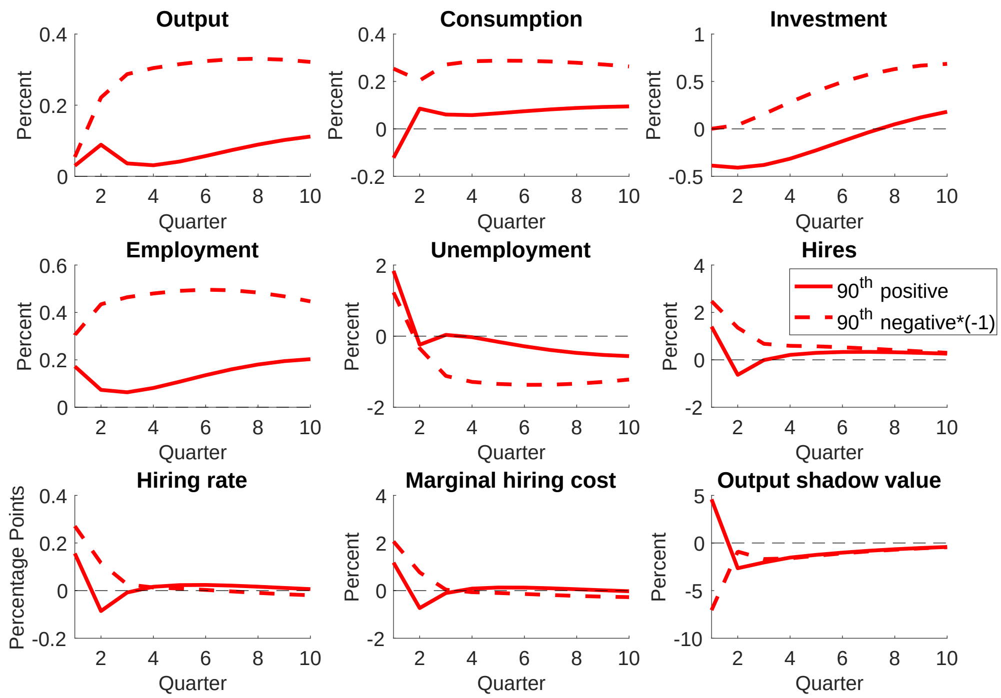


Figure 1.7 – **Impulse response functions to a positive and negative government expenditure shock:** 90^{th} **percentile**

Note: The figure compares impulse responses to a positive and negative fiscal shock of the same magnitude (one standard deviation) simulated from the state corresponding to the 90^{th} percentile of the hiring rate distribution. For the sake of comparison, impulse responses to a negative shock are multiplied by -1.

1.6 Allowing for Vacancy Costs

In Section 1.4.5 I have modelled hiring costs $\tilde{g}_{i,t}$ as dependent only on the hiring rate of firms. However, as highlighted in Section 1.3, the more traditional, though minor component of the hiring frictions is related to pre-match costs. In this Section, I allow the hiring costs to depend on the vacancy filling rate q_t. The latter is meant to capture the conditions of the aggregate labor market and be a proxy for the magnitude of the pre-match costs. The specification of this hiring cost function follows Sala et al. (2013), Faccini and Yashiv (2019), and Faccini and Melosi (2019):

$$\tilde{g}_{i,t} = \frac{e}{2} q_t^{-\eta} \left(\frac{H_{i,t}}{N_{i,t}} \right)^2 , \tag{1.33}$$

where $e > 0$ is a a scale parameter. With this specification, hiring costs depend on two factors: i) external conditions of the aggregate labor market as captured by the vacancy filling rate q_t; ii) firm-level conditions as captured by the hiring rate $H_{i,t}/N_{i,t}$, that is the ratio of new hires to the workforce of the firm. The parameter $\eta \in [0, 2]$ controls the relative share of external (pre-match) vs internal (post-match) costs of hiring. When $\eta = 0$, only internal costs are present, as in Section 1.4.5. When $\eta = 2$, because $H_{i,t} = q_t V_{i,t}$, the function simplifies to $\tilde{g}_{i,t} = \frac{e}{2} \left(\frac{V_{i,t}}{N_{i,t}} \right)^2$, thus capturing only vacancy posting costs. For every value $\eta \in (0, 2)$, both internal and external hiring costs are present. I calibrate the parameter η following Sala et al. (2013), who estimate a value of 0.49.

With this extended specification of hiring costs, I carry out a similar exercise to the one in Section 1.4.11. Yet, instead of using the hiring rate to identify the state of the labor market, I now use labor market tightness V_t/U_t. In particular, I simulate the fiscal shock starting from two different states: the stochastic steady state and the state in which labor market tightness is at its 90^{th} percentile. Figure 1.8 shows the responses to an expansionary fiscal shock starting from these two states. As can be observed comparing Figure 1.8 with Figure 1.4, state dependence is still present, but it is much milder. Output shadow value still increases more for the fiscal expansion simulated from a tight labor market, but the difference with the response from the stochastic steady state is much smaller than in the case of Figure 1.4. Hence, also the increase in hires is barely state dependent.

1.6.1 Denominating Hiring Costs in Pecuniary Terms

In line with micro evidence, the baseline model of Section 1.4 assumes that hiring frictions are denominated in units of forgone intermediate output. The standard DMP framework, though, denominates hiring frictions in units of the final good, which is the economy numeraire. To model hiring frictions in pecuniary terms, I would need to change the following equilibrium conditions: the intermediate good output, the resource constraint and the FOCs with respect to employment and hires. In particular, equations (1.20), (1.26), (1.28), and (1.29) would be substituted with conditions:

$$Y_{i,t} = f_{i,t} \tag{1.34}$$

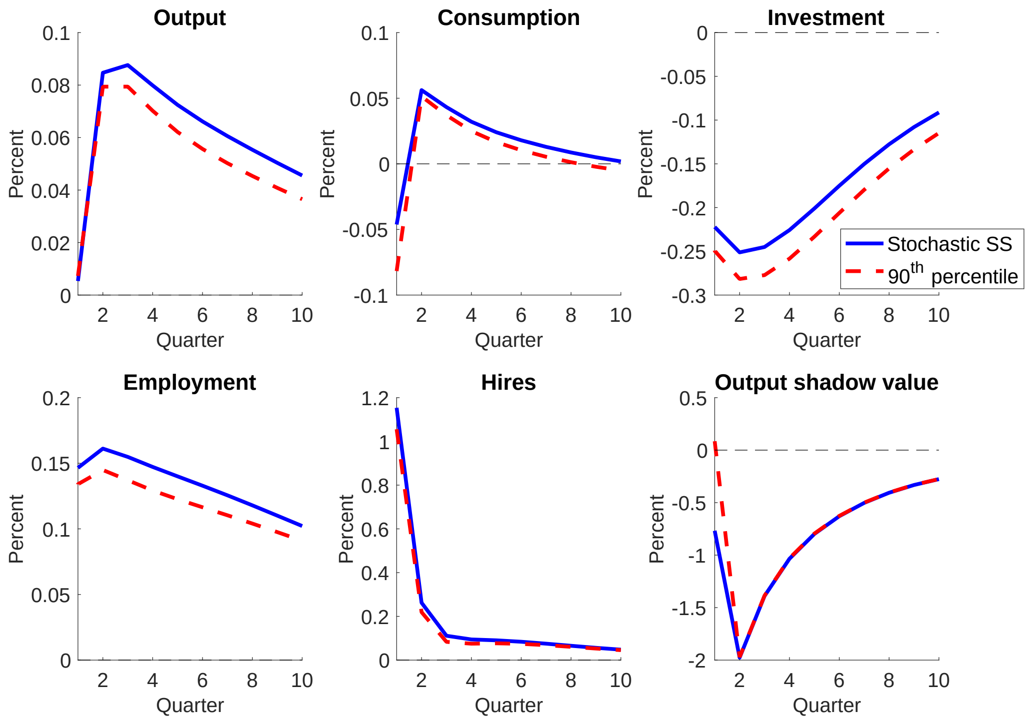


Figure 1.8 – **Responses to a one-standard deviation positive government expenditure shock depending on tightness**

Note: Responses are in deviation from their stochastic steady state. The figure shows responses to an expansionary fiscal shock simulated from two states: the stochastic steady state (solid blue line) and the state corresponding to the 90^{th} percentile of the tightness distribution (red dashed line). Both pre-match and post-match components are included in the hiring cost function.

$$\left[1 - \frac{\zeta}{2}\left(\frac{\Pi_t}{\bar{\Pi}} - 1\right)^2\right] Y_t = C_t + I_t + G_t + g_t, \tag{1.35}$$

$$\mathcal{Q}_t^N = \xi_t f_{N,t} - g_{N,t} - \frac{W_t}{P_t} + (1 - \delta_N) E_t \Lambda_{t,t+1} \mathcal{Q}_{t+1}^N, \tag{1.36}$$

$$Q_t^N = g_{H,t}. \tag{1.37}$$

As shown by equation (1.34), hiring costs are no longer deducted from the intermediate good output. Instead, being denominated in units of final rather than intermediate good, they enter the resource constraint (1.35). Equation (1.37) shows that the hiring decision does no longer depend on the shadow value of output ξ_t, but only on the marginal hiring cost $g_{H,t}$. Nonetheless, because of the convexity in the hiring cost, higher hiring rates still result in more significant hiring costs.

On a side, as already noticed by Faccini and Yashiv (2019), this model with pecuniary hiring costs is prone to indeterminacy when hiring and price frictions are high. The main reason behind this lies in the fact that both the price adjustment cost and the hiring cost enter the resource constraint. An increase in demand following an expansionary fiscal shock pushes firms to increase hires. As hiring costs add to the resource constraint, this further stimulates aggregate demand triggering self-fulfilling expectations of higher demand.

1.7 Conclusion

This paper has conjectured that fiscal policy transmission is dependent on labor market slackness. It has then shown that while no evidence of state dependence is found when using aggregate measures of labor market slackness, a stark state dependence is associated to the hiring rate of firms. In particular, it has brought reduced-form evidence that fiscal expansions are less effective when the hiring rate is higher. It has developed a theory to explain this empirical evidence. It has built a general equilibrium model with hiring frictions to study the propagation of expansionary fiscal shocks for different levels of the hiring rate. Hiring frictions have been modelled as training costs that are disruptive of firms' production. Hiring entails a temporary loss of firm-level production efficiency, as internal resources are temporarily diverted from production to recruiting and training the new hires. If a fiscal stimulus takes place when the hiring rate is already high, firms' ability to further expand hiring is limited, and their response to the increased aggregate demand is weaker. Due to this mechanism, the model is able to replicate the asymmetries obtained with the empirical estimation of impulse responses. In particular, the responses of output, consumption, and investment to an expansionary fiscal shock are weaker if implemented when the hiring rate of firms is higher. This result suggests that governments should time their fiscal expansions by taking the hiring rate of firms into consideration.

In this paper I have studied how hiring frictions affect the propagation of fiscal shocks. The initial trigger for the model dynamics is a rise in aggregate demand generated by an expansion in wasteful government purchases. This increase in aggregate demand could be generated by other types of shocks such as a monetary expansion. I leave the exploration of how the level of hiring frictions affects the propagation of other demand shocks to future studies.

Appendix 1.A Additional Figures

Figure 1.9 shows the distribution of forecast errors from Auerbach and Gorodnichenko (2012). Forecast errors are computed as the difference between the professional forecast made at time $t-1$ for government spending growth at t and the actual, first-release government spending growth rate at time t. Auerbach and Gorodnichenko (2012) splice the Greenbook forecasts, prepared by the Federal Reserve Board for the Federal Open Market Committee meetings and available from 1966 to 1981, and the forecast done by the Survey of Professional Forecasters (SPF), which is available from 1982 onwards. Forecast errors have both negative and positive sign, with mean -0.15, standard deviation 4.46, and skewness 0.42. I use this series as my identified unanticipated fiscal shocks.

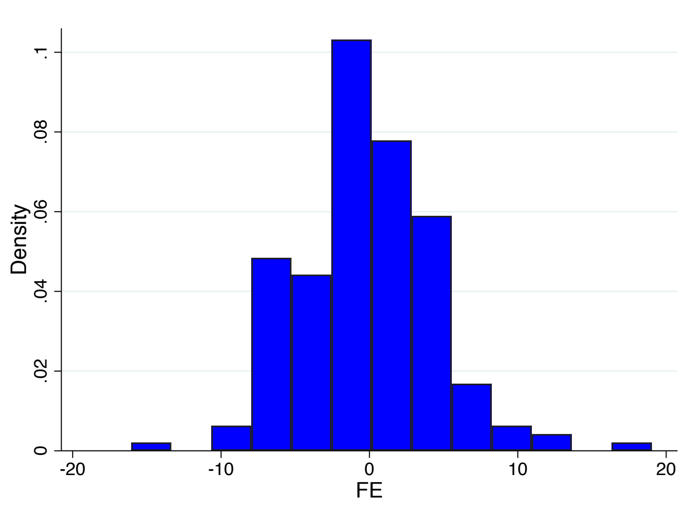


Figure 1.9 – **Distribution of the forecast errors of government spending growth**

Note: Forecast errors are computed by Auerbach and Gorodnichenko (2012) as the difference between the realised and the forecasted growth rate of government purchases (consumption and investment) at quarterly frequency. They are both negative and positive, with mean -0.15, standard deviation 4.46, and skewness 0.42.

Appendix 1.B Robustness Checks for the Local Projection

This Appendix shows additional robustness checks for the local projection. Appendix 1.B.1 reports impulse response functions to a positive fiscal shock (identified as the quarterly forecast error of government purchases growth) in the linear specification. Appendix 1.B.2 displays impulse response functions for the state dependence specification where alternative series to tightness are used to capture the aggregate labor market condition. Appendix 1.B.3 exhibits robustness checks concerning the specification of the local projection and the detrending method used for the hiring rate series. Appendix 1.B.4 reports robustness where the CPS hiring rate series is substituted with an extended version of the hiring rate series from JOLTS.

1.B.1 Linear Local Projection

This Appendix reports impulse response functions to a positive fiscal shock in the linear local projection. The five-year cumulative multiplier is 1.44, with SE=0.401.

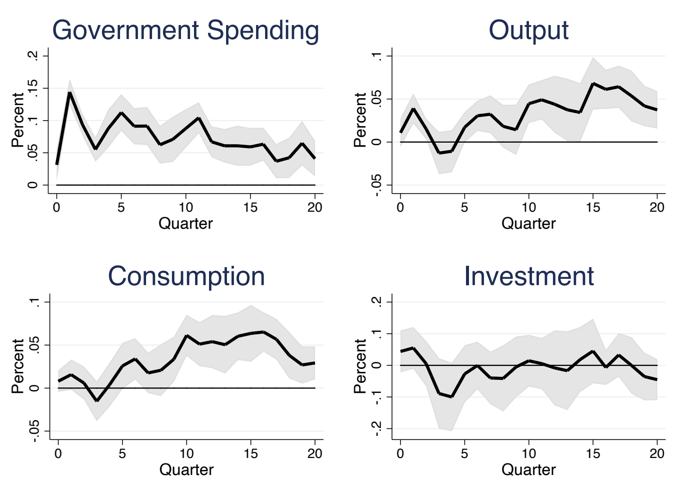


Figure 1.10 – **Empirical responses to a positive government expenditure shock: linear case**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors.

1.B.2 Robustness Checks for Tightness

This Appendix reports impulse response functions to a positive fiscal shock where alternative measures to tightness are used to identify the aggregate labor market state. Figure 1.11 shows state dependent responses where the labor market state is defined as tight if the unemployment rate is below the NAIRU and slack otherwise. In Figure 1.12 the labor market state is identified by using an HP filter trend as a threshold for the unemployment rate. Namely, labor market is defined as tight when the unemployment rate is above trend and slack otherwise. In both Figures, the state dependent impulse responses are not statistically different from each other, showing that expansionary fiscal policy is not dependent on the state of the aggregate labor market.

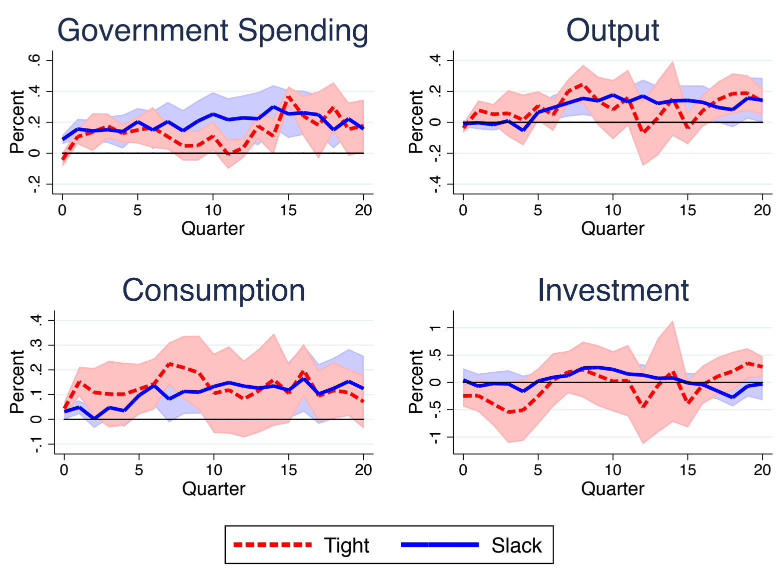


Figure 1.11 – **Empirical responses to a positive government expenditure shock using NAIRU as threshold**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of tight (unemployment rate below NAIRU) and slack (unemployment rate above NAIRU) labor market.

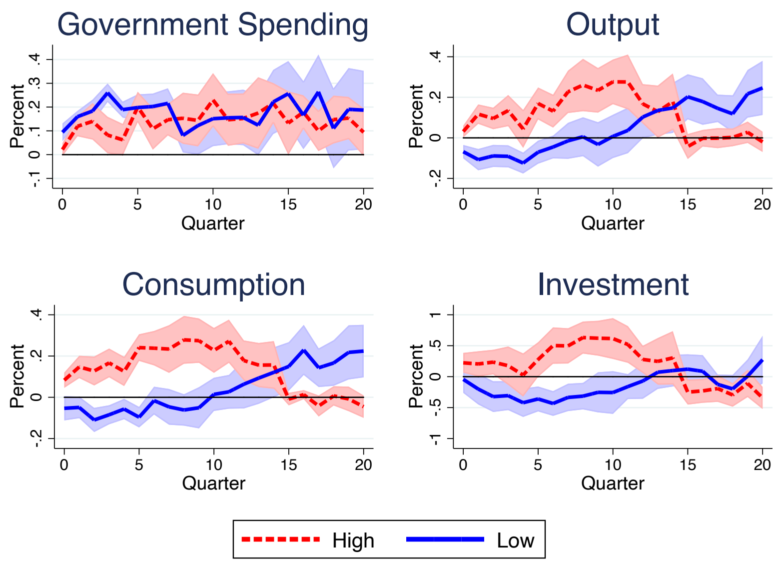


Figure 1.12 – **Empirical responses to a positive government expenditure shock using HP-filtered unemployment as threshold**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of tight (unemployment rate below trend) and slack (unemployment rate above trend) labor market. The unemployment rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 10000.

1.B.3 Robustness Checks for the CPS Hiring Rate

This Appendix shows the robustness checks for the state dependent local projection when the CPS hiring rate series is used to identify the state of the labor market. The first set of robustness checks concerns the specification of the regression model. Figure 1.13, Figure 1.14, and Figure 1.15 display the impulse responses where the following changes are made to the specification of the local projection: no time trend, two lags, and taxes and log employment as control variables in place of unemployment rate and debt-to-GDP. Results are robust to these changes.

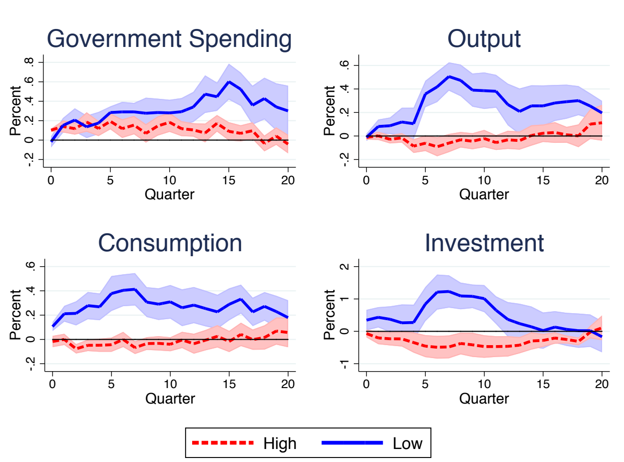


Figure 1.13 – **Empirical responses to a positive government expenditure shock: no trend included**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 10000. No trend is included in the local projection.

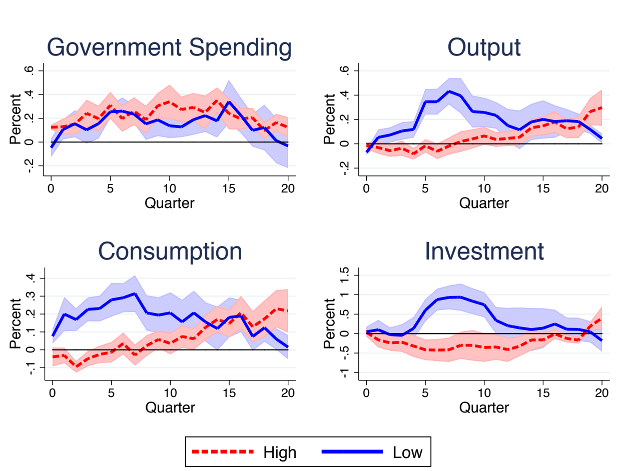


Figure 1.14 – **Empirical responses to a positive government expenditure shock: two lags included**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 10000. Two lags are included for the control variables in the local projection.

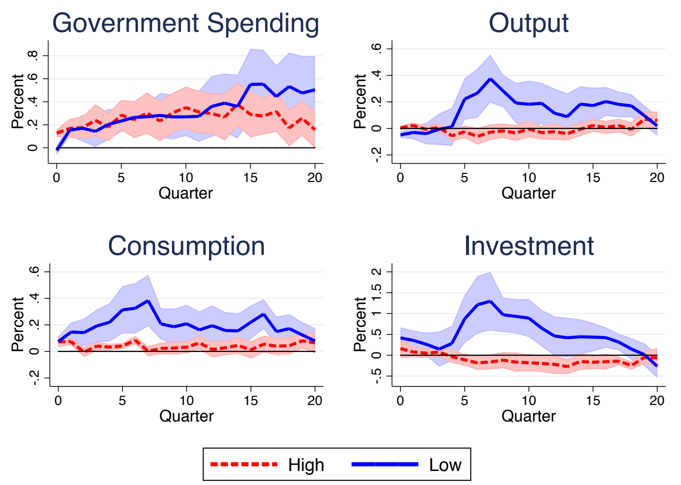


Figure 1.15 – **Empirical responses to a positive government expenditure shock: taxes and logged employment as controls**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 10000. Taxes and logged employment are included as controls in place of debt-to-gdp and unemployment rate.

The second set of robustness checks concerns the detrending method, as the state dependence may indeed be affected by the way the hiring rate series is filtered. Figure 1.16 and Figure 1.17 show the impulse responses for the case in which the smoothing parameter of the HP filter is lower (5000) or higher (16000) than the one in the baseline regression (10000). Figure 1.18 displays responses to a state dependent local projection where the threshold to identify the labor market state is defined by fitting a polynomial trend of degree four to the hiring rate series. Figure 1.19 shows responses when the threshold is defined by a moving average with fifteen lags and fifteen leads. Results still hold to these variations.

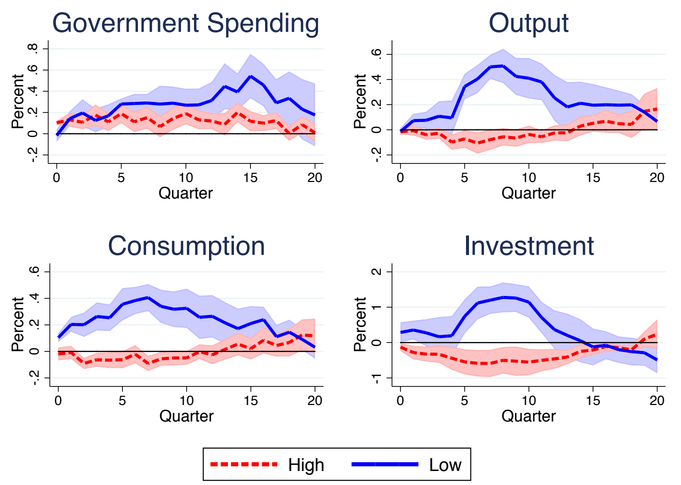


Figure 1.16 – **Empirical responses to a positive government expenditure shock: different HP smoothing parameter (5000)**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 5000.

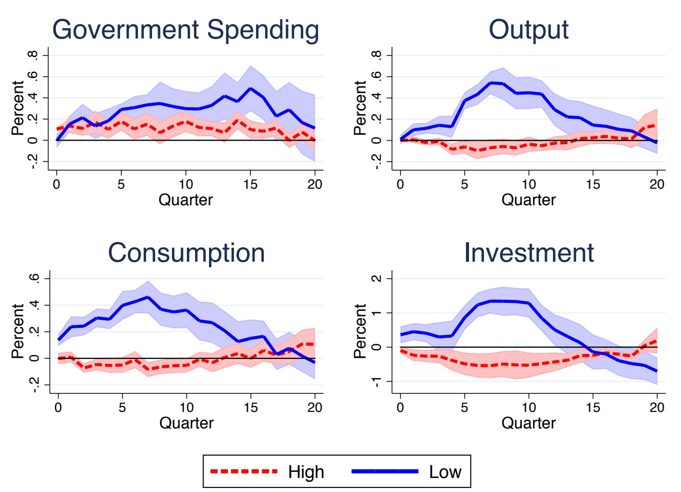


Figure 1.17 – **Empirical responses to a positive government expenditure shock: different HP smoothing parameter (16000)**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 16000.

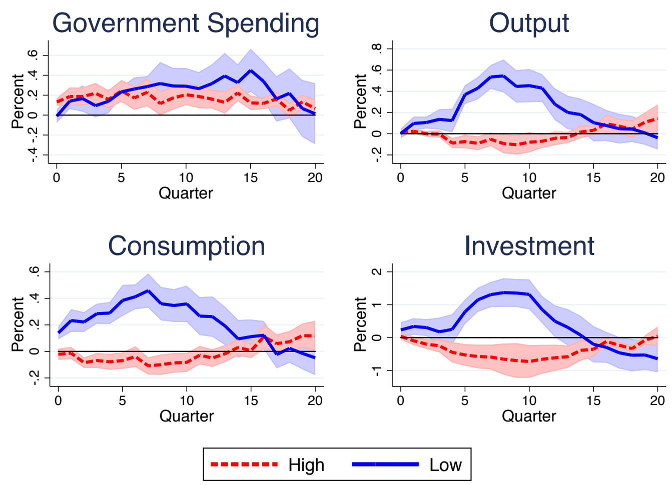


Figure 1.18 – **Empirical responses to a positive government expenditure shock: polynomial detrending**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by fitting a polynomial of degree four.

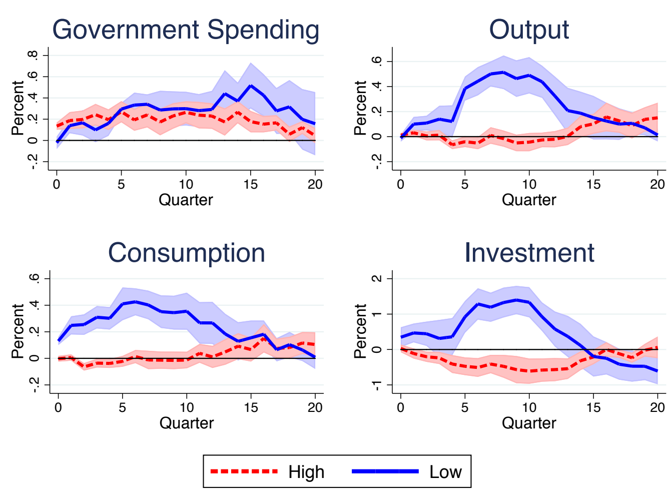


Figure 1.19 – **Empirical responses to a positive government expenditure shock: MA detrending**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by using a moving average with 15 leads and 15 lags.

Table 1.3 displays the cumulative multipliers corresponding to all the different specifications mentioned above. Results are in line with the cumulative multipliers in the baseline local projection.

Table 1.3 – **Cumulative multipliers for a positive shock: robustness I**

Robustness	Horizon	High	Low	p-value
no trend	5Y	-0.81	3.58	0.005
		(0.59)	(0.31)	
two lags	5Y	1.47	3.11	0.092
		(0.28)	(0.34)	
smoothing parameter = 5000	5Y	-1.12	3.68	0.002
		(0.57)	(0.37)	
smoothing parameter = 16000	5Y	-1.09	3.67	0.000
		(0.53)	(0.32)	
controls: log empl and taxes	5Y	-1.04	3.97	0.001
		(0.51)	(0.43)	
polynomial trend	5Y	-0.69	3.72	0.000
		(0.46)	(0.34)	
MA(15,1,15)	5Y	0.63	3.85	0.013
		(0.40)	(0.33)	

Note: The table shows fiscal multipliers computed with an instrumental variable-local projection approach. Columns 'High' and 'Low' report the expansionary cumulative multipliers when the hiring rate is above and below trend respectively.

1.B.4 Robustness Checks Using the Fitted Series From Davis et al. (2012)

Figure 1.20 shows the hiring rate series from Davis et al. (2012) as well as the fitted hiring rate computed as described in Section 1.2.5. The regression has an $R^2 = 0.93$.

I now use the fitted hiring rate series to define my labor market state. To make sure that results are robust to various filtering methods, I use different filters to detrend the series: Hodrick-Prescott, Butterworth, and Christiano and Fitzgerard filter.

Using the fitted hiring rate series, I rerun equation (1.2) and equation (1.4). Figure 1.21, Figure 1.22, and Figure 1.23 show the responses using the different filters to detrend the hiring rate series. Table 1.4 displays the corresponding cumulative multipliers to expansionary shocks. Responses are still state dependent, even though the state dependence is not always as stark as when using the CPS series. The reason could be that while the CPS series only contains hires from non-employment, the hiring rate series from Davis et al. (2012) includes hires both from non-employment and from employment. This may weaken the strength of the hiring rate friction – a new hire coming from employment may be faster at reaching the productivity of the other workers than a new hire coming from unemployment or inactivity.

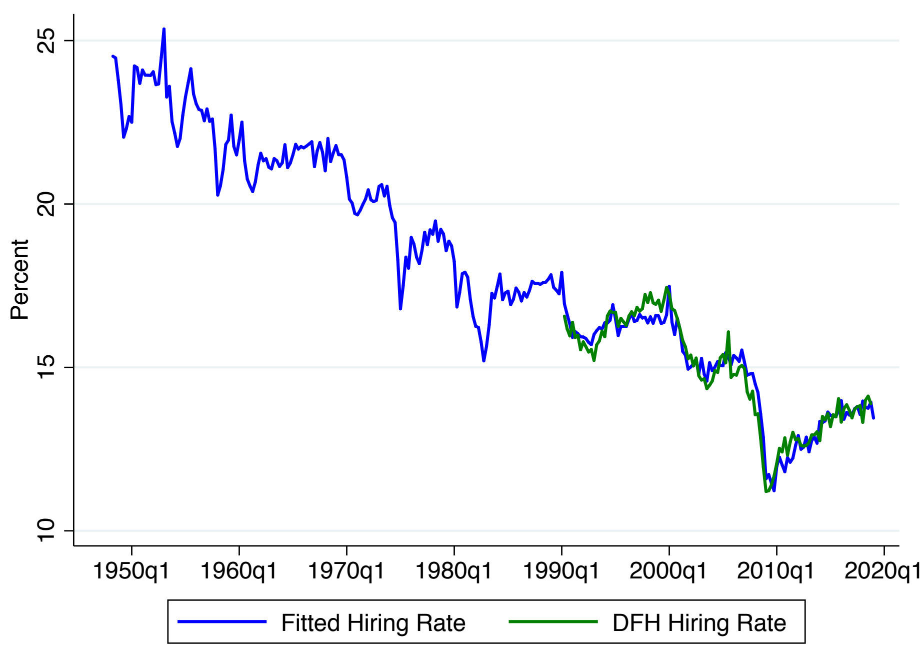


Figure 1.20 – **Fitted hiring rate and hiring rate from Davis et al. (2012)**
Note: The fitted values are obtained by estimating the following regression: $\frac{H_t}{N_t} = \beta_0 + \beta_1 u_t + \beta_2 \Delta \log N_t + \beta_3 t + \epsilon_t$, where u_t is the unemployment rate, N_t the employment and t is a time trend. $R^2 = 0.93$.

