Universitat Autònoma de Barcelona

ESSAYS IN MACROECONOMICS

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Contents

To Giovanna, whom I miss every day

PREFACE

This Thesis is the result of the work developed during my PhD studies at the Department of Economics of Universitat Autònoma de Barcelona. It consists of three Chapters related to three different topics in the area of Macroeconomics.

Chapter 1 investigates a research question related to Optimal Taxation with Heterogeneous Agents. Here I study how the optimal degree of redistribution guaranteed by the progressivity of the tax code code can be optimally adjusted in response to business cycle fluctuations. The main motivation for this work is provided by two well-established facts: i) income risk is counter-cyclical and ii) inequality tend to increase substantially during economic downturn. I study this question in the framework a heterogeneous agents incomplete markets model with earning and unemployment risk, where an unanticipated negative shock to TFP hits the economy at the steady state and temporarily increases idiosyncratic uncertainty. In this setup, I compute the optimal response of a government which maximizes welfare along the entire transition generated by the shock. I find that the optimal policy is a hump-shaped path of progressivity that peaks 30 quarters after the shock hits and slowly reverts to its steady state level. The welfare gains coming from adopting the optimal policy and as opposed to keeping progressivity constant, are computed to be around 0.49% in consumption terms along the transition.

Chapter 2 is a joint work with Luca Gambetti and Nicolò Maffei-Faccioli in the field of Applied Macroeconomics. In this paper, we study the way news media report positive and negative economic events and we investigate how this affects agents' information, expectations and consumption. To this end, we construct two measures of media coverage of bad and good unemployment figures based on three major US newspapers and we employ nonlinear time series techniques to document four facts. (i) There is no significant negativity bias in media coverage of economic events. The asymmetric responsiveness of newspapers to positive and negative economic shifts found in previous literature is entirely explained by the higher persistence of the effects on economic variables of bad shocks. (ii) Bad news are more informative than good news. (iii) Bad news increases agents' agreement about economic outcomes and modifies their expectations more than good news. (iv) Consumption reacts to bad news, but not to good news.

Chapter 3 is a work in the field of Applied Macroeconomics. It investigates the macroeconomic effects of the Asset Purchase Program (APP) and

the Pandemic Emergency Purchase Program (PEPP) by the European Central Bank on the aggregate of the Euro Area and on the four largest European economies. I construct a proxy variable for the unexpected component of the announced purchases and I use it to identify an Asset Purchase Program shock using zero and sign restrictions. I study the effects of the shock in a time-varying parameters Factor Augmented Vector Autoregressive moodel with Stochastic volatility (TVP-SV-FAVAR) to test for potential cross-country heterogeneities in the transmission mechanisms of the policy. I document substantial heterogeneity in the responses of European countries to the policy: i) Southern European economies experienced the largest decrease in government bond yields but the smallest decrease in the cost of credit to households and non-financial corporations; ii) the response of inflation has been stronger in Germany and Spain than in Italy and France; iii) Most of the observed cross-country differences reduced significantly over time and with later packages of the policy. Results on the aggregate of the Euro Area show that most of the channels of transmission of Quantitative Easing were active at the European level.

Chapter 1

Optimal Income Tax Progressivity Over the Business Cycle

Sarah Zoi[1]

Should income tax progressivity change over the business cycle? There is extended evidence that income risk is counter-cyclical and that inequality increases during economic downturns. In a heterogeneous agents incomplete markets model with earning and unemployment risk, I study the effects of an unanticipated negative shock to TFP which hits the economy at the steady state and temporarily increases idiosyncratic uncertainty. In this framework, I compute the optimal response of a government which maximizes welfare along the entire transition generated by the shock. The optimal policy is a hump-shaped path of progressivity that peaks 30 quarters after the shock hits and slowly reverts to its steady state level. As opposed to keeping progressivity constant, adopting the optimal policy implies a welfare gain of 0.49% in consumption terms along the transition. The gain is mainly due to re-distributive effects on consumption and a decrease in hours worked.

Keywords: Fiscal Policy, Optimal Taxation, Redistribution, Progressivity, Business Cycle
JEL: E62, E320, H21, H23

[1] I am thankful to Raül Santaeulàlia-Llopis for his continuous support and guidance. I thank Alexander Ludwig, Nezih Guner and Luis Rojas for their valuable comments and suggestions and the audience of the Macro Club at Universitat Autonoma de Barcelona for fruitful discussions.

1.1 Introduction

Should a government change the distribution of the tax burden in response to aggregate fluctuations? An extended literature has documented that both the distribution of idiosyncratic changes in earnings and inequality are sensitive to the business cycle. In particular, labor income risk is counter-cyclical and counter-cyclically left-skewed[2], while income and wealth inequality increase persistently during economic downturns [3]. In this context, fiscal policy provides a variety of instruments which partly complement private self-insurance against idiosyncratic income shocks (unemployment benefits, mean-tested transfers etc.). Among those, income tax progressivity not only provides partial insurance, but also guarantees redistribution with respect to differences in income. These insurance and re-distributive aspects of the policy establish a dependence of the optimal progressivity of a tax system to the degree of inequality and income uncertainty faced by the government. In particular, if risk and inequality change due to aggregate economic conditions, welfare improving adjustments in progressivity over the business cycle cannot be *a priori* ruled out.

While as a general rule governments respond to the business cycle with instruments other than progressivity, historically there have been few examples of tax reforms with the purpose of redistributing the tax burden during economic recessions (some of them for the US are discussed in Section 2). Looking at these examples highlights that there has been no systematic rule suggesting in which direction such adjustments should be implemented and by which magnitude. The main contribution of this paper is to identify such a rule.

As a first step, I report new empirical evidence on the response of the US government to aggregate shocks in terms of progressivity. With the purpose of setting a *status quo* for the policy, I construct a historical measure of statutory progressivity and use vector autoregressive techniques to test how this responds to changes in aggregate productivity. One of the contribution of the paper is to show that, historically, the US government has not responded to aggregate shocks by significantly adjusting the progressivity of the tax code.

Next, I develop an heterogeneous agents and incomplete market model *á la* (Aiyagari, 1994) with endogenous labor supply and idiosyncratic uncertainty over employment and productivity. The government has a balanced budget policy and

[2](Storesletten et al., 2004) show that labor income risk is counter-cyclical, increasing substantially during recessions; (Guvenen et al., 2014) and (Busch et al., 2020) find a-cyclical earning risk but show that the distribution of differences in earnings is pro-cyclically left-skewed; (Busch & Ludwig, 2020) find both counter-cyclical variance and pro-cyclical skewness

[3](Castañeda et al., 1998) report that the income share earned by the bottom three quintiles of the income distribution are pro-cyclical, with the lowest displaying the highest positive correlation with GDP growth, while the last two quintiles are counter-cyclical. More recently, (Bayer et al., 2020) show that business cycles have very persistent effects on inequality and can account for up to 50% of the rise in US wealth inequality from 1980 to 2015.

taxes agents' total income according to a log-linear progressive tax code in which progressivity is uniquely identified by one parameter. The approach to optimal policy adopted throughout this work is the one of (Ramsey, 1927).
I calibrate the model on the US and use this framework to briefly show that optimal progressivity is higher in stationary economies with higher earning risk and unemployment but it is not influenced by different TFP levels. On the one hand, the higher the degree of uncertainty over income and the resulting inequality, the larger the scope for partial insurance and redistribution. On the other hand, higher or lower TFPs shift the distribution of income without affecting inequality and therefore do not change the optimal degree of redistribution.

In this framework, I consider a single unexpected negative shock to TFP which hits the stationary economy at its optimal progressivity and increases income risk[4]. For the purpose of calibrating the joint dynamics of TFP and earning risk, I use VAR techniques to provide new evidence of the response of risk to a TFP shock. I study the effects of the shock on the aggregate economy and the responses of heterogeneous agents in the transition back to the original steady state under the *status quo* of the policy (i.e. the government doesn't adjust progressivity). The recessionary shock temporarily increases inequality in income, wealth and earnings, but this is only partly due to the increase in the dispersion of the idiosyncratic component of wages. Indeed, higher unemployment pushes aggregate wages up inducing heterogeneous responses across different productivity and wealth types. Due to their limited ability to self-insure, poorer agents are the ones suffering the most in terms of consumption: the per-capita consumption of the bottom 10% of the steady state wealth distribution decreases by more than 5% as opposed to the 0.7% decrease of the top 10%.

I compute the optimal path for income tax progressivity under full commitment assuming that a contemporaneous reaction to the shock from the government's side is possible. The progressivity policy which maximizes welfare along the transition is hump-shaped, increasing on impact, peaking 30 quarters after the shock hits and reverting back slowly to the steady state optimal level. The response is quantitatively large: at its peak progressivity is 68% higher than its steady state optimal level. Two main factors explain the shape of the optimal policy. First, the shock increases inequality and income risk, leaving room for a welfare improving increase in progressivity. Second, by inducing a reduction in investments, the shock has a persistent decreasing effect on capital which is reinforced by the policy. Because the government increases insurance in response to the shock, agents have less scope in keeping a large capital buffer. This, in turn, calls for a higher public insurance for a prolonged period of time and explains the long tail of the policy. Until the interest

[4]According to the empirical evidence previously mentioned, I consider a TFP shock which both increases the probability and the duration of unemployment and the earning risk in the employment state

rate doesn't increase enough for capital to start reverting back, it is optimal to keep progressivity higher than its steady state level.

Adopting the optimal policy is associated with an increase in welfare of 0.49% in consumption terms with respect to the *status quo*. Decomposing the total gain highlights a positive contribution of 1.34% increase in consumption terms due to a re-distributive effect on consumption, a 2.13% increase due to a decrease in average hours worked and a 2.92% decrease due to a decrease in average consumption level. The policy redistributes from wealth and earning-rich to the poor letting them enjoy a much higher level consumption than in the stationary economy for a limited period of time. Inequality increases less on impact than under the *status quo* but decreases substantially below the steady state level in subsequent periods. Finally, the price of embracing the optimal policy is a slower recovery. By increasing progressivity, the government reduces incentives to work and to save inducing a more severe recession. In particular, if GDP falls 5% under the *status quo*, by adopting the optimal policy the drop in GDP is approximately 3% points larger.

To the best of my knowledge, this is the first paper investigating potential welfare gains from adjustments in income tax progressivity in an environment in which aggregate and idiosyncratic shocks are correlated. Related to this work, (Werning, 2007) studies optimal adjustments in income taxation in response to aggregate shocks in a Mirleesian framework. Under the assumption of perfect insurable idiosyncratic shocks, he finds that marginal tax rates should not change in response to aggregate fluctuations. The key point of his result is the absence of the insurance motive provided by taxation which instead is the main focus of my analysis. (Bhandari et al., 2013) study optimal income taxation over the business cycle in an heterogeneous agents incomplete markets setup with linear taxes and lump sum transfers. Again, in their paper there is no interaction among aggregate fluctuations and the distribution of idiosyncratic shocks.

This work relates to a broader literature on optimal income tax progressivity which early contribution is (Conesa & Krueger, 2006). Works in this field focused exclusively on steady state dynamics ((Conesa et al., 2009), (Heathcote et al., 2017)) or on one-and-for-all tax reforms and their related transitions ((Krueger & Ludwig, 2013), (Bakış et al., 2015), (Ferriere et al., 2021), (Dyrda & Pedroni, 2021)). Other studies extended the basic framework to include human capital accumulation ((Krueger & Ludwig, 2013) and (Peterman, 2016)), separate capital taxation and top earnears taxation ((Conesa et al., 2009) and (Kindermann & Krueger, 2020)), revenue maximization ((Guner et al., 2016)) and joint optimal design of progressivity and lump-sum transfers (Ferriere et al (2021)). As for this literature, I abstract from additional mechanisms with respect to the standard insurance-efficiency trade-off, but investigate how aggregate business conditions may affect it. Even though the approach to optimal taxation adopted throughout this work is the one of (Ramsey, 1927), few authors have studied optimal income tax progressivity under flexible setups of Mirrleesian tradition ((Heathcote & Tsujiyama, 2022), (Farhi & Werning, 2013), (Golosov et al., 2016)).

The welfare gains coming from the optimal policy in my setup remind of the literature on the cost of business cycle when agents are heterogeneous and face counter-cyclical income risk ((Imrohoroğlu, 1989) and (Krusell & Smith, 1998)). With respect to the majority of the works in this field, I don't focus on a fully stochastic model but study a deterministic economy in its transition back to the steady state. Furthermore, and more similarly to (Storesletten et al., 2001), I consider a more comprehensive notion of income risk than what these authors usually do and include both unemployment and earning risk.

Other studies have addressed the optimal design of other automatic stabilizers, especially unemployment insurance, in response to aggregate fluctuations, see for example (Landais et al., 2010), (Mitman & Rabinovich, 2015) and (Birinci & See, 2019), but without including progressivity in the set of instruments available to the government. Closer to this paper, (McKay & Reis, 2021) study the optimal joint design of unemployment benefits and progressivity in the presence of business cycles. They find that taking business cycles into account implies higher unemployment benefits with respect to economies without aggregate shocks, while the degree of optimal progressivity is not significantly affected by the presence of aggregate fluctuations. As opposed to the present work which focuses on if and of how much progressivity should adjust in response to aggregate fluctuations, in their framework optimal progressivity is still a unique parameter which is kept constant throughout the cycle.

With respect to the empirical contribution of the paper, few works have measured the size of automatic stabilizers by identifying which budget components respond more to the cycle ((Fatás & Mihov, 2012), (Auerbach & Feenberg, 2000)), or assessed their quantitative importance in reducing the volatility of business cycles ((McKay & Reis, 2016)). The focus of the empirical exercise in this paper is instead on unveiling whether the government adjusts the degree of automatic stabilization provided by progressivity in response to aggregate shocks.

The remind of the paper is organized as follows. Section 2 presents new empirical evidence on how the US government has been responding with progressivity to aggregate productivity shocks. Section 3 describes the model. Section 4 presents the calibration. Section 5.1 reports and discusses a brief sensitivity analysis of optimal progressivity to changes in risk and TFP in stationary economies. Section 5.2 reports the responses to the MIT shock when the government keeps progressivity fixed at its optimal steady state level along the whole transition (i.e. the *status quo*). Section 6 illustrates the optimal policy and presents the aggregate and distributional responses to the MIT shock when the government undertakes the optimal policy. Section 7 discusses alternative non-optimal policies as a comparison. Section 8 concludes.

1.2 Stylized Facts

How does pogressivity evolve along the business cycle? Is the government actually responding to changes in aggregate business conditions by systematically adjusting progressivity?

As a first step, it is useful to make a distinction between *statutory progressivity*, which is embedded in the tax code and solely depends on the structure of tax brackets, deductions, phase-outs and credits, and *effective progressivity*, which is the one we actually observe in the data. Because *effective progressivity* is usually estimated on microdata from representative samples of tax-payers, its time variations may reflect both changes in the tax law and in the income distribution. As an illustrative example, consider the stylized case in which the economy is hit by a negative shock which induces a simple downward shift of the entire income distribution. If the government doesn't adjust the tax code or introduce/suppress deductions, phase-outs or credits, *statutory progressivity* will not change. However, a households' tax bill may decrease more than proportionally with respect to the decline in income: some taxable incomes will shift to a lower tax bracket and more households will become eligible for welfare programs they couldn't benefit of before the shock. In this case, the *effective progressivity* that one can retrieve from data on a representative sample of tax-payers before and after the shock can be substantially different even though the tax code remained unchanged. For the purpose of this study, the interest is in uncovering whether changes in business cycle conditions induces a response from the government in terms of adjustments in *statutory progressivity*. The exercise I present in this Section aims at setting a *status quo* to be compared with the welfare improving policy of Section 6.2. To this end, I start by constructing two time series which proxy *statutory* and *effective progressivity* following the methodology used by (Ferriere, Navarro, et al., 2016). Consider the log-linear progressive tax code (Feldstein(1969) and Benabou(2000)), which I will adopt throughout this work:

$$\tau(y) = 1 - \lambda(y)^{-\phi} \tag{1.1}$$

where y is total income, λ is a parameter governing the level of taxes, ϕ is the progressivity parameter and disposable income can be computed as $y^d = y(1 - \tau(y)) = \lambda y^{1-\phi}$.