Hodrick-Prescott Filter

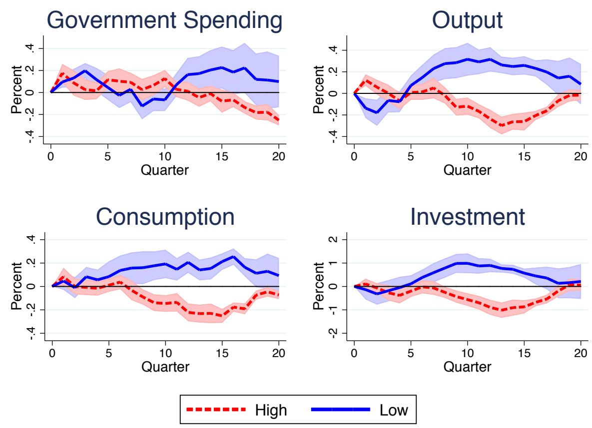


Figure 1.21 – **Empirical responses to a positive government expenditure shock: HP-filtered fitted series**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The hiring rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 5000. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate.

Butterworth filter

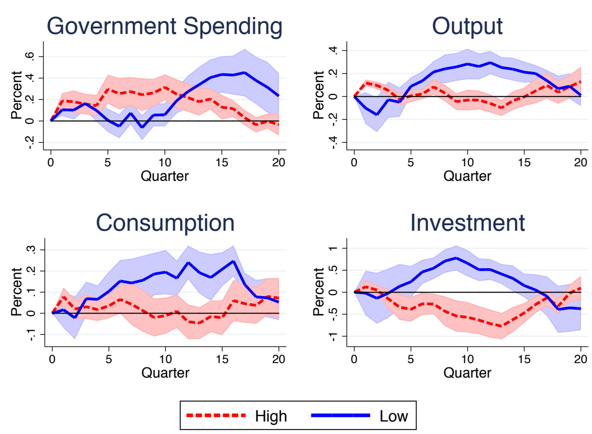


Figure 1.22 – **Empirical responses to a positive government expenditure shock: Butterworth-filtered fitted series**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The hiring rate series is detrended by using a Butterworth filter of order 1 with maximum period 32. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate.

Christiano and Fitzgerard filter

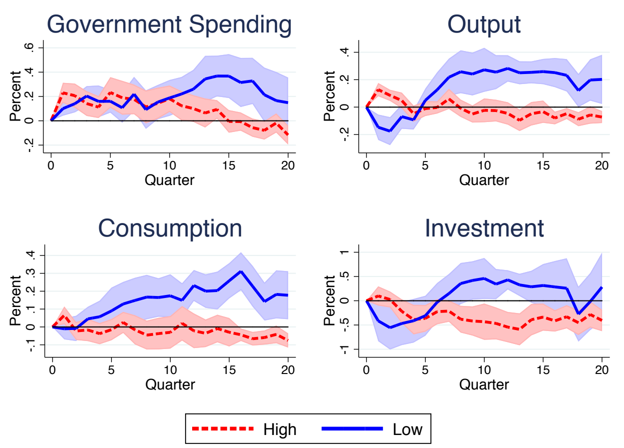


Figure 1.23 – **Empirical responses to a positive government expenditure shock: Christiano-Fitzgerard-filtered fitted series**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The hiring rate series is detrended by using a Christiano and Fitzgerard filter with minumum number of periods 2 and maximum 32. The figure compares impulse responses to a positive fiscal shock in the two states of high (above trend) and low (below trend) hiring rate.

Table 1.4 – **Cumulative multipliers for a positive shock: robustness II**

Robustness	Horizon	High	Low	p-value
Hodrick-Prescott filter	5Y	-1.52	3.30	0.036
		(0.91)	(0.55)	
Butterworth filter	5Y	-0.51	3.72	0.075
		(0.66)	(0.64)	
Christiano-Fitzgerard filter	5Y	-3.31	2.57	0.111
		(1.42)	(0.38)	

Note: The table shows fiscal multipliers computed with an instrumental variable-local projection approach. Columns 'High' and 'Low' report the expansionary cumulative multipliers when the hiring rate is above and below trend respectively.

1.B.5 Measures of Recessions vs Expansions

This Appendix shows that identifying the state of the labor market according to the hiring rate is different from using measures of business cycles that have been used in the literature. In particular, Figure 1.24 shows responses to a positive fiscal shock where the economy is defined to be in an expansion or a recession according the NBER timing of recession. Responses in the two states of expansion and recession are not statistically different from each other.

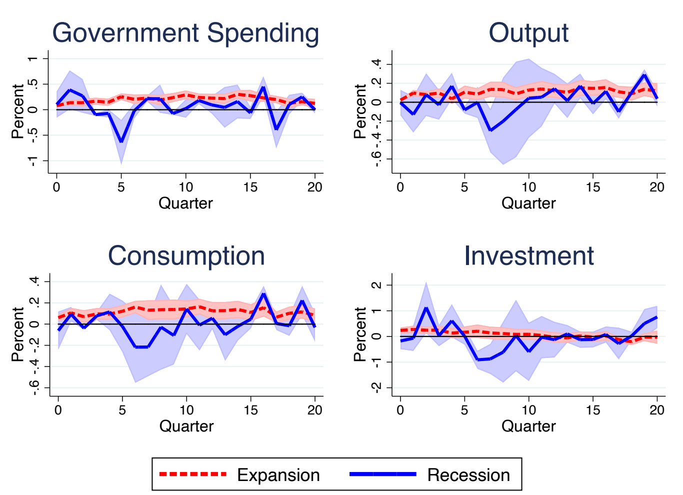


Figure 1.24 – **Empirical responses to a positive government expenditure shock: NBER recessions**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. Recessionary periods (blue solid line) correspond to NBER recessions.

Figure 1.25 displays responses where the state of the economy follows the definition of Auerbach and Gorodnichenko (2012). Accordingly, the state of the economy is defined with a smooth transition threshold based on a seven-quarter moving average of output growth, s_t. The transition function used is $F(s_t) = \frac{exp(-\gamma s_t)}{1+exp(-\gamma s_t)}$, where the parameter γ is calibrated by Auerbach and Gorodnichenko (2012) to 1.5 implying that the economy spends one fifth of of time in a recessionary period. Responses in the two states look different. However, both government purchases and output follow a similar pattern, being much more reactive and persistent in the recessionary period. When I compute the five-year cumulative spending multipliers I find that the two states are not statistically different from each other. This is shown by Table 1.5.

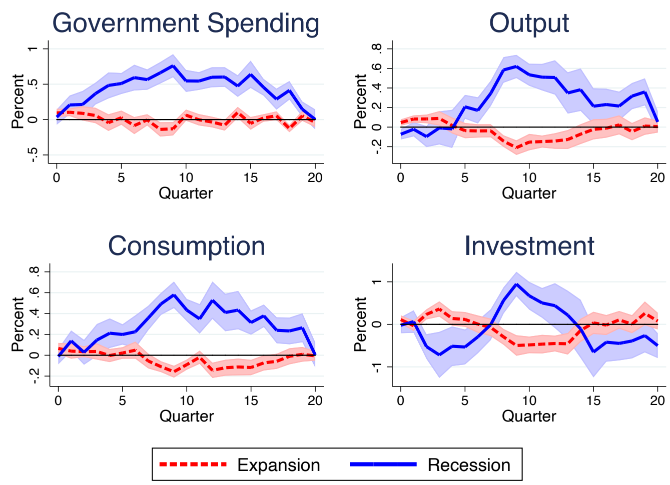


Figure 1.25 – **Empirical responses to a positive government expenditure shock: AG recessions**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. Recessionary (blue solid line) and expansionary (red dashed line) periods are defined according to smoothing transition of Auerbach and Gorodnichenko (2012).

Table 1.5 – **Cumulative multipliers for a positive shock: robustness III**

State Variable	Horizon	Tight	Slack	p-value
AG (2012) state	5Y	2.31	3.50	0.378
		(0.64)	(0.42)	

Note: Newey-West standard errors in parenthesis. 'p-value' indicates the p-value for the test that the multiplier estimates are different across states. It is based on heteroscedastic- and autocorrelation-consistent standard errors.

Table 1.6 reports the correlations between different measures of tightness. The Table highlights that periods in which the labor market is slack are not equivalent to the recessionary periods as measured by the NBER recessions or the Auerbach and Gorodnichenko (2012) business cycle measure. In particular, while the latter two measures are positively and highly correlated with each other (0.57), their correlations with the measures of labor market slackness in very low.

Table 1.6 – **Correlation between different measures of state in the local projection**

State	Hiring Rate	Tightness	Un. Rate (trend)	Un. Rate (NAIRU)	NBER rec.	AG (2012)
Hiring Rate	1					
Tightness	-0.26	1				
Un. Rate (trend)	-0.38	0.86	1			
Un. Rate (NAIRU)	-0.30	0.64	0.59	1		
NBER recessions	0.14	0.24	0.12	0.24	1	
AG (2012)	0.14	0.11	0.01	0.06	0.57	1

Note: For ‘Hiring Rate’ and ‘Tightness’ the state is defined as tight when they are above their trend, and slack otherwise. For ‘Un. Rate (trend)’ and ‘Un. Rate (NAIRU)’, the state is defined as tight when they are below trend or below the NAIRU respectively, and slack otherwise. For ‘NBER recessions’, the state is defined as slack when there is an NBER recession and tight otherwise. ‘AG (2012)’ indicate the case in which the state is defined according to the smooth transition threshold of Auerbach and Gorodnichenko (2012).

Appendix 1.C Responses to a Contractionary Shock

Figure 1.26 and Figure 1.27 display the impulse response functions of government spending, output, consumption and investment to a negative fiscal shock when respectively the hiring rate and the tightness are below (blue solid line) or above (red dashed line) trend. They correspond to the series of coefficients $\beta_{NS,h}$ and $\beta_{NT,h}$ for $h = 1, ..., 20$ in equation (1.2). The state dependence of the responses is not marked, especially in the case of labor market tightness.

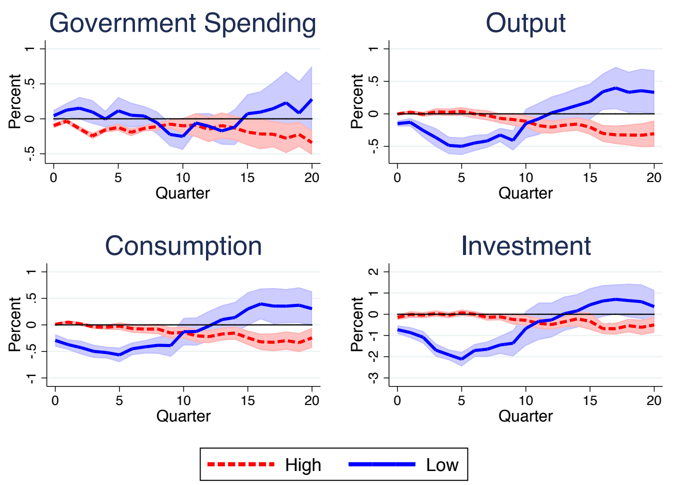


Figure 1.26 – **Empirical responses to a negative government expenditure shock depending on the hiring rate**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a negative fiscal shock in the two states of high (above trend) and low (below trend) hiring rate. The hiring rate series is detrended by using a Hodrick-Prescott filter with smoothing parameter 10000.

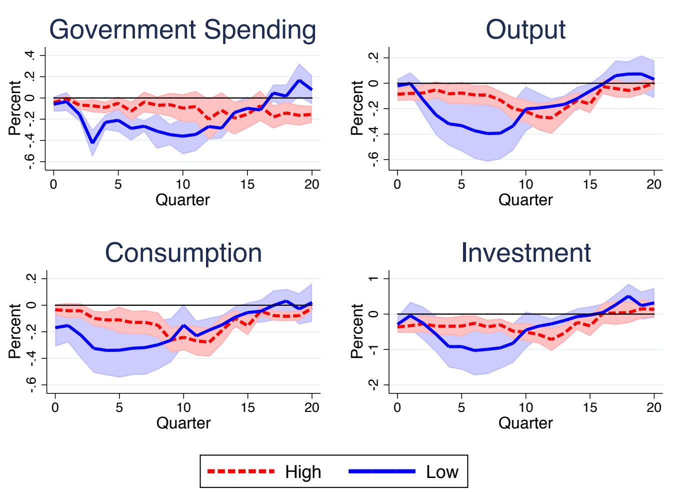


Figure 1.27 – **Empirical responses to a negative government expenditure shock depending on tightness**

Note: Impulse responses are estimated by local projection. Shaded areas are the 68% confidence intervals calculated using Newey-West standard errors. The figure compares impulse responses to a negative fiscal shock in the two states of high (above trend) and low (below trend) tightness. Tightness is detrended by using a Hodrick-Prescott filter with smoothing parameter 10000.

Appendix 1.D Model Equilibrium Conditions

This Appendix reports the Lagrangian for the household's and for intermediate firms' maximisation problem, as well as the model equilibrium conditions.

1.D.1 Household's problem

$$\max_{\{C_t,L_t,U_t,N_t,K_t,I_t,B_{t+1}\}} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \Bigg\{ \frac{\left[\eta_t^p C_t - \frac{\chi}{1+\phi} L^{1+\phi}\right]^{1-\sigma}}{1-\sigma}$$
$$+ \Phi_t \left[N_t + U_t - L_t\right]$$
$$- \lambda_t P_t \mathcal{V}_t \left[N_t - (1-\delta_N) N_{t-1} - H_t\right]$$
$$- \lambda_t \left[P_t C_t + P_t I_t + \frac{B_{t+1}}{R_t} - R_t^K K_{t-1} - W_t N_t - B_t - \Theta_t + T_t\right]$$
$$- \lambda_t Q_t^K P_t \left[K_t - (1-\delta_K) K_{t-1} - \eta_t^I \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t\right] \Bigg\}$$

1.D.2 Intermediate firms' problem

$$\max_{\{P_{i,t} H_{i,t}, N_{i,t}, K_{i,t}\}} \mathbb{E}_t \sum_{t=0}^{\infty} \Lambda_{t,t+1} \Bigg\{ \frac{P_{i,t}}{P_t} \left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon} Y_t - \frac{W_t}{P_t} N_{i,t} - \frac{R_t^k}{P_t} K_{i,t} - \frac{\zeta}{2} \left(\frac{P_{i,t}}{P_{i,t-1}\bar{\Pi}} - 1\right)^2 Y_t$$
$$- Q_t^N \left[N_t - (1-\delta_N) N_{t-1} - H_t\right]$$
$$+ \xi_t \left[f(K_{i,t}, N_{i,t}) - g_{i,t}(H_{i,t}, K_{i,t}, N_{i,t}) - \left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon} Y_t\right] \Bigg\}$$

1.D.3 First order conditions

Households

$$[C] \qquad \left[\eta_t^p C_t - \frac{\chi}{1+\phi} L_t^{1+\phi}\right]^{-\sigma} \eta_t^p = \lambda_t P_t \tag{1.1}$$

$$[L] \qquad \left[\eta_t^p C_t - \frac{\chi}{1+\phi} L^{1+\phi}\right]^{-\sigma} (-\chi L_t^{\phi}) = \Phi_t \tag{1.2}$$

$$[U] \qquad \Phi_t = -\frac{1}{\bar{\omega}} \lambda_t P_t \mathcal{V}_t \frac{x_t}{1-x_t} \tag{1.3}$$

$$[N] \qquad \mathcal{V}_t = \frac{\Phi_t}{\lambda_t P_t} + \frac{W_t}{P_t} + E_t \Lambda_{t,t+1} \mathcal{V}_{t+1}(1-\delta_N) \tag{1.4}$$

$$[K] \qquad Q_t^K = E_t \Lambda_{t,t+1} \left[\frac{R_{t+1}^K}{P_{t+1}} + (1-\delta_K) Q_{t+1}^K \right] \tag{1.5}$$

$$[I] \qquad Q_t^K = \frac{1 - E_t \Lambda_{t,t+1} Q_{t+1}^K \eta_{t+1}^I S'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2}{\eta_t^I \left[1 - S\left(\frac{I_t}{I_{t-1}}\right) - S'\left(\frac{I_t}{I_{t-1}}\right)\left(\frac{I_t}{I_{t-1}}\right)\right]} \tag{1.6}$$

$$[B] \qquad \frac{1}{R_t} = \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \tag{1.7}$$

Firms

$$[K] \qquad \frac{R_t^K}{P_t} = \xi_t (f_{K,t} - g_{K,t}) \tag{1.8}$$

$$[H] \qquad Q_t^N = \xi_t g_{H,t} \tag{1.9}$$

$$[N] \qquad Q_t^N = \xi_t (f_{N,t} - g_{N,t}) - \frac{W_t}{P_t} + (1-\delta_N) E_t \Lambda_{t,t+1} Q_{t+1}^N \tag{1.10}$$

$$\left(\frac{\Pi_t}{\bar{\Pi}} - 1\right)\left(\frac{\Pi_t}{\bar{\Pi}}\right) = \frac{1}{\zeta}(1-\epsilon) + \xi_t \frac{\epsilon}{\zeta} + E_t \Lambda_{t,t+1} \left(\frac{\Pi_{t+1}}{\bar{\Pi}} - 1\right) \frac{Y_{t+1}}{Y_t} \left(\frac{\Pi_{t+1}}{\bar{\Pi}}\right) \tag{1.11}$$

Wage

$$\frac{W_t}{P_t}^{NASH} = \gamma \xi_t \left[f_{N,t} - g_{N,t} \right] - (1-\gamma) \left[\frac{\Phi_t}{\lambda_t P_t} \right] \tag{1.12}$$

$$\frac{W_t}{P_t} = \left(\frac{W_{t-1}}{P_{t-1}}\right)^{\omega} \left(\frac{W_t}{P_t}^{NASH}\right)^{1-\omega} \tag{1.13}$$

Output and hiring cost functions

$$Y_t = f_t - g_t \tag{1.14}$$

$$f_t = (A_t N_t)^{\alpha} K_{t-1}^{1-\alpha} \tag{1.15}$$

$$g_t = \frac{e}{2} q_t^{-\eta} \left(\frac{H_t}{N_t}\right)^2 f_t \tag{1.16}$$

$$f_{N,t} = \alpha \frac{f_t}{N_t} \tag{1.17}$$

$$f_{K,t} = (1-\alpha)\frac{f_t}{K_{t-1}} \tag{1.18}$$

$$g_{H,t} = e q_t^{-\eta} \frac{H_t}{N_t^2} f_t \tag{1.19}$$

$$g_{K,t} = (1-\alpha)\frac{g_t}{K_{t-1}} \tag{1.20}$$

$$g_{N,t} = (\alpha - 2)\frac{e}{2} q_t^{-\eta} {H_t}^2 A_t^{\alpha} K_{t-1}^{1-\alpha} N_t^{\alpha-3} \tag{1.21}$$

Resource constraint

$$\left[1 - \frac{\zeta}{2}\left(\frac{\Pi_t}{\bar{\Pi}} - 1\right)^2\right] Y_t = C_t + I_t + G_t, \tag{1.22}$$

Taylor rule

$$\frac{R_t}{R^*} = \left(\frac{R_{t-1}}{R^*}\right)^{\rho_R} \left[\left(\frac{\Pi_t}{\Pi^*}\right)^{r_\pi} \left(\frac{\tilde{Y}_t}{Y^*}^{r_y}\right)\right]^{1-\rho_R} \eta_t^R \tag{1.23}$$

Capital law of motion

$$K_t = (1-\delta_K)K_{t-1} + \eta_t^I \left[1 - \frac{\phi}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right] I_t \tag{1.24}$$

Government purchases

$$\ln G_t = (1-\rho_G)\ln \bar{G} + \rho_G G_{t-1} + \epsilon_{G,t}, \tag{1.25}$$

Labor force

$$L = N + U \tag{1.26}$$

Employment law of motion

$$N_t = (1-\delta_N)N_{t-1} + H_t \tag{1.27}$$

Hires

$$H_t = x_t \frac{U_t}{1-x_t} \tag{1.28}$$

Vacancy filling rate

$$q_t = m \left(\frac{x_t}{m}\right)^{-\frac{l}{1-l}} \tag{1.29}$$

Stochastic discount factor

$$\Lambda_{t,t+1} = \beta E_t \frac{\lambda_{t+1} P_{t+1}}{\lambda_t P_t} \tag{1.30}$$

2 Macro Uncertainty and Unemployment Risk

Joint with Joonseok Jason Oh

Abstract

This chapter shows how uninsurable unemployment risk is crucial to qualitatively and quantitatively match macro responses to uncertainty shocks. Empirically, uncertainty shocks i) generate deflationary pressure; ii) have considerably negative consequences on economic activity; iii) produce a drop in aggregate consumption, which is mainly driven by the response of the households in the bottom 60% of the income distribution. Standard representative-agent New Keynesian models have difficulty to deliver these effects. A heterogeneous-agent framework with search and matching frictions and Calvo pricing allows us to jointly attain these results. Uncertainty shocks induce households' precautionary saving and firms' precautionary pricing behaviors, triggering a fall in aggregate demand and supply. These precautionary behaviors increase the unemployment risk of the imperfectly insured households, who strengthen precautionary saving. When the feedback loop between unemployment risk and precautionary saving is strong enough, a rise in uncertainty leads to i) a drop in inflation; ii) amplified negative responses of macro variables; iii) heterogeneous consumption responses of households, which are consistent with the empirical evidence.

2.1 Introduction

The Great Recession has sparked a wide debate on the impact of uncertainty on the macroeconomy. After the seminal paper of Bloom (2009), close attention has been devoted to study the consequences of uncertainty shocks over the business cycle. An increase in uncertainty has been empirically shown to cause a contraction of output and its subcomponents, as well as a drop in inflation, and an increase in unemployment.[1] Yet, the theoretical literature has found it challenging to generate a significant drop in output and its subcomponents in response to a rise in uncertainty.[2] In addition, it has not been successful in robustly explaining why inflation drops.[3] This paper shows how households' uninsurable unemployment risk is crucial to qualitatively and quantitatively match the drop in aggregate output and inflation generated by a positive uncertainty shock.

To corroborate the already existing empirical evidence on the propagation of macro uncertainty shocks, we estimate a vector autoregression (VAR) of macro variables, labor market variables, and the macro uncertainty index of Jurado et al. (2015). We use a recursive identification where macro uncertainty is ordered first. We show that a rise in macro uncertainty leads to a drop in output, the job finding rate, consumption, and inflation, and an increase in the unemployment rate and the separation rate. To gain a deeper understanding of what drives the aggregate macro responses, we then estimate a VAR by using consumption and income micro data from the Consumer Expenditure Surveys (CEX). This allows us to study the heterogeneous response of consumption across households' income distribution. We show that the response of aggregate consumption is driven by the response of households belonging to the bottom 60% of the income distribution. Instead, the consumption response of households in the top 40% of the income distribution is not significant.

To rationalize these empirical findings, we propose a theoretical mechanism whereby an increase in macro uncertainty results in a drop in inflation and generates responses of output, consumption, unemployment rate, job finding rate, and separation rate, which are quantitatively, as well as qualitatively in line with the empirical evidence.

[1] Following the macro literature, we use the word 'uncertainty' to refer to 'objective uncertainty' or 'risk', in which the probabilities are well understood by all agents. There could be an alternative source of uncertainty, that is ambiguity, in which the probabilities are not well understood.

[2] See Born and Pfeifer (2014), Cesa-Bianchi and Fernandez-Corugedo (2018), de Groot et al. (2018), and Katayama and Kim (2018).

[3] The result of Leduc and Liu (2016), who argue that an uncertainty shock resembles an aggregate demand shock as it increases unemployment, while decreasing inflation, has been shown to critically hinge upon the Taylor rule specification (Fasani and Rossi, 2018). In their setup, this result can be easily overturned by assuming some empirically plausible interest rate inertia.

In particular, we develop a heterogeneous-agent New Keynesian (HANK) model with the following features: household heterogeneity induced by unemployment risk and imperfect risk sharing, labor market search and matching (SaM) frictions, and Calvo-type price rigidities. We model uncertainty as a second moment shock to technology.

Within this framework, we study how a positive uncertainty shock propagates throughout the economy. In representative-agent New Keynesian models such as Born and Pfeifer (2014), Fernández-Villaverde et al. (2015), and Mumtaz and Theodoridis (2015), uncertainty shocks have two effects. The first effect is on aggregate demand and works through the precautionary saving behavior of risk-averse households. Due to the convexity of the marginal rate of substitution between present and future consumption, higher uncertainty induces households to increase their savings. The second effect is on aggregate supply and works through the precautionary pricing behavior of firms. When uncertainty increases, firms that are allowed to reset their price, increase it to self-insure against the risk of being stuck with low prices in the future. Since the increase in prices induced by the precautionary pricing behavior of firms is stronger than the drop in prices induced by the precautionary saving behavior of risk-averse households, inflation increases after a positive uncertainty shock. Enhancing this framework with households' heterogeneity adds an indirect channel of precautionary savings, which has powerful implications on the propagation of uncertainty shocks. This channel works as follows. The drop in aggregate demand and aggregate supply induces firms to lower vacancy posting. This reduces households' job finding rate and increases unemployment risk. Since some households are borrowing constrained and subject to only partial risk sharing, an increase in unemployment risk pushes them to further strengthen their precautionary saving behavior. When the feedback loop between precautionary savings and unemployment risk sufficiently amplifies the negative demand effects of uncertainty shocks, the latter have deflationary effects. Moreover, this feedback effect is able to reinforce the responses of output, consumption, and unemployment rate so as to be quantitatively in line with the empirical evidence.

Importantly, we clarify that, were price rigidities assumed to be à la Rotemberg (1982) instead of à la Calvo (1983), there would be no precautionary pricing behavior of firms. We could therefore obtain a small drop in prices for some parametrizations of the Taylor rule. However, absent the precautionary pricing channel, we would not trigger any amplification mechanism for the response of the other macro variables, thus not being able to quantitatively match the empirical evidence on uncertainty propagation to output and its subcomponents. This result on the lack of amplification in absence of precautionary pricing confirms the difficulty that other studies have found in generating amplified macro responses, which are empirically consistent - see e.g. de Groot et al. (2018), who show that Basu and Bundick (2017)'s results become muted once the asymptote present in their preference specification is removed, Cesa-Bianchi and Fernandez-Corugedo (2018), and Katayama and Kim (2018). Differently from the existing literature, the presence of households who are imperfectly insured against unemployment risk, jointly with the precautionary pricing behavior of Calvo-price setters allows us to contemporaneously obtain a robust drop in inflation as well as a response in macro variables, which is empirically consistent.

We further show that our result on both the qualitative and quantitative response of inflation and the main macro variables cannot be obtained by introducing an alternative Taylor rule to representative-agent models such as Fernández-Villaverde et al. (2015), where the nominal interest rate directly reacts to an increase in uncertainty. This type of Taylor rule at best generates a mild drop in macro variables and inflation, which is certainly not in line with the empirical evidence. To obtain responses quantitatively consistent with the data it is thus necessary to assume households' heterogeneity.

In our baseline specification and in line with the vast majority of the literature on uncertainty propagation, we mainly focus on TFP uncertainty. Yet, the macro uncertainty index by Jurado et al. (2015), which we use in our empirical analysis, captures a broader concept of uncertainty affecting the macro economy. We therefore assess the sensitivity of our main result by showing that it is robust to other forms of uncertainty, like monetary policy uncertainty.

Related Literature The first stream of the literature our paper is related to is the one on uncertainty. This paper focuses specifically on macro uncertainty as estimated by Jurado et al. (2015). Based on a series of recent studies showing that macro uncertainty is exogenous to the business cycle (see e.g. Carriero et al., 2018a, Piffer and Podstawski, 2018, Angelini et al., 2019, and Angelini and Fanelli, 2019), this paper investigates how an exogenous shock to macro uncertainty affects the macroeconomy. Our main contribution is to highlight the importance of the interaction between households' heterogeneity, labor market SaM frictions, and Calvo pricing in the transmission of uncertainty shocks to the macroeconomy.[4] Critically, we show that it is this interaction that allows us to contemporaneously obtain a decrease in inflation as well as macro responses that are quantitatively in line with the empirical evidence. Papers like Born and Pfeifer (2014) and Mumtaz and Theodoridis (2015) obtain an increase in prices as a consequence of higher uncertainty. This increase is due to price rigidities à la Calvo, which trigger a precautionary pricing behavior of firms. Yet, the increase in inflation is not supported by empirical evidence, at least for the post-Volker period. Leduc and Liu (2016) and Basu and Bundick (2017), which assume price rigidities à la Rotemberg (1982), show that an increase in uncertainty can actually lead to a decrease in prices. Importantly, however, Fasani and Rossi (2018) show that the response of inflation to uncertainty shocks in Leduc and Liu (2016) is very much dependant on the Taylor rule specification. Namely, they argue that this response becomes positive once an empirically plausible degree of interest rate smoothing is considered. Also, the quantitative results of Basu and Bundick (2017) are shown by de Groot et al. (2018) to hinge upon their preference specification, which implies an asymptote. Once the asymptote is removed, their macro responses become muted and inconsistent with business cycle comovement. Other papers highlight how theoretically challenging it is to obtain quantitatively relevant responses of macro variables to uncertainty shocks (e.g. Born and Pfeifer, 2014, Cesa-Bianchi and Fernandez-Corugedo, 2018, de Groot et al., 2018, and Katayama and Kim, 2018). Differently from the existing literature and thanks to the feedback mechanism due to uninsured risk and the precautionary pricing behavior of firms, we are able to jointly obtain a drop in inflation as well as macro responses that are quantitatively in line with the data.

Our paper is also related to the fast growing literature of HANK models, such as those developed by McKay and Reis (2016), Kaplan et al. (2018), and Bilbiie (2019). More specifically, it is part of the novel literature of HANK models with SaM frictions, which studies how labor market frictions interact with households' precautionary saving behavior (see e.g. Gornemann et al., 2016, McKay and Reis, 2017, Ravn and Sterk, 2017, 2020, Cho, 2019, Lagerborg et al., 2019, Dolado et al., 2020). More precisely, our paper is related to a specific stream of the HANK literature, which introduces households' heterogeneity in a simplified, but effective framework. This setup allows us to gain

[4] We also confirm Riegler (2019)'s results on the effect of higher uncertainty on the job finding rate and the job separation rate.

tractability, which is essential to study the propagation of uncertainty shocks, while at the same time retaining the main feature of introducing households' heterogeneity, which is the precautionary saving motive.[5] This framework is presented by Challe et al. (2017), who construct and estimate a tractable HANK model with SaM frictions, where the cross-sectional heterogeneity of households remains finite dimensional. A similar framework where households' heterogeneity is kept to the minimum to retain model tractability is the one of Challe (2020), who studies optimal monetary policy in the presence of uninsured unemployment risk and nominal rigidities. To our knowledge, our paper is the first to study aggregate uncertainty shocks in the context of a HANK model with SaM frictions and highlight how these features are crucial to explain the propagation of uncertainty throughout the economy. Outside the HANK literature with SaM frictions, Den Haan et al. (2018) and Heathcote and Perri (2018) examine how the interaction between market incompleteness and unemployment risk gives rise to precautionary saving motives, but the business cycle fluctuations that they study are not generated by an increase in aggregate uncertainty.

Another paper focusing on uncertainty and heterogeneity is Bayer et al. (2019). Our paper differs from it along several dimensions. While Bayer et al. (2019) study individual households' income volatility, we focus on the propagation of aggregate macro uncertainty. In addition, when solving for aggregate dynamics, Bayer et al. (2019) use a first-order perturbation. Instead, we solve the model at third order, which allows us to obtain a precautionary pricing motive for firms, which would not be present at a first order approximation. Third, we have a frictional labor market, which is necessary to explain the feedback effect between unemployment risk and precautionary saving, which is the one driving our main results.