Under this tax function, given income y, one can identify the parameter ϕ by computing the ratio:

$$\frac{T'(y) - \tau(y)}{1 - \tau(y)} = \frac{(1 - \lambda(1-\phi)y^{-\phi}) - (1 - \lambda(y^{-\phi}))}{1 - (1 - \lambda(y^{-\phi}))} = \phi$$

where $T(y) = y - y^d$ is total tax liability and $T'(y) = 1 - \lambda(1-\phi)y^{-\phi}$ is the marginal tax rate.

To estimate ϕ, I use data on Average Tax Rate (ATR) and Average Marginal Tax Rate (AMTR) computed using microdata from the Statistics of Income (SOI) of the Internal Revenue Service (IRS)[5]. Tax liabilities are calculated using TAXSIM on each tax filing, according to the methodology described in (Feenberg & Coutts, 1993). Two versions of the data are provided. For the first, calculations are based on representative yearly samples of tax returns as reported by the IRS. Since the sample of tax filers is changing every year, the series obtained from this data captures variations in ATR and AMTR due to both changes in the income distribution and in the tax code. For the second, calculations are obtained by fixing the sample distribution of tax payers to the year 1984[6] and computing the tax liability of each tax return using TAXSIM. This second version of the data reflects changes in the ATR and AMTR which are solely due to changes in the tax law and not in the income distribution. Accordingly, the estimates of progressivity obtained using the two versions of the data reflect changes in *effective progressivity* and in *statutory progressivity*, respectively.

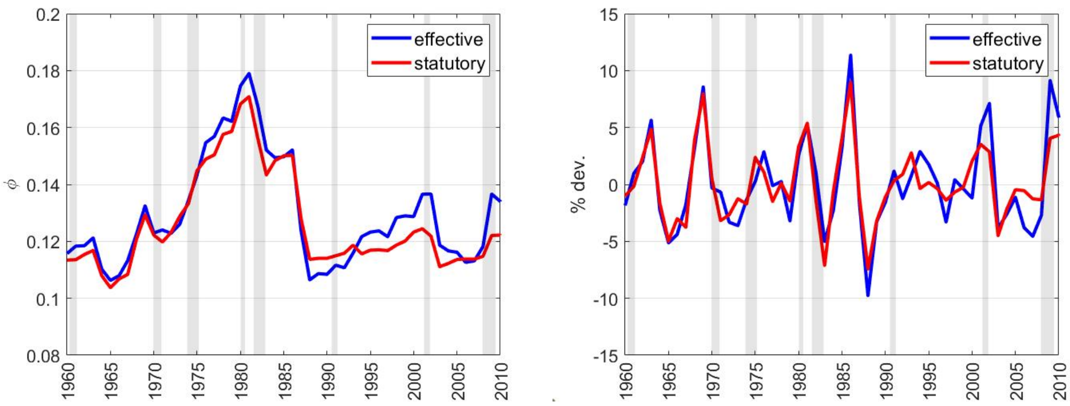

FIGURE 1.1: *Effective* (blu line) and *statutory progressivity* (red line), under the log-linear tax code in (3.2). Grey area correspond to NBER recession periods. Left panel: levels. Right panel: percentage deviations from the trend. Author's computation on SOI-IRS data and TAXSIM.

The left panel of figure (1.1) reports the two measures for the years 1960-2012. The two lines almost overlap between 1960 and 1975, suggesting that most fluctuations in progressivity during that period were due to changes in tax schedule rather than to changes in the distribution. Indeed, during the 60s and 70s, the US had stable levels of income inequality and experienced high economic growth which affected quite uniformly different percentiles of the income distribution (see (Piketty & Saez, 2003) and (Piketty et al., 2018)). Conversely, most of the variation in *effective progressivity* after the second half of the 80s is mainly attributable to changes in the distribution.

[5]Data are available at: `http://users.nber.org/~taxsim/allyup/`

[6]For each year other than 1984, dollar amounts in the sample are inflated or deflated to match the ratio of GNP deflator plus 1.4% annual real growth with respect to 1984

Interestingly, changes in the tax law happened before 1988 shifted progressivity significantly, while starting from the 90s, most policy interventions brought only minor fluctuations around an average ϕ of 0.116. The two variables captures quite well the most relevant tax reforms in the US during the reference period. The decrease in progressivity in 1964 corresponds to the Revenue Act with which the Kennedy Administration cut the top marginal tax rates from 91 and 80% to 60 and 70%[7]. The steady increase of progressivity in the 70s was driven by a variety of reforms which extended the Minimum Deduction, introduced and raised the Alternative Minimum Tax on top income earners and increased income credits. The two large drops in the 80s correspond to the two Reagan's reforms with which the government intended to bolster economic activity during and after a severe economic crisis. In 1981, the Economic Recovery Tax Act reduced all marginal tax rates but represented a major fiscal ease for top incomes: the lowest tax rate fell from 14 to 11%, while the top rate decreased from 70% to 50%[8]. In 1986, the Tax Reform Act lowered again top marginal rates from 50% to 28% and reduced considerably the number of tax brackets, resulting in a huge drop in progressivity[9]. Statutory progressivity remained quite stable until the early 2000 when it dropped again with the two reforms approved under the Bush Administration. Both reforms aimed at boosting the economy during the crisis followed to the 'dotcom' bubble and the terrorist attack of 2001. In both cases marginal tax rates were cut at the top and at the bottom, but with a clear advantage for high income tax-payers. Finally, the increase in progressivity during the Great Recession is associated with the stimulus packages approved under Obama's presidency. These measures didn't change the tax schedule but temporarily decreased pay-roll taxes and increase substantially tax credits (EITC).

To isolate higer-frequency fluctuations, I detrend the two series using the Hodrick and Prescott filter and report them in the right panel of figure (1.1). From visual inspection only, there is no clear pattern suggesting a cyclical behaviour of progressivity. Both *effective* and *statutory progressivity* seem to have decreased during the 1969's, 1982's and 2001's recessions, but to increase during the 1974's and 2009's recessions. This is consistent with the short overview of past tax reforms given above. Historically, different Administrations have responded differently to economic downturns, either by easing the tax burden on top incomes (e.g. Reagan) or bottom incomes (e.g. Obama), or not adjusting the tax code.

[7]This measure came together with a (smaller) cut of tax rates at the low end of the income distribution, the introduction of the Minimal Standard Deduction and an increase in the number of tax brackets. Even though these measures resulted in a substantial ease for low income households, the cut of the top rates more than compensated for these redistributive policies resulting in an overall decrease in progressivity

[8]Among other things, the reform introduced the inflation indexing of tax brackets which addressed the severe fiscal drag that had plagued tax payers during the 70s.

[9]These measure came together with an increase in EITC, deductions and exemptions which mostly benefited low income household. However, the net effect on progressivity was negative.

To formally test whether there was a systematic response of progressivity to the business cycle, I use a VAR model to estimate the response to a productivity shock. I proxy productivity using TFP[10] and real GDP, alternatively, both taken in percentage deviations from their trend. I order productivity first, *statutory* or *effective* progressivity second and choose one lag. I apply Cholesky decomposition and take the first shock[11].

Figure (1.2) reports the responses of *statutory* (red) and *effective progressivity*

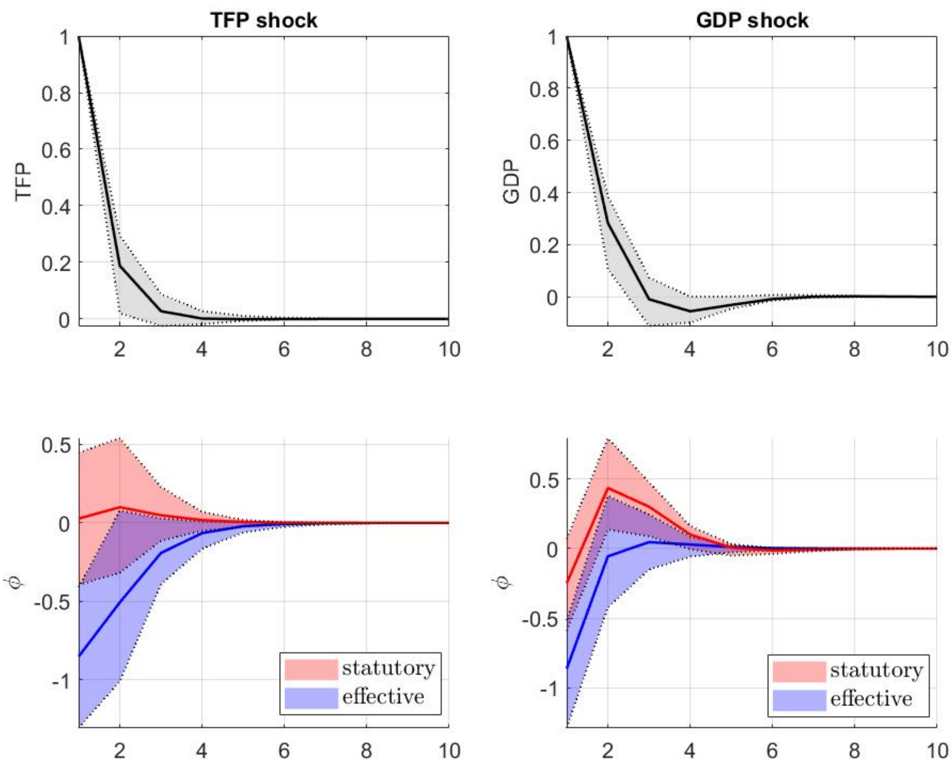

FIGURE 1.2: IRFs of statutory (red) and effective (blue) progressivity to a 1% productivity shock. Left column: Productivity is proxied using TFP. Right column: Productivity is proxied using real GDP. All series have been linearly de-trended and filtered using Hodrick-Prescott filter.

(blue) to a positive 1% deviation of productivity from its long-run trend. In each column a different proxy for productivity is used. In both cases the response of *effective* progressivity is negative on impact (around -0.85%) and reverts to zero between three and four years after the shock. When controlling for changes in the income distribution, the responses of *statutory* progressivity is approximately zero when TFP is used, or slightly positive after the first year when GDP is used. On one hand, this suggests that a positive productivity shock affects the income distribution in a way

[10]I use the time series of (Fernald, 2014)
[11]I do want to allow for a contemporaneous response of progressivity

that decreases the observed progressivity in the data with respect to its trend. On the other hand, the government doesn't respond to business cycle fluctuations by adjusting the progressivity of its tax schedule, or if anything, its response is slightly pro-cyclical and delayed.

1.3 Model

The economy is populated by a continuum of *ex-ante* identical agents, endowed with one period of time and facing idiosyncratic uncertainty over their employment condition, $s_{i,t} \in \{u, e\}$. The transition among different employment states (s, s') is disciplined by a first-order Markov chain with transition matrix:

$$\pi = \begin{bmatrix} \pi_{ee} & \pi_{eu} \\ \pi_{ue} & \pi_{uu} \end{bmatrix} \tag{1.2}$$

with $\pi_{ee} + \pi_{eu} = \pi_{ue} + \pi_{uu} = 1$. If employed at time t, agent i faces additional uncertainty over her labor productivity, $\varepsilon_{i,t}$. In particular, the logarithm of wage of an employed agent is given by:

$$log(w_t) + log(\varepsilon_{i,t}) \tag{1.3}$$

where w_t is the market wage and the idiosyncratic component and $\varepsilon_{i,t}$, follows a geometric AR(1) process:

$$log(\varepsilon_{i,t}) = \rho_\varepsilon log(\varepsilon_{i,t-1}) + \xi_t$$

where $\xi_t \sim N(0, \sigma^2_\xi)$.
If unemployed ($s_{i,t} = u$), an agent is not subjected to any additional productivity shock, $\varepsilon_{i,t} = \varepsilon_{i,t-1}$, and receives a unemployment benefit which is a proportion R of her last labor income labor income, $w_{t-j}h_{i,t-j}\varepsilon_{i,t-j}$ being j the last period of employment.

Progressive tax code

Taxation of total income is progressive, according to a log-linear tax function ((Feldstein, 1973), (Benabou, 2000)). Let y be total income, the tax code $\tau(y)$ is of the form:

$$\tau(y) = 1 - \lambda(y)^{-\phi}$$

which implies a threshold level $\bar{y} = \lambda^{\frac{1}{\phi}}$, below which agents receive a transfer and above which they pay taxes. Parameter λ captures the level of taxes, with higher values of λ corresponding to lower taxes and higher transfers for each level of income. Parameter ϕ captures the degree of progressivity of the tax system, with $\phi \in [0, 1]$ Under this tax function, disposable income is given by:

$$y^d = (1 - \tau(y))\, y = \lambda(y)^{1-\phi}$$

Figure (1.3) reports the average tax rates (ATR) and the marginal tax rates (MTR) for two values of λ (left panel) and ϕ (right panel). Increasing λ implies a uniform upward shift of both the ATR and MTR (left panel) across all income levels. Moreover, a higher λ moves the threshold $\bar{y}$ to the left reducing the set of incomes with negative ATR (i.e. eligible for net transfers). Increasing ϕ (right panel) changes the distribution of taxes by rotating the ATR and MTR towards left. This implies a reduction in the tax burden (or increase in the transfer) for lower incomes and an increase in taxes for higher incomes. As for the increase in λ, a higher ϕ shifts $\bar{y}$ to the left implying a lower set of income with negative ATR (receiving a net transfer).