The rest of the paper is structured as follows. Section 2.2.1 shows empirical evidence on the responses of macroeconomic variables to an increase in macro uncertainty. Using the CEX micro data, Section 2.2.2 provides additional evidence that the aggregate response of consumption is driven by households' heterogeneous response across their income distribution. Taking stock of these empirically relevant features, Section 2.3 builds a New Keynesian model with uninsured unemployment risk and aggregate uncertainty. Section 2.4 displays our main quantitative results on the model dynamics

[5] Studying uncertainty shocks requires to solve the model to a third-order approximation or a fully global solution method. This gets extremely complicated in fully fledged heterogeneous models.

in response to an increase in uncertainty. Section 2.5.1 illustrates how much each precautionary saving and pricing channel contributes to our quantitative results, Section 2.5.2 shows model responses using an alternative Taylor rule, Section 2.5.3 illustrates responses to a different type of uncertainty, and Section 2.5.4 conducts additional sensitivity analyses. Section 2.6 concludes.

2.2 Empirical Evidence

2.2.1 Macro Evidence

Recent papers such as Carriero et al. (2018a), Piffer and Podstawski (2018), Angelini et al. (2019), and Angelini and Fanelli (2019) argue that macroeconomic uncertainty is exogenous when evaluating its effects on the US macroeconomy.[6] Based on this extensive evidence, we consider macro uncertainty as exogenous to the business cycle. To show how the U.S. economy reacts to an exogenous increase in uncertainty, we estimate a quarterly frequency VAR with a constant and two lags suggested by the Hannan-Quinn information criterion. The variables included in our VAR are: macroeconomic uncertainty, log of per capita real GDP, the job finding rate, the separation rate, the unemployment rate, log of per capita real consumption (including nondurable goods and services), inflation (first-differenced logged consumer price index), and the policy rate. To measure macroeconomic uncertainty we use the macro uncertainty index estimated by Jurado et al. (2015).[7] For the job finding rate and the separation rate we use the series computed by Shimer (2012) and updated by Pizzinelli et al. (2018).[8] As for the policy rate, we use the quarterly average of the effective Federal funds rate. However, since the sample includes a period during which the Federal funds rate hits the zero lower bound (ZLB), from 2009Q1 to 2015Q3 we use the shadow Federal funds

[6] For a thorough review on macro uncertainty and its exogeneity to the business cycle, see Castelnuovo (2019), Section 2.

[7] The updated version of the macro uncertainty series is obtained from the author's website, `https://www.sydneyludvigson.com/data-and-appendixes`. We use the quarterly average of their monthly series with $h = 3$ (i.e., 3-month-ahead uncertainty).

[8] We are grateful to Carlo Pizzinelli for sharing with us the updated version of Shimer's series as can be found at `https://sites.google.com/site/robertshimer/research/flows`.

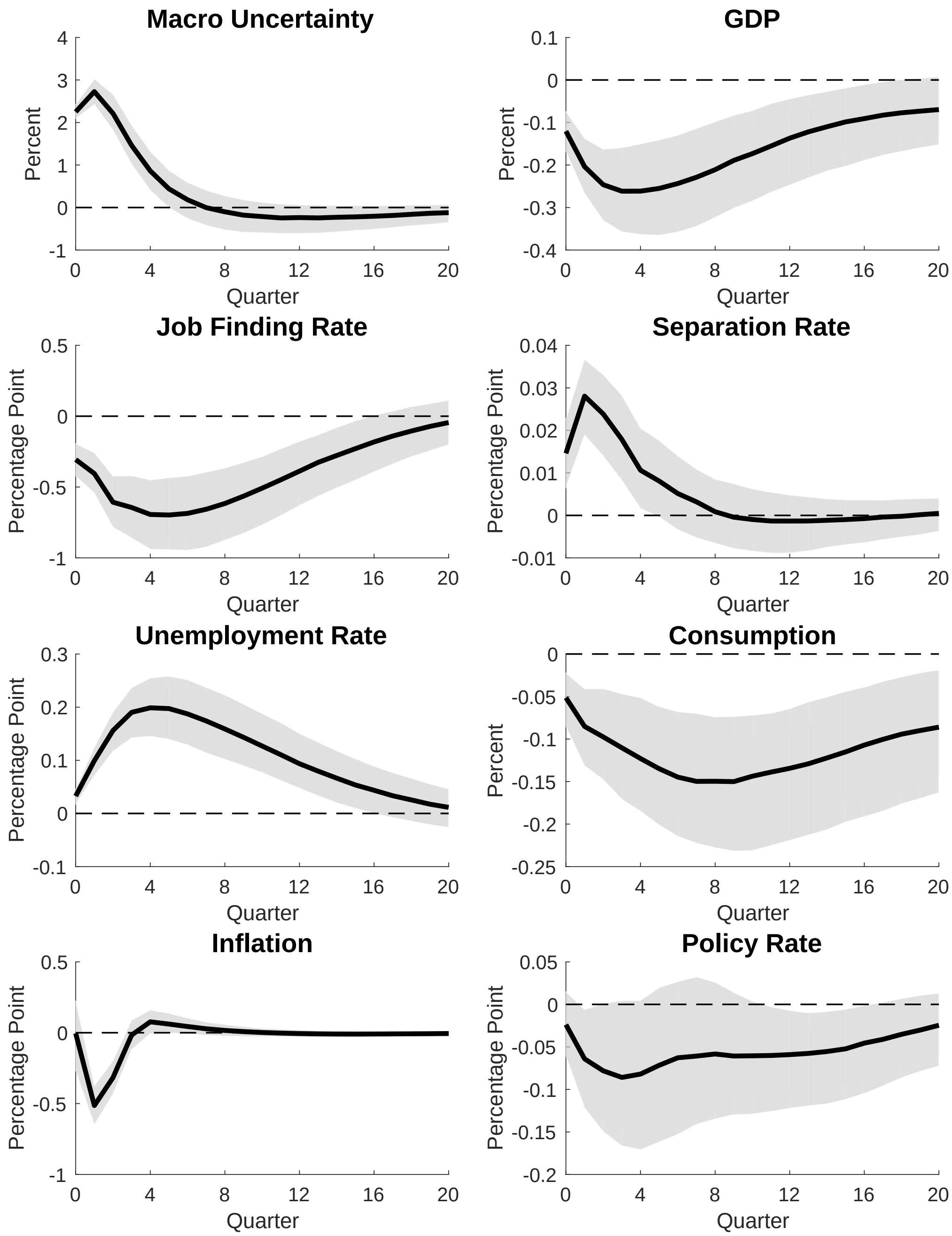


Figure 2.1 – **Empirical responses to one-standard deviation macro uncertainty shocks**

Note: Grey areas indicate 68 percent bootstrap confidence bands.

rate constructed by Wu and Xia (2016).[9] This shadow rate is not bounded below by zero and better summarizes the stance of monetary policy. The remaining series are retrieved from the FRED of St. Louis Fed.[10]

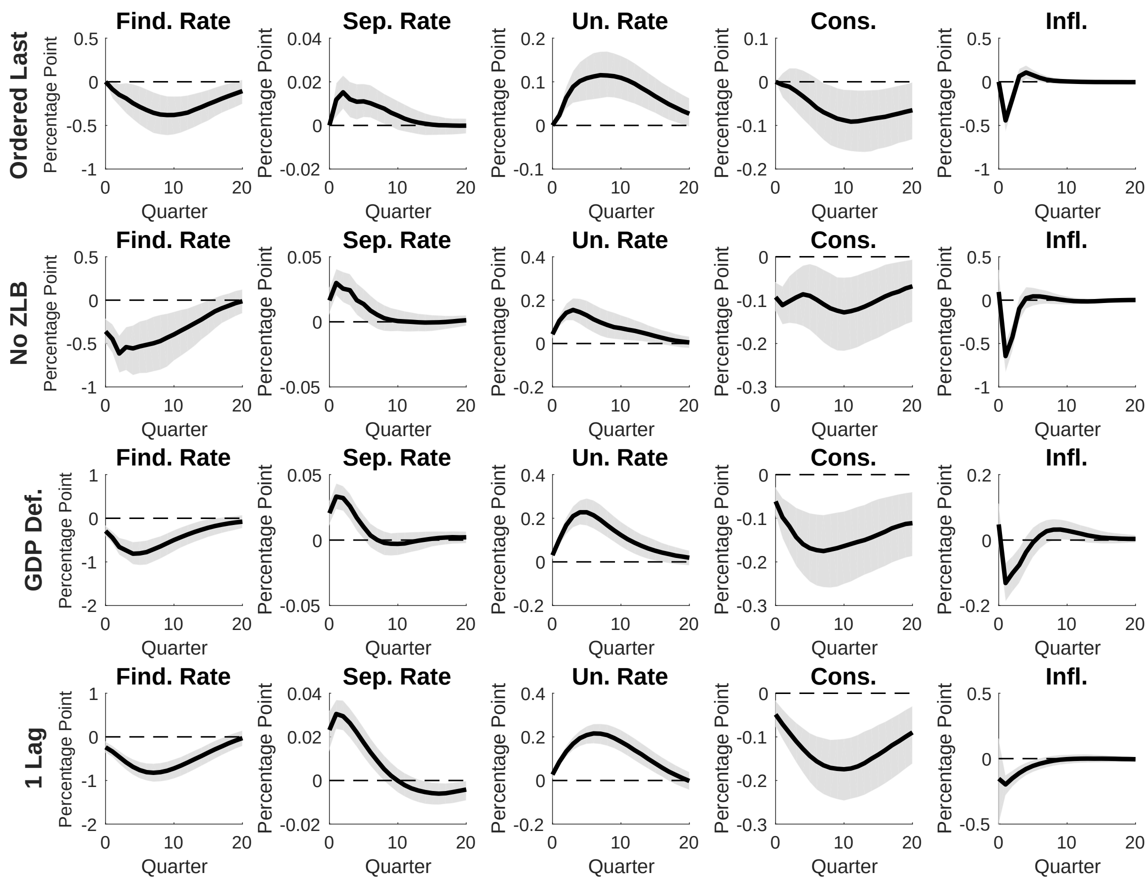


Figure 2.2 – **Robustness checks for empirical responses to one-standard deviation macro uncertainty shocks**

Note: Grey areas indicate 68 percent bootstrap confidence bands.

[9]The shadow Federal funds rate is obtained from the author's website, `https://sites.google.com/view/jingcynthiawu/shadow-rates`.

[10]The retrieved series are the following (FRED series IDs are in parentheses): Gross Domestic Product (GDP), Consumer Price Index for All Urban Consumers: All Items (CPIAUCSL), Civilian Unemployment Rate (UNRATE), Personal Consumption Expenditures: Nondurable Goods (PCND), Personal consumption expenditures: Nondurable goods (chain-type price index) (DNDGRG3M086SBEA), Personal Consumption Expenditures: Services (PCESV), Personal consumption expenditures: Services (chain-type price index) (DSERRG3M086SBEA), and Effective Federal Funds Rate (FEDFUNDS). Then, we obtain the quantity indices by deflating the expenditures. Per capita variables are divided by Civilian Noninstitutional Population (CNP16OV).

We identify uncertainty shocks by using a Cholesky decomposition where macro uncertainty is ordered first. This ordering implies that uncertainty does not react contemporaneously to the other variables included in the VAR. We use US quarterly data over the sample period 1982Q1-2015Q3. As it is common practice in this literature, to avoid parameter instability we start our sample only after the beginning of Paul Volcker's mandate as the Federal Reserve Chairman.[11]

Figure 2.1 shows the impulse responses to a one standard deviation shock in the macro uncertainty index. GDP and the job finding rate drop significantly and persistently for sixteen quarters, while the separation rate rises significantly for four quarters. The response of the unemployment rate is positive and persistent and reaches a 0.2 percentage point increase at its peak. The unemployment rate response is in line with the linear specification results of Caggiano et al. (2014), who examine the impact of uncertainty on unemployment dynamics. Moving to the consumption response, we find that it declines at its minimum by more than 0.15 percent after seven quarters. The policy rate drops, but is only mildly significant. Importantly, inflation falls by 0.5 percentage points after one quarter. The response of inflation is in line with what other papers studying uncertainty shocks find - see Fernández-Villaverde et al. (2015), Bonciani and van Roye (2016), Leduc and Liu (2016), Basu and Bundick (2017), and Oh (2020).[12]

To make sure that our results are robust to different Cholesky ordering, sample periods, data series, and VAR specifications, we conduct several robustness checks, which are shown by Figure 2.2. The first row displays responses of a VAR where we put macro uncertainty as last in the recursive ordering of the variables. The second row reports the impulse responses when we exclude the ZLB period. The third row replaces the CPI inflation with the GDP deflator inflation. The last row shows responses of a VAR with one suggested by the Bayesian information criterion, instead of two lags. In all cases, following a positive uncertainty shock we get: a drop in the finding rate, an increase in the separation rate and the unemployment rate, and decrease in consumption and inflation.

Given this empirical evidence, Section 2.3 is going to build a model, which is able to

[11] Paul Volcker started his mandate on August 6, 1979.

[12] The few exceptions are Mumtaz and Theodoridis (2015), Katayama and Kim (2018), and Carriero et al. (2018b). The former finds an inflationary effect of uncertainty shocks, while the last two find a non-significant response of inflation to uncertainty shocks. However, they start their sample in 1975Q1, 1960Q3, and 1961M1 respectively, thus including the pre-Volcker period.

replicate our empirical findings. In particular, our goal is to obtain a drop in inflation and a significant amplification in the response of macro and labor market variables following a positive uncertainty shock.

2.2.2 Suggested Micro Evidence: Heterogeneous Response of Consumption

To gain a deeper understanding of the mechanism driving the macroeconomic dynamics, we carry out a similar VAR exercise to Section 2.2.1, but we now use consumption micro data instead of aggregate consumption. This allows us to disentangle the responses of households' consumption across their income distribution. We use the Consumer Expenditure Survey (CEX) data on consumption and income over the period 1982Q1-2015Q3. We follow Heathcote et al. (2010), Anderson et al. (2016), and Ma (2019) in defining nondurable consumption. This comprises food and beverages, tobacco, apparel and services, personal care, gasoline, public transportation, household operation, medical care, entertainment, reading material, and education. As in Ma (2019), income is defined as before-tax income, which is the sum of wages, salaries, business and farm income, financial income, and transfers. To get income and nondurable consumption for households in real per capita values, we divide them by family size (the number of family members), deflate by CPI-U series, and seasonally adjust by X-12-ARIMA.[13]

Figure 2.3 exhibits the consumption responses to macro uncertainty shocks for the bottom 60% and the top 40% of the households' income distribution.[14] The response of consumption is heterogeneous between these two groups. In particular, what Figure 2.3 illustrates is that the drop in aggregate consumption is mainly driven by the consumption response of the bottom 60%. Instead, the consumption response of households in the top 40% is not significant. To show that the heterogeneity in the consumption responses is significant, the third plot of Figure 2.3 displays the response of the ratio between the consumption of the bottom 60% and the consumption of the top 40%.

[13] We are grateful to Eunseong Ma for sharing with us his CEX data on consumption.

[14] We chose the breakdown between the bottom 60% and the top 40% of the income distribution to match the calibration of our model in Section 2.3, as in Challe et al. (2017). However, we have also run the VAR across the five quintiles of the income distribution and we have found that the aggregate response is driven by the response of households in the three lowest quintiles. The response of households in the fourth quintile is only mildly significant, while the response of households in the fifth quintile is not significant.

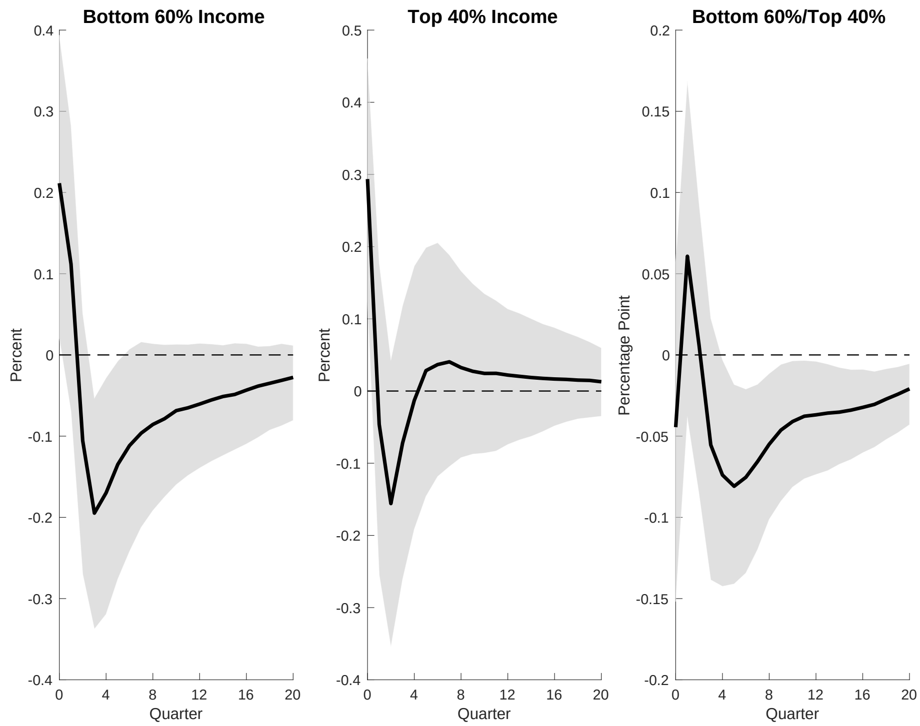


Figure 2.3 – **Empirical responses of consumption across income distribution to one-standard deviation macro uncertainty shocks**

Note: "Bottom 60% Income" and "Top 40% Income" denote the consumption response of households respectively in the lowest 60% and the highest 40% of the income distribution. Grey areas indicate 68 percent bootstrap confidence bands.

This response is negative and significant from the fourth quarter onward and remains persistently negative until the twentieth quarter. This indicates that the consumption response of households is heterogeneous: the most responsive to uncertainty are those who are at the bottom of the income distribution.[15]

[15] Figure 2.3 shows responses of consumption in three different VARs: in the first we insert the consumption of the bottom 60%, in the second the consumption of the top 40%, and in the third the ratio between the two consumption series. We have also run a single VAR where we insert these three series at once and our results are robust.

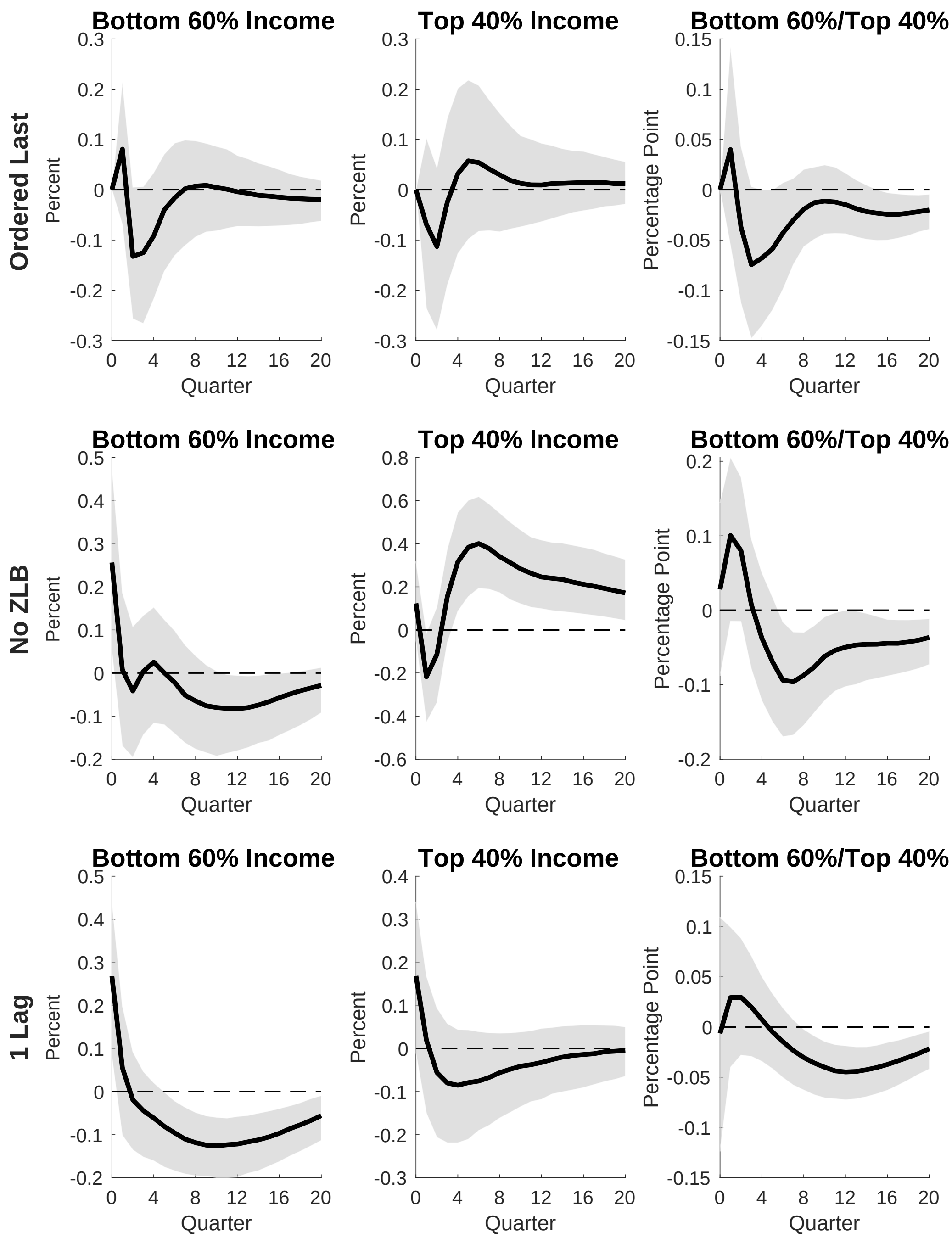


Figure 2.4 – **Robustness checks for empirical responses of consumption across income distribution to one-standard deviation macro uncertainty shocks**

Note: "Bottom 60% Income" and "Top 40% Income" denote the consumption response of households respectively in the lowest 60% and the highest 40% of the income distribution. Grey areas indicate 68 percent bootstrap confidence bands.

We check the robustness of our results to the recursive ordering, the sample period, and the VAR specification. Results are shown by Figure 2.4. The first row reports responses to an uncertainty shock when the macro uncertainty is ordered last in the Cholesky recursion. The second row exhibits responses of the two income groups when we exclude the ZLB period. The last row displays responses when we run a VAR with only one lag. All robustness checks indicate that the aggregate response of consumption is driven by the response of households in the bottom 60%.

This micro data evidence suggests that households respond in a heterogeneous way across their income distribution. Therefore, households' heterogeneity is an important feature of the data that should not be overlooked when studying the propagation of uncertainty shocks. Hence, in Section 2.3 we build a tractable model with heterogeneous agents subject to uninsurable unemployment risk to study the propagation of uncertainty shocks throughout the economy.

2.3 The Model

To reproduce our empirical findings, we build a tractable New Keynesian model with imperfectly insured unemployment risk, where we introduce a technology process with stochastic volatility. We then simulate a temporary increase in the stochastic volatility of technology and study how the economy reacts. The reduced-form analysis conducted in Section 2.2 studies the impact of macro uncertainty. This is a comprehensive measure, which aims to capture 'uncertainty that may be observed in many economic indicators at the same time, across firms, sectors, markets, and geographic regions', Jurado et al. (2015). In our baseline theoretical analysis we capture macro uncertainty by focusing on a technology uncertainty shock. In the robustness checks, we also study the sensitivity of our main results to other sources of uncertainty shocks such as interest rate uncertainty.

Following Challe et al. (2017), the model features *imperfect* insurance against idiosyncratic unemployment risk in a New Keynesian framework with labor market frictions à la Mortensen and Pissarides (1994). There are two types of households, a perfectly and an imperfectly insured one. Only perfectly insured households can own firms. Both perfectly and imperfectly insured households participate in the labor and bond market and are subject to idiosyncratic unemployment risk. However, while perfectly insured households fully share risk among each other, imperfectly insured households cannot fully insure themselves against unemployment risk and face a borrowing constraint. The two latter features generate precautionary saving motives for employed households who are not perfectly insured.

To simplify the introduction of both labor market frictions and nominal rigidities, the production side is made of four types of firms as in Gertler et al. (2008b). First, labor market intermediaries hire labor from both perfectly and imperfectly insured households, subject to search and matching frictions, and transform it into labor services. Second, wholesale goods firms buy labor services in a competitive market to produce wholesale goods used by intermediate goods firms. Third, intermediate goods firms buy wholesale goods, differentiate it, and sell it monopolistically while facing price stickiness à la Calvo (1983). Fourth, a competitive final good sector aggregates the intermediate good into a final good used for consumption and vacancy posting costs. The nominal interest rate is set by a central bank which follows a standard Taylor rule.

To specify the timing of events within a period, every period can be divided into three sub-periods: a labor market transition stage, a production stage and a consumption-saving stage. In the first stage, the exogenous state is revealed, workers are separated from firms, firms open vacancies and new matches are created. In the second stage, production takes place and the income components are paid out to the economy agents as wages, unemployment benefits, and profits. In the third stage, asset holding choices are made and the family heads redistribute assets across household members.

Challe et al. (2017)'s assumptions on imperfect risk sharing and a tight borrowing constraint faced by imperfectly insured households allow us to reduce the state space to a finite dimensional object. If we also assume that the borrowing constraint becomes binding after one period of unemployment spell, we can further reduce the heterogeneity of imperfectly insured households to three types. In Section 2.3.1 - 2.3.6, we are going to describe the model in detail by focusing on the specific case in which imperfectly insured households are reduced to three types. For notation purposes, aggregate variables are in bold characters. In addition, variables corresponding to the beginning of the labor transition stage are denoted with a tilde.

2.3.1 Households

There is a unit mass of households in the economy. Each household is endowed with one unit of labor. If at the beginning of the production stage the household is employed, she supplies her unit of labor inelastically. All households are subject to idiosyncratic changes to their employment status. A share $f \in [0,1]$ of the unemployed households at the beginning of the labor market transition stage finds a job by the beginning of the production stage, while a share $s \in [0,1]$ looses her job over the same period. There are two types of households: a measure $\Omega \in [0,1)$ of imperfectly insured ones and a measure $1-\Omega$ of perfectly insured ones. They have different subjective discount factors. In particular, the discount factor β^P of perfectly insured households is higher than the discount factor β^I of imperfectly insured ones. They all share the same period utility function $u(c) = \frac{(c-h\mathbf{c})^{1-\sigma}}{1-\sigma}$, where c is consumption, $\mathbf{c}$ is the level of consumption habits, and h is a constant habit parameter. Consumption habits are external. We define $\mathbf{c}^P$ as the common consumption habits of the perfectly insured households in the current period. These habits are assumed to be the average of the perfectly insured households' consumption in the previous period. Consumption habits of the imperfectly insured, instead, depend on their unemployment spell $N \geq 0$. Namely, we assume that imperfectly insured households with unemployment spell N are going to have consumption habits $\mathbf{c}^I(N)$. These habits are equal to the average consumption of the imperfectly insured households with unemployment spell N in the previous period.

Imperfectly Insured Households

Imperfectly insured households face idiosyncratic shocks to their employment state and are subject to a borrowing limit that prevents them from borrowing beyond a given threshold $\underline{a}$.

Employed households earn a wage w that gets taxed by a rate τ to pay for the unemployment benefit b^u that unemployed households receive. Since the unemployment insurance scheme is balanced every period, the following equation has to hold:

$$\tau w \mathbf{n}^I = b^u \left(1 - \mathbf{n}^I\right), \tag{2.1}$$

where $\mathbf{n}^I$ is the imperfectly insured households' employment rate at the end of the labor market transition stage. Following the literature, we adopt the family structure according to which every imperfectly insured household belongs to a representative family, whose head makes consumption and saving decisions to maximize the family current and expected utility.

There are two crucial assumptions that Challe et al. (2017) make to keep the model tractable, while still preserving the heterogeneity across imperfectly insured households: i) the borrowing limit is tighter than the natural debt limit; ii) there is only partial risk sharing across members of the imperfectly insured households. In particular, only employed members can fully insure each other by transferring assets. Instead, no transfer is admitted between employed and unemployed members or across unemployed members.

Because of idiosyncratic shocks and imperfect risk sharing, there is heterogeneity across imperfectly insured households. This heterogeneity implies a distribution $\mu\left(a^I, N\right)$ of imperfectly insured households over assets a^I and unemployment spells $N \geq 0$. Thanks to the two aforementioned assumptions, for every N the cross-sectional distribution $\mu(a^I, N)$ of imperfectly insured households can be summarized by the unique mass point $a^I\left(N\right)$ and the associated number of imperfectly insured households $n^I\left(N\right)$.

Given X the vector of aggregate states,[16] the head of a representative family of imperfectly insured households maximizes the family current and future utility with respect to assets $a'\left(N\right)$ and consumption $c\left(N\right)$:

$$\begin{aligned} V^I\left(a^I\left(N\right), n^I\left(N\right), X\right) = \max_{\{a^{I\prime}(N), c^I(N)\}_{N \in Z_+}} & \left\{ \sum_{N \geq 0} n^I\left(N\right) u\left(c^I\left(N\right) - h\mathbf{c}^I(N)\right) \right. \\ & \left. + \beta^I \mathbb{E}_{\mu,X}\left[V^I\left(a^{I\prime}\left(N\right), n^{I\prime}\left(N\right), X'\right)\right] \right\}, \end{aligned} \tag{2.2}$$

subject to:

$$a^{I\prime}\left(N\right) \geq \underline{a}, \tag{2.3}$$

$$a^{I\prime}\left(0\right) + c^I\left(0\right) = \left(1-\tau\right)w + \left(1+r\right)A, \qquad N = 0, \tag{2.4}$$

$$a^{I\prime}\left(N\right) + c^I\left(N\right) = b^u + \left(1+r\right)a, \qquad N \geq 1. \tag{2.5}$$

[16]See Section 2.3.6 for the aggregate state definition.

Equation (2.3) is the borrowing constraint, where $\underline{a}$ is higher than the natural borrowing limit. Equation (2.4) is the budget constraint of an employed household (the unemployment spell N is zero). An employed household consumes $c^I(0)$ and buys assets $a^I(0)$, while receiving after tax income $(1-\tau)w$ and return from previously held assets $(1+r)A$. Equation (2.5) is the budget constraint of a household, who has been unemployed for N periods. This household consumes $c^I(N)$, buys assets $a^I(N)$, gets the unemployment benefit b^u and the return $(1+r)a$ from previously held assets (of course, if these are negative assets, i.e. debt, r is the interest paid on debt).

If $N=0$, the value of assets and the employed households' law of motion are given by:

$$A' = \frac{1}{n^{I\prime}(0)}\left[(1-s')\,a^{I\prime}(0) + f'\sum_{N\geq 1} a^{I\prime}(N)\,n^I(N)\right], \tag{2.6}$$

$$n^{I\prime}(0) = (1-s')\,n^I(0) + f'\left(1-n^I(0)\right). \tag{2.7}$$

Equation (2.6) says that the next period value of assets that each employed imperfectly insured household gets is the total of assets that next period employed imperfectly insured households bring divided by the total number of employed imperfectly insured households $n^{I\prime}(0)$, who belong to the family. The total of assets that next period employed imperfectly insured households bring is given by the fraction of assets that households who *remain* employed bring to the family $(1-s')\,a^{I\prime}(0)$, plus the fraction of assets that households, who *become* employed bring to the family $f'\sum_{N\geq 1} a^{I\prime}(N)\,n^I(N)$. Equation (2.7) says that next period employed imperfectly insured households are given by the fraction of this period employed imperfectly insured households who *remain* employed $(1-s')\,n^I(0)$, plus the fraction of this period unemployed imperfectly insured households who *become* employed $f'\left(1-n^I(0)\right)$.

If $N \geq 1$, the value of next period assets and next period unemployed households' law of motion are given by:

$$a^I(N) = a^{I\prime}(N-1), \tag{2.8}$$

$$n^{I\prime}(1) = s'n^I(0) \;\text{ and }\; n^{I\prime}(N) = (1-f')\,n^I(N-1) \;\text{ if } N\geq 2. \tag{2.9}$$

Equation (2.8) says that the value of next period assets of an imperfectly insured household, who has been unemployed for $N-1$ periods is equal to the value of this period assets of an imperfectly insured household, who has been unemployed for N

periods. Equation (2.9) says that next period unemployed people with one period unemployment spell are the fraction of this period employed households, who become unemployed, while next period unemployed with more than one period unemployment spell are the fraction of this period unemployed households, who stay unemployed.