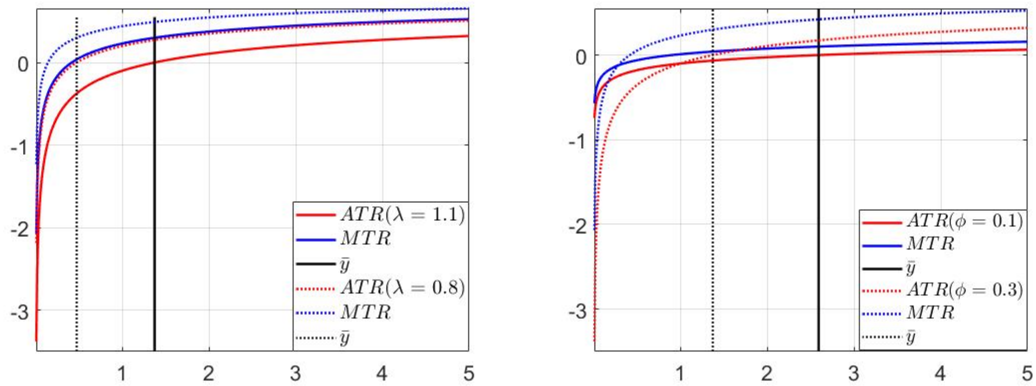

FIGURE 1.3: Average, Marginal Tax Rates and threshold $\bar{y}$ under the log-linear tax function for different levels of λ (left panel) and ϕ (right panel)

Employed Agents ($s = e$)

At the beginning of the period an agent receives the employment shock, $s_{i,t} \in \{e, u\}$. Conditional on the realization of s, she solves the corresponding problem. If employed, the agent receives a second shock ε on her productivity and decides how much work to supply at wage $w_t\varepsilon$ and how much to consume and save. The recursive formulation of the problem of an employed agents reads as follow:

$$V_t^e(a,\varepsilon) = \max_{\{a,c>0,0\leq h\leq 1\}} \frac{c^{1-\gamma}}{1-\gamma} - \kappa \frac{h^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}$$
$$+ \beta(1-\pi_{ee,t})V_{t+1}^u(a',\varepsilon,h)$$
$$+ \beta\pi_{ee,t}\int_{\varepsilon'} V_{t+1}^e(a',\varepsilon')\, dF_{t+1}(\varepsilon'|\varepsilon)$$

$$s.t.\;\; c - a = \lambda(\varepsilon h w_t + r_t a)^{1-\phi} + a$$
$$a' \geq 0$$

where π_{ee} is the probability of being employed in the next period, $\varepsilon h w$ is labor income, $r_t a$ is financial income and $\lambda(\varepsilon h w_t + r_t a)^{1-\phi}$ is total disposable income. The FOCs of the problem for an employed agent are:

$$h:\;\; c^{-\gamma}(1-\phi)\lambda_t(h\varepsilon w_t + r_t a)^{-\phi} + \beta(1-\pi_{ee})(c')^{-\gamma}w_t\varepsilon R(1-\phi)\lambda_t(h\varepsilon w_t R + ra')^{-\phi} = \kappa h^{\frac{1}{\nu}} \tag{1.4}$$

$$a':\;\; c^{-\gamma} = \beta E\left[(1 + r_{t+1}(1-\phi)\lambda_t(y' + r_{t+1}a')^{-\phi})(c')^{-\gamma}\right] \tag{1.5}$$

where $y' = h'\varepsilon' w_t$ if the agent is employed in t' and $y' = h^{-'}\varepsilon^{-'}w_t R$ if unemployed. As the unemployment benefit is a function of previous period earnings, the FOC for hours implies an inter-temporal trade-off: higher labor supplied today implies higher insurance against the unemployment state in the next period. Taxation of total income implies that the net interest rate in the Euler equation (1.5) is a function of future earnings and requires solving for h'.

Unemployed agents ($s = u$)

If unemployed, the agent doesn't face additional uncertainty on her productivity, so that $\varepsilon = \varepsilon^{-'}$. Unemployed agents receive a benefit ω and decide how much to save and to consume:

$$V_t^u(a,\varepsilon,h^{-'}) = \max_{\{a,c>0\}} \frac{c^{1-\gamma}}{1-\gamma}$$
$$+ \beta\; \pi_{uu}\; V_{t+1}^u(a',\varepsilon,h^{-'})$$
$$+ \beta\;(1-\pi_{uu})\int_{\varepsilon'} V_{t+1}^e(a',\varepsilon')\, dF_{t+1}(\varepsilon'|\varepsilon)$$

$$s.t.\;\; c - a = \lambda_t(\omega + r_t a)^{1-\phi} + a$$
$$a' \geq 0$$

where π_{uu} is the probability of being unemployed in the next period, and ω is the unemployment benefit provided by the government which is a proportion R of last period labor income, i.e. $\omega = h^{-'}\varepsilon w_{t-1}R$. The FOC of the problem for a unemployed agent is:

$$a': \quad c^{-\gamma} = \beta E\left[(1 + r_{t+1}(1-\phi)\lambda(y' + r_{t+1}a')^{-\phi})(c')^{-\gamma}\right] \tag{1.6}$$

where $y' = h'\varepsilon' w_{t+1}$ if the agent is employed in t' and $y' = h^{-'}\varepsilon w_{t-j}R$ being j the last period of employment.

Production

A representative firm operates in a competitive market and produces with a CRS technology:

$$Y_t = z_t\, K_t^{\theta} N_t^{1-\theta}$$

Government

The government has a balanced budget policy. Every period, the government collects revenues from taxation with which it finances unemployment benefits and transfers to low income agents through the progressive tax code. Government's budget reads:

$$\int \mathbf{1}_{y<\bar{y}}\; y\tau(y)\; dy + \int \omega\; d\omega = \int \mathbf{1}_{y>\bar{y}}\; y\tau(y)\; dy \tag{1.7}$$

where y is total income computed as the sum of financial and labor income (or unemployment benefit) and ω is the unemployment benefit[12].

To study optimal progressivity over the business cycle, I define two types of equilibrium: i) a recursive competitive equilibrium along a transition where TFP, income risk and unemployment risk follow deterministic paths; ii) a stationary recursive competitive equilibrium corresponding to the starting and ending points of the transition.

1.3.1 Recursive Competitive equilibrium

A recursive competitive equilibrium along a deterministic transition is a set of policy functions for employed $\{c_t^e(a,\varepsilon)\}_{t=0}^{\infty}$, $\{h_t^e(a,\varepsilon)\}_{t=0}^{\infty}$, $\{a_t^{e\prime}(a,\varepsilon)\}_{t=0}^{\infty}$, and unemployed

[12] Few key feature of the UI system in the US justify the choice of a single government budget in (1.7). The UI is a joint federal-state system, where benefits are mostly provided by social security systems at the state level and financed through state-payroll taxes. However, the federal government levies an additional payroll tax to finance the Unemployment Trust Fund (UTF) which provides loans to insolvent state unemployment funds when needed and finances extensions of standard benefits during severe economic downturns. Finally, when resources coming from the UTF are insufficient to cover the expenditure due to the mentioned extended benefits, the Federal government responds directly with its own budget.

$\{c^u_t(a,\varepsilon,h^{-'})\}_{t=0}^{\infty}$, $\{a^{u\prime}_t(a,\varepsilon,h^{-'})\}_{t=0}^{\infty}$, value functions $\{V^e_t(a,\varepsilon)\}_{t=0}^{\infty}$ and $\{V^u_t(a,\varepsilon,h^{-'})\}_{t=0}^{\infty}$, prices $\{r_t,\, w_t,\, \lambda_t\}_{t=0}^{\infty}$, and $\{\Omega\}_{t=0}^{\infty}$, such that:

1. Households maximize

2. Firms set prices to factors' marginal productivities:

$$r_t = z_t\theta\left(\frac{N_t}{K_t}\right)^{1-\theta} - \delta \qquad w_t = z_t(1-\theta)\left(\frac{K_t}{N_t}\right)^{\theta}$$

3. Government budget balances at every t

4. Markets clear

$$\int a'_t(a,s,\varepsilon,h^{-'})\, d\Omega_t = K_{t+1}$$
$$\int \varepsilon h_t(a,\varepsilon)\, d\Omega_t = N_t$$
$$\int\ c_t(a,s,\varepsilon,h^{-'})d\Omega_t + (1-\delta)K_t = z_t K_t^{\theta} N_t^{1-\theta} + K_{t+1}$$

To solve for the transition, I choose a maximum number of periods T in which the economy reverts back to its steady state and guess two sequences of prices $\{\lambda^0\}_{t=1}^{T}$, $\{r^0\}_{t=1}^{T}$. Given these, I solve backwards for policy functions $\{c^e_t(a,\varepsilon)\}_{t=1}^{T}$, $\{h^e_t(a,\varepsilon)\}_{t=1}^{T}$, $\{a^{e\prime}_t(a,\varepsilon)\}_{t=1}^{T}$, $\{c^u_t(a,\varepsilon,h^{-'})\}_{t=1}^{T}$ and $\{a^{u\prime}_t(a,\varepsilon,h^{-'})\}_{t=1}^{T}$. I solve for the distribution $\{\Omega\}_{t=1}^{T}$ forward using a Montecarlo method. I compute the sequences of $\{\lambda\}_{t=1}^{T}$ and $\{r\}_{t=1}^{T}$ implied by the solution of the transition and take a convex combination between these and $\{\lambda^0\}_{t=1}^{T}$, $\{r^0\}_{t=1}^{T}$ to obtain new guesses $\{\lambda^1\}_{t=1}^{T}$, $\{r^1\}_{t=1}^{T}$. I iterate over $\{\lambda\}_{t=1}^{T}$, $\{r\}_{t=1}^{T}$ until the difference between $\{\lambda^i\}_{t=1}^{T}$, $\{r^i\}_{t=1}^{T}$ and $\{\lambda^{i-1}\}_{t=1}^{T}$, $\{r^{i-1}\}_{t=1}^{T}$ in two consecutive iterations is smaller than a fixed tolerance. I report a detailed explanation of the algorithm in Appendix A.3.

The results I present in Section 5 and 6 are based on a simplified version of the model in which the unemployment benefit only depends on previous period productivity i.e. $\omega = \varepsilon R$.

1.3.2 Stationary Recursive Competitive Equilibrium

A stationary equilibrium is the set of policy functions for the employed $\{c_e(a,\varepsilon)$, $h(a,\varepsilon), a'_e(a,\varepsilon)\}$ and unemployed, $\{c_u(a,\varepsilon,h^{-'}), a'_u(a,\varepsilon,h^{-'})\}$, value functions $V_e(a,\varepsilon)$, $V_u(a,\varepsilon,h^{-'})$, prices $\{r,\ w,\ \lambda\}$ and distribution, Ω, of agents across assets, ability types, productivity shocks, employment states and previous period labor supply $(a,\varepsilon,s,h^{-'})$, such that:

1. Agents solve their maximization problem

2. Firm optimizes, equating prices to marginal productivity:

$$r = z\theta \left(\frac{N}{K}\right)^{1-\theta} - \delta \qquad w = z(1-\theta)\left(\frac{K}{N}\right)^{\theta}$$

3. Government budget balances

4. Markets clear

$$\int a'(a,s,\varepsilon,h^{-'})\, d\Omega = K'$$
$$\int \varepsilon h(a,\varepsilon)\, d\Omega = N$$
$$\int c(a,\varepsilon,h^{-'},s) d\Omega + \delta K = zK^{\theta}N^{1-\theta}$$

To solve for the stationary equilibrium I iterate over r and λ until the asset market and the government budget clear. For a given guess of $\{r,\lambda\}$, I solve for the policy functions of the employed and the unemployed using the Endogenous Grid Method ((Carroll, 2006)). I approximate the stationary distribution using a Montecarlo simulation with 150 thousands individuals for 500 periods

The results I present in Section 5.1 are based on a simplified version of the model in which the unemployment benefit only depends on previous period productivity i.e. $\omega = \varepsilon R$.

1.4 Calibration

I calibrate the model so that one period corresponds to a quarter and set θ to 0.36 and δ to 0.025. I choose risk aversion parameter, γ, to be 1.5, and Frisch elasticity of labor supply, ν, to be 0.5. For the results I present in the next Sections I consider a simplification of the unemployment insurance and take it to depend on the last period idiosyncratic productivity. In particular, I choose the unemployment benefit parameter R to be 0.05 so that, *ex-post*, agents' labor earnings are always higher than the unemployment benefits they are eligible for.

For the stationary economy, I normalize the TFP parameter z to 1 and choose probabilities $\pi_{ss'}$ to match average unemployment duration of 18 weeks (1.5 model periods) and the average unemployment rate of 6.2% over the period 1970-2018. Following (Imrohoroğlu, 1989), I pin down π_{uu}, using the fact that the average duration of any state is $D^S = (1-\pi_{ss})^{-1}$. Hence, given D^U, one can easily retrieve π_{uu} as $\pi_{uu} = 1 - \frac{1}{D^U}$. Given π_{uu}, I choose π_{ee} such that the proportion of unemployed agents in the model matches the average non-employment rate. For the idiosyncratic productivity process, I rely on the estimates in (Storesletten et al., 2004) and set ρ_ε to match the annual autocorrelation of 0.94 and σ^2_ξ to match annual frequency weighted standard deviation of 0.17. I use a minimum distance estimator to calibrate the discount factor, β, and the disutility of labor, κ, to match quarterly capital-to-output ratio of 10.26 and average hours worked of 1/3 when $\phi = 0.125$ (the average progressivity over 1960-2012 according to the estimates reported in figure (1.1)). Table (1.1) reports a summary of the calibrated parameters.

Parameter	Interpretation	Value	Target/Source
Production			
z	TFP	1	
θ	capital share	0.36	
δ	capital depreciation	0.025	
Preferences			
γ	risk aversion	1.5	
ν	Frisch elasticity	0.5	
β	discount factor	0.988	$K/Y = 10.26$
κ	disutility of work	27.63	average hours 1/3
Income process			
π_{ee}	transition prob. (e, e)	0.956	unempl. rate 0.062
π_{uu}	transition prob. (u, u)	0.339	unemp. duration 18 weeks
ρ_{ε}	autocorr. persistent component	0.989	annual 0.94
σ_{ε}	earning risk	0.086	annual 0.17
			(Storesletten et al. 2004)
Government			
ϕ	progressivity	0.125	average 1960-2012
R	UB (proportion of productivity)	0.05	

TABLE 1.1: Summary of model calibration for the stationary economy
.

Joint Dynamics of TFP, earning risk and unemployment

To calibrate the income process along the transition it is necessary to pin down paths for σ^2_{ξ}, π_{ee} and π_{uu} in response to a TFP shock. For this purpose, I estimate the responses of the unemployment rate, average unemployment duration and earning risk to a 1% shock in TFP using three separate VARs with one lag. To get a time series of earning risk, I first estimate an income process using PSID data on males head of households aged between 25 and 60 for the period 1969 to 1996. As the series of earning risk is at annual frequency while the shock I consider is quarterly, I use a MF-VAR with one lag. Details of the estimation are reported in the Appendix A.1 and A.2. For all the three VARs, I previously de-trend the series linearly, order TFP first, apply Cholesky decomposition and take the first column. The choice of three separate models instead of a unique VAR for the four time series is dictated by the need of having smooth paths for σ^2_{ξ}, π_{ee} and π_{uu} and avoid the bumps due to additional joint dynamics and higher number of lags in the calibration. In Appendix A.2, I report results of a joint Mixed Frequency VAR (MF-VAR) for the four variables as a robustness check. Responses from the joint model and the three smaller scale models are very similar. Finally, since the dynamics of the TFP shock in the three separate models is slightly different, I choose a unique process for the shock. The process I choose is

$$log(z_t) = \rho_z \, log(z_{t-1}) + u_t^z$$

and I set ρ_z to 0.78 to guarantee an average duration of a cycle[13] of 25 quarters. Given empirical responses of unemployment and unemployment duration, I set transition probabilities π_{ee} and π_{uu} accordingly. The joint dynamics of the shocks in the model are reported in figure (1.4).

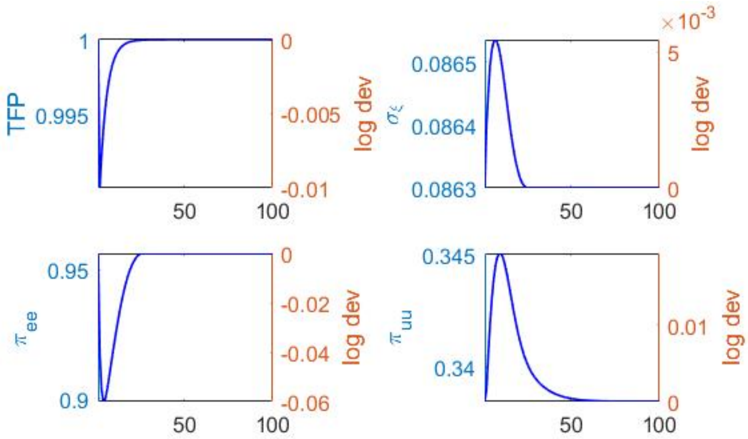

FIGURE 1.4: IRFs of TFP, earning risk (σ_ξ) and transition probabilities (π_{ee} and π_{uu}) to a 1% negative TFP shock.

1.5 Model Dynamics after a TFP Shock

In this Section I compute optimal progressivity for the benchmark stationary economy and provide a brief sensitivity analysis to different levels of TFPs, earning and unemployment risk. Next, I analyze the responses of the economy to 1% negative shock to TFP which hits the benchmark stationary economy at its optimal progressivity level and increases earning risk and unemployment.

1.5.1 The Stationary Economy

The objective of this Section is to show how optimal progressivity varies across stationary economies with different levels of income risk and TFP. To this end, I solve for the optimal progressivity in the benchmark stationary economy and consider four sensitivity exercises. In the first, I compare economies identical in every aspect but displaying different levels of earning risk. In the second, economies differ in

[13]The definition used for "cycle" is the time between two peaks

their levels of TFP only. In the third, economies have different unemployment risk. In the fourth, economies have different levels of TFP, earning and unemployment risk. The details of the parametrization for this experiment are reported in table (A.1) in Appendix A.4.

The Planner's Problem

The approach to optimal progressivity I adopt throughout this work is the one of (Ramsey, 1927). Consider a progressive fiscal rule $\tau(\phi)$ and let $V(a, \varepsilon, s, h^{-'}; \tau(\phi))$ be the *ex-ante* lifetime utility of an agent under policy $\tau(\phi)$. The optimal degree of progressivity ϕ^* at the Steady State is the solution to the maximization problem:

$$\max_{\phi} \int V(a, \varepsilon, s, h^{-'}; \tau(\phi)) \, d\Omega$$

Each panel of figure (A.9) illustrates welfare as a function of progressivity parameter ϕ for a different group of model economies [14]. Black crosses in figure (A.9) indicate the maximum of each welfare function. Blue lines correspond to lower risk and/or high TFP, while red lines correspond to high risk and/or low TFP. Black lines refer to the benchmark economy. The optimal progressivity for the benchmark economy is $\phi* = 0.221$, in line with what (Ferriere et al., 2021) find in a setup similar to mine[15]. Four main results emerge.

First, optimal progressivity is an increasing function of earning risk. As panel a) shows, higher levels of σ_{ζ}^2 are associated with higher ϕ^*. This result is related with the insurance and re-distributive aspect of progressivity: the higher the income risk faced by agents and the resulting inequality, the larger the scope for insurance and re-distribution. This is reflected also in the curvature of the welfare function: the higher the risk is, the larger the sensitivity of welfare to marginal increases in ϕ. Interestingly, the welfare functions associated with riskier economies lie above the welfare of the lower risk economies for values of ϕ above a certain low threshold. Because of precaurtionary motives, riskier economies tend to have higher accumulation of capital which, in turn, translates in larger output and consumption. However, to finance this higher capital buffer, agents in riskier economies have to supply more labor which brings a welfare cost that partly compensates the gains from higher consumption. Figure(A.4) in Appendix A.4 clearly shows this point by reporting the consumption equivalent variations (CEV) of moving from the optimal progressivity ϕ^* to each ϕ in the grid for the benchmark economy.

[14] Appendix A.4 reports the details of how the main aggregates, prices and inequality in total income change as a function of ϕ for the four groups of economies

[15] These authors have a very similar setup as mine with unemployment and earning shocks and find $\phi* = 0.22$

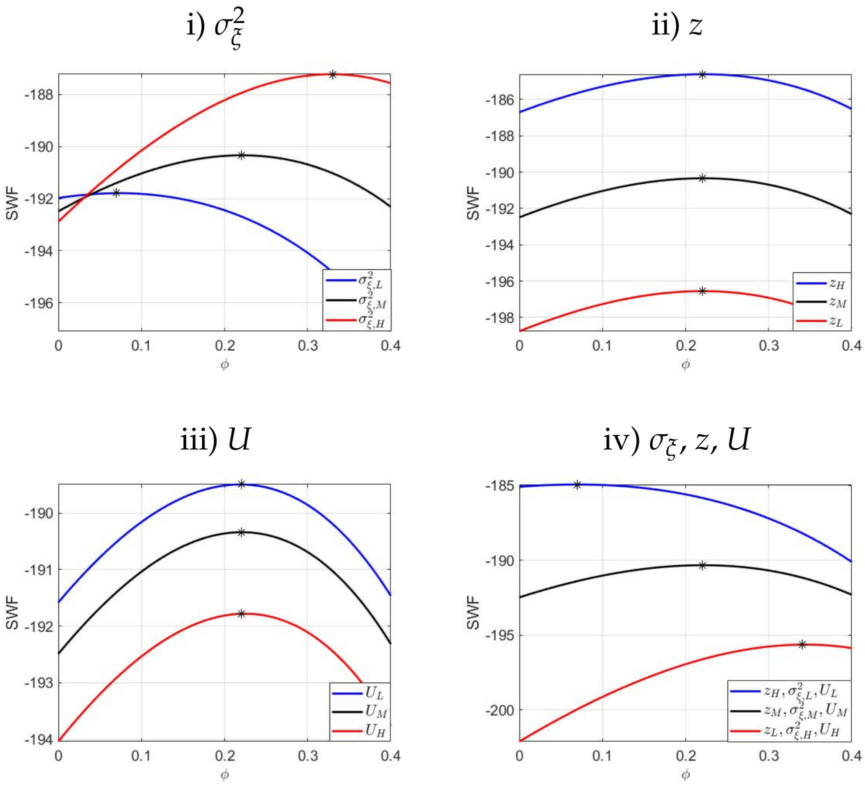

FIGURE 1.5: Welfare as a function of progressivity parameter ϕ for the four groups of economies in table(A.1)

Second, optimal progressivity is not sensitive to changes in TFP. As TFP increases (decreases), welfare moves upwards (downwards) with parallel displacements which do not affect its concavity with respect to ϕ. Indeed, shifts in TFP increase or decrease the output level without affecting inequality in total income[16].

Third, as the unemployment risk increases, optimal progressivity increases only slightly, reducing to 0.21 for the lower risk economy and increasing to 0.23 for the higher risk economy. This result is due to the fact that, even if the probability and the duration of unemployment increase or decrease, the corresponding compensation doesn't change. In other words, from the agents' perspective, the dispersion of income between the employment and the unemployment states remains constant through changes in the unemployment probability.

Fourth, there is no interaction among the mechanisms at work in the three cases. When moving across economies with different combinations of TFP, earning and unemployment risk, the resulting optimal progressivity reflects only the shifts in earning and unemployment risk.

The next Section analyzes the effect of the MIT shock which hits the stationary benchmark economy under the assumption that the optimal progressive tax system is implemented (i.e. progressivity is $\phi^* = 0.221$).

[16]Figure (A.9) in Appendix A.4 shows that the changes in the gini of total income across economies with different TFP levels are extremely tiny

1.5.2 The constant progressivity policy

Figure(1.4) reports the joint dynamics of TFP, σ_ξ and transition probabilities π_{ee} and π_{uu} in response to a 1% decrease in TFP as described previously in the calibration.

This Section describes the case in which the government has already implemented the optimal policy in the stationary economy and keeps it constant along the whole transition. Making a slight abuse of language, I will refer to this policy as the *status quo* policy. Indeed, as discussed in Section 2, not adjusting progressivity is a stylized representation of the policy that US government has been adopting during the last 50 years. The main difference here is that I assume that the government enters the transition at its optimal progressivity and not at its actual level (around 0.12 in 2012). Figure (1.6), reports the response of the the main aggregates and prices. The TFP shock pushes both capital and labor prices down. However, the decline in labor supply due to higher unemployment implies an increase in the capital-labor ratio which more than compensates the downward pressure on wages. The shock induces a decrease in investments which translates in a slow decline in the capital stock. Lower labor supply and less investment implies a fall in output and consumption of around 5% and 2%, respectively. The recessionary shock increases the financing needs of the government. On the one hand, due to the higher unemployment rate, the expenditure in unemployment compensations soars. On the other hand, the decline in income implies that a larger number of individuals becomes entitled to transfers. To satisfy its budget, the government adjusts λ downwards with two main effects. First, the decrease in λ increases the level of taxes and decrease the generosity of the transfer for each level of income. As it was highlighted in Section 3, the shifts in ATR and MTR generated by a decrease in λ are uniform across income levels if ϕ is not adjusted. Second, the threshold $\bar{y}$ shifts downwards reducing the set of incomes taxed at negative average tax rate. Overall, the decline in income more than compensates the tighter threshold so that the total number of transfer-receivers (second panel in the last row) increases by around 1%.

Figure (1.10) reports the responses of three types of individuals along the transition: a low productive individual with a level of assets that places her at the 10% of steady state wealth distribution, a high productive agent at the 90% of the wealth distribution and a medium productive at the median wealth. The shock generates quite heterogeneous responses across different wealth and productivity types. The wealth and earning-poor (and worse insured) cuts his consumption dramatically in response to the shock. Due to the increase income risk, and absent any additional insurance policy, this agent is pushed to build up a capital buffer in order to be able to cushion against future income volatility. To finance her investment in capital, she increases labor supply earning a higher income. This, together with the effect of a lower λ implies a decline in the transfer to which this agent is entitled. On the other

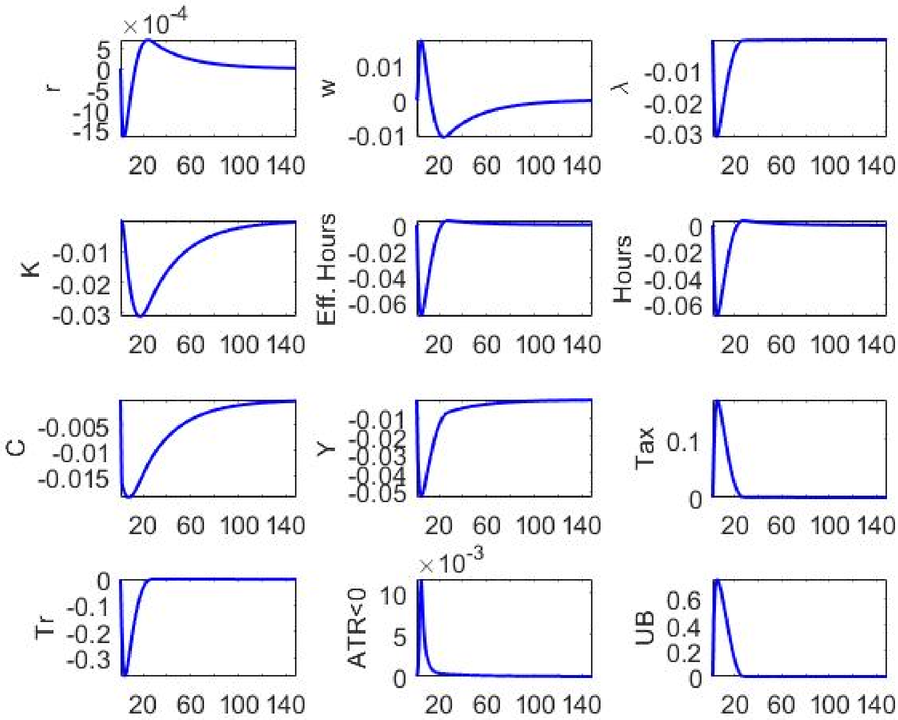

FIGURE 1.6: IRFs of main aggregates and prices to a 1% TFP shock which increases unemployment and earning risk under the constant progressivity policy $\phi(t) = \phi^{SS}$. Log-deviations from steady state quantities.

tail of the distribution, the wealth and earning-rich can better smooth out consumption by eating up part of her capital buffer. In response to the increase in wages, this agent increases slightly her labor supply and earnings but not enough to compensate the lower capital income. Even though her total income reduces, the decrease in λ implies a positive net effect on her tax bill.

Inequality increases in response to the shock. The solid lines in figure(1.12) report the responses of the gini indexes of wealth, total income and hours and the proportion of agents who are hand-to-mouth. The largest increase is for total income (the gini index increases more than 4%). The increase in hours worked for the wealth and earning-poor relative to the smaller decrease in the hours of the wealth-rich implies an increase in the correspondent gini coefficient. Inequality in earnings increases because of the increase in inequality in hours and in earning risk.

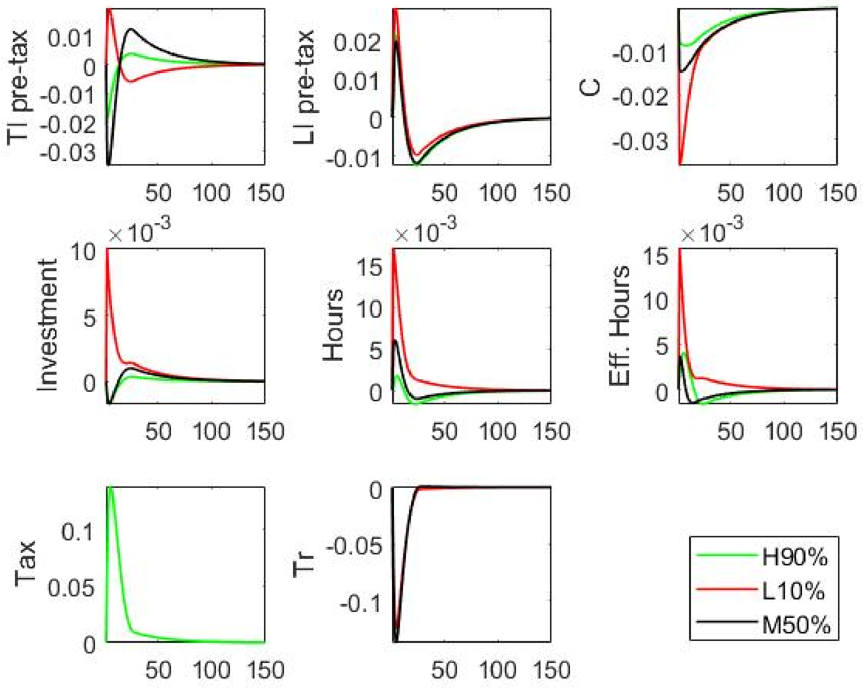

FIGURE 1.7: Responses of three type of agents to a 1% TFP shock which increases unemployment and earning risk under the constant progressivity policy $\phi(t) = \phi^{SS}$. Agents are defined by their productivity and wealth level at the steady state: 1) red: low productivity type with the 10th percentile of steady state wealth; 2) black: medium productivity type at the median steady state wealth; 3) green: high productivity type at the 90th percentile of the steady state wealth distribution.

1.6 Optimal Progressivity over the Business Cycle

The Planner's Problem along the transition

Let $V_1(a, \varepsilon, s, h^{-'}; \{\phi(t)\}_{t=1}^{T})$ be the *ex-ante* lifetime utility of an agent born in $t = 1$ and living the whole transition under progressivity path $\phi(t)$. The optimal path for progressivity is the sequence $\{\phi^*(t)\}_{t=1}^{T}$ which maximize the Social Welfare Function in the first period of the transition:

$$\{\phi^*(t)\}_{t=1}^{T} = argmax \int V_1(a, \varepsilon, s, h^{-'}; \{\phi(t)\}_{t=1}^{T})\, d\Omega_1 \tag{1.8}$$

To compute the optimal policy I use an iterative procedure: conditioning on a guess over the entire path of the policy, I maximize the objective function choosing one at the time all the points of the transition and iterating over until the convergence of the entire sequence. A detailed description of the algorithm is given in the Appendix A.3.