Imperfectly insured households face a binding borrowing limit after $\hat{N}$ consecutive periods of unemployment. This problem has a particularly easy solution for the case of $\hat{N} = 1$, which, following Challe et al. (2017), is supported by empirical evidence (liquid wealth is fully liquidated after one period). When $\hat{N} = 1$, in every period there are *three* types of imperfectly insured households: $N = 0$, $N = 1$, and $N \geq 2$. To these three types, there are the three following associated consumption levels $c^I(0)$, $c^I(1)$, and $c^I(2)$ for all $N \geq 2$, and the two following assets levels $a^I(0)$, and $\underline{a}$. $a^I(0)$ is the asset level of employed households, while $\underline{a}$ is the asset level of unemployed households. Since all unemployed households face a binding borrowing constraint, their asset level is the same regardless of their unemployment spell. These three types of imperfectly insured households are in number $\Omega \mathbf{n}^I$, $\Omega s \tilde{\mathbf{n}}^I$, and $\Omega \left(1 - \mathbf{n}^I - s\tilde{\mathbf{n}}^I\right)$. In equilibrium, for any $N \geq 0$ the Euler condition for imperfectly insured households is:

$$\mathbb{E}_{\mu,X}\left[M^{I\prime}(N)\left(1+r'\right)\right] = 1 - \frac{\Gamma(N)}{u_c\left(c^I(N) - \mathbf{c}^I(N)\right) n(N)}, \tag{2.10}$$

where $M^I(N)$ is the intertemporal marginal rate of substitution (IMRS) and $\Gamma(N)$ is the Lagrange multiplier associated to the borrowing limit. When the household is employed ($N = 0$), the borrowing limit is not binding. Therefore, $\Gamma(N) = 0$ and the Euler condition holds with equality:

$$\mathbb{E}_{\mu,X}\left[M^{I\prime}(0)\left(1+r'\right)\right] = 1. \tag{2.11}$$

Instead, when the household is unemployed ($N \geq 1$), the borrowing limit is binding, $\Gamma(N) > 0$, and $\mathbb{E}_{\mu,X}\left[M^{I\prime}(N)\left(1+r'\right)\right] < 1$. The IMRS is the ratio of the next-period and the current period marginal utility:

$$M^{I\prime}(0) = \beta^I \frac{\left(1-s'\right) u_c^{I\prime}(0) + s' u_c^{I\prime}(1)}{u_c^I(0)}, \qquad N = 0, \tag{2.12}$$

$$M^{I\prime}(N) = \beta^I \frac{(1-f')\, u_c^{I\prime}(N+1) + f' u_c^{I\prime}(0)}{u_c^I(N)}, \qquad N \geq 1. \tag{2.13}$$

Equation (2.12) is the IMRS of an employed household. The denominator is the current period marginal utility. The numerator is the next period marginal utility, which is a weighted average of the household's marginal utility if she remains employed $u_c^{I\prime}(0)$ times the probability of remaining employed $1-s'$, and her marginal utility if she becomes unemployed $u_c^{I\prime}(1)$ times the probability of becoming unemployed s'. Similarly, Equation (2.13) is the IMRS of an unemployed household. In this case, the numerator is the weighted average of the household's marginal utility if she remains unemployed $u_c^{I\prime}(N+1)$ times the probability of remaining unemployed while already being unemployed $1-f'$, and her marginal utility if she becomes employed $u_c^{I\prime}(0)$ times the probability of becoming employed f'.

Perfectly Insured Households

The fraction of employed members within every family of perfectly insured households before and after the labor-market transitions stage are denoted by $\tilde{n}^P$ and n^P, respectively. We thus have:

$$n^{P\prime} = (1-s')\, n^P + f' \left(1 - n^P\right), \tag{2.14}$$

$$n^P = \tilde{n}^{P\prime}. \tag{2.15}$$

As before, these are family-level variables. The corresponding aggregate variables are denoted by $\tilde{\mathbf{n}}^P$ and $\mathbf{n}^P$. Employed perfectly insured households earn after tax wage $(1-\tau)w^P$, while unemployed perfectly insured households get unemployment benefit b^{uP}. Also the unemployment insurance scheme of perfectly insured households is balanced every period, thus the following equation holds:

$$\tau w^P \mathbf{n}^P = b^{uP}\left(1 - \mathbf{n}^P\right). \tag{2.16}$$

Besides having a higher discount factor, what differentiates perfectly insured households from imperfectly insured ones is that there is full risk sharing among their family members, regardless of their employment status. This implies that all family members are symmetric, consume c^P and save $a^{P\prime}$. The family head of perfectly insured households solves:

$$V^P\left(a^P, n^P, X\right) = \max_{a^{P\prime}, c^P} \left\{ u\left(c^P - h\mathbf{c}^P\right) + \beta^P \mathbb{E}_{n^P, X}\left[V^P\left(a^{P\prime}, n^{P\prime}, X^\prime\right)\right]\right\}, \tag{2.17}$$

subject to:

$$c^P + a^{P\prime} = w^P n^P + (1+r)\, a^P + \Pi, \tag{2.18}$$

where w^P is the real wage that perfectly insured households get and Π is the profit from intermediate goods firms and labor intermediaries, which are owned by perfectly insured households.

Since all perfectly insured households are homogeneous, they have the same Euler equation:

$$\mathbb{E}_X\left[M^{P\prime}\left(1 + r^\prime\right)\right] = 1, \tag{2.19}$$

where the IMRS $M^{P\prime}$ is given by:

$$M^{P\prime} = \beta^P \frac{u_c^{P\prime}}{u_c^P}. \tag{2.20}$$

2.3.2 Firms

There are four types of firms in the economy. Labor intermediaries hire labor in a frictional labor market and sell labor services to wholesale goods firms. Wholesale goods firms buy labor to produce wholesale goods in a competitive market. Intermediate goods firms buy wholesale goods and sell them to the final goods firms while facing Calvo (1983) price rigidities. Final goods firms aggregate intermediate goods into a final good.

Final Goods Firms

A continuum of perfectly competitive final goods firms combine intermediate goods, which are uniformly distributed on the interval $[0, 1]$, according to the production function:

$$y = \left(\int_0^1 y_i^{\frac{\varepsilon-1}{\varepsilon}} di\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{2.21}$$

where ε is the elasticity of substitution between two intermediate goods. Let p_i denote the real price of intermediate good variety i in terms of final good price. The final goods firm solves:

$$\max_y y - \int_0^1 p_i y_i di, \tag{2.22}$$

subject to Equation (2.21). The solution of the maximization gives the final firm's demand of intermediate good:

$$y_i(p_i) = p_i^{-\varepsilon} y, \tag{2.23}$$

while the zero-profit condition for final goods firms gives:

$$\left(\int_0^1 p_i^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}} = 1. \tag{2.24}$$

Intermediate Goods Firms

Intermediate goods firm i produces x_i with a linear technology $y_i = x_i$. Firm i's profit is then given by $\Xi = (p_i - p_m) y_i$, where p_m is the real price of intermediate goods in terms of final goods. Intermediate goods firms choose p_i to maximize the present discounted value of future profits subject to the demand curve (2.23). They face pricing frictions à la Calvo (1983). Therefore, every period only a share $1 - \theta \in [0, 1]$ of firms is allowed to reoptimize over the price. The value of an intermediate goods firm $V^R(X)$ that is allowed to reoptimize is:

$$V^R(X) = \max_{p_i} \left\{ \Xi + \theta \mathbb{E}_X \left[M^{P\prime} V^N(p_i, X') \right] + (1-\theta) \mathbb{E}_X \left[M^{P\prime} V^R(X') \right] \right\}. \tag{2.25}$$

The value of an intermediate goods firm $V^N(p_{i,-1}, X)$ that is not allowed to reoptimize is:

$$V^N(p_{i,-1}, X) = \Xi + \theta \mathbb{E}_X \left[M^{P\prime} V^N(p_i, X') \right] + (1-\theta) \mathbb{E}_X \left[M^{P\prime} V^R(X') \right]. \tag{2.26}$$

Intermediate goods firms which do not reoptimize set their price by fully indexing it to steady state inflation $\bar{\pi}$:

$$p_i = \frac{1+\bar{\pi}}{1+\pi} p_{i,-1}. \tag{2.27}$$

Instead, optimizing firms set their price as:

$$p^{\star} = \frac{\varepsilon}{\varepsilon - 1} \frac{p^A}{p^B}, \tag{2.28}$$

where

$$p^A = p_m y + \theta \mathbb{E}_X \left[M^{P\prime} \left(\frac{1+\pi'}{1+\bar{\pi}} \right)^{\varepsilon} p^{A\prime} \right], \tag{2.29}$$

$$p^B = y + \theta \mathbb{E}_X \left[M^{P\prime} \left(\frac{1+\pi'}{1+\bar{\pi}} \right)^{\varepsilon - 1} p^{B\prime} \right]. \tag{2.30}$$

The inflation law of motion associated with the optimal price $p^{\star}$, the indexation rule (2.27) and the zero profit condition (2.24) is

$$\pi = \frac{\theta(1+\bar{\pi})}{(1-(1-\theta)p^{\star 1-\varepsilon})^{\frac{1}{1-\varepsilon}}} - 1. \tag{2.31}$$

This pricing generates price dispersion. The price dispersion index $\Delta = \int_0^1 p_i^{-\varepsilon} di$ evolves according to the following law of motion:

$$\Delta = (1-\theta)\, p^{\star -\varepsilon} + \theta \left(\frac{1+\pi}{1+\bar{\pi}} \right)^{\varepsilon} \boldsymbol{\Delta}_{-1}. \tag{2.32}$$

Wholesale Goods Firms

The wholesale good y_m is produced by a continuum of perfectly competitive identical firms, which use a linear technology in labor $y_m = z\check{n}$, where $\check{n}$ is labor demand and z is technology. These firms solve:

$$\max_{n^d} \{ p_m z \check{n} - Q \check{n} \}. \tag{2.33}$$

The real unit price Q of labor services n is given by the first order condition:

$$Q = p_m z. \tag{2.34}$$

Labor Intermediaries

Labor intermediaries hire labor from both perfectly and imperfectly insured households in a frictional labor market and sell labor services to wholesale goods firms. Every period there is exogenous separation rate ρ between employers and workers. At the same time, labor intermediaries post vacancies at the unit cost κ. There is a skill premium for perfectly insured households over imperfectly insured ones.[17] In particular, while an employed imperfectly insured household provides one unit of labor services and earns a wage w, an employed perfectly insured household provides $\psi > 1$ units of labor services and earns $w^P = \psi w$. Hence, the values for a labor intermediary of a match with imperfectly and perfectly insured households are:

$$J^I = Q - w + \mathbb{E}_X \left[(1 - \rho') \, M^{I\prime} J^{I\prime} \right], \tag{2.35}$$

$$J^P = \psi Q - \psi w + \mathbb{E}_X \left[(1 - \rho') \, M^{P\prime} J^{P\prime} \right], \tag{2.36}$$

which implies that $J^I = \psi J^P$. Moreover, given the vacancy filling rate λ, the free entry condition of labor intermediaries implies that the value of opening a vacancy has to equalize its cost:

$$\lambda \left(\Omega J^I + (1 - \Omega) \, J^P \right) = \kappa. \tag{2.37}$$

The aggregate employment rate at the beginning and at the end of the labor market transition stage are given respectively by

$$\tilde{\mathbf{n}} = \Omega \tilde{\mathbf{n}}^I + (1 - \Omega) \psi \tilde{\mathbf{n}}^P, \tag{2.38}$$

$$\mathbf{n} = \Omega \mathbf{n}^I + (1 - \Omega) \psi \mathbf{n}^P, \tag{2.39}$$

which implies that $\tilde{\mathbf{n}}' = \mathbf{n}$.

The aggregate unemployment rate $\mathbf{u}$ is given by the unemployed households $\mathbf{1} - \tilde{\mathbf{n}}$ at the beginning of the labor market transition stage plus the fraction ρ of employed

[17] We follow Challe et al. (2017) in introducing a skill premium for the perfectly insured. As a matter of fact, consumption heterogeneity in the U.S. cannot be fully imputed to the heterogeneity in asset income. Some heterogeneity in labor income is needed to match the heterogeneity in consumption. We test the sensitivity of our results to the skill premium in Section 2.5.

households, who loose their job over the period:

$$\mathbf{u} = 1 - \tilde{\mathbf{n}} + \rho\tilde{\mathbf{n}}. \tag{2.40}$$

Firm-worker matches are created through the following matching technology

$$m = \mu\mathbf{u}^{\chi}v^{1-\chi}, \tag{2.41}$$

where v are the posted vacancies, μ is the matching efficiency parameter, and χ is the elasticity of matches with respect to unemployed households. The aggregate job finding and job filling rates are given by:

$$f = \frac{m}{\mathbf{u}}, \tag{2.42}$$

$$\lambda = \frac{m}{v}. \tag{2.43}$$

Since the workers who loose their job at the beginning of the labor market transition period can be rematched within the same period, the period-to-period separation rate is:

$$s = \rho\left(1 - f\right). \tag{2.44}$$

Given the job finding rate f and the job separation rate s, the law of motion of aggregate labor is:

$$\mathbf{n} = f\tilde{\mathbf{n}} + \left(1 - s\right)\tilde{\mathbf{n}}. \tag{2.45}$$

We assume that wages are set according to the following wage rule:

$$w = \bar{w}\left(\frac{\mathbf{n}}{\bar{n}}\right)^{\phi_w}, \tag{2.46}$$

where ϕ_w indicates the elasticity of wages to deviations of employment from its steady-state value $\bar{n}$ and $\bar{w}$ is the steady state wage.

2.3.3 Monetary Authority

The monetary authority follows a standard Taylor rule, where the nominal interest rate R reacts to inflation and output growth. The rule is:

$$\frac{1+R}{1+\bar{R}} = \left(\frac{1+\pi}{1+\bar{\pi}}\right)^{\phi_\pi} \left(\frac{y}{\mathbf{y}_{-1}}\right)^{\phi_y}, \tag{2.47}$$

where $\bar{R}$ is the steady-state nominal interest rate, and ϕ_π and ϕ_y are the reaction coefficients to inflation and output growth.

The real interest rate is determined as follows:

$$1+r = \frac{1+\mathbf{R}_{-1}}{1+\pi}. \tag{2.48}$$

2.3.4 Exogenous Processes

The technology z used by wholesale goods firms is subject to first and second moment shocks according to the following stochastic processes:

$$\log z = \rho_z \log z_{-1} + \sigma^z \varepsilon^z, \tag{2.49}$$

$$\log \sigma^z = (1-\rho_{\sigma^z}) \log \bar{\sigma}^z + \rho_{\sigma^z} \log \sigma^z_{-1} + \sigma^{\sigma^z} \varepsilon^{\sigma^z}. \tag{2.50}$$

In particular, $\varepsilon^z \sim N(0,1)$ is a first-moment shock capturing innovations to the level of technology, while $\varepsilon^{\sigma^z} \sim N(0,1)$ is a second moment shock capturing innovations to the standard deviation σ^z of technology. ρ_z and ρ_{σ^z} indicate the persistence of the two processes and σ^{σ^z} is the standard deviation of σ^z. The second moment shock is how we introduce uncertainty into the model.[18] We interpret a positive second moment shock as an increase in uncertainty in the economy.

[18] Oh (2020) shows that responses of macro variables do not qualitatively depend on the source of uncertainty.

2.3.5 Market Clearing

Labor Market

All households face the same job finding rate f and job separation rate s. Since we assume that employment is symmetric between perfectly and imperfectly insured households at the beginning of period zero, for the law of large numbers it remains symmetric at every point in time. Hence, the share of perfectly and imperfectly insured agents which is employed is the same, and family-level variables are equal to aggregate variables:

$$\tilde{n}^P = \tilde{n}^I = \tilde{\mathbf{n}}^P = \tilde{\mathbf{n}}^I \equiv \tilde{\mathbf{n}}, \tag{2.51}$$

$$n^P = n^I = \mathbf{n}^P = \mathbf{n}^I \equiv \mathbf{n}. \tag{2.52}$$

Moreover, the aggregate labor supply is:

$$\Omega \mathbf{n}^I + (1-\Omega)\,\psi \mathbf{n}^P = (\Omega + (1-\Omega)\,\psi)\,\mathbf{n}, \tag{2.53}$$

and the labor market clearing condition is:

$$(\Omega + (1-\Omega)\,\psi)\,\mathbf{n} = \check{n}. \tag{2.54}$$

Assets Market

All households participate in the assets market, which is in zero net supply:

$$\Omega\,(A + (1-\mathbf{n})\,\underline{a}) + (1-\Omega)\,a^P = 0. \tag{2.55}$$

There are Ω imperfectly insured households and $1-\Omega$ perfectly insured households. Imperfectly insured households own either A if their budget constraint is not binding or $\underline{a}$ if it is binding.[19] Perfectly insured households own assets a^P.

[19] Since we have assumed that the borrowing constraint of unemployed imperfectly insured households becomes binding after one period of unemployment spell, the assets that they own is equal to the borrowing limit $\underline{a}$ regardless of the length of their unemployment spell N. This would not be the case if the borrowing limit became biding after more than one period of unemployment spell.

Goods Market

The final good production y has to be equal to the final good aggregate consumption c plus the cost of posting vacancies:

$$c + \kappa v = y. \tag{2.56}$$

Aggregate consumption is the share Ω of imperfectly insured households' consumption plus the share $1 - \Omega$ of perfectly insured households' consumption c^P. The former is made of the consumption of imperfectly insured households who are employed $n^I(0)\,c^I(0)$, who have been unemployed for one period $n^I(1)\,c^I(1)$, and who have been unemployed for at least two periods $n^I(2)\,c^I(2)$:

$$c \equiv \Omega\left(n^I(0)\,c^I(0) + n^I(1)\,c^I(1) + n^I(2)\,c^I(2)\right) + (1-\Omega)\,c^P. \tag{2.57}$$

Intermediate goods market is in equilibrium when the intermediate goods demand Δy is equal to its supply $y_i - \Phi$:

$$\Delta y = y_m - \Phi. \tag{2.58}$$

Finally, the market clearing condition for the wholesale goods is:

$$\int_0^1 x_i di = y_m = z\check{n}. \tag{2.59}$$

2.3.6 Aggregate State and Equilibrium

We focus on symmetric equilibrium, where variables at family-level are identical. The aggregate state X is then given by:

$$X = \left\{\tilde{\mu}(\cdot), a^P, a^I(0), \mathbf{c}^P, \mathbf{c}^I(N)_{N\geq 0}, \mathbf{R}_{-1}, \mathbf{y}_{-1}, \boldsymbol{\Delta}_{-1}, \tilde{\mathbf{n}}, z, \sigma^z\right\}. \tag{2.60}$$

When $\hat{N} = 1$, i.e. when the borrowing constraint becomes binding after one period of unemployment spell, the heterogeneity of the imperfectly insured households can be reduced to three types: the employed type $N = 0$, the unemployed type for one period $N = 1$, and the unemployed type for more than one period $N \geq 2$. These types are in shares of respectively: $\Omega\mathbf{n}$, $\Omega s\tilde{\mathbf{n}}$, and $\Omega(1 - \mathbf{n} - s\tilde{\mathbf{n}})$. In this specific case, a symmetric equilibrium is given by the following conditions:

1. the Euler condition (2.19) and the IMRS (2.20) for the perfectly insured households hold, and the Euler condition (2.11) and the IMRS (2.12) for the imperfectly insured households hold;

2. the budget constraint for the perfectly insured households (2.18) and the budget constraints for the three types of imperfectly insured households (2.4) and (2.5) with assets determined by (2.6) and (2.7);

3. the price set by optimizing firms, the inflation rate and the price dispersion are determined by (2.28) to (2.32), and the real unit price of labor services by (2.34);

4. the aggregate employment and unemployment rates are given by (2.38), (2.39), and (2.40), the job finding rate, the job filling rate, the period-to-period separation rate, and the matching function technology by (2.42), (2.43), (2.44) and (2.41), the aggregate labor law of motion by (2.45), the value of a match and the value of opening a vacancy are given by (2.35) to (2.37);

5. wages are determined according to (2.46), social contributions to (2.1) and (2.16), and nominal and real interest rates to (2.47) and (2.48);

6. the market clearing conditions (2.51) to (2.59) hold;

7. consumption habits are as follows: $\mathbf{c}^{P\prime} = c^P$, $\mathbf{c}^{I\prime}(0) = c^I(0)$, $\mathbf{c}^{I\prime}(1) = c^I(1)$, and $\mathbf{c}^{I\prime}(2) = c^I(2)$.

2.3.7 Precautionary Savings

The model features precautionary savings induced by positive uncertainty shocks through two different channels, a direct and an indirect one. The direct channel works through households' risk aversion. Because of its convexity, the IMRS of all households under uncertainty is larger than under certainty. A higher IMRS induces households to substitute out of consumption towards savings in a precautionary manner.

The indirect channel is due to uninsured unemployment risk. While both perfectly and imperfectly insured households bear unemployment risk, perfectly insured households fully share this risk, while imperfectly insured households face partial risk sharing.

Partial insurance further strengthens the precautionary saving behavior of imperfectly insured households. This indirect channel works as follows. Higher uncertainty triggers a drop in aggregate demand, which, in turn, generates a fall in production and a decrease in posted vacancies. Less vacancies lead to a drop in the finding rate f, which increases the endogenous separation rate $s = \rho(1 - f)$. A lower finding rate and a higher separation rate increase the imperfectly insured households' propensity to save. The last implication can be derived from the IMRS of imperfectly insured households. In particular, if imperfectly insured households are employed ($N = 0$), their IMRS is as follows:

$$M^{I\prime}(0) = \beta^I \frac{(1 - s') u_c^{I\prime}(0) + s' u_c^{I\prime}(1)}{u_c^I(0)}, \qquad N = 0. \tag{2.61}$$

Their marginal utility of consumption when becoming unemployed $u_c^{I\prime}(1)$ is higher than their marginal utility of consumption when remaining employed $u_c^{I\prime}(0)$, as falling into unemployment generates a drop in consumption and marginal utility is decreasing in consumption. Therefore, whenever the separation rate s' rises, the IMRS increases, thus pushing imperfectly insured households to save more. A similar reasoning applies to the IMRS of imperfectly insured households who are unemployed ($N \geq 1$):

$$M^{I\prime}(N) = \beta^I \frac{(1 - f') u_c^{I\prime}(N+1) + f' u_c^{I\prime}(0)}{u_c^I(N)}, \qquad N \geq 1. \tag{2.62}$$

Whenever the finding rate f' drops, the IMRS increases as the marginal utility of consumption when remaining unemployed $u_c^{I\prime}(N+1)$ is higher than the marginal utility of consumption when becoming employed.

Notice that since throughout the paper we assume that the borrowing limit becomes binding after one period of unemployment spell, only the Euler condition for $N = 0$ will hold with equality, while the Euler condition for $N > 0$ will be slack. This implies that the precautionary saving motive will only concern *employed* imperfectly insured households, who are the only type of imperfectly insured households allowed to save. To the contrary, *unemployed* imperfectly insured households will be at their borrowing limit, so their asset position will simply be $\underline{a}$.

2.4 Quantitative Results

2.4.1 Calibration and Solution Method

Table 2.1 reports the parameter values for a quarterly calibration to the U.S. economy over the period 1982Q1-2015Q3. We mainly follow Challe et al. (2017). The share of imperfectly insured households Ω is calibrated to 0.60. Risk aversion σ is set to the standard value of 1.00 to have log utility, while the habit persistence is in the range estimated by Challe et al. (2017). The discount factor of perfectly insured households β^P is set to match an annual interest rate of 3%, while the discount factor of imperfectly insured households β^I is set to target a 21% consumption drop when falling into unemployment. The unemployment benefits are calibrated to target a replacement rate of 33%. As for parameters related to firms, we set the elasticity of substitution between goods to get a 20% markup. The price stickiness θ is calibrated to have a price resetting spell of four quarters. Moving to labor market parameters, the matching efficiency μ is set to target a job filling rate of 71%, which follows Den Haan et al. (2000). The job separation rate ρ targets a job loss rate of 6.1% and a job finding rate of 73%. The former follows Challe et al. (2017). The latter is computed following Shimer (2005) by using unemployment and short-term unemployment data from the Current Population Survey. The matching function elasticity χ is set according to Petrongolo and Pissarides (2001). The vacancy posting cost κ is calibrated to being 1% of output following Challe et al. (2017). The skill premium ψ is set to 2.04 so as to match the consumption share (42%) of the poorest 60% of the households. The wage elasticity with respect to employment ϕ_w is in the range estimated by Challe et al. (2017). As far as monetary policy parameters are concerned, we set the steady-state inflation $\bar{\pi}$ to target a 2% annual inflation, the interest rate responsiveness to inflation ϕ_π to 1.50 and the interest rate responsiveness to output growth ϕ_y to 0.25. Moving to the shock processes, we set the persistence ρ_z and the steady-state volatility $\bar{\sigma}^z$ of the technology shock to the standard values of 0.95 and 0.007. As for the uncertainty shock process, we follow Katayama and Kim (2018) in modelling our counterpart to the macro uncertainty used in Section 2.2 as stochastic volatility to technology. We set the persistence ρ_{σ^z} and the volatility σ^{σ^z} to 0.85 and 0.37, values which are also in line with Leduc and Liu (2016).

Table 2.1 – **Quarterly calibration**

Parameter	Description	Value	Target/Source
	Households		
Ω	Share of imp. insured HHs	0.60	Challe et al. (2017)
$\underline{a}$	Borrowing limit	0	Challe et al. (2017)
σ	Risk aversion	1.00	Log utility
h	Habit persistence	0.60	Challe et al. (2017)
β^I	Discount factor of imp. insured HHs	0.961	21% consumption loss
β^P	Discount factor of perf. insured HHs	0.993	3% annual real interest rate
b^u	Unemployment benefits	0.27	33% replacement rate
	Firms		
ε	Elasticity of substitution btw goods	6.00	20% markup
θ	Price stickiness	0.75	4-quarter stickiness
	Labor Market		
μ	Matching efficiency	0.72	71% job filling rate
χ	Matching function elasticity	0.50	Petrongolo and Pissarides (2001)
ρ	Job separation rate	0.23	73% job finding & 6.1% job loss rates
κ	Vacancy posting cost	0.037	1% of output
ψ	Skill premium	2.04	Bottom 60% consumption share (42%)
ϕ_w	Wage elasticity wrt employment	1.50	Challe et al. (2017)
	Monetary Authority		
$\bar{\pi}$	Steady-state inflation	1.005	2% annual inflation rate
ϕ_π	Taylor rule coefficient for inflation	1.50	Standard
ϕ_y	Taylor rule coefficient for output	0.25	Standard
	Exogenous Processes		
ρ_z	Persistence of technology shock	0.95	Standard
$\bar{\sigma}^z$	Volatility of technology shock	0.007	Standard
ρ_{σ^z}	Persistence of uncertainty shock	0.85	Katayama and Kim (2018)
σ^{σ^z}	Volatility of uncertainty shock	0.37	Katayama and Kim (2018)

To study the effects of uncertainty shocks, we solve the model using a third-order perturbation method, as suggested by Fernández-Villaverde et al. (2011). The third-order perturbation moves the ergodic means of the endogenous variables of the model away from their deterministic steady-state values. Hence, we compute the impulse responses in percent deviation from the stochastic steady state of each endogenous variable. For that, we use the Dynare software package developed by Adjemian et al. (2011) and the pruning algorithm designed by Andreasen et al. (2018).

2.4.2 Baseline Results

Figure 2.5 shows the impulse responses of the variables of interest to a one standard deviation shock in technology uncertainty. The solid blue line shows the responses of the model with imperfectly insured unemployment risk as described in Section 2.3. The dashed red line shows the responses of the corresponding representative agent New Keynesian model where unemployment risk is fully insured. This model is identical to the former model except that there are no imperfectly insured households, that is $\Omega = 0$. In this case, there is only one type of households, the perfectly insured ones, who fully share risk. As a benchmark, we first describe the responses of the model with perfect insurance (PI), before illustrating the responses generated by the model with imperfect insurance (II).

Responses of the Model with Perfect Insurance

In the PI model, a positive uncertainty shock in technology has both an aggregate demand effect through households' saving decisions and an aggregate supply effect through firms' pricing decisions. On the one hand, higher uncertainty induces a negative wealth effect on risk-averse households, who increase savings and decrease consumption (see Fernández-Villaverde et al., 2015, Leduc and Liu, 2016, Basu and Bundick, 2017, and Oh, 2020 for this precautionary saving channel). This causes a drop in aggregate demand. The decrease in aggregate demand reduces the marginal cost that firms are facing and pushes them to lower prices to stimulate demand. On the other hand, an increase in uncertainty triggers a precautionary pricing behavior of firms, which are subject to Calvo pricing. When uncertainty increases, optimizing firms increase their prices to self-insure against the risk of being stuck with low prices in the future (see Born and Pfeifer, 2014, Fernández-Villaverde et al., 2015, and Oh, 2020 for this precautionary pricing channel). Since the increase in prices induced by the precautionary pricing behavior of firms is stronger than the drop in prices induced by the precautionary saving behavior of households, inflation increases after a positive uncertainty shock.

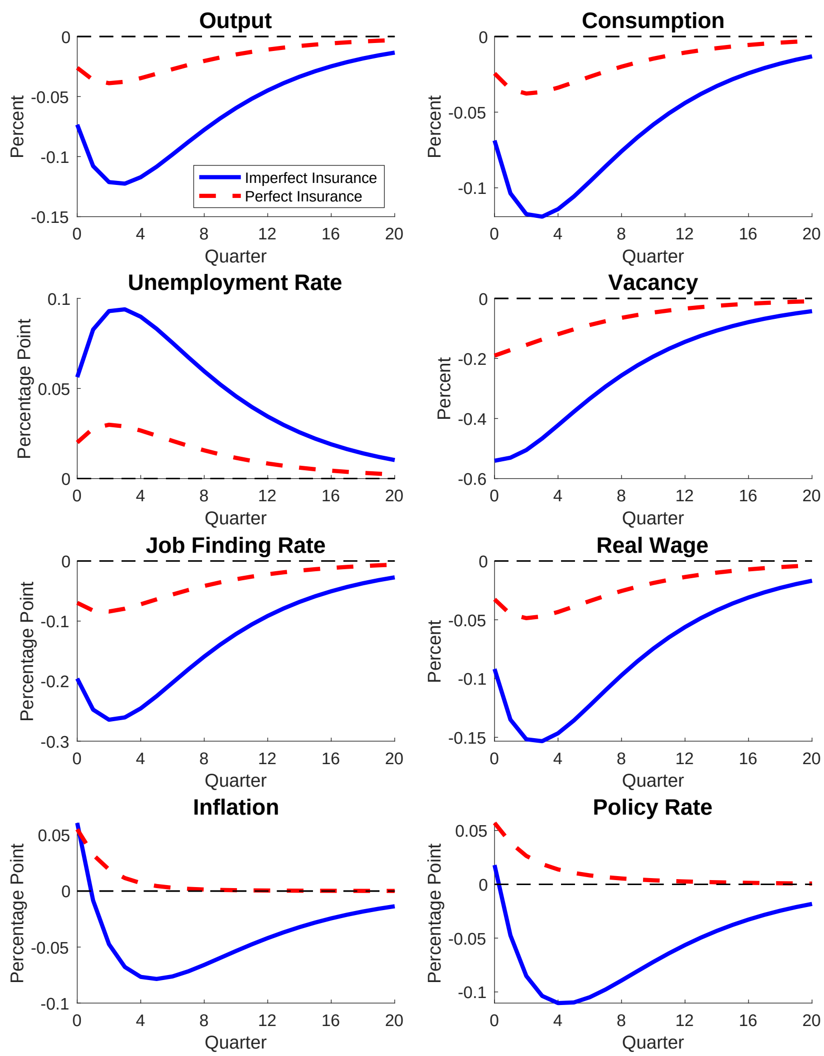


Figure 2.5 – **Impulse responses to one-standard deviation technology uncertainty shocks**

Note: Impulse responses of output, consumption, vacancy, and real wage are in percent deviation from their stochastic steady state, impulse responses of unemployment rate and job finding rate are in percentage point deviations from their stochastic steady state, while inflation and policy rate are in annualized percentage point deviations from their stochastic steady state.

Responses of the Model with Imperfect Insurance

The II model adds a new channel of transmission and amplification of the uncertainty shock to the precautionary saving and pricing behavior described above for the PI model. This is graphically illustrated by Figure 2.6.