The optimal policy, reported in figure (1.8), consists in a hump-shaped in-

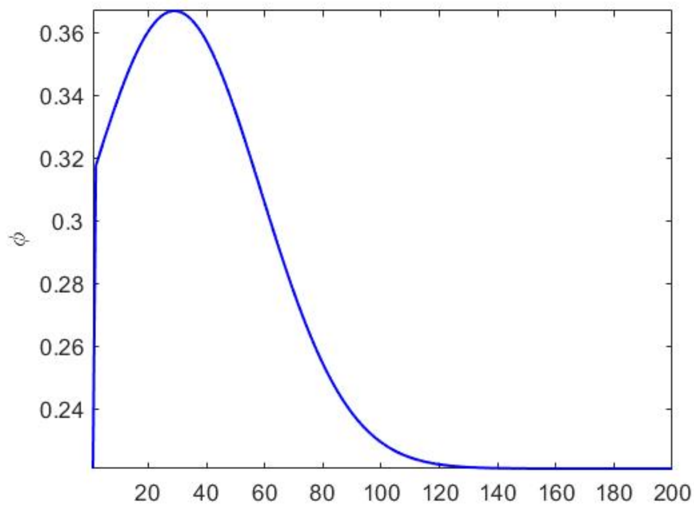

FIGURE 1.8: Optimal progressivity policy, $\{\phi^*(t)\}_{t=1}^{T}$, in response to a TFP shock of 1% which increases income and unemployment risk

crease in progressivity which reaches its maximum approximately 30 periods after the shock and reverses slowly towards its steady state level. The increase in progressivity under the optimal policy is quantitatively significant: the impact response represents a 45% increase with respect to the steady state optimal level, while at the maximum point it reaches the 65% increase. This is represents a quite big adjustment especially if compared with the "constant progressivity policy'" that the US government has adopted according to the evidence in Section 2. However, few important remarks are in order when looking at this result from the quantitative standpoint. First, the stylized unemployment benefit under which this result is obtained is an approximation of the complex structure of the unemployment insurance in the US. In particular, the unemployment benefits in the model amounts on average to only 10% of earnings, while in the US the replacement rate is set to 52%. Moreover, the unemployment policy in the model is a-cyclical, as opposed to extended unemployment benefits that are often granted during severe economic downturns[17]. The fact that the unemployment compensation in the model is understated pushes towards higher progressivity in response to an increase in unemployment risk. Second, there are different types of mean tested transfers on which the US government relies to implement redistribution to low income households[18] which are not modeled in this framework but could be quantitatively relevant. Some of these benefits are given to individuals and families with no taxable income and hence are not redistributed through taxation. Conversely, in the model, redistribution happens only through

[17]Examples of this are the Great Recession and the last Covid crisis.

[18]Examples are the Temporary Aid to Needy Families (TANF), Food Stamps and Medicaid

unemployment compensation and taxation while the log-linear tax function is not defined at zero income.

Figure(1.9) reports the policy responses of the three productivity and wealth types described above under the optimal policy $\{\phi^*(t)\}_{t=1}^{T}$. The policy provides a large stream of transfers to the wealth and earning-poor and to the median agent by increasing substantially the fiscal burden on the wealth and earning-rich. Being well insured by the policy against the increase in risk, the poor eats up her capital buffer in response to the shock to prevent the decrease in consumption. This highlights the insurance aspect of the policy: the upward revision in progressivity guarantees a shelter which allows poor income households to enjoy higher consumption by decreasing their precaurtionary savings and pushing them closer to the borrowing limit. Indeed, the proportion of hand-to-mouth agents increases on impact more than under the *status quo* policy (panel 2 of figure(1.12)). After the effect of the shock vanishes and the interest rate increases, these agents can use government transfers to build back their previous capital buffer and enjoy higher consumption.

The increase in progressivity lowers the incentive to work for all types of agents

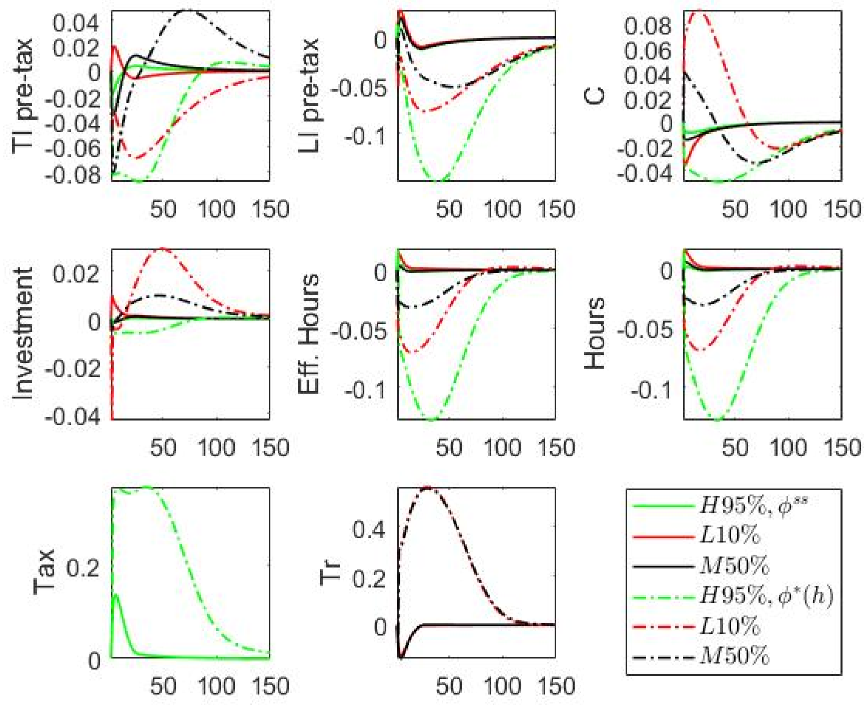

FIGURE 1.9: Responses of three type of agents to the shock under the constant progressivity policy $\phi(t) = \phi^{SS}$ (solid lines) and the optimal policy (dashed lines). Agents are defined by their productivity and wealth level at the steady state: 1) red: low productivity type at the 10th percentile of steady state wealth; 2) black: medium productivity type at the median steady state wealth; 3) green: high productivity type at the 90th percentile of the steady state wealth distribution.

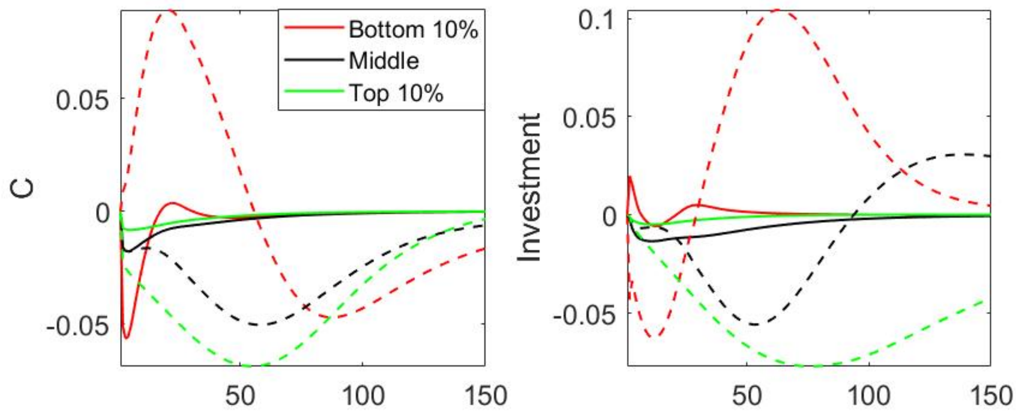

FIGURE 1.10: Aggregate per-capita responses of different percentiles defined of the steady state wealth distribution: 1) red: bottom 10%; 2) black: next 80% ; 3) green: top 90%.

but has larger effect on the higher productive who decrease her labor supply by more than 10%. This translates in lower income and consumption. The policy reverts the effects of the shocks for the three types. Figure(1.10) reports the aggregate per-capita responses of the bottom 10%, the next 80% and the top 10% of the steady state wealth distribution. Under the *status quo*, the bottom 10% is the one suffering the largest decrease in consumption, around 5%, while the decrease for the top 10% barely reaches the 0.7%. In contrast, the optimal policy let the bottom 10% enjoy a even larger consumption than in the steady state (around 8% more at the peak) at the cost of reducing it for the top 10% and the middle 80%. The contribution of the bottom percentile to the decrease in capital is larger at the beginning but reverts after 40 periods displaying certain volatility, while the negative contribution of the top 10% builds up slowly but persistently. This explains the larger increase in wealth inequality at the beginning of the transition under the optimal policy. Because the capital buffer decreases sharply at the beginning for the poor but reduces slowly for the rich, the divide between the capital share at the top and the bottom soars.

The policy reduces the effects of the shock on total income inequality: the gini increases on impact less than under the *status quo* and decreases persistently below the steady state value driven by the decrease in inequality of hours and wealth. Under the optimal policy the planner exchanges inequality inter-temporally: it tolerates a higher inequality at the beginning in order to achieve much lower inequality during a prolonged period of time later on in the transition.

Figure (1.11) illustrates the responses of main aggregates and prices to the shock when the government commits to the optimal policy. The price of the policy is a more pronounced crisis and a slower recovery. The increase in progressivity decreases the incentives to work both for high and low productive agents which transaltes in a decrease in investment which persistently reduces aggregate capital.

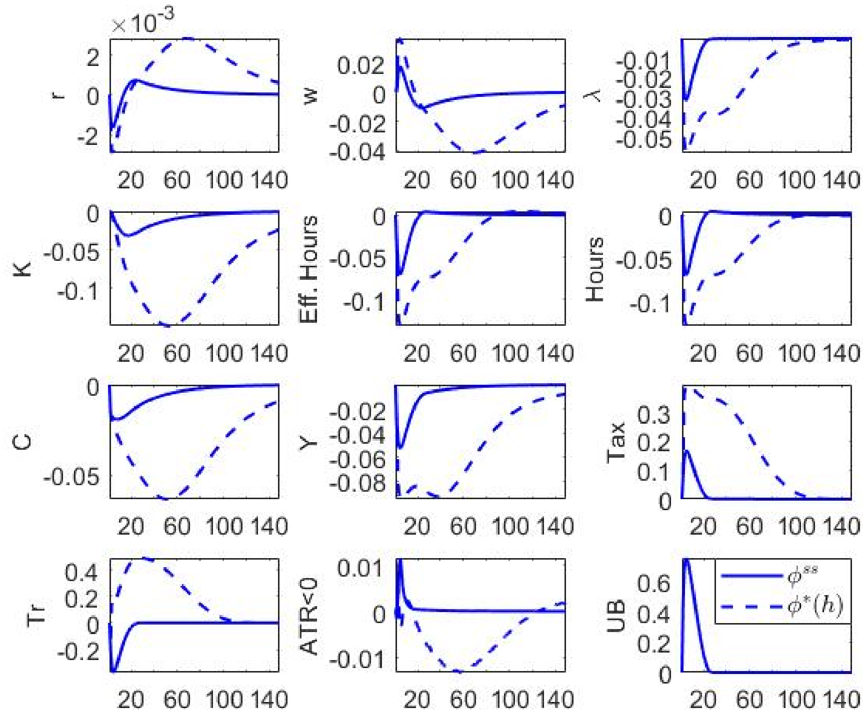

FIGURE 1.11: IRFs to a 1% TFP shock under the constant progressivity policy $\phi(t) = \phi^{SS}$ (blue solid line) and under the optimal policy $\phi(t) = \phi^*(t)$ (dashed line)

Indeed, the decrease in capital is much more pronounced under the policy than under constant progressivity. Because the policy is providing higher insurance against income shocks, agents reduce significantly their capital buffer and this affect their future capability to self-insure. When the effect of the shock dies out, the lower level of capital with respect to the initial steady state calls for a still higher degree of progressivity and justifies the persistent tail of the optimal policy. The increase in ϕ brings a heavier tax burden for high incomes to finance more generous transfers to lower incomes. This adjustment comes with an downward revision in λ which balances the budget. The combined increase in ϕ and λ, shifts the threshold $\bar{y}$ to the left reducing the number of agents eligible for transfers (who have negative ATR).

The first column of table (1.2) reports the consumption equivalent variations in welfare coming from adopting the optimal policy with respect to the "constant progressivity policy". Adopting the policy bring a total welfare gains of 0.49% increase in consumption terms along the transition. Of this total amount, the main gains comes from a redistribution effect of the policy on consumption (1.34%) and to a level decrease in hours worked (2.16%), while the redistribution of hours plays a marginal role (0.03%). The welfare costs of the policy is represented by a decrease in consumption level (-2.92%) which reflects the decline in aggregate output.

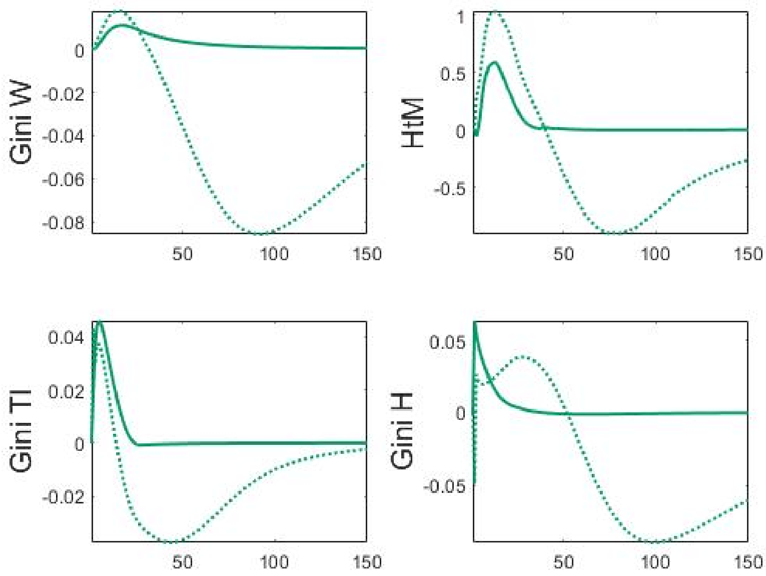

FIGURE 1.12: Responses of inequality under the constant progressivity policy $\phi(t) = \phi^{SS}$ (solid line) and under $\phi(t) = \phi^{*}(t)$ (dashed line).

1.7 Assessing Alternative Non-optimal Policies

In this Section I compare the optimal policy with alternative policies with the purpose of illustrating the link between the welfare gains connected with the optimal policy and its dynamics over the cycle. I start by considering three candidates: a) a short-lived increase in progressivity which peaks at the time in which inequality in total income is at its maximum; b) a milder and delayed increase in progressivity; c) a persistent decrease in progressivity. The right panel figure(1.13) illustrates the three policies together with the optimal policy for comparison. The first four columns of table(1.2) reports the CEV decomposition of the welfare gains/losses of moving from the constant progressivity policy to the corresponding policy.

The class of policies which consist in an increase in progressivity implies similar dynamics to the optimal policy but with lower magnitude effects. Policy A addresses exclusively the increase in total income inequality but doesn't compensate for the reduced ability of agents to self-insure due to the decrease in capital. This policy implies a severe decrease in output (around 10%) within the first 10 periods and a quite fast recovery with respect to the optimal policy. Overall, the loss in welfare due to lower aggregate consumption is smaller than under the optimal policy, but the associated re-distributive effects are also limited. Under policy B, the increase in progressivity is much smaller and delayed. Aggregate output falls less than under the optimal policy reflecting in a smaller loss deriving from consumption. However, distributional gains are much smaller. Comparing policy A and B suggests that the

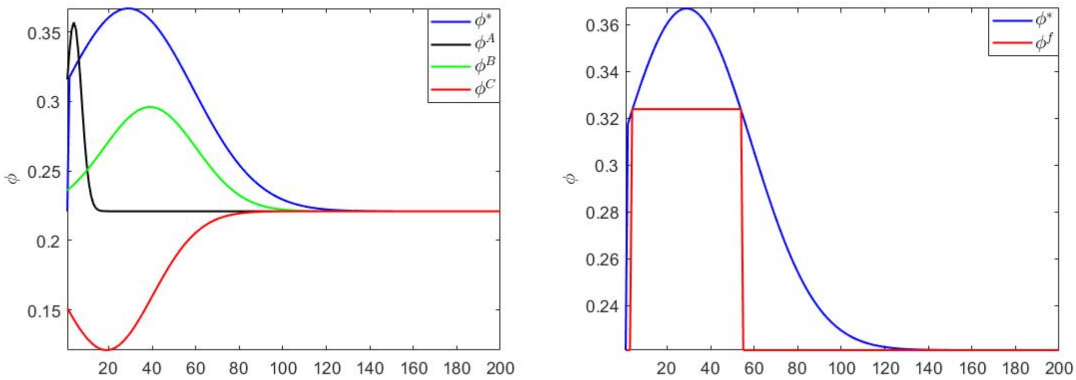

FIGURE 1.13: Optimal policy $\phi^*(t)$ and alternative policies. Left panel: optimal policy (blue) and three non-optimal policies. Right panel: optimal policy (blue) and an alternative policy implying a unique reform of the tax code (red).

contribution of the tail of the policy for welfare is larger than the contribution of the initial adjustment.

Policy C consists in a pro-cyclical response of progressivity which recalls of the Reagan's response to the 1981's crisis. This policy partly counteracts the decrease in output by reducing both the marginal tax rates on high productive types and the insurance granted to lower incomes. As a result, agents are pushed to increase their labor supply (welfare gains from hours are negative) and their precaurtionary savings with a positive effect on the aggregate output and consumption (positive welfare effects from consumption level). The price of this policy is an even more severe increase in inequality due to a redistribution of consumption from lower to higher incomes.

A potential drawback of the optimal policy is its difficult implementability: undertaking the policy implies a quarterly change in the tax code for a quite prolonged period of time. Given that in modern fiscal systems any reform should be first presented and it's usually discussed by the Parliament for several months, the optimal policy would not be feasible unless an automatic rule which indexes the tax code to the business cycle is implemented. Moreover, the policy is derived under the assumption that the government is able to immediately realize that the economy is hit by a recession and can react contemporaneously to the shock. In practice, it usually takes time for the policy maker to realize that the economy is transitioning into a recession and to evaluate the effects of a negative shock (e.g. unemployment and gdp data are available only with some delay). The last policy I consider, reported as $\phi^f(t)$ in the right panel of figure (1.13), addresses these potential feasibility issues. This policy is characterized by a delayed response to the shock consisting in a first reform of the tax code which increases progressivity after one year and a later reform

	$\phi^*(t)$	$\phi^A(t)$	$\phi^B(t)$	$\phi^C(t)$	$\phi^f(t)$
	%	%	%	%	%
CEV	**0.49**	**0.07**	**0.31**	**-0.61**	**0.36**
$\mathbf{CEV_c}$	**-1.63**	**-0.29**	**-0.5**	**0.58**	**-1.01**
CEV_{cl}	-2.92	-0.50	-1.17	1.40	-1.86
CEV_{cd}	1.34	0.21	0.59	-0.82	0.86
$\mathbf{CEV_l}$	**2.16**	**0.36**	**0.91**	**-1.19**	**1.38**
CEV_{ll}	2.13	0.35	0.09	-1.16	1.36
CEV_{ld}	0.03	0.01	0.01	-0.03	0.02

TABLE 1.2: Consumption equivalent welfare changes of moving from the constant policy $\phi(t) = \phi_{ss}$ to the corresponding policy $\phi^i(t)$

which bring progressivity back at its optimal steady state level after approximately 10 years. This policy allows the government to pick up the 73% of the total gain delivered by the optimal policy while feasibility is guaranteed by the limited number of changes to tax schedule.

1.8 Conclusions

This paper characterizes the optimal policy in terms of income tax progressivity in response to aggregate fluctuations in a heterogeneous agent incomplete market setup where aggregate shocks are correlated with earning risk and unemployment and under full commitment. The optimal degree of progressivity in a tax system balances the benefits deriving from a higher degree of insurance and re-distribution with the efficiency costs of discouraging labor supply and capital accumulation. This establishes a certain dependence of the optimal progressivity of a tax system with the degree of income risk and inequality faced by the government. An extended literature has documented that both the distribution of idiosyncratic changes in earnings and inequality are sensitive to the business cycle. These facts motivates potential welfare improving adjustments in progressivity over the cycle which have not been yet explored in the literature. In the context of an heterogeneous agents incomplete market model with endogenous labor choice, I study the effect of a negative and unexpected shock to TFP which hits the economy at the steady state and increase income risk and unemployment. In this framework, I compute the optimal response, in terms of progressivity, of a government which maximizes welfare along entire transition generated by the shock. The optimal policy consists in a hump-shaped increase in progressivity which reaches its peak 30 periods after the shock and reverts back slowly to its steady state level. At its maximum, the optimal response implies an increase in progressivity of approximately 68%. With respect to keeping progressivity fixed, adopting the optimal policy implies a welfare gain of 0.49 % in consumption terms. Most of the gains come from a re-distribution in consumption and a level decrease in hours worked. The price of adopting the policy is a significant slowdown of the recovery: if the shock itself causes a drop of 5% in output, adopting the optimal policy makes output falling by additional 3% points.

Chapter 2

Bad News, Good News: Coverage and Response Asymmetries[1]

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We construct two measures of media coverage of bad and good unemployment figures based on three major US newspapers. Using nonlinear time series techniques, we document four facts: (i) There is no significant negativity bias in media coverage of economic events. The asymmetric responsiveness of newspapers to positive and negative economic shifts is entirely explained by the higher persistence of the effects on economic variables of bad shocks; (ii) Bad news is more informative than good news; (iii) Bad news increases agents' agreement about economic outcomes and modifies their expectations more than good news; (iv) Consumption reacts to bad news, but not to good news.

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2.1 Introduction

In modern macroeconomics, expectations about current and future economic developments are at the root of agents' decision-making process. Expectations, in turn, are formed on the basis of an agent's information set, with different sets inducing potentially different economic behaviors.[3] Under the full-information rational expectations paradigm, agents have a perfect knowledge of the economy. In the real world, however, individuals have to acquire the relevant information through a variety of channels. News media represent one of these channels and are a major source of information about economic events (see (Blinder & Krueger, 2004)). This establishes a potentially important link between media news coverage and economic dynamics.

This paper investigates this link. More specifically, we address three major issues. First, we investigate whether newspapers cover positive and negative economic events symmetrically. Second, we explore how bad and good news about the economy contributes to agents' information and shapes agents' expectations. Third, we examine how the macroeconomy responds to news coverage, in particular whether there is any asymmetry in the response of consumption to bad and good news. To this end, we construct two novel measures of newspaper coverage of bad and good economic events using three major US newspapers.[4] We focus our attention on articles reporting negative and positive developments in the unemployment rate, since this variable represents an important cyclical indicator and is central to the news selection process (see (Fogarty, 2005)). We call the bad news variable U-news^{+} and the good news variable U-news^{-}. We define two standard measures of information based on our indicators: the *negative tone*, the difference between U-news^{+} and U-news^{-}, and *total information*, the sum of U-news^{+} and U-news^{-}. While the first indicator captures the prevailing tone of news, the second reflects the overall coverage of the topic. We then use nonlinear Structural Vector Autoregression (SVAR) techniques to assess the dynamic link between news coverage, agents' information and expectations, and the macroeconomy.

We document the following facts. First, a bad economic shock which increases the unemployment rate generates a much larger and persistent effect on the *negative tone* than a good shock. This is in line with previous evidence from the political science literature which points towards the existence of a negativity bias in media coverage of economic events (see e.g. (Soroka, 2006a)). However, the shock has also a substantial nonlinear effect on the unemployment rate: a bad shock generates larger and more persistent effects than a good shock. If the effects on the negative

[3] See, among others, (Mankiw & Reis, 2002), (Sims, 2003) and (Woodford, 2002).

[4] Textual analysis has become a powerful tool not only for macroeconomic analysis as it is used here, but also for forecasting. For instance, (Larsen & Thorsrud, 2019a) shows that many news topics are good predictors of economic variables in Norway. (Mueller & Rauh, 2018) builds a large dataset of news to construct an indicator for predicting armed conflicts.

tone are normalized by the effects on the unemployment rate, asymmetries in media coverage vanish. Indeed, the response of the negative tone becomes extremely similar for negative and positive shocks. This result represents evidence against the existence of a negativity bias in economic news coverage. A similar finding is obtained for *total information*. The negativity bias previously found in the literature is exclusively attributable to the fact that bad economic events are bigger and more persistent.

Second, an increase in the negative tone, a rise of bad news relative to good news, is much more informative to the agents than a reduction. Indeed, the percentage of informed individuals, i.e. the fraction of Michigan Survey respondents reporting that they heard economic news, increases (reduces) when the negative tone increases (reduces).

Third, agents agree more about economic outcomes and change their expectations more markedly facing an increase in the negative tone than a reduction. These results point to a substantially higher information content of bad news compared with good news.

Fourth, consumption, especially of durable goods, reacts significantly to an increase in the negative tone but not to a reduction. This result highlights an important asymmetry in the transmission of news to the economy. The findings are robust to several changes in the model specification. In particular, these also hold when the Great Recession, which represents an unprecedented period of bad news, is excluded.

Media coverage of economic events has been studied, to some extent, in the economics literature (see (Mullainathan & Shleifer, 2005) and (Nimark & Pitschner, 2019)), but the bulk of contributions comes from the political science literature. The key finding in this field is the existence of a negativity bias in economic news reporting: negative events receive higher media attention than positive events, see (Goidel & Langley, 1995), (Fogarty, 2005), (Soroka, 2006a) and (Soroka, 2012). A notable exception is (Casey & Owen, 2013). In this paper the opposite conclusion is reached: news significantly respond to positive forecast of GDP growth but not to negative forecast, a sort of positivity bias. Our findings are different from all of the existing ones. We document the absence of any bias in the news reporting process once the effects of economic shocks on economic variables are explicitly taken into account. News coverage reacts significantly and very similarly, both qualitatively and in terms of magnitudes, to positive and negative economic shocks.

Our paper also closely relates to a vast literature studying how news affects both macroeconomic outcomes and agents' confidence and expectations. News shocks to productivity have been documented to be an important driver of the business cycle.[5] With respect to this literature, we make three main contributions. First, we do not

[5] A partial list of contributions includes (Beaudry & Portier, 2004), (Beaudry & Portier, 2006), (Cochrane, 1994), (Den Haan & Kaltenbrunner, 2009), (Forni et al., 2017), (Jaimovich

limit our attention to news about technology, but consider general news about future unemployment developments. Second, we use a measure of news constructed from newspaper articles rather than relying on a theory-based identification.[6] Third, and most importantly, we allow bad and good news to have asymmetric effects on the economy.

Several studies have focused on the link between news and consumers' expectations, see for instance (Larsen et al., 2020). Empirical evidence suggests that agents update their expectations more frequently during periods of high news coverage, typically during recessions, see (Doms & Morin, 2004) and (Carroll, 2003). Also, bad news is found to have larger effects than positive news on consumers' opinion and confidence, see (Soroka et al., 2015a) and (Soroka, 2014), Chapter 1, for a review. Our results largely confirm this finding.

Finally, the asymmetric behaviour of expectations and consumption that we document in this paper contradicts the standard Life-Cycle/Permanent Income Hypothesis and seems to be more consistent with the assumption of *loss aversion* (see (Kahneman, 1979)), by which agents value losses more than equivalent gains (see (Bowman et al., 1999)), or with the theoretical framework proposed by (Tutino, 2013). She replaces the assumption of linear quadratic utility with CRRA preferences in a rational inattention setup. Risk-averse individuals in her model are most worried about future decreases in their wealth and optimally allocate more attention to bad news than to good news. By doing so, they are able to smooth future negative changes in wealth by immediately increasing their savings. As a consequence of their attention allocation, agents will receive more precise signals about bad events and will react faster to bad news than to good news.

The remainder of the paper is organized as follows. Section 2 describes our measures of bad and good news and their relation to the unemployment rate and measures of news from the *Michigan Survey of Consumers*. Section 3 discusses the extent of news coverage of economic events. Section 4 presents how agents' information, agents' expectations and agents' consumption respond to bad and good news. Section 5 discusses the robustness of our main findings. Section 6 concludes.

2.2 The U-news indexes

This section describes the construction of our news variables and discusses their time series properties.

& Rebelo, 2009), (Barsky & Sims, 2011), (Schmitt-Grohé & Uribe, 2012)), (Barsky & Sims, 2012).

[6] In this respect, our work is closely related to (Larsen & Thorsrud, 2019a) and (Chahrour et al., 2021), which use textual information from newspapers to identify the news shock.

2.2.1 Constructing the indexes

We construct two measures of newspaper coverage of bad and good unemployment figures, which we refer to as, respectively, the U-news^{+} index and the U-news^{-} index. For this purpose, we use Dow Jones Factiva, a comprehensive database of news articles, and focus our analysis to three major newspapers in the United States for the period from June 1980 to December 2019: *The New York Times*, *The Wall Street Journal* and *The Washington Post*. The choice of the three outlets is motivated by the fact that they have consistently appeared among the largest US newspapers by circulation during the period of interest and all aim for national audiences. We focus our attention on articles about the unemployment rate since this variable represents a major cyclical indicator and its fluctuations are closely monitored by the news media (see (Fogarty, 2005)).

We construct the time series of bad news, U-news^{+}, by counting the number of articles each month in which the word "unemployment" appears near to another word denoting an increase or high level. Similarly, for the good news variable, U-news^{-}, we count the number of articles in which the word "unemployment" appears close to words denoting a decrease or low level.[7] We then clean these two measures by subtracting from each of them the number of articles which are selected under both *good* and *bad* criteria. Thus, we explicitly exclude those articles (approximately 6% of the total sample) that cannot unambiguously be classified in one of the two categories. We acknowledge the fact that this class of news can also be of some interest, since this news may convey information about periods of relatively stable unemployment or reflect mixed signals about the labor market. However, for the purpose of the present study, which is concerned with potentially asymmetric effects of good and bad news, it is of primary importance to have a clear measure of news polarization.[8] The final dataset includes a total of 35933 bad news items and 22317 good news items over the period considered.