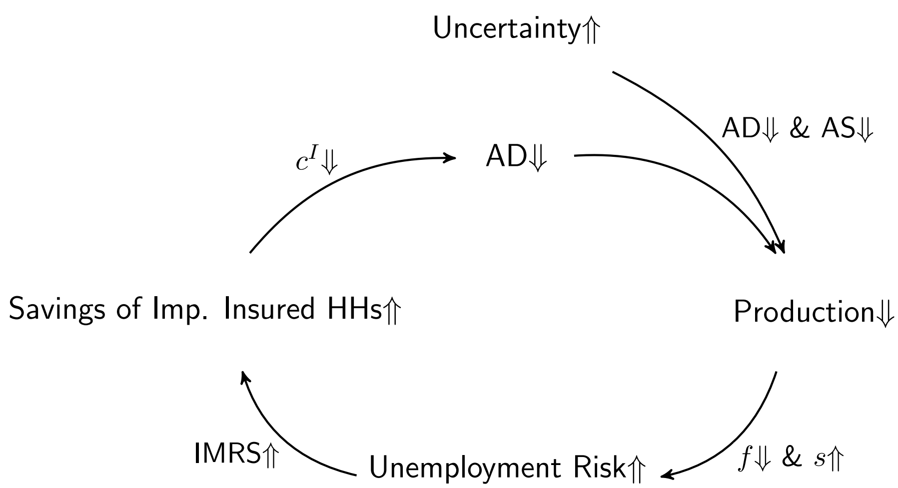


Figure 2.6 – **Propagation mechanism of a positive uncertainty shock**

As explained for the PI model, an uncertainty shock causes a drop in aggregate demand triggered by the precautionary saving behavior of households. The drop in demand induces firms to lower their vacancy posting, thus reducing the job finding rate and increasing the unemployment rate. At this point the presence of imperfectly insured households becomes key to explain the dynamics of the model. Since imperfectly insured households cannot fully insure against unemployment as they are subject to *imperfect* risk sharing, a higher unemployment risk induces them to further increase savings and decrease consumption. The imperfectly insured households' precautionary saving behavior triggers a feedback loop, which reinforces the drop in aggregate demand. At the same time, firms precautionary pricing behavior generates a reduction in vacancy posting and an increase in unemployment. This further reinforces the precautionary saving behavior of imperfectly insured households and strengthen the feedback loop. Figure 2.7 illustrates the responses of consumption for both imperfectly (dashed line) and perfectly (dotted line) insured households. Because of the precautionary saving behavior that partial risk sharing induces on imperfectly insured households, their consumption response is much stronger than the one of perfectly insured households.

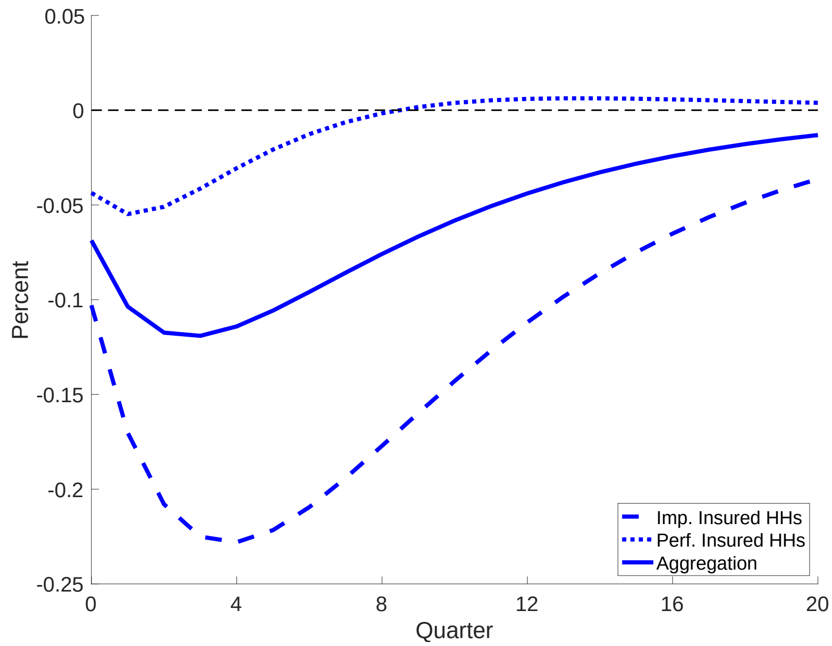


Figure 2.7 − **Consumption heterogeneity**

Note: Impulse responses of consumption are in percent deviation from their stochastic steady state.

The presence of heterogeneous agents bears two consequences on the propagation mechanism of uncertainty shocks. First, the feedback loop triggered by the precautionary saving behavior of imperfectly insured households is strong enough to induce a drop in prices that outweighs the increase in prices due to the precautionary pricing behavior of optimizing firms. This is the reason why, after two quarters, inflation response becomes negative, which is in line with our empirical results as shown by Figure 2.1. Second, the feedback loop amplifies all the responses. The precautionary behavior of imperfectly insured households triggers a drop in aggregate demand, which is much stronger than in the PI model. In parallel, the decrease in vacancy posting and the increase in unemployment rate are sharper.

It is worth noticing that our results hinge upon the interaction between the precautionary saving behavior of agents induced by imperfect risk sharing and the precautionary pricing behavior of firms induced by price rigidities à la Calvo (1983). It is the interaction between these two features that allows us to obtain a drop in inflation and an amplification of responses, which quantitatively match the empirical evidence.

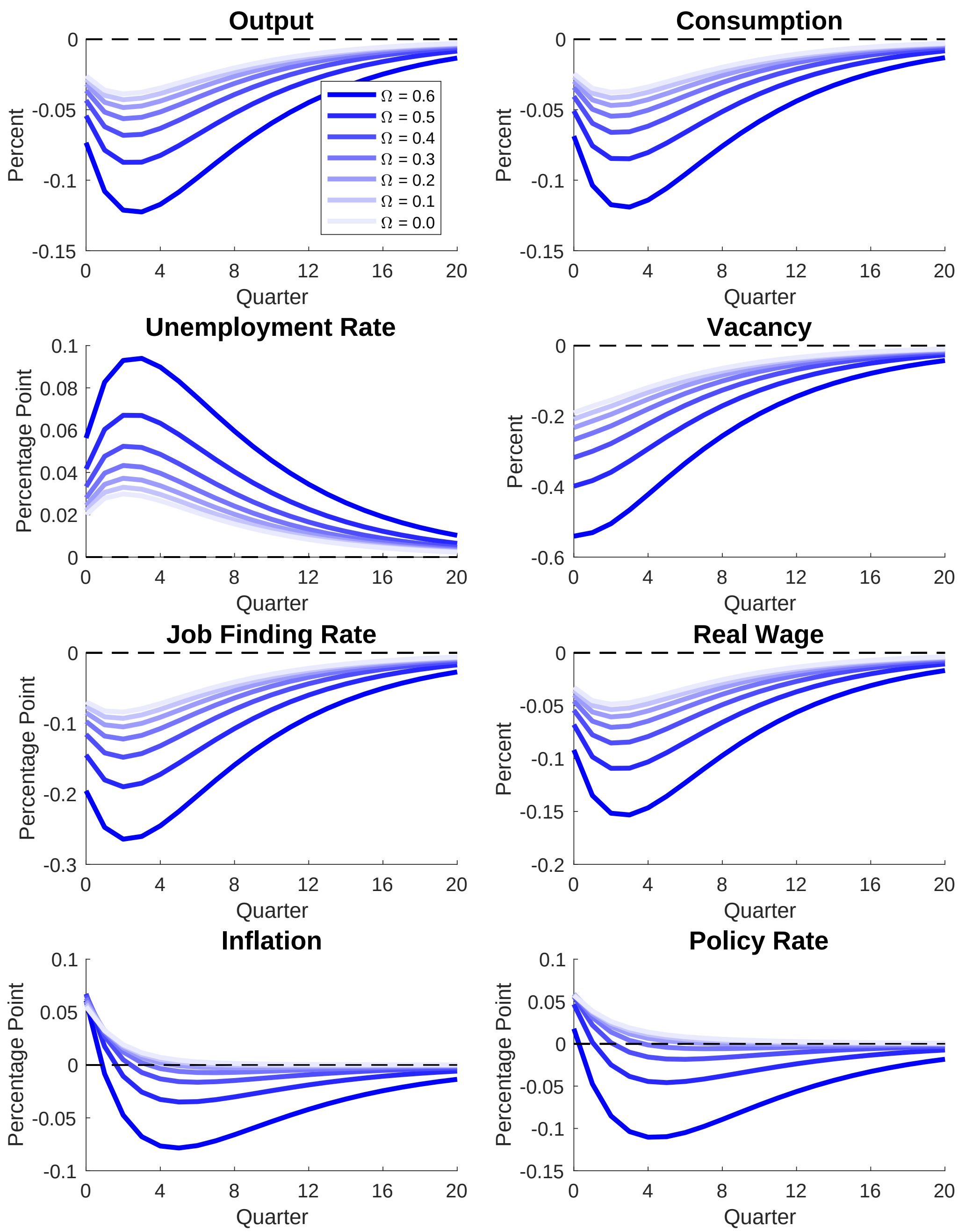


Figure 2.8 – **Different degrees of heterogeneity**

Note: Impulse responses of output, consumption, vacancy, and real wage are in percent deviation from their stochastic steady state, impulse responses of unemployment rate and job finding rate are in percentage point deviations from their stochastic steady state, while inflation and policy rate are in annualized percentage point deviations from their stochastic steady state.

Since the presence of imperfectly insured households is crucial both to determine the response of inflation and to amplify the responses of the other variables, Figure 2.8 shows how the impulse responses vary when varying the share of imperfectly insured households. On impact, inflation increases regardless of the share of imperfectly insured households. As soon as the negative feedback loop on aggregate demand induced by the precautionary saving behavior of imperfectly insured households kicks in, inflation decreases. Indeed, the higher is the share of imperfectly insured households, the stronger the feedback effect becomes and the more inflation drops. Figure 2.8 also shows that a bigger share of imperfectly insured households amplifies the responses of the other variables. In particular, output, consumption, vacancies, job finding rate, and wages drop more, while unemployment rate increases more, the higher is the share of imperfectly insured households.

2.5 Robustness Checks

2.5.1 Rotemberg Pricing

To decompose how much of our results is driven by the direct and the indirect precautionary saving channel as well as by the precautionary pricing channel, this section compares the PI and the II models studied in the previous sections to identical models where we substitute the Calvo (1983)-type price rigidity with the Rotemberg (1982)-type price rigidity. As the Rotemberg pricing assumption does not feature any precautionary pricing effect, comparing the responses of models with the two different pricing assumptions allows us to quantify how much of the uncertainty shock propagation is due to the precautionary pricing effect. Before exploring in detail how comparing II and PI models with Calvo and Rotemberg pricing is helpful in disentangling the three precautionary channels, let us discuss what changes need to be made to the model when we substitute Rotemberg pricing to Calvo pricing.

As before, an intermediate good firm chooses price p_i to maximize the present discounted value of future profits subject to the demand curve (2.23). Now, its value is given by:

$$V^{Rotem}\left(p_{i,-1},X\right)=\max_{p_i}\left\{\Xi-\frac{\eta}{2}\left(\frac{\left(1+\pi\right)p_i}{\left(1+\bar{\pi}\right)p_{i,-1}}-1\right)^2 y+\mathbb{E}_X\left[M^{P\prime}V^{Rotem}\left(p_i,X'\right)\right]\right\}, \tag{2.63}$$

where $\frac{\eta}{2}\left(\frac{(1+\pi)p_i}{(1+\bar{\pi})p_{i,-1}}-1\right)^2 y$ is a quadratic price adjustment cost. Imposing a symmetric equilibrium across firms implies that $p_i = 1$ and $y_i = y$. The optimal Calvo price equilibrium conditions (2.28), (2.29), and (2.30) are now replaced with the following equation:

$$\eta\left(\frac{1+\pi}{1+\bar{\pi}}-1\right)\frac{1+\pi}{1+\bar{\pi}}=\eta\mathbb{E}_X M^{P\prime}\left(\frac{1+\pi'}{1+\bar{\pi}}-1\right)\frac{1+\pi'}{1+\bar{\pi}}\frac{y'}{y}+1-\varepsilon+\varepsilon p_m. \tag{2.64}$$

Moreover, the intermediate goods market clearing condition (2.58) is replaced with

$$y=y_m-\Phi, \tag{2.65}$$

as Rotemberg-type frictions do not generate price dispersion. On the other hand, they generate price adjustment costs, which appear in the final good market clearing condition. Hence, condition (2.56) is replaced with

$$c+\kappa v+\frac{\eta}{2}\left(\frac{1+\pi}{1+\bar{\pi}}-1\right)^2 y=y. \tag{2.66}$$

Except for the equations mentioned above, all the other equilibrium conditions stay the same.

Figure 2.9 plots impulse responses to a positive uncertainty shock for the II ($\Omega = 0.6$) and the PI ($\Omega = 0$) model with Calvo and Rotemberg pricing. By comparing the four models we can precisely isolate the three precautionary channels: the direct precautionary saving channel, the indirect precautionary saving channel, and the precautionary pricing channel.

Let's first focus on the PI models. The PI model with Rotemberg pricing only features the direct precautionary saving channel. Through this channel, a positive uncertainty shock generates a negative wealth effect on risk-averse households, who decrease their consumption and increase their savings, thus lowering aggregate demand. While the only precautionary channel at play in the PI model with Rotemberg pricing is the direct precautionary saving one, the PI model with Calvo pricing adds the precautionary pricing channel. Hence, the difference between the responses of the PI model with Calvo pricing and the PI model with Rotemberg pricing helps us gauging the strength of the precautionary pricing channel.

As explained in Section 2.4.2, with Calvo-type frictions firms engage in a precautionary pricing behavior. This behavior leads them to increase prices to such an extent to overcompensate the downward pressure that the aggregate demand drop exerts on prices. That is the reason why the inflation response is positive on impact in the Calvo PI model. On the contrary, the precautionary pricing motive is absent in the Rotemberg pricing model, where all firms are symmetric and are allowed to reset their price every period, even though subject to an adjustment cost - see Oh (2020) for a thorough comparison between the Calvo and Rotemberg pricing models in response to uncertainty shocks. The absence of the precautionary pricing motive results in a drop in the inflation response to an increase in uncertainty. In addition to the opposite response of inflation, a further difference between the two PI models is that the Calvo pricing model generates more amplified responses. This difference is again induced by the precautionary pricing behavior of firms. Higher prices reduce consumption and push firms to cut their vacancy posting, thus decreasing the job finding rate and increasing the unemployment rate more than in the Rotemberg model. To generate even more amplification and a response of inflation fully in line with the data, a II model with Calvo pricing is necessary. This model features all three precautionary channels: the direct precautionary saving, the indirect precautionary saving and the precautionary pricing channel. Comparing the responses of the II model with Calvo pricing to the PI model with Calvo pricing allows us to isolate the effect of the indirect precautionary saving channel, which is the only precautionary channel that differentiates the two models. The heterogeneity of households in the II model enriches the dynamics of the PI model with the precautionary saving behavior of imperfectly insured households, who reduce their consumption more when unemployment risk rises. This depresses aggregate demand more than in the PI model. This indirect precautionary saving channel is necessary to contemporaneously obtain a drop in inflation as well as an amplification in the responses of the other variables that is quantitatively in line with the empirical evidence.

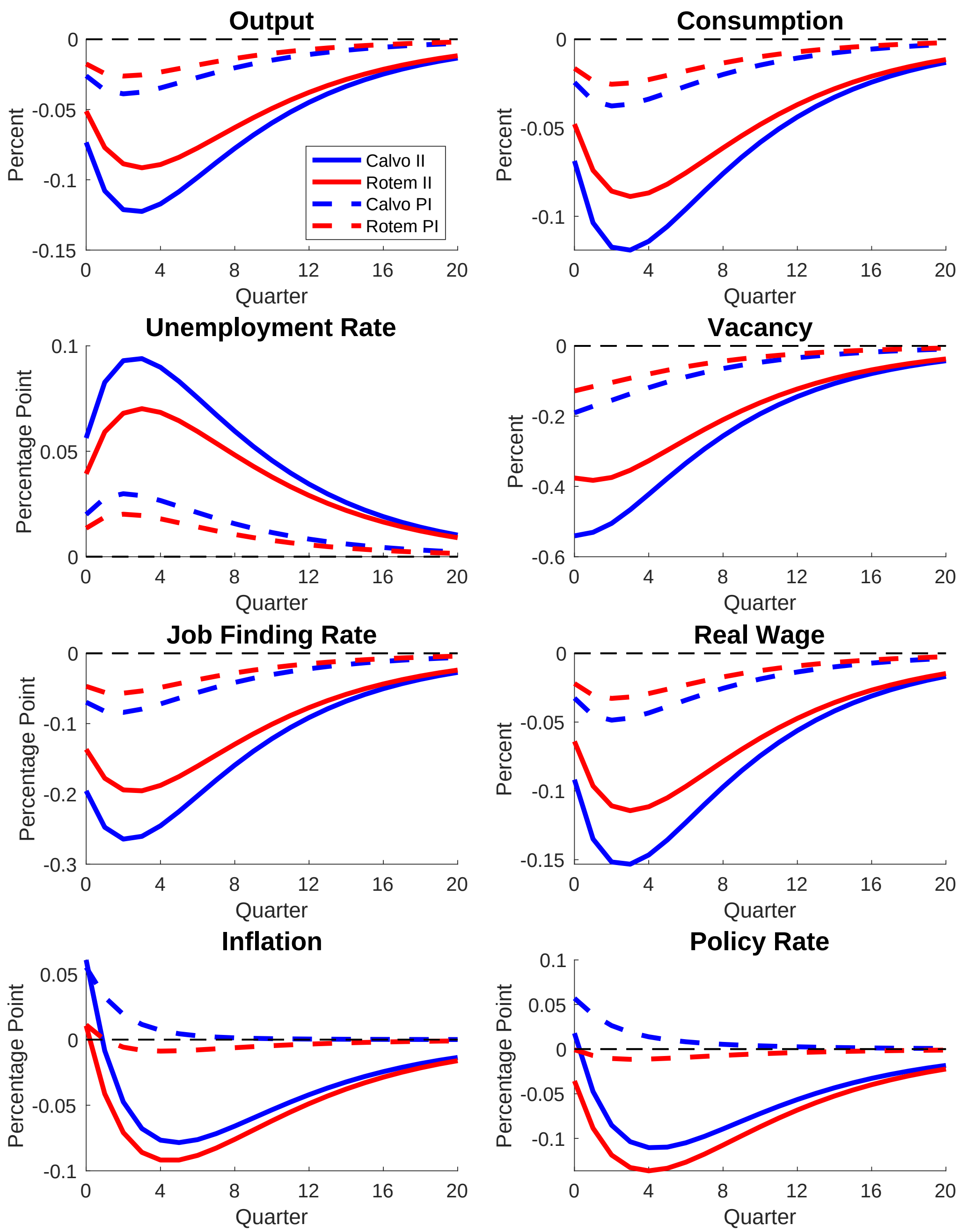


Figure 2.9 – **Comparison to Rotemberg pricing**

Note: Impulse responses of output, consumption, vacancy, and real wage are in percent deviation from their stochastic steady state, impulse responses of unemployment rate and job finding rate are in percentage point deviations from their stochastic steady state, while inflation and policy rate are in annualized percentage point deviations from their stochastic steady state.

2.5.2 Alternative Monetary Policy Rule

A potential concern regarding the response of inflation to uncertainty shocks might be that our result is dependant on the specification of the Taylor rule. In particular, it could be argued that, already in a representative agent model with only perfectly insured households, a direct response of monetary policy to uncertainty would not lead to a rise in inflation.

As a matter of fact, Fernández-Villaverde et al. (2015) modify the standard Taylor rule to address the counterfactual result that inflation increases in response to higher fiscal policy uncertainty. They assume that the nominal interest rate directly respond to fiscal volatility shocks. To assess how our result on inflation is robust to a Taylor rule specification à la Fernández-Villaverde et al. (2015), we modify the Taylor rule as follows:

$$\frac{1+R}{1+\bar{R}} = \left(\frac{1+\pi}{1+\bar{\pi}}\right)^{\phi_\pi} \left(\frac{y}{\mathbf{y}_{-1}}\right)^{\phi_y} \left(\frac{\exp\left(\sigma^z\right)}{\exp\left(\bar{\sigma}^z\right)}\right)^{\phi_\sigma}, \tag{2.67}$$

where σ^z is the TFP volatility, and $\phi_\sigma \geq 0$ is the responsiveness of the nominal interest rate to that volatility. Figure 2.10 shows the impulse responses of the main variables in our model under the assumption that there are only perfectly insured households, i.e. $\Omega = 0$.

The Figure reports three calibrations for ϕ_σ: $\phi_\sigma = 0$, which is our baseline case when the Taylor rule does not respond to uncertainty; $\phi_\sigma = 0.005$, which is the value calibrated by Fernández-Villaverde et al. (2015); and $\phi_\sigma = 0.03$, which captures a much stronger responsiveness to uncertainty. The Figure shows that with the Fernández-Villaverde et al. (2015) calibration inflation still rises in our setup with only perfectly insured households. Moreover, even with a much stronger monetary response to uncertainty, inflation drops only mildly at its trough. In addition, the responses of the other variables are quantitatively much smaller and not in line with the empirical evidence. This shows that a Taylor rule that reacts to uncertainty is not enough to obtain responses quantitatively in line with the data. To this end, it is necessary to assume heterogeneous agents to introduce a powerful enough amplification mechanism to the propagation of uncertainty.

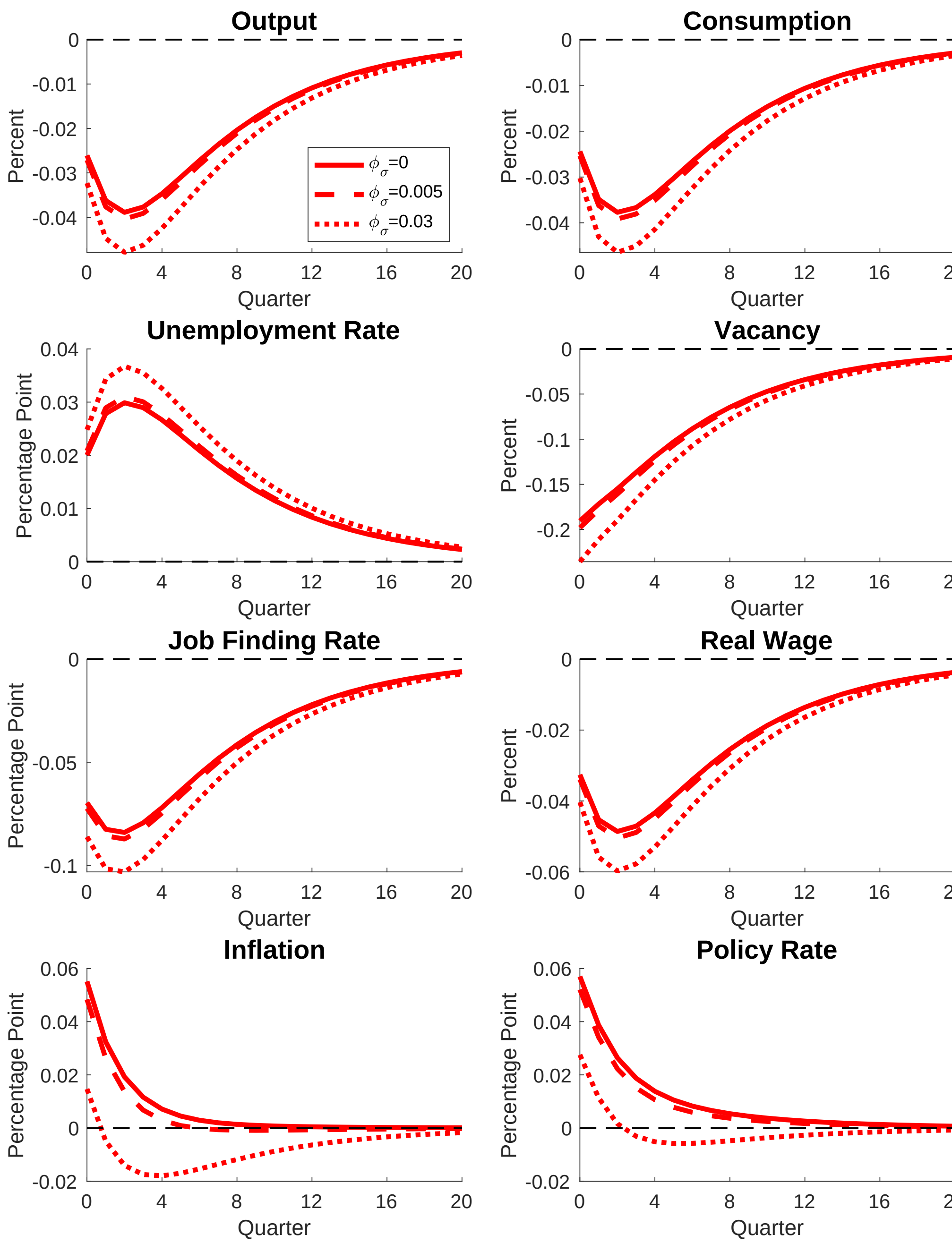


Figure 2.10 – **Alternative monetary policy rule in perfect insurance model**

Note: Impulse responses of output, consumption, vacancy, and real wage are in percent deviation from their stochastic steady state, impulse responses of unemployment rate and job finding rate are in percentage point deviations from their stochastic steady state, while inflation and policy rate are in annualized percentage point deviations from their stochastic steady state.

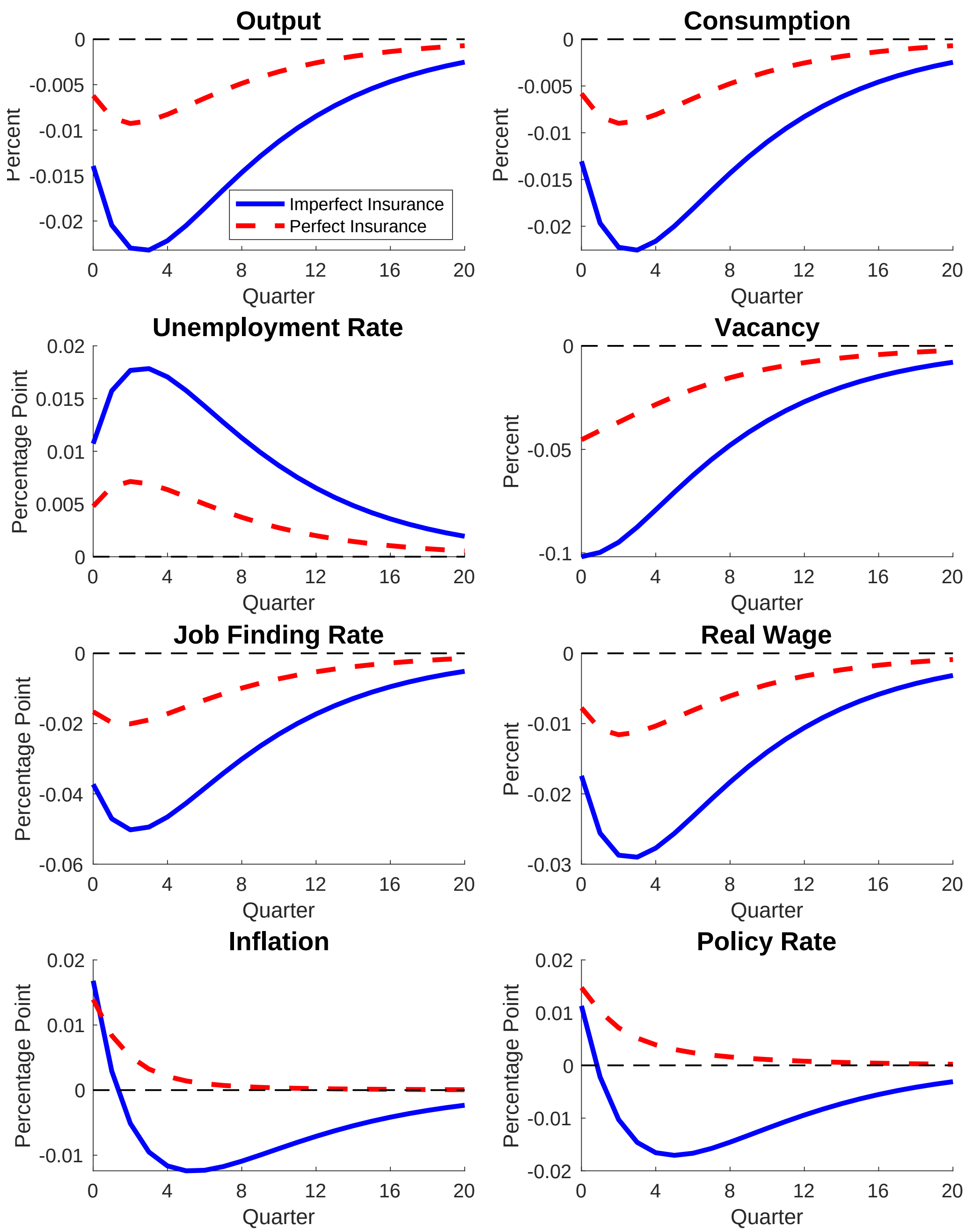


Figure 2.11 – **Impulse responses to one-standard deviation interest rate uncertainty**

Note: Impulse responses of output, consumption, vacancy, and real wage are in percent deviation from their stochastic steady state, impulse responses of unemployment rate and job finding rate are in percentage point deviations from their stochastic steady state, while inflation and policy rate are in annualized percentage point deviations from their stochastic steady state.

2.5.3 Different Source of Macro Uncertainty

In line with the vast majority of the literature on uncertainty propagation, we have focused so far on TFP uncertainty. Yet, the macro uncertainty index by Jurado et al. (2015) that we use in our empirical analysis captures a broader concept of uncertainty affecting the macro economy. Thus, in this section we extend our analysis to study how the economy reacts to an increase uncertainty on the demand side of the economy. In particular, we modify Equation (2.47) by assuming that there is a monetary policy shock z^R, subject to time varying volatility σ^R as follows:

$$\frac{1+R}{1+\bar{R}} = \left(\frac{1+\pi}{1+\bar{\pi}}\right)^{\phi_\pi} \left(\frac{y}{\mathbf{y}_{-1}}\right)^{\phi_y} z^R, \tag{2.68}$$

$$\log z^R = \rho_R \log z^R_{-1} + \sigma^R \varepsilon^R, \tag{2.69}$$

$$\log \sigma^R = (1-\rho_{\sigma^R}) \log \bar{\sigma}^R + \rho_{\sigma^R} \log \sigma^R_{-1} + \sigma^{\sigma^R} \varepsilon^{\sigma^R}. \tag{2.70}$$

We parametrize the persistence and the volatility of the monetary policy shock to $\rho_R = 0.7$ and $\bar{\sigma}^R = 0.0025$, while we set the persistence and volatility of the monetary policy uncertainty shock to $\rho_{\sigma^R} = 0.85$ and $\sigma^{\sigma^R} = 0.37$, consistently with the persistence and volatility of the TFP uncertainty shock. Figure 2.11 shows the responses to the monetary policy uncertainty shock. As can be seen, when there are only perfectly insured households inflation increases both on impact and in the following quarters. Only the presence of imperfectly insured households, who amplify the drop in demand triggered by the rise in uncertainty, allows us to obtain a persistent drop in inflation from the second quarter onward. Moreover, as in the case of TFP uncertainty shocks, imperfectly insured households generate an amplification of the responses of the other macro variables.

2.5.4 Additional Sensitivity Analyses

This section illustrates sensitivity exercises on various parameters, which affect the strength of the precautionary saving motive for imperfectly insured households.

The first row of Figure 2.12 shows how consumption and inflation respond when we vary households' risk aversion σ. A higher risk aversion generates a stronger precautionary response of imperfectly insured households, who cannot fully insure against risk. Hence, the more risk-averse imperfectly insured households are, the bigger the shift of their response out of consumption and towards savings. At the same time, inflation, which increases on impact, drops faster the higher the risk aversion is. This is due to the feedback effect that the precautionary saving behavior of households has on aggregate demand.

The second row of Figure 2.12 shows sensitivity of consumption and inflation response to various consumption differences between employed and unemployed households. Indeed, the bigger the consumption differential is between the two employment states, the stronger the precautionary saving motive that leads employed imperfectly insured households to save more, thus triggering a sharper drop in consumption and inflation.

The third sensitivity exercise that we carry out is on imperfectly insured households' consumption share ($C60/C$). This share is important as it negatively affects the skill premium ψ of perfectly insured households over imperfectly insured ones (as shown in Table 2.1, we calibrate the skill premium by targeting the share of imperfectly insured households' consumption). The bigger the imperfectly insured households' consumption share, the more the precautionary saving behavior of imperfectly insured households affects aggregate consumption, thus amplifying the drop in consumption and inflation caused by an uncertainty shock.

The next sensitivity exercise is on the elasticity of substitution between two intermediate goods ε. As shown in Oh (2020), a higher elasticity makes the marginal profit curve of intermediate firms more convex, thus strengthening the precautionary pricing behavior of firms. This is why, on impact, a higher elasticity causes a sharper increase in inflation. On the contrary, as soon as the higher prices set by intermediate firms trigger an increase in unemployment, the amplification effect of imperfectly insured households' precautionary saving behavior on aggregate demand kicks in, thus counteracting the price increase and leading to a sharper fall in inflation.

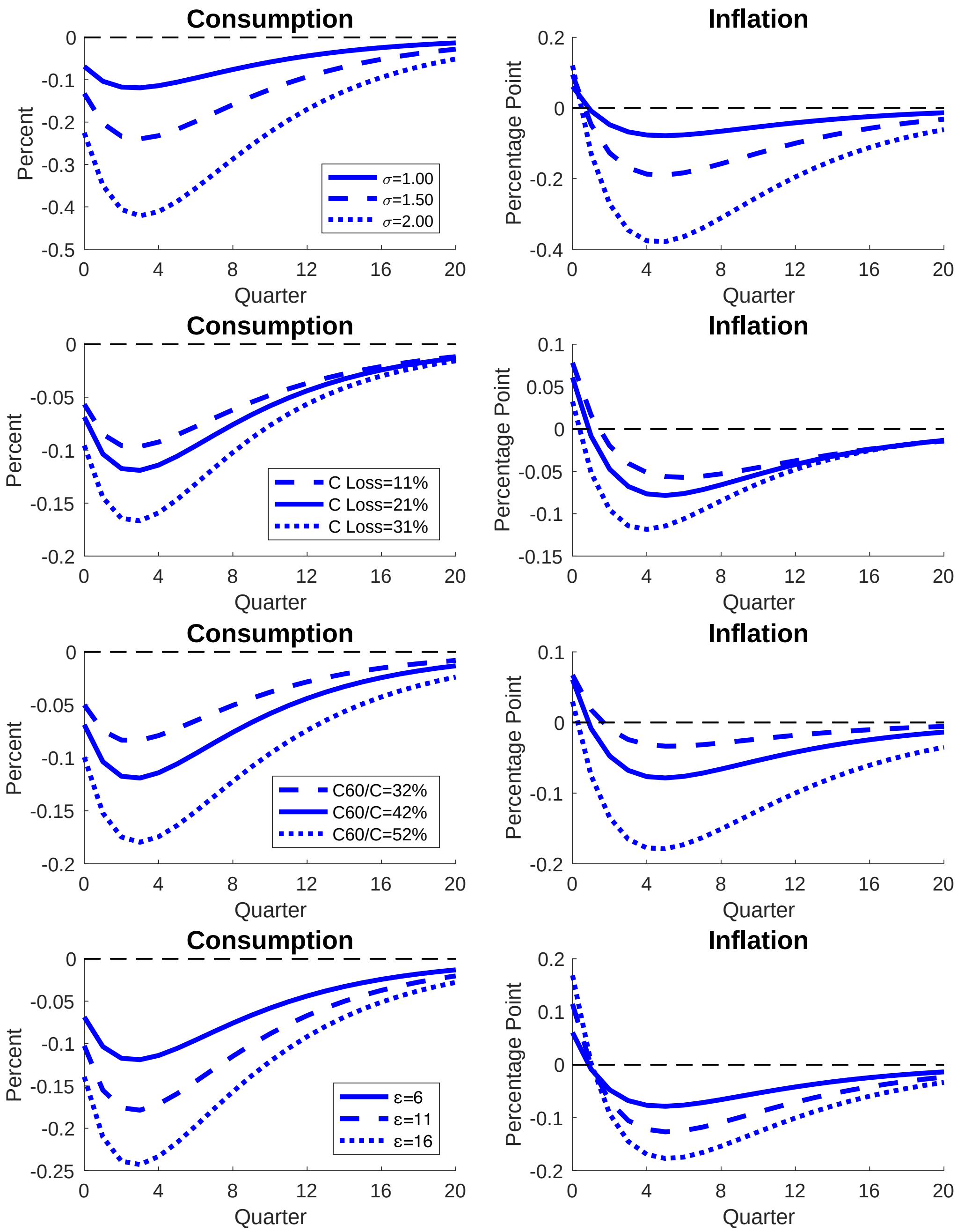


Figure 2.12 – **Sensitivity analyses 1**

Note: Impulse responses of consumption are in percent deviation from their stochastic steady state, while impulse responses of inflation are in annualized percentage point deviations from their stochastic steady state.

In our baseline model, we have assumed that there is no wage rigidity. Nevertheless, some degree of wage inertia may affect the consumption response of the households as well as the pricing behavior of firms. We therefore check what happens when we modify Equation (2.46) to introduce some wage rigidity:

$$w = \mathbf{w}_{-1}{}^{\gamma_w} \left(\bar{w} \left(\frac{\mathbf{n}}{\bar{n}} \right)^{\phi_w} \right)^{1-\gamma_w}, \tag{2.71}$$

where γ_w indicates the indexation to previous period wage. The first row of Figure 2.13 shows the sensitivity of consumption and inflation responses to different levels of wage rigidity. The effect of more rigid wages on consumption is not particularly strong. In response to stickier wages, firms tend to increase their prices on impact, thus generating higher inflation.

The next sensitivity exercises concern the parameters of the Taylor rule. In the baseline model we have assumed no persistence in the interest rate. We now check what happens when there is some persistence. We therefore modify Equation (2.47) as follows:

$$\frac{1+R}{1+\bar{R}} = \left(\frac{1+\mathbf{R}_{-1}}{1+\bar{R}} \right)^{\phi_R} \left(\left(\frac{1+\pi}{1+\bar{\pi}} \right)^{\phi_\pi} \left(\frac{y}{\mathbf{y}_{-1}} \right)^{\phi_y} \right)^{1-\rho_R}, \tag{2.72}$$

where ϕ_R is the parameter controlling the degree of persistence. The second row of Figure 2.13 shows consumption and inflation responses when we vary the persistence ϕ_R of the interest rate in the Taylor rule. While interest rate persistence barely affects the consumption response, inflation drops by less the higher the persistence is.

The third and fourth rows of Figure 2.13 show consumption and inflation responses to an uncertainty shock for different levels of monetary policy responsiveness. In particular, the more responsive monetary policy is to inflation (the higher ϕ_π), the smoother the real interest rate. A smoother real interest rate path reduces the inter-temporal substitution of imperfectly insured households, thus dampening the drop in consumption induced by an uncertainty shock. Indeed, the more responsive monetary policy is to inflation, the less inflation responds to an uncertainty shock. To the contrary, when monetary policy is more responsive to output growth, we get more volatility in consumption and inflation response.

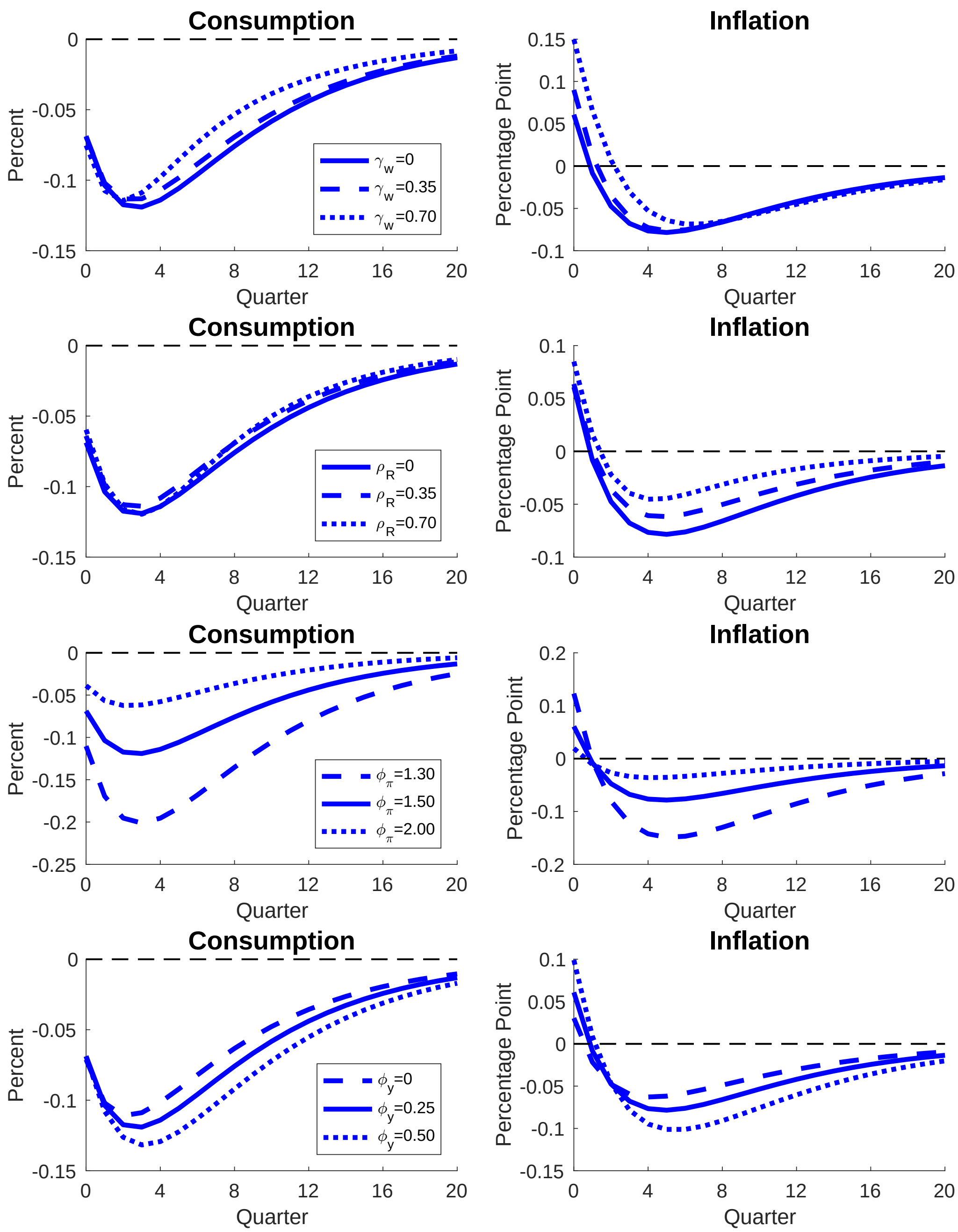


Figure 2.13 – **Sensitivity analyses 2**

Note: Impulse responses of consumption are in percent deviation from their stochastic steady state, while impulse responses of inflation are in annualized percentage point deviations from their stochastic steady state.

2.6 Conclusion

This paper has shown how households' heterogeneity is important to explain the propagation of uncertainty shocks to the macroeconomy. First, by estimating a VAR of macro variables and the macro uncertainty index of Jurado et al. (2015), it has provided empirical evidence that an increase in macro uncertainty generates a drop in output, consumption, inflation, and the job finding rate rate, and triggers a rise in the unemployment and the separation rate. Second, it has shown how heterogeneous households' consumption response is important in explaining the macro dynamics of the aggregate responses. To do so, it has estimated a VAR by using disaggregated CEX data instead of aggregate consumption data. It has shown that households respond heterogeneously across their income distribution: households belonging to the bottom 60% of the income distribution are more responsive to uncertainty shocks than those belonging to the top 40%. To rationalize these empirical findings, it has built a model with imperfectly insured unemployment risk, SaM frictions, and Calvo-type price rigidities. In response to a positive uncertainty shock, the interaction between the precautionary saving behavior of partially insured households, the labor market SaM frictions, and the precautionary pricing behavior of firms is able to generate: i) a drop in inflation, and ii) responses of output, consumption, and the policy rate, which are quantitatively as well as qualitatively in line with the empirical evidence. The goal of our model has been to study the propagation of uncertainty shocks in a model with unemployment risk and imperfect insurance. This has been possible thanks to the tractability of our framework. Our setup has allowed us to introduce a minimal heterogeneity across households, while at the same time retaining the main precautionary saving motive implied by heterogeneity. As our heterogeneity is kept to the minimum, it does not make our model particularly suitable to study distributional issues.

Lastly, our model abstracts from capital and investment. Introducing capital would provide households with an illiquid asset through which to precautionarily save when uncertainty increases. The option to accumulate capital would dampen the decrease in aggregate demand following a rise in uncertainty. This would somewhat weaken the feedback loop triggered by the precautionary saving behavior of uninsured households, which would nevertheless still be present. To get a response in aggregate demand similar to the model without capital, we would need to give households the possibility to also save through a liquid bond. Further, this addition would allow us to match a more realistic distribution of marginal propensities to consume. We leave the inclusion of capital and a liquid bond as well as a more thorough analysis of their implications to future studies.

3 Risk Sharing and the Adoption of the Euro

Joint with Alessandro Ferrari

Abstract

This chapter empirically evaluates whether adopting a common currency has changed the ability of euro area member states to share risk. We construct a counterfactual dataset of macroeconomic variables through the synthetic control method. We then use the output variance decomposition of Asdrubali, Sorensen and Yosha (1996) on both the actual and the synthetic data to study if there has been a change in risk sharing and through which channels. We find that the euro has reduced consumption smoothing. We further show that this reduction is mainly driven by the periphery countries of the euro area who have experienced a decrease in risk sharing through private credit.

3.1 Introduction

In 1999, eleven countries adopted a newly created currency, the euro. Sharing a common currency has eliminated the exchange rate risk between member states and guaranteed a high degree of price stability. This has favoured higher trade and financial integration across euro area members.[1] At the same time, member states have given up the possibility to rely on monetary policy to respond to idiosyncratic shocks. As explored by the vast literature on currency areas initiated by Mundell (1961), while higher financial and trade linkages help increasing risk sharing, the loss of monetary policy independence deprives countries of a valuable stabilisation tool against idiosyncratic shocks. Given the tension between higher risk sharing provided by deeper economic and financial integration and lower shock absorption capacity due the loss of monetary independence, it is not clear whether and in what direction the adoption of the euro has affected the ability of euro area countries to share risk.

This paper aims to empirically answer these questions by evaluating how adopting a common currency has changed the ability of the euro area members to share risk. A major obstacle when evaluating the effect of a policy intervention like the adoption of the euro is the absence of an appropriate counterfactual. We tackle this problem by building a synthetic counterfactual dataset of macro variables for the scenario of no adoption of the euro. We then use our synthetic dataset along with the actual one to gauge how different risk sharing measures and channels have changed with the adoption of the euro.

As a first measure of risk sharing ability, we compute the correlation between consumption and output within each country. At the one end of the spectrum, a correlation of one indicates that there is no absorption of output shocks, as all fluctuations in output translate to fluctuations in consumption. At the other end, a correlation of zero indicates that output shocks are fully absorbed and do not get transmitted to consumption. A correlation between zero and one suggests that there is partial absorption, but does not allow us to disentangle whether risk is absorbed via international or national

[1]See Kalemli-Ozcan et al. (2010) for a discussion on the impact of the euro on financial integration and Saia (2016) for a focus on trade.

channels. To dig deeper into whether risk is shared across countries, we compute two measures of international risk sharing. Economic theory suggests that countries that share risk should experience a comovement in consumption. We thus compute bilateral consumption correlations across euro area members. To capture the ability of sharing risk internationally, we also compute the bilateral risk sharing indicator proposed by Brandt et al. (2006). While these measures allow us to understand how the adoption of the euro has changed the ability to share risk across countries, as a next step we want to decompose more systematically the channels through which risk is shared. We then carry out an output variance decomposition à la Asdrubali et al. (1996). With this method, we can be more precise in isolating four possible channels of risk sharing: international risk sharing through private cross-border investments, international risk sharing through government taxes and transfers, private savings, and public savings. While the first two channels are international as they involve cross border absorption of shocks, the other two channels refer to consumption smoothing that happens within the national borders.

We present our results in a difference in difference framework, where our treatment is the adoption of the euro. The treated group is composed of the euro area member states,[2] and our control group is made of their synthetic counterfactual for the scenario of no adoption of the euro. Our main result is that international risk sharing through capital markets and public taxes and transfers has not increased due to the adoption of the common currency. At the same time, we show that consumption smoothing has decreased. This decline is mainly due to a lower risk sharing through private savings. When we split the sample into core and periphery countries,[3] we find that the euro has not significantly affected consumption smoothing in core countries. To the contrary, the decrease that we uncover for the full sample is driven by the drop in consumption smoothing in periphery countries. Further, we show that the decrease in consumption smoothing is not due to the Great Recession period. In fact, we find that the decrease for periphery countries is even sharper once we exclude the financial crisis. We provide

[2] To be precise, we include the first eleven countries to adopt the euro: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain.

[3] Core countries: Austria, Belgium, Finland, France, Germany, Netherlands. Periphery countries: Greece, Ireland, Italy, Portugal, Spain.

a potential explanation for our result on the lower consumption smoothing to the inability of private agents to insure against larger shocks to output compared to the pre euro period. As a matter of fact, we show that the common currency has had a positive effect on output growth and volatility.

Our paper is related to two main lines of the literature. First, by building our counterfactual dataset via the synthetic control method (SCM), we are related to the research stream that employs the SCM to generate counterfactual scenarios in absence of natural ones. The SCM is introduced by Abadie and Gardeazabal (2003) to test for the impact of the outbreak of terrorism in the Basque Country in the late 60s, and further employed by Abadie et al. (2010) to estimate the effect of a large-scale tobacco control programme implemented by California in 1988. Billmeier and Nannicini (2012) use it to investigate the impact of economic liberalization on real GDP per capita in a worldwide sample of countries. Closer to our focus, Campos et al. (2014) use the SCM to evaluate the benefits of being part of the European Union, while Saia (2016) employs it to estimate counterfactual trade flows between the UK and Europe under the counterfactual scenario that the UK had joined the euro. Born et al. (2019a) use the SCM to study the impact of the Brexit vote on the UK output, while Born et al. (2019b) to study the effect of Trump's election on the US growth and job creation. Terzi (2020) relies on a propensity score matching model to build a counterfactual for the per capita GDP in the euro area countries and study the impact of macroeconomic adjustment in the euro area. The closest to our paper are Puzzello and Gomis-Porqueras (2018) and Duque Gabriel and Pessoa (2020), who use the SCM to evaluate the impact of the euro on real per capita income. These two papers focus on the effects of the euro on the general economic performance, which is measured through real per capita income. Our paper goes a step further, and evaluates how the adoption of the euro directly affects the risk sharing ability of member states.

Our paper is also related to the stream of the literature that studies cross-regional risk sharing. To identify different risk sharing channels, we follow the output variance decomposition introduced by Asdrubali et al. (1996) to examine risk sharing in the US. This methodology is also used by Furceri and Zdzienicka (2015) to analyse and compare risk sharing across euro area countries and the US states. The analysis of Furceri and

Zdzienicka (2015) is updated with more recent data by van Beers et al. (2014), who assess the functioning of insurance mechanisms in the euro area, and Kalemli-Ozcan et al. (2014) who consider separately countries hit by the sovereign debt crisis in 2010. Poncela et al. (2016) use the Asdrubali et al. (1996)'s decomposition to study risk sharing channels across OECD members. Our paper innovates over the previous literature by studying how the adoption of the euro has changed the risk sharing channels of euro area member states. We do so by adopting a new approach as we build a counterfactual for the euro area countries. Some existing papers like Poncela et al. (2016) and Furceri and Zdzienicka (2015) aim to assess the effect of the euro on risk sharing channels by comparing the channels before and after the adoption of the common currency. While this exercise compares risk sharing channels between two different time periods, it does not allow them to properly assess how the adoption of the euro has changed risk sharing ability after 1999. Only a counterfactual for euro area countries under the scenario of no adoption of the euro provides an accurate comparison against which to measure how risk sharing has changed. This is precisely the exercise that our paper carries out. Also related to our paper, Hoffmann et al. (2019) study how the inception of the euro area has affected risk sharing through banking and capital market integration, focusing especially on the Great Recession. Finally, Cimadomo et al. (2020) study how financial integration and official financial assistance have contributed to consumption smoothing in the euro area.

The rest of the paper is organised as follows. Section 3.2 describes the SCM, our risk sharing measures, the output variance decomposition and the data. Section 3.3 presents our main results, while Section 3.4 shows our robustness checks. Section 3.5 concludes.

3.2 Methodology

3.2.1 The Synthetic Control Method

This paper aims to assess whether the adoption of the euro has had any effects on the ability of member states to share risk. To address this question, we would ideally need to estimate risk sharing between euro area member states under the alternative scenario in which the currency area had not been established. As a real counterfactual for this scenario does not exist, we use the SCM by Abadie and Gardeazabal (2003) to generate a synthetic counterpart. The SCM is a data driven procedure that allows us to estimate the effect of a policy intervention in the absence of a natural counterfactual.

Our first step is to generate the synthetic counterpart of the following macroeconomic variables in per capita terms: gross domestic product (GDP), household final consumption (C), government expenditure (G), national income (NI), and disposable national income (DNI). We will need these variables to compute some measures of risk sharing as discussed in sections 3.2.2 and 3.2.3. To generate the synthetic counterpart of our macroeconomic variables, we proceed as in Abadie and Gardeazabal (2003). The idea of the SCM is to create a synthetic counterpart for the macro variables of the countries that are subject to a policy intervention (the euro area countries) by using a convex combination of macro variables of countries that are not subject to the policy intervention (some non euro area countries). More formally, let N be the number of countries in the potential counterfactual pool (some non euro area countries), and let $W = (w_i)_{i=1}^{N}$ an $N \times 1$ vector of country weights such that $\sum_i w_i = 1$ for $i = 1, ..., N$. Let X_1 be the $K \times 1$ vector of our variables of interest for euro area member states before the introduction of the euro. Similarly, let X_0 be the $K \times N$ matrix values of the same K variables of interest for all N non euro area countries in our counterfactual pool before the introduction of the euro. In addition, let V be a $K \times K$ diagonal matrix with non negative components representing the relevance of our variables of interest in determining the macroeconomic outcome variables. As discussed in Abadie and Gardeazabal (2003), while the choice of the matrix V could be arbitrarily based on economic considerations, we compute it through a factor model. Then, the algorithm of Abadie and Gardeazabal (2003) looks for the vector W^* of weights that minimises

$$(X_1 - X_0 W)' V (X_1 - X_0 W)$$

subject to

$$w_i \geq 0 \text{ and } \sum_i w_i = 1 \text{ for } i = 1, ..., N.$$

The vector W^* determines the convex combination of macroeconomic variables for non euro area countries, which best reproduces each variable of interest for the euro area countries in the period before the introduction of the euro. Therefore, let Y_1 and Y_0 be the outcome variables for respectively the euro area and the non euro area countries. Then, the method uses $Y_1^* = Y_0 W^*$ as counterfactual for the outcome variables of euro area countries after the introduction of the euro. The choice of the variables in matrix X_0 is such that it maximises the ability of the synthetic series to reproduce the behaviour of the series of the euro area countries in the period before the introduction of the euro. For example, to generate the counterfactual series of Portuguese C for the scenario in which Portugal had not adopted the euro, the method uses the variables GDP, C, G, NI, DNI of the non euro area countries in our sample and it chooses the vector of weights W so as to minimise the distance between Portuguese C and the combination of the macroeconomic variables we have at our disposal in the subsample before the introduction of the euro. Once we have a synthetic series of Portuguese C that mimics the actual series in the matching period before the euro, we can use that series as a counterfactual for Portuguese C in the scenario where Portugal had not joined the euro in the period after the introduction of the euro. The matching is carried out for one euro area country at a time, so that the procedure always involves one euro area country and N non-euro area countries.

A relevant assumption for the correct use of the SCM is that the non euro area group is unaffected by the adoption of the euro. This assumption can be troublesome since, given the potential magnitude of the effect of the euro, one might think that its introduction has indirectly affected all countries in the world. This could be especially true for the countries in our non euro area group, which is composed of OECD countries with strong trade and financial linkages with our euro area sample. This concern is legitimate if we look at the total effect of the introduction of the euro. However, this effect can be thought of as being made of two components: i) the effect of the mere existence of the euro; ii) the effect of having adopted the euro and being a member of the currency union. Under this decomposition, even though all countries in the world are potentially subject to the first effect, only euro area member states are subject to the second one. Hence, the effect that we isolate is the adoption of the euro, conditional on the existence of the euro itself.

While the literature has discussed ways of evaluating the robustness of the SCM estimates, no analytical result is available to compute their standard deviation. Robustness checks can then be carried out in three possible ways: i) performing bootstrap, by randomly resampling the donor pool of non euro area countries (see Saia, 2016); ii) estimating a difference in difference regression and testing whether the outcome is significantly different from zero (see Campos et al., 2014); iii) running placebo studies on units in the donor pool in order to assess whether the method delivers spurious effect of the adoption of the euro. To check the robustness of our results, we use the last two techniques, i.e. we test the significance of the coefficients for the difference in difference estimation and run placebo studies.

3.2.2 Consumption and Output Correlations and the BCS Index

We start by computing the correlation between consumption and output in each country. If shock absorption is complete, we expect to find zero correlation between the two. If shock absorption is null, there should be perfect correlation. If idiosyncratic shocks to output are not fully transmitted to consumption, there are some risk sharing channels at play that partially absorb the shocks. While the correlation between consumption and output tells us whether some portion of the output shock is absorbed, it does not help us distinguishing whether risk is absorbed internationally or nationally.

To understand if risk is absorbed through international channels, we compute two additional measures. The first is the bilateral consumption correlation across euro area members. Economic theory predicts that, under the assumption of no arbitrage and complete markets, countries fully share risk. This implies that the stochastic discount factors (henceforth SDFs) of two countries that fully share risk are equalised – see for example Cochrane (2001). Let $M_{i,t} = \beta \frac{u'(c_{i,t+1})}{u'(c_{i,t})}$ and $M_{j,t} = \beta \frac{u'(c_{j,t+1})}{u'(c_{j,t})}$ be the SDF of country i and country j respectively. Under complete markets, $M_{i,t} = M_{j,t}$. When this is the case, the growth of marginal utility is perfectly correlated across individuals. In addition, if preferences u and discount factors β are assumed to be the same across countries, the growth rate of consumption is identical. Whenever the assumption of complete markets is violated, SDFs between countries are not equalised and part of the risk remains untraded – see Svensson (1988). If the adoption of the euro affects international risk sharing, the bilateral consumption correlation across countries should change.

The third measure that we compute is the bilateral risk sharing indicator proposed by Brandt et al. (2006). This indicator, referred to as BCS index, captures the level of risk sharing between country i and country j and takes the following form:

$$BCS_{i,j} = 1 - \frac{\text{var}(\log M_{i,t+1} - \log M_{j,t+1})}{\text{var}(\log M_{i,t+1}) + \text{var}(\log M_{j,t+1})} \tag{3.1}$$

The numerator measures how far apart the SDFs of two countries are from one another, i.e. what portion of risk is not shared. The denominator quantifies the volatility of SDF in the two countries, i.e. what is the total portion of risk to be shared. This metric ranges between minus one and one with a higher number meaning a higher degree of risk sharing. As noted in Brandt et al. (2006) this index differs from correlation. Indeed, like a correlation, it is equal to one when the two SDFs are the same, it is zero when they are uncorrelated, and it is minus one if $M_{i,t+1} = -M_{j,t+1}$. However, differently from a correlation, it detects violations of scale in the growth rate of marginal utilities. In fact, full risk sharing requires the SDFs of two countries to be equal, not just perfectly correlated. Nevertheless, both the BCS index and the correlation of SDFs are statistical descriptions of how far we are from perfect risk sharing. In terms of computation, we assume that households in the two countries have the same preferences and, in particular, CRRA utilities with risk aversion $\sigma = 2$ and discount factor $\beta = 0.95$.[4] Given this, their SDFs look as follows:

$$M_{i,t} = \beta \left(\frac{C_{i,t+1}}{C_{i,t}} \right)^{-\sigma}$$
$$M_{j,t} = \beta \left(\frac{C_{j,t+1}}{C_{j,t}} \right)^{-\sigma}.$$

[4] Indeed, the fact that the domestic and foreign representative investors have the same level of relative risk aversion is a simplifying assumption, but it makes the comparison between all pairs of countries more viable.

We present our three risk sharing measures in a difference in difference framework where the treatment is the adoption of the euro. This allows us to evaluate what is the impact of the adoption of the euro on them. To be more specific, we compute the three measures both with actual and synthetic data, across two sample periods: 1990-1998, and 1999-2011. We then take the difference of the risk sharing measures obtained with the actual and the synthetic data both in the first and the second subsample. We finally compute the difference of the two sub-sample differences to get the difference in difference estimate. The obtained estimates tell us whether the adoption of the euro has any impact on the risk sharing measures. To test the significance of the estimates that we get, we compute t-statistics using bootstrap techniques. We randomly drop one country from the donor pool needed to generate the synthetic series and we compute the synthetic series. We repeat the exercise for 100 iterations. We then compute the sample distribution of the synthetic estimate and its t-statistics.

3.2.3 GDP Decomposition

To identify different channels of risk sharing, we follow Asdrubali et al. (1996). Starting from an output decomposition, we isolate different channels of risk sharing and study how these channels are able to absorb output shocks. This is implemented by decomposing GDP into the following national account aggregates: Gross Domestic Product (GDP), Net National Income (NI), Disposable National Income (DNI), and Private and Government Consumption (C+G). According to this decomposition, GDP can be disaggreagated as the following accounting identity:

$$\text{GDP} = \frac{\text{GDP}}{\text{NI}} \frac{\text{NI}}{\text{DNI}} \frac{\text{DNI}}{\text{DNI+G}} \frac{\text{DNI+G}}{\text{C+G}} (\text{C+G}) \tag{3.2}$$

Because of the differences in the national account aggregates, the ratios on the right-hand side can be interpreted as specific channels through which risk is absorbed. The first ratio, $\frac{\text{GDP}}{\text{NI}}$, accounts for income insurance stemming from internationally diversified investment portfolios. This is because NI measures the income (net of depreciation) earned by residents of a country, whether generated on the domestic territory or abroad, while GDP refers to the income generated by production activities on the economic territory of the country. Therefore, the ratio $\frac{\text{GDP}}{\text{NI}}$ captures the *private* insurance channel due to private cross-border investments or, as Kalemli-Ozcan et al. (2014) refer to, holding of claims against the output of other regions. The ratio $\frac{\text{NI}}{\text{DNI}}$, instead, can be interpreted as the *public* insurance channel due to government taxes and transfers as DNI is the income that households are left with after subtracting taxes and adding transfers. Finally, the ratios $\frac{\text{DNI}}{\text{DNI+G}}$ and $\frac{\text{DNI+G}}{\text{C+G}}$ account for smoothing through respectively *public* and *private* saving channels.