Using the two raw indexes, we construct two additional variables. The first, which we call *negative tone*, is the difference between the two indexes of bad and good news: U-tone = U-news^{+} − U-news^{-}. If U-tone is positive, newspaper coverage of unemployment figures is prevailingly negative, and vice-versa. The variable is expected to be positively correlated with the unemployment rate and its average depends on the averages of good and bad news. The second variable is a

[7]The index is similar in spirit to the R-Word index constructed by The Economist and to the media coverage series used in the seminal paper (Soroka, 2006a). The difference with the R-Word index is that our search is based on the word unemployment and differentiates between positive and negative news. A detailed explanation of the search queries is included in the Appendix. Notice that our news variable is not a sentiment-based indicator. We believe it would be interesting to try to construct such an indicator and study potential differences with ours. We plan to do this in the future.

[8]The results presented below are robust to the inclusion of this ambiguous news. The reason is that this set of news is relatively small over the sample considered.

measure of *total information* and it is defined as the sum of good and bad news: U-total $=$ U-news$^+$ $+$ U-news$^-$.

A potential concern related to the construction of the news indexes could be that the three newspapers considered may cover unemployment developments differently, depending on their political view. Figure B.1 in the Appendix reports our news indexes disaggregated by newspaper. Overall, the coverage of both bad and good unemployment developments is remarkably consistent across different newspapers. Indeed, all of the indexes track each other very well over the sample period. The finding rules out the existence of a relevant political bias in the unemployment news reporting for the newspapers considered.

2.2.2 Descriptives

In the left-hand column of Figure 2.1 we report our two news indexes (blue lines) together with the unemployment rate (red lines). The averages of bad and good news are, respectively, 76 and 47 articles per month, and the standard deviations are 46 and 20. News reporting of bad unemployment figures is, on average, higher and more volatile than the reporting of good unemployment figures. The most striking difference between the two indexes, however, is in terms of the correlation with the unemployment rate: 0.78 for bad news and -0.28 for good news. This is also clear from a simple visual inspection of the pattern of co-movement of the two indexes with the unemployment rate. The measure of bad news, U-news$^+$, tracks the unemployment rate extremely closely, with two major spikes of similar magnitude in correspondence of the early 1980s recession and the Great Recession. On the contrary, and quite surprisingly, the measure of good news, U-news$^-$, seems largely unrelated to the unemployment rate, except in three episodes: the end of the 1980s, the end of the 1990s and after 2015. The news reporting of negative economic events appears substantially more cyclical than the coverage of positive economic events.

We report the U-tone index in the bottom right-hand panel of Figure 2.1. As expected, the negative tone has a high correlation with the unemployment rate (0.79). The average negative tone is 29 and statistically different from zero. The top right-hand panel of Figure 2.1 reports the U-total index together with the unemployment rate. The information content is countercyclical, with a correlation of 0.64 with the unemployment rate. This result can be seen as *prima facie* evidence supporting a larger degree of news coverage of bad economic events than good events. We explore the issue more formally in the next section. A possible reason for the absence of a relevant negative correlation between good news and the unemployment rate might be the fact that positive news refers to increases in employment rather than decreases in unemployment. In Appendix B.2 we discuss the construction of an alternative measure of good news, the E-news$^+$ index, based on the word "employment". In a similar way to the other two measures, we select articles in which the word “employment” appears within a specified distance of another word denoting an increase or high level. We report this alternative measure together with the unemployment rate and with the U-news^{-} index in Figure 10 in the Online Appendix. The correlation among U-news^{-} and E-news^{+} is 0.14, while the correlation of E-news^{+} and unemployment is even positive (0.28). This suggests that the unemployment-based measure is more reliable and that its small negative correlation is not the result of a poor search strategy.

2.2.3 U-news indexes and consumer survey information

At first glance, the relatively small procyclicality of the U-news^{-} index might be puzzling, since *a priori* it would be reasonable to expect a pattern close to the reverse of the U-news^{+} index. In what follows, we compare our news indexes with other measures of news taken from the *Michigan Survey of Consumers* in order to assess the consistency of our measures with the information of the agents from the survey.

The survey provides a wide variety of variables that reflect agents’ information and expectations about the current and future state of the economy. The variable NEWS in the survey corresponds to the percentage of individuals who recently heard of any favorable or unfavorable changes in business conditions. Question A6 of the questionnaire asks the following: *“During the last few months, have you heard of any favorable or unfavorable changes in business conditions?“. There are two possible answers: “Yes”*■ and *“No, haven't heard“. If the individual answers “Yes”*■, then the second question is A6a: “What did you hear?“, which is an open-ended question. The Michigan Survey provides few variables constructed on the basis of the type of answer to these two questions. Among those, we focus on the following variables: “No News”, which is the percentage of respondents choosing the corresponding option in question A6; “Favorable“ and “Unfavorable”, which correspond to the percentage answering positively and negatively to question A6a; and “Favorable: employment“ and “Unfavorable: unemployment”, corresponding to answers to question A6a which are specifically related to positive and negative evaluations of, respectively, employment and unemployment figures.

While our indicators of bad and good news represent *objective* measures of the amount of negative and positive published news items related to unemployment figures, the last two variables from the Michigan Survey represent the *subjective* information that the agents perceive from the media. In principle, agents’ *subjective* information may not coincide with our measures of *objective* information. For example, agents may mostly get informed through other channels (TV, social networks, etc.) or they may be *rational inattentive* even in information-rich environments (see (Sims, 2003), (Nimark & Sundaresan, 2019)).

The first column of Figure 2.2 illustrates our U-news^{+} and U-news^{-} indexes together with the corresponding measures in the *Michigan Survey of Consumers*, namely the “Unfavorable: unemployment“ and “Favorable: employment” items of NEWS. Both indexes track the variables of the Michigan Survey extremely closely over the sample considered. The correlation between unfavorable and U-news$^+$ is 0.68, and the correlation between favorable and U-news$^-$ is 0.46. Overall, our indexes and the survey measures are remarkably consistent with each other. This suggests that newspaper information is a relevant channel for consumers’ information and it could be important for shaping consumers’ expectations and decisions. The second column of Figure 2.2 reports our measures of negative tone and total information together with their counterparts constructed using the variables of the Michigan survey. As far as total information is concerned, the correlation between the two variables is 0.61, while the correlation is 0.65 for the negative tone. This again confirms the consistency between our newspaper measures and the survey measures.

2.3 Asymmetric coverage of economic events

This section studies how news reporting relates to economic events. More specifically, we investigate how the negative tone and total information of unemployment news respond to positive and negative changes in the unemployment rate.

To study asymmetries, we use a Threshold SVAR model (TSVAR). With respect to the simple regressions used in the political science literature, this type of model allows us both to address potential reverse causality issues and to capture interesting non-linear dynamics. The model *per se* is standard, but the way we use it is innovative. The main novelty is represented by the fact that the state variable in the model depends on the sign of the shock itself. Therefore, shocks of different signs imply different dynamics since the threshold variable is different. This feature, absent in standard TSVAR, is our methodological contribution and is discussed in detail below.

2.3.1 The model

Let y_t be a time series vector including the variables of interest following

$$y_t = (1 - F(z_t))[a + A(L)]y_{t-1} + F(z_t)[b + B(L)]y_{t-1} + \varepsilon_t \tag{2.1}$$

where $\varepsilon_t \sim WN(0, \Sigma)$, $A(L) = A_1 + A_2 L + ... + A_p L^{p-1}$, $B(L) = B_1 + B_2 L + ... + B_p L^{p-1}$ (L being the lag operator), z_t is a scalar variable, $F(\cdot)$ is a function taking value zero or one, and a and b are vectors of constant terms. In this section, the dependent variable includes, in this order, the unemployment rate change and either the negative tone (Section 3.2) or total information (Section 3.3) of unemployment news. The state variable is the lag of the change in the unemployment rate,

$z_t = \Delta U_{t-1}$, where U_t denotes the unemployment rate. This ensures that z_t is exogenous with respect to ε_t. We then set $F(z_t) = 0$ if $\Delta U_{t-1} \leq 0$ and $F(z_t) = 1$ if $\Delta U_{t-1} > 0$. The choice of the threshold variable is motivated by the fact that we are interested in understanding potential asymmetries in news dynamics to increases and reductions in the unemployment rate. Thus, $A(L)$ are the VAR parameters governing the dynamics of the system of variables when the first lag of the unemployment rate change is negative, while $B(L)$ are the VAR parameters in place when the change is positive. Under these assumptions, the model can be simply estimated using OLS.

To explore whether increases and reductions in the unemployment rate receive asymmetric news coverage, i.e. generate different effects on the tone or the total information of news, we investigate the impulse response functions to an innovation in the unemployment rate change which is orthogonal to the remaining shocks in the system. To identify the shock, let S be the Cholesky factor of Σ, i.e. S is lower triangular and $SS' = \Sigma$, and let $u_t = S^{-1}\varepsilon_t$ be a vector of orthonormal shocks. The first shock, u_{1t}, is the innovation in the unemployment rate change which is orthogonal to u_{2t}, and it captures any factor that changes the unemployment rate unexpectedly. Let us be very clear: such a shock is not meant to have any structural interpretation. The Cholesky decomposition should be seen simply as a statistical device to obtain the orthogonal innovation in the unemployment rate. However this is completely irrelevant to our purposes, since our aim is just to understand whether news media react differently to positive and negative unpredictable changes in the unemployment rate, regardless of the nature of the underlying shock.

Notice that, with this model specification, the sign of the innovation in ΔU_t becomes the relevant state for the impulse response functions. To better understand the point, let

$$\beta(L) = (I - B(L)L)^{-1}S = \beta_0 + \beta_1 L + \beta_2 L^2 + ...$$

be the moving average representation of the model when $\Delta U_{t-1} > 0$ and

$$\alpha(L) = (I - A(L)L)^{-1}S = \alpha_0 + \alpha_1 L + \alpha_2 L^2 + ...$$

when $\Delta U_{t-1} < 0$. Call $\tilde{\beta}(L)$ and $\tilde{\alpha}(L)$ the coefficients associated with u_{1t}, i.e. the first row of $\beta(L)$ and $\alpha(L)$ respectively. Due to our identification strategy, the impact effects are the same across regimes and do not depend on the sign of the shock, i.e. $\tilde{\alpha}_0 = \tilde{\beta}_0 = S_1$, where S_1 is the first column of S.[9] For the generic horizon $h > 0$, the responses to the shock will be $\tilde{\alpha}_h$ if the change in the unemployment rate in $h-1$ is negative, and $\tilde{\beta}_h$ if positive. If the responses of the change in unemployment rate are sufficiently persistent, then one can simply condition, as we do here, on the sign

[9] The assumption $\tilde{\alpha}_0 = \tilde{\beta}_0 = S_1$ is made for sake of interpretability of the results. The results are very similar to those obtained in the restricted model when we relax this assumption and we allow for two different impact effects.

of the impact effect and the responses are $\tilde{\beta}(L)$ for a positive shock and $\tilde{\alpha}(L)$ for a negative shock.

To construct the confidence bands of the impulse responses, we use the bias-corrected estimator described in (Kilian, 1998), where we bootstrap the threshold variable, ΔU_{t-1}, together with the other regressors.

2.3.2 U-tone

In the first specification, we set $y_t = [\Delta U_t \text{ U-tone}_t]'$ and $p = 2$, as suggested by the BIC criterion.[10] The first two rows of Figure 2.3 report the results. The left-hand panels show the responses to negative (blue lines) and positive (red lines) shocks to the unemployment rate change. The solid lines are point estimates, while the dashed-dotted lines are 68% confidence bands. The right-hand panels report the sum of the impulse response functions (black lines) to positive and negative shocks. The solid line is the sum in the point estimates, while the dashed-dotted lines are the 68% confidence bands. This sum can be interpreted as a measure of asymmetry. Under perfect symmetry of the responses, the sum is zero. The larger (in absolute value) the sum is, the larger the degree of asymmetry is.

The negative tone reacts more, and with a higher degree of persistence, to an increase in the unemployment rate than to a reduction. Indeed, the asymmetry index is positive and significant over the horizon considered. The magnitude of this asymmetry is sizable. An increase in the unemployment rate of 0.15 percentage points on impact generates, on average over the horizon considered, about 5 more bad news items than good news items per month. However, a reduction of the same magnitude generates less than one good news more than bad news items per month. This suggests that the tone of media coverage reacts asymmetrically to economic developments, giving a substantially greater weight to negative events than to positive events.

This result is in line with the findings in (Soroka, 2006a) and (Soroka et al., 2018). If our analysis was to stop here, we would confirm the existence of a *negativity bias* in newspaper coverage of economic events. However, as noticeable from the first row of Figure 3, there is also a sizable and significant asymmetry in the effects on the unemployment rate change: positive shocks have larger and more persistent effects than negative shocks. So, when comparing the effects on media tone of increases and decreases in the unemployment rate, the different dynamics of unemployment should be taken into account. Indeed, the larger response of the negative tone to an increase in the unemployment rate could simply be due to a larger and more prolonged effect of the positive shock on unemployment.

We therefore compute a dynamic *Media Multiplier* of economic fluctuations. The multiplier is constructed as the cumulative sum of the impulse response functions

[10] Using the levels of the unemployment rate or using more lags yields very similar results.

of the negative tone divided by the cumulative sum of the changes in the unemployment rate at every horizon. For instance, at a horizon of 48 months ahead (the last horizon of the impulse response functions), the multiplier can be interpreted as the total number of bad news items in excess of good news items produced over four years following a 1 percentage point change in the unemployment rate. The responses are shown in the two bottom panels of Figure 3. The multipliers for increases and reductions in the unemployment rate are extremely similar, with no significant asymmetries. At the four year horizon, a 1 percentage point increase in unemployment generates 305 bad news items in excess of good news items, while a decrease of the same magnitude generates 292 good news items in excess of bad news items. The result suggests that, when nonlinearities in the dynamics of the unemployment rate are taken into account, the media bias towards bad events disappears. The result is new and contrasts with most of the existing evidence pointing to the existence of a *negativity bias* in news coverage of economic events (see (Soroka et al., 2018) for a review). The reason our result differs substantially from previous findings in the literature is the fact that none of the earlier studies accounted for the asymmetry in the dynamics of unemployment.

2.3.3 U-total

We repeat the analysis of the previous subsection, using model (2.1) with a different variable specification. Now, $y_t = [\Delta U_t \text{ U-total}_t]'$. Apart from this, the model specification is identical to the previous one. The first two rows of Figure 2.4 report the results. The left-hand panels report the responses to negative and positive shocks to the unemployment rate change. The right-hand panels report the sum of the impulse response functions to positive and negative shocks.

The asymmetry between positive and negative shocks is clear. Shocks that push up unemployment increase total information substantially more, and with a higher degree of persistence, than shocks that improve unemployment figures. The asymmetry index is always significant over the horizon considered and the differences are sizable. A 0.15 percentage point increase in the unemployment rate on impact generates up to 25 news items more than a 0.15 percentage point reduction. However, the shock, as for the negative tone, generates a marked non-linearity in the response of the unemployment rate change, which is much more persistent for bad shocks than for good shocks. As before, we compute the *Media Multiplier*, i.e. we re-scale the cumulative impulse response functions of total information by the cumulative change in unemployment. The responses are reported in the third row of Figure 2.4. When taking into account the dynamics of unemployment, the asymmetries in the news reporting process are substantially dampened, the responses of information to positive and negative shocks being essentially the same and the asymmetry index being never significantly different from zero.