To measure how much of the variation in output is absorbed by each channel, we proceed as in Asdrubali et al. (1996). We take logs of equation 3.2, difference the series, multiply by the change of log GDP, and take expectations to get:

$$\begin{aligned}
\text{Var}(\Delta \log GDP_{i,t}) &= \text{Cov}(\Delta \log GDP_{i,t}, \Delta \log GDP_{i,t} - \Delta \log NI_{i,t}) \\
&+ \text{Cov}(\Delta \log GDP_{i,t}, \Delta \log NI_{i,t} - \Delta \log DNI_{i,t}) \\
&+ \text{Cov}(\Delta \log GDP_{i,t}, \Delta \log DNI_{i,t} - \Delta \log(DNI_{i,t} + G_{i,t})) \\
&+ \text{Cov}(\Delta \log GDP_{i,t}, \Delta \log(DNI_{i,t} + G_{i,t}) - \Delta \log(C_{i,t} + G_{i,t})) \\
&+ \text{Cov}(\Delta \log GDP_{i,t}, \Delta \log(C_{i,t} + G_{i,t})).
\end{aligned}$$

Dividing both sides by $\text{Var}(\Delta \log GDP_{i,t})$ we get the following identity:

$$1 = \beta^m + \beta^g + \beta^p + \beta^s + \beta^u,$$

where we define

$$\beta^m \equiv \frac{\text{Cov}(\Delta \log GDP_{i,t}, \Delta \log GDP_{i,t} - \Delta \log NI_{i,t})}{\text{Var}(\Delta \log GDP_{i,t})}$$

$$\beta^g \equiv \frac{\text{Cov}(\Delta \log GDP_{i,t}, \Delta \log NI_{i,t} - \Delta \log DNI_{i,t})}{\text{Var}(\Delta \log GDP_{i,t})}$$

$$\beta^p \equiv \frac{\text{Cov}(\Delta \log GDP_{i,t}, \Delta \log DNI_{i,t} - \Delta \log(DNI_{i,t} + G_{i,t}))}{\text{Var}(\Delta \log GDP_{i,t})}$$

$$\beta^s \equiv \frac{\text{Cov}(\Delta \log GDP_{i,t}, \Delta \log(DNI_{i,t} + G_{i,t}) - \Delta \log(C_{i,t} + G_{i,t}))}{\text{Var}(\Delta \log GDP_{i,t})}$$

$$\beta^u \equiv \frac{\text{Cov}(\Delta \log GDP_{i,t}, \Delta \log(C_{i,t} + G_{i,t}))}{\text{Var}(\Delta \log GDP_{i,t})}.$$

All β coefficients can be estimated through the system of equations proposed by Asdrubali et al. (1996):

$$\Delta \log GDP_{i,t} - \Delta \log NI_{i,t} = \beta^m \Delta \log GDP_{i,t} + \epsilon^m_{i,t} \tag{3.3}$$

$$\Delta \log NI_{i,t} - \Delta \log DNI_{i,t} = \beta^g \Delta \log GDP_{i,t} + \epsilon^g_{i,t} \tag{3.4}$$

$$\Delta \log DNI_{i,t} - \Delta \log(DNI_{i,t} + G_{i,t}) = \beta^p \Delta \log GDP_{i,t} + \epsilon^p_{i,t} \tag{3.5}$$

$$\Delta \log(DNI_{i,t} + G_{i,t}) - \Delta \log(C_{i,t} + G_{i,t}) = \beta^s \Delta \log GDP_{i,t} + \epsilon^s_{i,t} \tag{3.6}$$

$$\Delta \log(C_{i,t} + G_{i,t}) = \beta^u \Delta \log GDP_{i,t} + \epsilon^u_{i,t}, \tag{3.7}$$

where each β coefficient represents the share of output variation smoothed by a given channel. In particular, β^m accounts for the share of GDP variation smoothed by capital markets, β^g by fiscal transfers, β^p by public savings, and β^s by private savings. What is left, β^u, is the unsmoothed part of the GDP variation. A β^u equal to zero means that a shock to GDP is fully absorbed through capital markets, fiscal transfers, public and private savings, thus leaving consumption unchanged. Instead, a high β^u means that only a minor part of the shock is absorbed through risk sharing, while a significant part stays unsmoothed.

The estimation of coefficients in Equations 3.3 - 3.7 is carried out using ordinary least squares (OLS) with time fixed effects and clustered standard errors, or OLS with time fixed effects and panel correlated standard errors. The inclusion of time fixed effects is important as it allows us to take out euro area business cycle fluctuations. In this way, we make sure that the effects that we find are deviations from the euro area business cycle and not fluctuations of the euro area business cycle itself.

We show the results of this estimation as computed in a difference in difference model. We stack together our actual and synthetic samples and include the independent variable interacted with the four possible combinations of actual/synthetic and euro/no euro. In particular, the regressions that we estimate are:

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t} + \beta_2 \mathrm{Tr}_i x_{i,t} + \beta_3 \mathrm{Eur}_t x_{i,t} + \beta_4 (\mathrm{Tr}_i * \mathrm{Eur}_t) x_{i,t} + \nu_t + \epsilon_{i,t}, \tag{3.8}$$

where x_i is $\Delta \log \mathrm{GDP}_{i,t}$ and y_i are the dependant variables in Equations 3.3 - 3.7. Tr_i is a dummy variable taking the value of 1 if the series comes from the actual dataset and 0 if it comes from the synthetic dataset. Eur_t is a dummy taking the value of 1 after the adoption of the euro in 1999 and 0 otherwise. ν_t are time fixed effects. β_2 represents the share of GDP variation smoothed by a given channel for our actual data before the introduction of the euro in deviations from its synthetic counterpart β_1. If our matching is successful, we should find that β_2 is not significantly different from zero. For our euro period, i.e. for the period in which $\mathrm{Eur}_t = 1$, we should compare β_4 with β_3. If the euro has had an effect on the analysed risk sharing channel, β_4 should be significantly different from zero.

If we have a good match for the pre euro period, the difference in difference assumption of common trend should be fulfilled. We provide an example of this in Figure 3.2, which shows the last dependent variable, $\Delta \log(\mathrm{C} + \mathrm{G})$ (the one that delivers us the coefficient of the unsmoothed component) for both the actual and the synthetic group over the whole sample period. We also formally test that the trends are parallel and our estimation always passes the test.[5]

[5] The significance level of the F-test $\beta_1 = \beta_2$ for the five risk sharing channels is respectively: 3%, 25%, 87%, 59%, and 13%. This means that we can never reject the hypothesis that $\beta_1 = \beta_2$ at the 1% level.

3.2.4 Data

We take the data used in our analysis from the OECD National Account Statistics. In particular, we use household final consumption expenditure for C, general government expenditure for G, gross domestic product computed following the output approach for GDP, net national income for NI, and net disposable income for DNI.

Our dataset covers 31 countries from 1960 to 2011. However, as the SCM requires the data not to display any missing values, we limit our matching window to the period 1990-1998 to keep the biggest number of countries in our sample. This limitation leaves us with 21 countries. Out of these countries, 11 are euro area member states, while 10 are OECD countries not in the currency area.[6]

3.3 Results

3.3.1 Matching with the SCM

We start by generating synthetic national account aggregates to be used as counterfactual series for the period after the introduction of the euro. The SCM algorithm produces the vector $W = (w_1, ..., w_N)$ of weights that maximise the matching between the actual and the synthetic series before the adoption of the euro. Table 3.1 to 3.5 display the optimal weights that generate the synthetic GDP, consumption, net disposable national income, net national income, and government expenditure. For example, the Finnish synthetic GDP is made of Canadian, Mexican, New Zealander, and Swedish GDP in the percentages of 15.1, 12.40, 7.70, and 64.80 respectively. This is the convex combination of non euro area countries' GDP, which best matches the Finnish GDP before the adoption of the euro. An example of our match for GDP is shown by Figure 3.1. The figure displays the actual and the synthetic series of GDP for all euro area countries in our sample. The two series are very close in the matching period 1990-1998 and diverge in the post euro period. In line with the existing literature – see Puzzello and Gomis-Porqueras (2018) and Duque Gabriel and Pessoa (2020) –, we find that

[6]Euro area countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain; Non euro area countries in in our sample: Australia, Canada, Denmark, Japan, Korea, Mexico, New Zealand, Sweden, UK, US.

Ireland is the country that benefitted the most from adopting the euro in terms of real per capita output. At the same time, France, Italy, and Portugal appear to be mild losers, at least in terms of output.

3.3.2 Consumption and Output Correlations and the BCS Index

Table 3.6 reports the difference in difference estimates of the following indicators of risk sharing: $\mathrm{Corr}(C_i, Y_i)$, $\mathrm{Corr}(C_i, C_j)$, and $\mathrm{BCS}_{i,j}$ where i and j refer to countries. The difference in difference estimates are averaged across our panel of countries. The first column shows the average estimates for the full sample, the second column excludes the crisis period, while the last two columns are estimates for two subsamples of core and periphery countries.

The first row of the table displays a significant increase in the average difference in difference estimate for $\mathrm{Corr}(C_i, Y_j)$. This indicates a reduction in risk sharing: with the adoption of the euro consumption and output within countries are more synchronised. Results for the sample split between core and periphery countries show that the reduction in risk sharing is even sharper in periphery countries than in core countries. The second row of the table shows the average difference in difference estimates of $\mathrm{Corr}(C_i, C_j)$. All the values are negative (though not significant), meaning that country pairwise consumption correlation decreases with the adoption of the euro. This drop points towards a reduction in international risk sharing. The last row reports the average values for the difference in difference estimates of pairwise BCS indices. The estimates are negative and significant for the sample which excludes the crisis period and for the sample of only periphery countries, again implying a reduction in international risk sharing due to the adoption of the euro. Our results are in line with the evidence on business cycle statistics provided by Enders et al. (2013), who show an increase in cross-country consumption correlations for the euro countries compared to the non-euro area countries after the introduction of the euro.

3.3.3 Risk Sharing Channels

Table 3.7 displays the results of our difference in difference estimation as in Equation 3.8 for Equations 3.3 - 3.7. Estimates are carried out using OLS with clustered standard errors using actual and synthetic national account series over the full sample period 1990-2011. Results in Table 3.7 should be read as follows. Each column corresponds to the difference in difference estimation as in Equation 3.8 of each Equation 3.3 - 3.7. For example, the first column is the difference in difference estimation of Equation 3.3 and reports coefficients β_1 to β_4 of Equation 3.8.[7] β_1 is the portion of GDP variation absorbed through capital markets before the adoption of the euro (Pre-tr) and computed with the synthetic data (Synthetic). β_2 is the portion of GDP variation absorbed through capital markets before the adoption of the euro (Pre-tr) and computed with the actual data (Actual) in deviations from the portion computed with its synthetic counterpart. β_3 is the portion of GDP variation absorbed through capital markets after the adoption of the euro (Post-tr) and computed with the synthetic data (Synthetic) in deviations from the portion computed before the adoption of the euro. β_4 is the portion of GDP variation absorbed through capital markets after the adoption of the euro (Post-tr) and computed with the actual data (Actual) in deviations from the portions computed before. Coefficients reported in the other columns have a similar interpretation, but refer to different channels of risk sharing. Notice that since we started from an accounting identity, the estimated coefficients of Table 3.7 add up to one.

The first result is the risk sharing channel decomposition concerning the pre euro period 1990-1998. This is shown by the first row of coefficients (Pre euro Synthetic) in Table 3.7. International risk sharing happens only through international transfers, which absorb 4% of the shocks to GDP. Most of the shock absorption happens through consumption smoothing via public and private savings, which absorb respectively 14% and 35% of GDP shocks. The unsmoothed portion of risk is 50%.[8]

[7]While usually only the estimated difference in difference coefficient is reported (β_4 in Equation 3.8), here we report also coefficients β_1 to β_3. As a matter of fact, the estimated coefficient β_1 allows us to compare our estimates to the existing results in the literature, while the estimated coefficient β_2 to test the quality of our match.

[8]These estimates are in line with the literature and can be compared, for example, to column II of Table 13 in Furceri and Zdzienicka (2015).

The second result shown in Table 3.7 refers to the quality of our matching in the pre euro period and is displayed by the second row of coefficients (Pre euro Actual). These coefficients capture the portion of GDP variation absorbed through the different channels before the adoption of the euro and computed with the actual data in deviations from the portion computed with its synthetic counterpart. None of these coefficient is significant. As we computed our synthetic series by minimising the distance from the actual series in the pre euro period, the synthetic and the actual series should be very close to each other in the pre euro period. This should also imply that the regressions run by using either the actual or the synthetic series should give very similar results. This implication is tested by finding that the channels of absorption computed by using the actual data are never significantly different from those computed by using the synthetic data for the pre euro period.

Our third and main result concerns the effect of the adoption of the euro on the risk sharing channels. This is shown by the fourth row of coefficients (Post euro Actual) in Table 3.7. None of the coefficients for the risk sharing channels is significant. To the contrary, the coefficient for the unsmoothed component of GDP variation is high and significant. We find that the adoption of the euro has increased the unsmoothed component of GDP variation by 18%. This means that adopting the euro has decreased euro area countries' ability to share risk compared to the counterfactual scenario in which they had not adopted the euro.

3.3.4 Sample Split between Core and Periphery Countries

To evaluate whether there are heterogeneous cross country effects of the adoption of the euro, we carry out the same difference in difference estimation as in Table 3.7 on two subsamples of countries, core and periphery.[9] Results are shown in Tables 3.8 and 3.9 for core and periphery countries respectively. The first result is that countries in the two subgroups had a different level of risk sharing before the adoption of the euro. In particular, we find that core countries were able to smooth a larger share of output variations than the periphery counterpart. This difference is mostly explained by the

[9] Core countries: Austria, Belgium, Finland, France, Germany, Netherlands; periphery countries: Greece, Ireland, Italy, Portugal, Spain.

higher ability of public and private savings channels to smooth consumption.

Regarding the effect of the adoption of the euro, we do not find changes in any of the risk sharing channels for the core countries. Instead, we find that the adoption of the euro has lowered consumption smoothing through private dissavings for the periphery countries. The effect is an increase in the unsmoothed component of the shock by 34%.

3.3.5 A Possible Explanation of the Lower Consumption Smoothing

A surprising result is that we find no evidence of an effect of euro membership on pure international risk sharing, that is the absorption of GDP variation through capital markets and international transfers. This suggests that the elimination of exchange rate risk has not generated an increase in the component of output variation smoothed through cross border lending and foreign direct investment. What has increased the unsmoothed portion of the shock is the decrease in consumption smoothing through private savings, at least in the periphery countries.

A possible explanation for this decrease could be that the lower consumption smoothing is the consequence of an increase in GDP growth and volatility following the adoption of the euro. The common currency has triggered a boost in GDP growth for the countries that adopted it, by eliminating exchange rate risk and increasing cross-member trade – at least before the outburst of the 2008 financial crisis. Figure 3.3 displays how much the cross-country average of actual GDP has increased compared to its synthetic counterpart. The left-hand side panel shows that, with the adoption of the euro, countries have displayed on average higher GDP per capita. The right-hand side panel tells us a similar story. The red line depicts the growth rate of the actual GDP over its synthetic counterpart as a cross-country average. The blue area represents the central 80 percentiles of this growth rate. The plot shows that after the adoption of the euro GDP has grown significantly.

Figures 3.4 and 3.5 show how the volatility of the average GDP of euro area members has increased following the adoption of the euro. The left-hand side chart of Figure 3.4 exhibits the variance of the average actual and synthetic GDP. The right-hand side panel of Figure 3.4 shows the percentage difference in the variance of the average actual and synthetic GDP. To only capture cyclical variations, GDP is detrended by using a linear quadratic trend. Both panels indicate that, following the adoption of the euro, GDP has been more volatile than it would have been without the adoption of the common currency. Figure 3.5 shows the same graphs for the coefficient of variation of detrended GDP. The coefficient of variation is computed as the volatility of detrended GDP scaled by each subsample average GDP. The left-hand side chart shows actual and synthetic samples statistics, while the right-hand side chart displays the percentage difference of a coefficient of variation of detrended GDP computed from the actual and the synthetic series. These charts provide suggestive evidence that the euro area member states saw an increase in GDP growth and volatility after the adoption of the euro, which were higher than the ones they would have observed had they not adopted the common currency.

We proceed by econometrically testing this claim with a difference in difference estimator. Using the same difference in difference setup that we had in the analysis of risk sharing channels, we regress our outcomes of interest, namely GDP growth, the variance of GDP and the coefficient of variation of GDP, on a set of dummies spanning the possible combinations of pre euro/post euro and euro/no euro. Table 3.10 displays the results of this estimation. We find that the adoption of the euro has had a positive and significant effect on GDP growth, as well as on measures of volatility. An increase in the output volatility of euro area members is in line with the evidence brought by Enders et al. (2013). Our econometric test confirms the intuition suggested by Figures 3.3-3.5 and provides a rationale for the effect that we found on the ability to smooth consumption.

It is worth noticing that this result is not imputable to a Deatonesque growth boom (Aguiar and Gopinath, 2007), which would imply an increase in the comovement between consumption and output due to an increase in permanent income. As a matter of fact, while we detrend GDP to capture only cyclical fluctuations, we still find an increase in the growth and volatility of GDP due to its cyclical component. Thus, the increase in volatility that we find is not in the trend, but in the cycle. Credit markets mainly allow to smooth against transitory shocks. As we find a decrease in the smoothing of income shocks, this should not be imputed to its permanent component.

3.4 Robustness Checks

3.4.1 Panel Correlated Standard Errors

To check the robustness of our baseline results to the way standard errors are computed, Table 3.11 displays OLS estimates with panel correlated standard errors instead of clustered standard errors. Our main results are robust. First, the significance of the international transfers, public savings and private savings channels in the pre euro period is confirmed. Second, our result on the quality of the matching is also confirmed as the estimated coefficients in the row 'Pre euro Actual' are not significant. Finally, the third result on how the risk sharing channels have changed with the adoption of the euro remains (the row Post euro Actual'). The main difference compared to our baseline results is that now also the private saving channel becomes significant. As it is negative, it should be interpreted as a reduction in the consumption smoothing happenings through private savings compared to the scenario with no adoption of the euro.

3.4.2 Match on First Differences

Our main results are based on a difference in difference estimation. Among the assumptions underlying this method, the hardest to fulfill is usually that of parallel trends in the pre treatment period. As in our setup the control variables are generated through the SCM, the fulfilment of this assumption becomes easier as this method aims at minimising the distance between actual and synthetic series in the pre-treatment period. What is less straightforward in our analysis is that, while we produce our matching on variables that are in levels, we run the difference in difference estimation on first-differenced data. In fact, even though our matching on levels is such that the dynamics of the synthetic series are very close to the ones of the actual series, this is not enough to ensure that the first-differenced data have the same trend.

To address this potential issue, we replicate the matching by using already first-differenced covariates and outcomes, while still maintaining pre euro averages in levels. In other words, when using covariates X_0, we actually match on $\{\Delta X_{0,t}\}_{t=0}^{T^*-1}$ and $\overline{X}_0$, where the bar variables stand for pre euro period averages. The reason for this matching strategy is that we want to replicate as closely as possible the first differenced data, hence the matching on ΔX_0. The drawback of this methodology is that, by replicating the first-differenced data, we may find some countries with similar year-to-year changes, but very distant fundamentals from the actual series to be an excellent match. To shield against this possibility, we keep some predictors in levels and match with a relatively homogeneous non-euro area group, namely OECD countries.

The results of this estimation are displayed in Table 3.12. As can be observed, our main results are confirmed, though their magnitude is partially reduced. We find a reduction in the ability of private savings to absorb income variation by around 9% and an overall increase in the unsmoothed component of 8%.

3.4.3 Match Using Fixed Weights for all Variables

In our baseline analysis, we allow each country's variable to be generated using different weights. For example, we allow Austrian synthetic consumption to be generated by a different convex combination of donor pool countries than Austrian synthetic GDP. A different approach to this could be to have a synthetic Austria, where all Austrian synthetic variables are generated using the same weights. We run this exercise by first carrying out the match for GDP, and then by using the weights found for the synthetic GDP also for NI, DNI, private consumption and government consumption expenditure. With this dataset of synthetic variables we rerun our difference-in-difference regressions. Estimations are displayed in Table 3.13. We confirm our baseline results that the adoption of the euro has increased the unsmoothed component of the shock. This is mainly due to a reduction in the smoothing provided through the private savings channel.

3.4.4 Placebo Test

A standard check to evaluate the robustness of an estimated treatment effect are placebo tests. In our framework, this involves matching macro variables for non euro area countries that have never adopted the euro, as if they had adopted it. For example, we try to find the best match for a country like the US, which has never adopted the euro, as a convex combination of other countries that have never done so. If we were to find any effect of the adoption of the euro on countries that have never adopted it, then it would be possible that our euro effect picks up some spurious correlation.

After building a synthetic dataset for all OECD non euro area countries, we run the same risk sharing decomposition that we used for the euro area countries. The results of this estimation are displayed in Table 3.14. All our difference in difference estimators are extremely close to zero and never significant, meaning that we find no effect of the adoption of the euro on our non euro area group.

3.4.5 Change the Assumed Year of Adoption of the Euro

One of the identifying assumptions of the SCM is that the covariates on which the matching is carried out are not affected by the adoption of the euro. If this assumption is violated, the matrix of weights may be biased by matching on series that already incorporate the effect of the adoption of the euro. It is possible that some effect of the introduction of the euro has materialized between the announcement and the actual introduction of the physical currency. In this sense, our approach is already conservative as it uses 1999 as year of adoption of the euro. This year corresponds to the introduction of the euro as an accounting currency, while physical euro coins and banknotes entered into circulation only in 2002. As evidence of anticipation effects has been found – see Frankel (2010) for an application to trade –, we run our analysis again using 1998 as the year of adoption. The results of this estimation are displayed in Table 3.15. Our estimates are in line with our baseline results. We find that the adoption of the euro has increased the unsmoothed component of GDP variation by 15%.

3.4.6 Exclusion of the EU members

Another robustness check that we carry out is to exclude EU countries outside the euro area from our non euro area group. The rationale for this check is that countries geographically in Europe may have endogenously decided not to join the common currency, as the UK, or simply be indirectly affected by the existence of the euro. For this reason we exclude these countries from our non euro area group and run the decomposition. The results are displayed in Table 3.16. As in the previous case, our estimates are very close to our main results, but are not significantly different from zero. A possible explanation is that our non euro area group is now very limited since it only includes 7 OECD countries.

3.4.7 Exclusion of the Financial Crisis Period

It could be argued that, despite the time fixed effects, the decrease in the unsmoothed component of the GDP variation might be driven by the financial crisis period starting in 2008. To check whether this is the case, we rerun our estimations by excluding the financial crisis period. Table 3.17 shows our estimates over the sample 1990-2007. Our baseline results are robust to this check. In fact, the coefficient for the unsmoothed component grows even further. In particular, we find that 27% of an idiosyncratic variation to GDP remains unsmoothed against 18% found for the full sample period. This suggests that the crisis has increased consumption smoothing. Table 3.18 and 3.19 show the estimated coefficients over the period 1990-2007 for the sample split into core and periphery countries respectively. While the coefficient for the unsmoothed component is not significant for the core countries, it is positive and very significant for the periphery countries (42%). This means that the increase in the unsmoothed component for the full sample is driven by the periphery countries. In particular, the decrease in consumption smoothing is mainly due to a reduction in their shock absorption capacity through the private savings channel (-35%).

3.4.8 Measurement Error

A legitimate concern regarding our methodology is that by using generated data through the SCM we may be including measurement error in our estimation. More precisely, by estimating our counterfactual, we may generate our data with some statistical error. This error is observationally equivalent to measurement error in our dependent and independent variable. The former is more troublesome due to the standard result that the presence of measurement error in the regressors implies a bias in the estimated coefficient.

We address this problem by following the solutions suggested by Ferrari and Garcia Galindo (2018). They show that, under certain conditions, the bias can be either signed or corrected for. Section 3.D.1 formalises the bias problem and discusses potential solutions. In brief, there are two main ways to compute the bias. The first derives the bias from the aggregate macro variables of the countries that have never adopted the euro – the ones used in our placebo test. For these countries, the only difference between the actual and the synthetic series both before and after the introduction of the euro is due to the statistical error. Hence, this difference can be computed and used to correct our baseline estimates. The second way to estimate the bias requires the assumption that the measurement error is time invariant and, more precisely, that it does not change after the adoption of the euro. If this is the case, the bias can be estimated from the difference between the actual and the synthetic macro variables before the adoption of the euro. Before the adoption of the euro, the only difference between the actual and the synthetic series is due to the minimisation procedure that the matching routine involves. This difference can be computed both for the placebo countries and the euro area countries and can be used to correct our baseline estimates for the period after the adoption of the euro.

Table 3.20 reports our bias-corrected estimates of the effect of the euro adoption on the risk sharing channels. The estimates are obtained by correcting for the bias the fourth row of coefficients (Post euro Actual) in Table 3.7. Table 3.20 reports three different bias-corrected estimates. The row *Placebo full sample* reports the bias-corrected estimates when the bias is computed using the difference between the actual and the synthetic series for placebo countries. The correction, while reducing the unsmoothed component of GDP variation from 18% to 8%, still confirms our baseline finding that the adoption of the euro has increased the unsmoothed component of the shock. The correction also implies a higher risk sharing through capital markets, and a lower consumption smoothing due to private savings. The row *Placebo pre euro* reports the bias-corrected estimates when the bias used for correction is computed using placebo countries only for the pre euro period. The corrected estimates are similar to the previous ones, even though both the unsmoothed component of the shock and the private dissavings are lower. The row *Euro area pre euro* reports the bias-corrected estimates when the bias used for correction is computed only from the pre euro period using euro area countries. Again, the picture is similar and the unsmoothed component of the shock is now 10%. Regardless of the way we correct for the bias, we confirm our baseline result that the adoption of the euro has decreased the ability of countries to smooth consumption. The main difference between the baseline and the bias-corrected result is that only the latter provides evidence of an increase in risk sharing through capital markets due to the adoption of the euro.

3.5 Conclusion

This paper has evaluated whether the adoption of the common currency has changed the ability of euro area member states to smooth consumption and share risk. We have tackled the major challenge of not having a natural counterfactual by building it synthetically via the synthetic control method. We have then examined how some standard measures of risk sharing have changed in our actual dataset compared to its synthetic counterfactual. To further explore the different channels through which risk is shared, we have carried out an output variance decomposition à la Asdrubali et al. (1996). With this decomposition, we could identify the risk shared through capital markets, international transfers, public savings, and private savings.

Our main result is that international risk sharing through private and public channels across euro area member states has not increased after the adoption of the common currency. At the same time, we find evidence of a decrease in consumption smoothing. We show that the adoption of the euro has had a positive effect on output growth, accompanied by an increase in output volatility. We interpret our result on the lower level of consumption smoothing as driven by larger output shocks, which agents have not been able to insure against. Further, we provide evidence of heterogeneous effects across member states. In particular, we find that the drop in consumption smoothing is mainly driven by a reduction of risk sharing through private savings in the periphery countries. We also show that this decrease is not attributable to the Great Recession period.

All in all, while the common currency does not seem to have affected the international channels through which risk is shared, it has had a severely negative impact on consumption smoothing through private savings in the periphery countries. This result would call for a bigger effort on the policy side to make sure that private credit is provided uniformly throughout the area, especially in response to asymmetric shocks.

Appendix 3.A Synthetic Control Method

Table 3.1 – **Matrix of weights: GDP**

Non euro area	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Australia	14.10	.	.	18.10	.	.	37.40	12.40	.	.	.
Canada	.	.	15.10	.	.	.	.	.	.	.	.
Denmark	.	32.60	.	22.70	.	4.500	11.20	.	71.20	.	5.200
Japan	32	30.60	.	14.50	55.30	14.60	.	45.90	1.900	.	.
Korea	.	.	.	.	.	2.800	.	.	.	17.10	9.600
Mexico	.	.	12.40	5.400	.	27.50	31.40	1.800	0.900	33	24
New Zealand	.	.	7.700	.	.	.	.	.	.	.	.
Sweden	33.60	26.60	64.80	29.80	37.40	50.60	.	38.60	19.80	49.90	59.20
United Kingdom	.	.	.	.	.	.	2.700	.	.	.	.
United States	20.30	10.20	.	9.500	7.300	.	17.20	1.300	6.300	.	2

Table 3.2 – **Matrix of weights: consumption**

Non euro area	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Australia	4.100	.	.	.	.	.	48.60	.	.	.	.
Canada	.	.	8.800	.	.	.	.	.	.	.	.
Denmark	7.100	.	.	.	.	.	.	8.600	15.20	.	.
Japan	54.50	38.40	.	49.10	55.10	7.500	.	19.30	.	11.80	24.40
Korea	.	.	.	.	.	.	28.80	.	9.700	4.100	.
Mexico	0.900	0.600	17.60	7.900	.	28.50	6	11.30	.	39.50	33.70
New Zealand	.	.	.	11.10	.	.	.	.	.	.	.
Sweden	10.60	47.20	29.30	.	39.30	58.70	16.70	25.80	.	44.60	18.50
United Kingdom	.	.	44.30	.	.	5.400	.	.	43.70	.	.
United States	22.70	13.90	.	32	5.600	.	.	35	31.40	.	23.50

Table 3.3 – **Matrix of weights: net disposable national income**

Non euro area	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Australia	10.70	.	.	4.200	.	.	26.80	13.90	.	.	.
Canada	13.50	14.90	10.90	10.30	.	40.50	.	16.60	.	.	16.90
Denmark	.	26.10	.	23	22.60	.	2.900	.	.	.	.
Japan	41.70	7.600	.	38.20	48.10	36.80	.	30.70	25.90	58.70	46.60
Korea	.	.	.	.	.	.	10	.	11.60	.	.
Mexico	.	.	11.20	5.800	.	22.60	22.50	0.200	.	38.40	24.70
New Zealand	.	19.40	12.80	.	.	.	.	.	.	.	.
Sweden	18.60	18.70	65.10	13.50	14.50	0.100	.	25.50	5.100	2.900	11.80
United Kingdom	.	.	.	.	.	.	37.80	.	19	.	.
United States	15.50	13.20	.	5	14.80	.	.	13	38.50	.	.

Table 3.4 – **Matrix of weights: net national income**

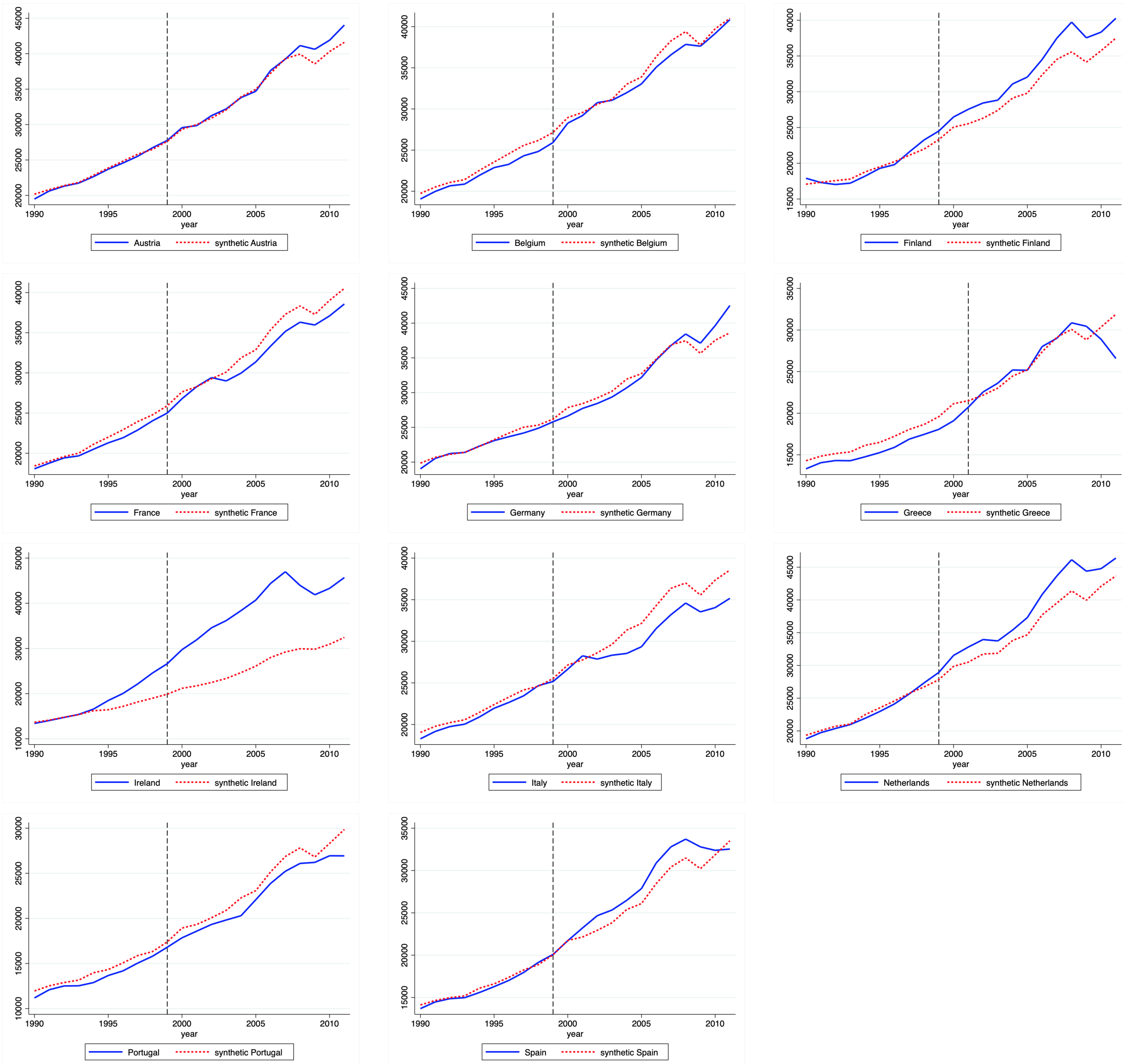
Non euro area	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Australia	.	.	.	12.60	.	.	13.30	16.50	.	12.60	.
Canada	.	.	.	.	.	59.30	.	17	10.30	.	19.20
Denmark	16.90	35.70	.	15.50	.	.	.	.	.	.	.
Japan	62.10	18.30	.	31.80	99.80	16.40	.	43.70	.	47.40	42.40
Korea	.	.	1.800	.	.	.	9.700	.	0.200	.	.
Mexico	.	.	6.800	7.100	.	24.20	23.50	0.500	7.800	40	30.70
New Zealand	.	8.500	6.800	.	.	.	.	3.100	.	.	.
Sweden	5.300	23.80	84.60	22.70	0.200	.	.	8.500	6.800	.	.
United Kingdom	.	.	.	.	.	.	53.50	1.400	30.10	.	.
United States	15.70	13.70	.	10.30	.	.	.	9.300	44.80	.	7.700

Table 3.5 – **Matrix of weights: government expenditure**

Non euro area	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Australia	30.10	35.40	.	.	.	.	28.70	34.30	38.10	58.70	13.20
Canada	.	.	.	10	.	.	.	.	36.40	.	.
Denmark	.	.	.	43.50	1.400	13.10	.	.	6.800	.	.
Japan	41.40	40.70	.	30.10	47.60	.	.	3.700	.	.	28.60
Korea	.	.	.	.	.	4.200	34.60	.	.	.	4.800
Mexico	6.300	.	.	.	.	8.200	13.80	.	9.200	9.100	11.50
New Zealand	.	.	100	.	.	.	.	.	.	19.40	.
Sweden	22.20	20.10	.	16.40	39.40	40	.	62	.	5	41.90
United Kingdom	.	.	.	.	.	34.50	22.90	.	0.800	7.800	.
United States	.	3.700	.	.	11.50	.	.	.	8.600	.	.

Note: Table 3.1 to 3.5 show the matrix of weights that generate the convex combination of non euro area countries' macro variables that best reproduce those of euro area countries over the matching window 1990-1998. For example, Finnish GDP is best reproduced by a vector of Canadian, Mexican, New Zealander, and Swedish macro variables in the percentages of 15.1, 12.4, 7.7, and 64.8. The weights are computed using the synthetic control method of Abadie and Gardeazabal (2003).

Figure 3.1 – **Actual and synthetic series**



Note: The figure shows the actual (blue solid) and the synthetic (red dashed) GDP series computed using the synthetic control method of Abadie and Gardeazabal (2003). The matching window is 1990-1998. The series are in euros per capita.

Figure 3.2 – **Parallel trends**

Note: The matching window is 1990-1998. The figure displays the pre euro and post euro trends as well as the cross-country unsmoothed component of the output shock both before and after the euro with the actual (blue line) and the synthetic series (red line). The straight lines are the fitted trends to both the actual and the synthetic series before and after the adoption of the euro.

Appendix 3.B Consumption and Output Correlation and BCS Index

Table 3.6 – **Correlations and BCS index: difference in difference estimates**

	All countries 1990-2012	**All countries 1990-2007**	**Core countries 1990-2012**	**Periphery countries 1990-2012**
Corr(C_i, Y_i)	0.19***	0.15***	0.16***	0.23***
	(6.03)	(4.38)	(14.78)	(13.49)
Corr(C_i, C_j)	-0.02	-0.02	-0.02	-0.10
	(-0.29)	(-0.28)	(-0.13)	(-0.72)
BCS$_{i,j}$	-0.07	-0.18***	-0.02	-0.08**
	(-1.47)	(-2.62)	(-0.27)	(-2.05)

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis and are obtained through bootstrap by resampling the donor pool of countries to generate the synthetic variables. The table reports the average across the panel of the difference in difference estimates of Corr(C_i, C_j), Corr(C_i, Y_i), and bilateral BCS Index. To compute the difference in difference estimates, we proceed in two steps. First, we take the difference between the measure obtained using the actual and the synthetic data both pre and post euro. Then, we take the difference between the post euro and the pre euro differences. All estimates point towards a reduction in risk sharing after the adoption of the euro.

Appendix 3.C Estimates of Risk Sharing Channels

Table 3.7 – **Risk sharing channels: full sample**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre euro	Synthetic	-0.02	0.04***	0.14***	0.35***	0.50***
		(-0.20)	(3.50)	(4.43)	(3.10)	(6.57)
	Actual	-0.05	-0.01	0.00	0.06	-0.00
		(-0.37)	(-0.21)	(0.03)	(0.38)	(-0.00)
Post euro	Synthetic	0.12	-0.01	-0.11^{***}	-0.03	0.03
		(0.97)	(-0.52)	(-3.01)	(-0.28)	(0.31)
	Actual	-0.00	-0.02	0.01	-0.17	0.18**
		(-0.02)	(-0.57)	(0.17)	(-1.23)	(2.18)
N		462	462	462	462	462
R^2		0.20	0.11	0.67	0.54	0.95

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The table displays OLS estimates with clustered standard errors over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. The row *Post euro Actual* displays the effect of the introduction of the euro. The adoption of the euro increases the unsmoothed component of the shock by 18%.

Table 3.8 – **Risk sharing channels: core countries**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre euro	Synthetic	-0.17	0.04**	0.24***	0.63***	0.27
		(-1.76)	(2.52)	(8.54)	(4.25)	(1.60)
	Actual	-0.07	0.01	0.00	-0.08	0.14
		(-0.53)	(0.29)	(0.03)	(-0.37)	(0.77)
Post euro	Synthetic	0.27	-0.01	-0.17***	-0.45***	0.37**
		(1.76)	(-0.57)	(-3.82)	(-3.87)	(2.35)
	Actual	-0.02	-0.04	0.02	0.18	-0.15
		(-0.11)	(-0.75)	(0.38)	(0.92)	(-0.79)
N		252	252	252	252	252
R^2		0.32	0.16	0.74	0.62	0.96

Note: The countries included as core are: Austria, Belgium, Finland, France, Germany, Netherlands.

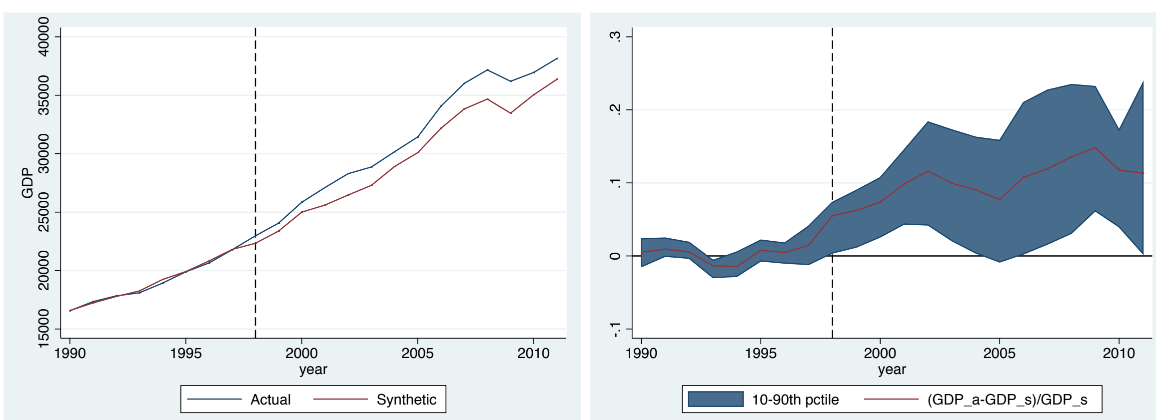
Table 3.9 – **Risk sharing channels: periphery countries**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre euro	Synthetic	0.06	0.05**	0.10***	0.24**	0.56***
		(0.54)	(2.86)	(3.56)	(2.32)	(8.67)
	Actual	-0.00	-0.02	-0.03	0.06	-0.01
		(-0.02)	(-0.90)	(-0.80)	(0.55)	(-0.11)
Post euro	Synthetic	-0.02	-0.02	-0.07*	0.29***	-0.17
		(-0.13)	(-0.73)	(-2.14)	(3.27)	(-1.41)
	Actual	0.04	-0.00	0.04	-0.41***	0.34***
		(0.25)	(-0.12)	(0.88)	(-4.84)	(4.26)
N		210	210	210	210	210
R^2		0.34	0.23	0.67	0.63	0.96

Note: The countries included as periphery are: Greece, Ireland, Italy, Portugal, Spain. ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The tables display OLS estimates with clustered standard errors over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. The tables show the following facts. First, before the adoption of the euro core countries were able to smooth a larger share of output variations than the periphery counterpart. Second, the adoption of the euro has not affected consumption smoothing in the core countries in a significant way, while it has decreased consumption smoothing in the periphery countries by 34%. Third, risk sharing through private saving has decreased.

3.C.1 GDP Growth and Volatility

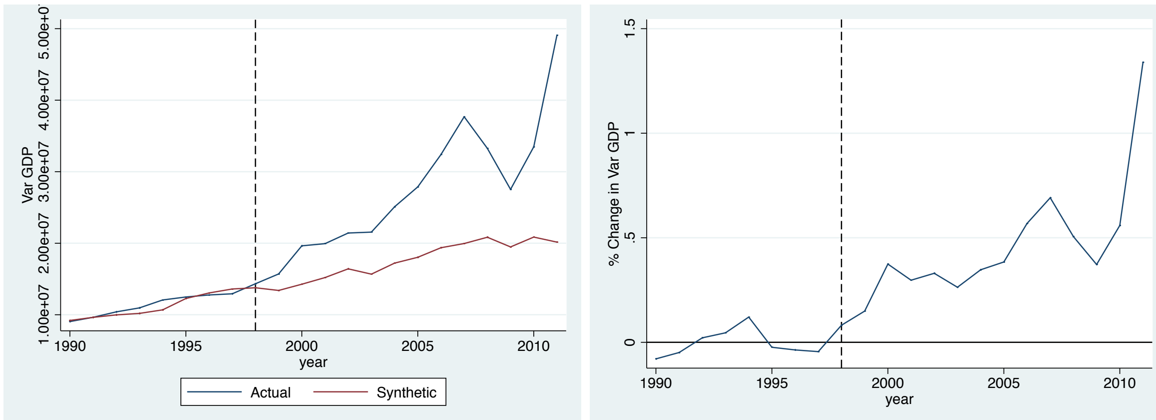
Figure 3.3 – **GDP growth in euro area countries**



(a) Actual and synthetic cross-country average (b) Percentage difference

Note: Panel (a) shows that, with the euro (blue line), euro area countries display on average higher GDP per capita than without the euro (red line). In panel (b), GDP_a and GDP_s indicate the actual and the synthetic GDP. The red line is the cross-country average of the percentage change in GDP, while the blue area represents its 80 central percentiles.

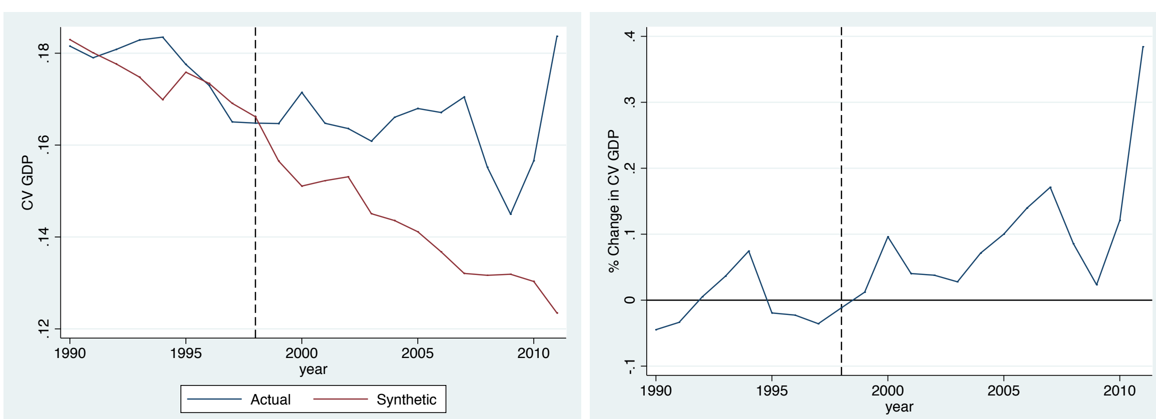
Figure 3.4 – **GDP variance**



(a) Actual and synthetic (b) Percentage difference

Note: Panel (a) exhibits the variance of the average actual and synthetic GDP across euro area countries. Panel (b) shows the percentage difference in the variance of the average actual and synthetic GDP. GDP is detrended with a linear quadratic trend. Both panels indicate that, following the adoption of the euro, GDP has been more volatile than it would have been without the adoption of the common currency.

Figure 3.5 – **GDP coefficient of variation**



(a) Actual and synthetic (b) Percentage difference

Note: Panel (a) shows the coefficient of variation of the actual and the synthetic average detrended GDP across euro area countries. Panel (b) portrays the percentage difference of the coefficient of variation of average detrended GDP computed from the actual and the synthetic series. GDP is detrended with a linear quadratic trend. The coefficient of variation is computed as the volatility of detrended GDP scaled by each subsample average GDP.

Table 3.10 – **GDP growth and volatility: difference in difference estimates**

		GDP Growth	GDP Variance	GDP Coeff Var
Pre euro	Synthetic	−0.02*	17.37***	0.15***
		(-1.87)	(262.32)	(20.13)
	Actual	0.00	0.06***	0.00***
		(0.61)	(53.75)	(13.46)
Post euro	Synthetic	0.02**	−0.10***	−0.01**
		(2.17)	(-3.14)	(-2.35)
	Actual	0.02**	0.16***	0.01***
		(2.45)	(4.95)	(2.84)
N		462	44	44
R^2		0.51	0.91	0.89

Note: GDP is detrended using a linear quadratic trend. In columns (2) and (3) it is averaged within actual or synthetic. ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. Sample period is 1990-2011. The table displays regressions of respectively GDP growth, logged variance of GDP and coefficient of variation of GDP on a set of dummies spanning the possible combinations of pre euro/post euro and actual/synthetic data. The results show that the adoption of the euro had a positive and significant effect both on GDP growth and on measures of volatility.

Appendix 3.D Robustness Checks

Table 3.11 – **OLS estimates with panel correlated standard errors**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre euro	Synthetic	−0.02	0.04*	0.14***	0.35***	0.50***
		(−0.30)	(1.87)	(5.28)	(5.21)	(7.18)
	Actual	−0.05	−0.01	0.00	0.06	−0.00
		(−0.59)	(−0.20)	(0.05)	(0.63)	(−0.00)
Post euro	Synthetic	0.12	−0.01	−0.11***	−0.03	0.03
		(1.46)	(−0.49)	(−3.49)	(−0.39)	(0.39)
	Actual	−0.00	−0.02	0.01	−0.17*	0.18*
		(−0.03)	(−0.53)	(0.24)	(−1.70)	(1.73)
N		462	462	462	462	462
R^2		0.20	0.11	0.67	0.54	0.95

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The table displays OLS estimates with panel correlated standard errors over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. The row *Post euro Actual* displays the effect of the introduction of the euro. The adoption of the euro increases the unsmoothed component of the shock by 18%, while it decreases private consumption smoothing by 17%.

Table 3.12 − **Match on first differences**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre euro	Synthetic	−0.10*	0.05**	0.12***	0.41***	0.52***
		(−1.89)	(2.18)	(4.28)	(7.06)	(9.87)
	Actual	0.01	−0.00	−0.01	0.01	−0.01
		(0.39)	(−0.29)	(−0.66)	(0.30)	(−0.21)
Post euro	Synthetic	0.12**	−0.04	−0.08**	−0.11*	0.11*
		(1.97)	(−1.39)	(−2.30)	(−1.66)	(1.78)
	Actual	0.00	−0.00	0.01	−0.09*	0.08*
		(0.10)	(−0.25)	(0.42)	(−1.90)	(1.87)
N		462	462	462	462	462
R^2		0.20	0.06	0.47	0.53	0.95

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The table displays OLS estimates with clustered standard errors over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. Differently from our baseline results, synthetic data are generated by matching over first differenced data instead of data in levels. Our baseline results on the effect of the euro on risk sharing channels are confirmed, though their magnitude is partially reduced. In particular, the unsmoothed component of the shock is 8%.

Table 3.13 − **Match using fixed weights for all variables**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre euro	Synthetic	0.04***	0.03***	−0.08***	0.09***	0.93***
		(4.45)	(8.84)	(-9.90)	(9.83)	(93.92)
	Actual	−0.11	−0.00	0.23***	0.32**	−0.43***
		(-1.04)	(-0.06)	(3.99)	(2.62)	(-4.94)
Post euro	Synthetic	0.01	0.01***	−0.04***	−0.00	0.02***
		(1.71)	(3.95)	(-4.08)	(-0.32)	(3.21)
	Actual	0.04	−0.04	−0.02	−0.19*	0.21***
		(0.41)	(-1.46)	(-0.28)	(-1.81)	(2.91)
N		462	462	462	462	462
R^2		0.20	0.06	0.47	0.53	0.95

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The table displays OLS estimates with clustered standard errors over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. Differently from our baseline results, synthetic data are generated by using fixed weights for each country's variables. The weights are found by matching a country's GDP, and then using the same weights for the other synthetic variables of the same country. Our baseline results on the effect of the euro on risk sharing channels are confirmed.

Table 3.14 – **Placebo studies**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre euro	Synthetic	−0.12*	0.07***	0.06***	−0.08	1.06***
		(−1.94)	(4.15)	(2.74)	(−1.04)	(14.91)
	Actual	−0.07	−0.03	0.02	0.10	−0.02
		(−0.99)	(−1.39)	(0.66)	(1.08)	(−0.17)
Post euro	Synthetic	0.12	0.01	0.01	0.11	−0.25**
		(1.45)	(0.41)	(0.29)	(1.05)	(−2.53)
	Actual	0.03	−0.01	−0.02	−0.02	0.02
		(0.33)	(−0.53)	(−0.46)	(−0.14)	(0.14)
N		420	420	420	420	420
R^2		0.17	0.15	0.57	0.31	0.93

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The table displays OLS estimates over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. The analysis is run for placebo countries, which have never adopted the euro. Our difference in difference estimators are extremely close to zero and never significant, meaning that we find no effect of the adoption of the euro on our non euro area group.

Table 3.15 – **Matching over the period 1990-1997**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre-tr	Synthetic	-0.10	0.04**	0.16***	0.39***	0.51***
		(-1.03)	(2.20)	(6.47)	(4.77)	(9.11)
	Actual	0.01	0.00	-0.02	0.01	-0.01
		(0.09)	(0.13)	(-0.32)	(0.10)	(-0.20)
Post-tr	Synthetic	0.09	-0.01	-0.11***	-0.05	0.08
		(0.80)	(-0.60)	(-3.34)	(-0.45)	(0.79)
	Actual	0.01	-0.02	0.01	-0.15	0.15**
		(0.09)	(-0.85)	(0.14)	(-1.11)	(2.34)
N		462	462	462	462	462
R^2		0.26	0.13	0.69	0.57	0.96

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The table displays OLS estimates with clustered standard errors over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. The matching window is now 1990-1997 instead of 1990-1998. Our estimates are in line with our baseline results. With the adoption of the euro, we find an increase in the unsmoothed component, which is close to our main result and still significant.

Table 3.16 – **Exclusion of EU members from non euro area group of countries**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre-tr	Synthetic	−0.10	0.09***	0.18***	0.41***	0.42***
		(−1.36)	(3.64)	(6.04)	(5.21)	(5.96)
	Actual	0.01	−0.05*	−0.02	−0.00	0.07
		(0.06)	(−1.82)	(−0.68)	(−0.01)	(0.84)
Post-tr	Synthetic	0.15*	−0.05*	−0.13***	−0.04	0.07
		(1.71)	(−1.78)	(−3.63)	(−0.40)	(0.84)
	Actual	−0.03	0.03	0.02	−0.17	0.16
		(−0.29)	(0.80)	(0.38)	(−1.58)	(1.61)
N		462	462	462	462	462
R^2		0.20	0.16	0.69	0.55	0.95

Note: ***, **, and * denote significance at 1%, 5%, 10% respectively. t-statistics are in parenthesis. The table displays OLS estimates with clustered standard errors over the period 1990-2011 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. Only non-EU countries are used for the matching. When excluding countries that are part of the EU but not of the euro area, our estimates are very close to our main results in Table 3.7, but are now not significantly different from zero. A possible explanation for this is that our non euro area group is now very limited since it only includes seven OECD countries.

Table 3.17 – **Exclusion of the financial crisis period: full sample**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre-tr	Synthetic	-0.02	0.04***	0.14***	0.34***	0.50***
		(-0.19)	(3.56)	(4.44)	(3.08)	(6.56)
	Actual	-0.06	-0.01	0.00	0.06	-0.00
		(-0.37)	(-0.22)	(0.04)	(0.38)	(-0.00)
Post-tr	Synthetic	0.32**	0.03	-0.14***	-0.19	-0.03
		(2.18)	(1.11)	(-3.14)	(-1.54)	(-0.28)
	Actual	-0.16	-0.05	0.02	-0.08	0.27***
		(-0.96)	(-1.55)	(0.33)	(-0.60)	(3.09)
N		374	374	374	374	374
R^2		0.15	0.13	0.40	0.37	0.96

Note: *, **, and *** denote significance at 10%, 5%, 1% respectively. t-statistics are in parenthesis. The table displays OLS estimates with clustered standard errors over the period 1990-2007 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro. The table shows that, when excluding the financial crisis period, the unsmoothed component of the shock increases even further as compared to the baseline result. This confirms that the decrease in risk sharing is not due to the turbulences of the financial crisis.

Table 3.18 – **Exclusion of the financial crisis period: core countries**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre-tr	Synthetic	-0.17	0.04**	0.24***	0.63***	0.27
		(-1.76)	(2.52)	(8.52)	(4.24)	(1.59)
	Actual	-0.07	0.01	0.00	-0.08	0.14
		(-0.53)	(0.29)	(0.03)	(-0.37)	(0.77)
Post-tr	Synthetic	0.41**	0.04	-0.21***	-0.60***	0.35**
		(2.22)	(1.25)	(-3.43)	(-6.61)	(2.48)
	Actual	-0.25	-0.10	0.05	0.34*	-0.05
		(-1.42)	(-1.56)	(0.71)	(1.93)	(-0.35)
N		204	204	204	204	204
R^2		0.32	0.19	0.58	0.49	0.96

Note: The countries included as core are: Austria, Belgium, Finland, France, Germany, Netherlands.

Table 3.19 – **Exclusion of the financial crisis period: periphery countries**

		Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Pre-tr	Synthetic	0.06	0.05**	0.10***	0.24**	0.56***
		(0.56)	(2.90)	(3.58)	(2.29)	(8.79)
	Actual	-0.00	-0.02	-0.03	0.06	-0.01
		(-0.03)	(-0.91)	(-0.80)	(0.56)	(-0.10)
Post-tr	Synthetic	0.16	0.01	-0.08	0.13	-0.22**
		(0.99)	(0.25)	(-1.78)	(1.28)	(-2.35)
	Actual	-0.06	-0.03	0.02	-0.35***	0.42***
		(-0.34)	(-0.93)	(0.45)	(-3.54)	(3.82)
N		170	170	170	170	170
R^2		0.32	0.26	0.37	0.49	0.97

Note: The countries included as periphery are: Greece, Ireland, Italy, Portugal, Spain.

*, **, and *** denote significance at 10%, 5%, 1% respectively. t-statistics are in parenthesis. The table displays OLS estimates with clustered standard errors over the period 1990-2007 for the actual and the synthetic series before (*Pre euro*) and after (*Post euro*) the introduction of the euro.

Tables 3.18 and 3.19 show that the increase in the unsmoothed component of the shock in the full sample – see Table 3.17 – is driven entirely by the periphery countries, whose unsmoothed component increases by 42%. The decrease in the consumption smoothing is mainly due to the private savings channel, which decreases by 35%.

3.D.1 Bias in the Difference in Difference Estimation

This section computes the bias that may be present in a difference in difference setup when the series used for estimation are estimated with some error. Assume that there exists a true counterfactual for our experiment (the adoption of the euro). Denote by X_i the unit of interest, by superscripts T and C the treatment and control group, and by B and A the before and after treatment period. We would like to estimate via the SCM X_i^{CA}, the behaviour of the control group after the treatment, and compare it to X_i^{TA}, the behaviour of the treatment group after the treatment.

We estimate the counterfactual based on the pre treatment matching and obtain $\tilde{X}_i^{CA}$ and $\tilde{X}_i^{CB}$, the series of interest for the control group after and before the treatment. The $\sim$ indicates that the series is estimated with some error u, that is $\tilde{X}_i^{CA} = X_i^{CA} + u$.

The difference in difference setup described in equation 3.8 provides an estimate of the treatment effect β_4 that is equivalent to

$$\hat{\beta}_4 = (\beta^{TA} - \tilde{\beta}^{CA}) - (\beta^{TB} - \tilde{\beta}^{CB}).$$

This estimate will be different from the true treatment effect

$$\beta_4 = (\beta^{TA} - \beta^{CA}) - (\beta^{TB} - \beta^{CB}).$$

The difference arises from the statistical error in the estimation of the coefficients of the counterfactual. The bias can be written as

$$\hat{\beta}_4 - \beta_4 = (\beta^{TA} - \tilde{\beta}^{CA}) - (\beta^{TB} - \tilde{\beta}^{CB}) - (\beta^{TA} - \beta^{CA}) + (\beta^{TB} - \beta^{CB}).$$

Lastly, exploiting the standard result on additive measurement error on regressors we can denote the multiplicative bias by γ, meaning

$$\tilde{\beta} = \frac{\sigma_x^2 + \lambda}{\sigma_x^2 + \sigma_{ME}^2 + 2\lambda}\beta \equiv \gamma\beta,$$

where λ is the covariance between the true variable and the measurement error, σ_x^2 is the variance of the true variable, and σ_{ME}^2 is the variance of the measurement error.

We now turn our attention to possible ways to estimate γ in our setup in order to correct for or sign the bias.

Solutions to Measurement Error Bias

If we had a true counterfactual for the pre treatment period, we would get that the treated and the counterfactual group would behave the same way in the pre treatment period, that is $\beta^{TB} - \beta^{CB} = 0$. However, we do not have a true counterfactual, but we have to generate it ourselves. We do so by using the SCM. The SCM minimises the distance between the actual and the synthetic series in the pre treatment period. As the synthetic series are not the true counterfactual, but an estimated one, we do not compute exactly β^{CB}, but only $\tilde{\beta}^{CB} = \gamma\beta^{CB}$, where γ is the bias. From this, we can compute γ as follows:

$$\tilde{\beta}^{CB} = \gamma\beta^{CB} = \gamma\beta^{TB} \Rightarrow \gamma = \frac{\tilde{\beta}^{CB}}{\beta^{TB}}.$$

This bias γ is derived exploiting the difference between the actual and the synthetic series for the euro area countries in the pre treatment period.

Time Invariant Measurement Error If we assume that γ is time invariant, and in particular that it does not change in the post treatment period, we can use it to correct for the bias as follows:

$$\begin{aligned}\hat{\beta}_4 - \beta_4 =& (\beta^{TA} - \tilde{\beta}^{CA}) - (\beta^{TB} - \tilde{\beta}^{CB}) - (\beta^{TA} - \beta^{CA}) + (\beta^{TB} - \beta^{CB}) \\ &= -\tilde{\beta}^{CA} + \tilde{\beta}^{CB} + \beta^{CA} - \beta^{CB} \\ &= (\beta^{CA} - \beta^{CB})(1-\gamma)\end{aligned}$$

Rewriting in terms of observables:

$$\begin{aligned}\hat{\beta}_4 - \beta_4 &= \frac{1}{\gamma}(\tilde{\beta}^{CA} - \tilde{\beta}^{CB})\left(1 - \frac{\tilde{\beta}^{CB}}{\beta^{TB}}\right) \\ &= (\tilde{\beta}^{CA} - \tilde{\beta}^{CB})\frac{\beta^{TB} - \tilde{\beta}^{CB}}{\tilde{\beta}^{CB}}.\end{aligned}$$

Hence, the true treatment effect is

$$\beta_4 = \hat{\beta}_4 - (\tilde{\beta}^{CA} - \tilde{\beta}^{CB})\frac{\beta^{TB} - \tilde{\beta}^{CB}}{\tilde{\beta}^{CB}}.$$

Placebo Estimation of Bias In our robustness checks, we routinely estimate treatment effects for placebo countries. For these countries, we estimate the counterfactual and the treatment behaviour at the same time since, by definition, they coincide when no treatment occurs. We can then exploit this procedure to estimate the bias generated by statistical error. Note that for the placebo countries the estimated bias is available for both the pre treatment and the post treatment period.

More precisely, denoting $\hat{\gamma}^B$ the correction for the period before treatment and $\hat{\gamma}^A$ the one for the period after treatment, the corrected estimated treatment effect $\tilde{\hat{\beta}}_4$ is as follows:

$$\tilde{\hat{\beta}}_4 = \beta^{AT} - \frac{\tilde{\beta}^{CA}}{\hat{\gamma}^A} - \beta^{BT} + \frac{\tilde{\beta}^{BC}}{\hat{\gamma}^B}.$$

Neoclassical Measurement Error An alternative set of assumptions allows us to sign the bias. First note that the optimization problem of the SCM is effectively trying to minimize γ^B. Also, as shown before, γ^B is observable. In a difference in difference setting the second element of the vector β is $1 - 1/\gamma^B$. Hence whenever that element is not significantly different from zero, which means that the generated counterfactual mimics the treated unit well, then there is no measurement error in the pre treatment period.

This implies that one can rewrite the bias as

$$\hat{\beta}_4 - \beta_4 = -\tilde{\beta}^{CA}\left(\frac{1}{\gamma^A} - 1\right)$$

As long as the econometrician is willing to assume that $\gamma^A < 1$, which is a marginally weaker assumption than neoclassical measurement error,[10] then the sign of the bias

[10] Recall that the size of the bias γ depends on the sign and magnitude of the covariance between the measurement error and X. Neoclassical measurement error assumes that that covariance is zero,

follows from the sign of $\tilde{\beta}^{CA}$ since the term in the bracket is positive.

Discussion

There are a number of elements worth discussing in these possible solutions. First, the pre treatment statistical error is what the SCM is trying to minimise, while the key unobserved parameter is the bias in the post treatment period. By this very token, we should think about the pre treatment bias as in sample and targeted, while the post treatment bias is out of sample.

In addition, in sample errors are relatively small if the matching procedure is successful. This can be tested by checking the second coefficient of the difference in difference outputs, that is the one that indicates the difference between the treated and the control group in the pre treatment period. Again this is not surprising given that the difference is minimised by the procedure.

Lastly, note that the entire set of solutions to the bias relies on the crucial fact that using the SCM, in the pre treatment period control and treatment group coincide. In more practical terms for our application this is just stating that Italy before the introduction of the euro is identical whether the euro will be introduced or not.[11] This is exactly what allows us to say that any observed difference between the treatment and the control group in the pre treatment period must be due to the statistical error, thereby providing an estimate of the bias itself. In more practical terms this implies that we can get a handle on the pre treatment bias both in the actual sample and in the placebo sample, whereas the post treatment bias is only available in the latter.

generating attenuation bias. In general the following holds

$$\gamma < 1 \quad \text{if} \ -Cov(X, ME) < \sigma^2_{ME}$$
$$\gamma > 1 \quad \text{if} \ -Cov(X, ME) > \sigma^2_{ME}.$$

[11] Recall that the lack of anticipation effects is one of the identifying assumptions of SCM. In our application we test this in the robustness checks by changing the treatment year to before the actual introduction of the common currency.

Table 3.20 – **Bias-corrected estimates of the effect of the euro adoption on the risk sharing channels**

	Capital Markets	International Transfers	Public Savings	Private Savings	Unsmoothed
Placebo full sample	0.07	-0.00	-0.00	-0.590	0.08
Placebo pre euro	0.06	0.01	-0.01	-0.112	0.05
Euro area pre euro	0.07	0.01	-0.01	-0.16	0.10

Note: The table reports the bias-corrected estimates of our baseline results. These estimates are obtained by correcting the fourth row of coefficients (Post euro Actual) in Table 3.7 for the bias. The row *Placebo full sample* reports the bias-corrected estimates when the bias is computed from the placebo countries both pre and post adoption of the euro. The row *Placebo pre euro* reports the bias-corrected estimates when the bias used for correction is computed only from the pre euro period using placebo countries. The row *Euro area pre euro* reports the bias-corrected estimates when the bias used for correction is computed only from the pre euro period using euro area countries.

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