The conclusion of this first part of the analysis is that the apparent asymmetry in the news reporting process of economic events found in previous work does not depend on media bias *per se*. It depends on the large non-linearity in the unemployment rate response to economic shocks. Unemployment responds more, and with a higher degree of persistence, to bad shocks, i.e. shocks that imply an increase in unemployment. This triggers an important asymmetry in both the tone and total information of news.

To understand whether our results are consistent with the evidence from previous studies, we run two simple linear regressions where the dependent variables are, respectively, our measures of negative tone and total information of news, and the regressors are the current value of positive unemployment changes, the current value of negative unemployment changes and four lags of the dependent variable. This specification closely resembles the regression in (Soroka, 2006a). The results of the two regressions are displayed in Table 2.1. In both regressions the coefficients associated with increases in unemployment are larger than those associated with a reduction, and only the former are significant. So, by neglecting the non-linearity in the response of the unemployment rate change, one would conclude, as previously done in the literature, in favor of a negativity bias in news reporting of economic events. Above we showed that the conclusion is different if asymmetries in the response of unemployment are also considered.

	U-tone		U-total	
	Estimate	t-stat	Estimate	t-stat
$\Delta U_t > 0$	29.66*	2.37	28.09*	2.25
$\Delta U_t < 0$	2.30	0.19	14.84	1.18
Lag 1	0.44*	9.30	0.55*	11.65
Lag 2	0.30*	6.05	0.19*	3.57
Lag 3	0.18*	3.54	0.07	1.37
Lag 4	-0.01	-0.24	0.08	1.83
Constant	0.53	0.32	12.06*	3.49

Note: $*$ means significant at the 5% significance level.

TABLE 2.1: Regression

2.4 Asymmetric responses to news

We now investigate asymmetries in the response of macroeconomic variables to changes in the negative tone. We employ model (2.1) again, but we now consider a shock to the negative tone using the change in the negative tone as a state variable.

2.4.1 The model

The first problem we have to confront when assessing the role of bad and good news is that the negative tone is highly correlated with the unemployment rate: unemployment increases and the tone increases. This implies that potential asymmetries could mistakenly be attributed to a different response of economic agents to good and bad news, while these actually arise simply because agents' responses differ in the face of good and bad economic shocks.

To cope with this issue, we use the model of the previous section. There, the shock u_{2t} has the interpretation of a news shock: it triggers a change in the negative tone with a zero impact effect on the unemployment rate. Thus, the component of the tone generated by this shock can be interpreted as news that is not driven by current or past changes in the unemployment rate.[11] Using this component will therefore allow us to avoid confounding asymmetries due to news with other types of asymmetries associated with positive and negative changes in the unemployment rate.

This component of the negative tone is unrelated to changes in the unemployment rate and is obtained from the TSVAR of Subsection 3.1 by filtering the shock which is orthogonal to unemployment changes with the corresponding impulse response functions of the two regimes:[12]

$$x_t = (1 - F(z_t))\alpha_{22}(L)u_{2t} + F(z_t)\beta_{22}(L)u_{2t}, \tag{2.2}$$

With this variable at hand, we estimate a new TVAR model (2.1) with an alternative variable specification. Next, we set $y_t = [\Delta x_t \;\; w_t]'$, where w_t is a vector of time series of interest. Again, we select two lags of the dependent variable using the BIC criteria. The state variable is now the difference of the news component of the negative tone, $z_t = \Delta x_{t-1}$. We define $F(z_t) = 1$ if the change in the tone is positive, $\Delta x_{t-1} > 0$, and $F(z_t) = 0$ if the change in the tone is negative, $\Delta x_{t-1} \leq 0$. Thus, with this specification, the coefficients $A(L)$ in (2.1) are the VAR parameters governing the dynamics when the first lag of the difference in the tone is negative, while $B(L)$ are the VAR parameters in place when the difference is positive.

[11]This component can be interpreted as news about expected future unemployment, fake news, news reporting bias, among others.

[12]Recall that $\alpha_{22}(L)$ and $\beta_{22}(L)$ are the elements (2,2) of, respectively, the impulse response functions $\alpha(L)$ and $\beta(L)$ obtained using the specification of Section 2.3.2.

To study the potentially asymmetric effects of an increase and a reduction in the news components of the negative tone, Δx_t, we study the impulse response functions to an innovation in Δx_t which is orthogonal to the other shocks in the system. The implementation is the same as before, but with the new specification. Let S be the Cholesky factor of Σ, i.e. S lower triangular and $SS' = \Sigma$, and let $u_t = S^{-1}\varepsilon_t$. The first shock, u_{1t}, is the innovation in the tone which is orthogonal to u_{2t}. Again, conditional on a shock, the sign of the shock becomes the relevant state. When the shock u_{1t} is positive, Δx_t is positive, and the relevant impulse response functions are the first column of $\beta(L) = (I - B(L)L)^{-1}S$, call it $\beta_1(L)$. When the shock is negative, Δx_t is negative and the impulse response functions will be the first column of $\alpha(L) = (I - A(L)L)^{-1}S$, call it $\alpha_1(L)$.

Notice again that the Cholesky decomposition is just a statistical device to obtain the orthogonal innovation to the news variable. The shock admittedly lacks of any structural interpretation: it could be an economic news shock, a shock capturing any distortions in journalists view, a fake news shock etc. However, independently on its nature, the shock represents an unexpected change in the number of news which is orthogonal to current and past economic conditions. This is precisely the component we aim at disentangling in order to study the causality link from news to economic variables.

As we did for the first step estimation, we construct confidence bands using the bias-corrected estimator described in (Kilian, 1998) and we bootstrap the threshold variable, Δx_{t-1}, together with the other regressors.

We use three different TVAR models to study the effects on consumers' information, expectations and personal consumption expenditures. The choice of not using a single model with all of the variables is essentially driven by parsimony considerations and to avoid the curse of dimensionality.

2.4.2 Consumers' information

In the first specification, we include in w_t three variables of the Michigan Survey of Consumers related to consumers' information (Questions A6 and A6a). The first variable is simply the difference between the percentage of "unfavorable" and "favorable" responses to question A6a. The second variable is the percentage of "No news" to question A6. This second variable measures the percentage of individuals who have not heard any news about current economic conditions and can therefore be interpreted as a proxy of the inverse of information. The third measure is the entropy associated to the answers in question A6 and A6a. Entropy can be interpreted as a proxy for consumers' agreement about news and is constructed as follows. Let P_t be the sum of responses "No, haven't heard" in question A6, "Favorable" and "Unfavorable" in question A6a. Let p_{1t} be the proportion of "Favorables" over P_t at time t and p_{2t} the proportion of "Unfavorable" over P_t. Entropy is constructed as

$$e_t = -(p_{1t}\log(p_{1t}) + p_{2t}\log(p_{2t}) + (1 - p_{1t} - p_{2t})\log(1 - p_{1t} - p_{2t}))$$

The larger the entropy is, the larger the disagreement among agents about the news heard, and vice versa.

Figure 2.5 reports the impulse response functions of the three variables, and Figure 2.6 reports the asymmetry indexes. As before, solid lines are point estimates, while the dashed-dotted lines are 68% confidence bands constructed using the Kilian (1998) bias-corrected bootstrap. Conditional on being informed, agents' information reacts quite symmetrically to positive and negative changes in the negative tone. Indeed, the response of "Unfavorable" minus "Favorable" to a positive shock is essentially the mirror image of the response to a negative shock. This is reflected in the asymmetry index for this variable, which is mostly insignificant over the horizon considered. The key difference is the response of "No news". A positive shift in the negative tone, namely a rise of bad news relative to good news, significantly increases the number of informed consumers. Indeed, the percentage of consumers reporting "No, haven't heard" decreases. A negative shift, on the other hand, significantly increases the number of individuals who have no information. While bad news is informative, good news is not. A similar indication is obtained by inspecting the response of entropy. An increase in bad news relative to good news increases agents' agreement, while the reverse increases disagreement. In conclusion, a rise in the negative tone of unemployment news increases consumers' information and agreement, while a reduction has the opposite effect.

We now re-scale the responses for the cumulative effect on the negative tone to take into account the potential non-linearity in the response of news itself. Again, the differences could simply be due to a larger increase in the negative tone following a bad shock. Figures 2.7 and 2.8 plot the normalized responses and the corresponding asymmetry indexes. The main results are unchanged, confirming the above evidence suggesting that bad news is more informative and agents agree more in response to bad rather than good news.

2.4.3 Consumers' confidence

In the second specification, we add the current economic conditions index (ICC) and the index of consumer expectations (ICE) from the *Michigan Survey of Consumers* in vector w_t. The two indexes are constructed using survey variables relative to expected current and future general economic conditions and personal economic conditions, and are components of the index of consumer sentiment. Figure 2.5 reports the impulse response functions of the two variables to positive and negative shocks to the difference of the negative tone. Figure 2.6 reports the asymmetry indexes. An increase in the negative tone has larger and more persistent effects on the two indexes of consumer sentiment than a reduction. The asymmetry index reduces significantly and persistently over the horizon considered, suggesting that agents' expectations react more to bad news than to good news.

Figures 2.7 and 2.8 plot the normalized responses and the corresponding asymmetry indexes. Once we re-scale the responses for the potentially non-linear effect on the negative tone, the main results are unchanged. This finding confirms the above evidence, suggesting that expectations indeed react more to a rise in the negative tone than to a decline. This result is in contrast to those obtained in (Casey & Owen, 2013) who find that the exogenous components of good and bad news have no effect on consumer confidence, but confirm the findings of (Doms & Morin, 2004) and (Soroka, 2006a).

2.4.4 Consumption

In the previous two subsections, we investigated the effects of news on consumers' information and expectations, and we showed that bad news is more informative and has larger effects on expectations than good news. Since expectations and information are at the core of consumption decisions, the above evidence suggests that consumption might react differently to bad and good news about the economy. We study the response of consumption with a third specification where we include in w_t real total personal consumption expenditures, real durable goods consumption expenditures and real non-durable goods consumption expenditures.

The topic studied in this subsection is closely connected to a vast literature on the effects of news shocks. Most of the contributions have focused on news about total factor productivity, see (Beaudry & Portier, 2006) and (Jaimovich & Rebelo, 2009), (Barsky & Sims, 2011), (Schmitt-Grohé & Uribe, 2012)). Here we focus on news about future unemployment developments or, generally, developments that are not related to current or past unemployment changes. Most interestingly, the literature so far has considered only the symmetric effects of news, while here we can distinguish between positive and negative news shocks. This is especially important because the results in the previous section point to a different reaction of consumers' information and expectations to bad and good news. This could suggest different behavior in terms of consumption decisions, and therefore a different effect on aggregate consumption.

Figure 2.5 reports the effects of positive and negative shocks in the negative tone of news coverage on consumption. Figure 2.6 shows the asymmetry indexes. A clear-cut result emerges. An increase in bad news relative to good news significantly and persistently reduces the three types of consumption, while a decline in the negative tone has essentially no effects. The three asymmetry indexes are significantly negative at almost all of the horizons. The result closely relates to previous empirical evidence presented in (Shea, 1995) and (Bowman et al., 1999), which find a stronger response of consumption growth to predictable income declines than to predictable income increases.

Figures 2.7 and 2.8 plot the normalized responses of the three types of consumption to the negative tone shocks and the corresponding asymmetry indexes. As for the consumer confidence indexes, the responses are simply a re-scaled version of the non-normalized ones. Asymmetries are still apparent, with the asymmetry indexes significantly negative over the horizons considered. Consumption reacts asymmetrically to positive and negative shifts in the negative tone.

These results are consistent with the findings discussed in the previous subsection. A rise in the negative tone is much more informative than a decline, it makes agents revise their expectations more deeply and, consequently, their consumption path. This expectation revision cannot be explained by a higher number of negative news (for which we control here), as previously documented in the literature and as implied by models of *sticky expectations* ((Carroll, 2003)). On the contrary, the type of asymmetry we document suggests that, given an equal number of good and bad news items, agents give greater weight to negative information than positive information. The existence of a negativity bias in consumers' response to news has been extensively discussed and studied in political science, biology and psychology (see (Soroka, 2014) and (Baumeister et al., 2001)). In economics, the idea that agents may value losses more than equivalent gains is formalized in the concept of *loss aversion*. This could explain why agents are more attentive to signals (news) reporting a higher risk of utility losses than gains. Another potential explanation of our finding is given by the model in (Tutino, 2013). In her framework, agents are risk-averse and face an information-processing constraint as in a standard *rational inattention* setup. Risk-aversion implies that individuals in her model are more concerned with future decreases in their wealth than increases, implying that they will optimally allocate more attention to bad news than to good news. By doing so, they are able to respond to future negative changes in wealth by increasing their savings to smooth out this possible loss. As a consequence of their attention allocation, agents will receive more precise signals about bad events and will react faster and more strongly to bad news than to good news.

2.5 Robustness

We perform three main robustness checks. First, we estimate the model excluding the Great Recession period, using data up to December 2007. Results are reported in Figures B.3-B.6 in the Online Appendix. The responses of the negative tone and total information are very similar to those obtained using the full sample. A positive change in unemployment causes a much larger and persistent increase in negative tone and total information than a negative change. The two asymmetry indexes are always positive and significant. As far as the re-scaled responses are concerned, asymmetries are again mitigated, although for total information the difference is statistically significant. By excluding the Great Recession, media negativity bias seems to be somehow more important when considering total information. The response of "no news", entropy and the two confidence indexes are qualitatively similar to those obtained in the full sample, conveying the same message: bad news appears to be more informative, reduces disagreement and has a more marked effect on confidence. Total consumption and durable consumption still decrease to a greater extent in the face of negative news, while non-durable consumption is not responsive to negative or positive news. All in all, the results, although with some quantitative differences, depict a similar picture to that arising from the full sample case.

Second, we repeat the analysis including in the VAR of Sections 3.1 and 3.2 also industrial production growth and PCE inflation, ordered after the unemployment rate. The *rationale* for this exercise is that the unemployment rate is a lagging variable, so the estimated news component in our baseline model could still include cyclical shocks which affect unemployment with some delay. Figures B.7-B.10 in the Online Appendix report the results, which are very similar to the baseline specification.

Third, we add to the baseline model of Section 3.1 stock prices growth (as measured by the S&P500 index) to the system of variables, ordered last. Figures B.11-B.14 in the Online Appendix present the results, which are essentially unchanged compared to the baseline specification.

2.6 Conclusion

We provide novel empirical evidence on the asymmetric relationship between news coverage, agents' information and expectations, and economic dynamics. Using nonlinear SVAR techniques and two novel measures of newspaper coverage of bad and good economic events, we document four facts: (i) There is no significant negativity bias in newspaper coverage of economic events. News coverage is more responsive to negative than positive shifts in the economy because bad economic shocks have larger and more persistent effects than good shocks; (ii) Bad news is more informative for agents than good news. Indeed, the percentage of informed individuals increases facing a rise in bad news relative to good news, while it decreases for the reverse; (iii) Bad news increases agents' agreement about economic outcomes and modifies their expectations more than good news; (iv) Consumption, especially of durable goods, reacts to bad news but not to good news. Notably, these results also hold when the Great Recession, which represents an unprecedented period of bad news, is excluded.

A potential explanation for the existence of a negativity bias in the consumer's reaction to news is loss aversion. In a world where the utility reduction induced by a loss is higher than the utility increase from a gain of the same amount, agents can be more attentive to economic news reporting a risk of losses than a risk of gains. Higher agents' information can in turn lead to larger consumption fluctuations. We plan to test this implication in our future research.

Figures

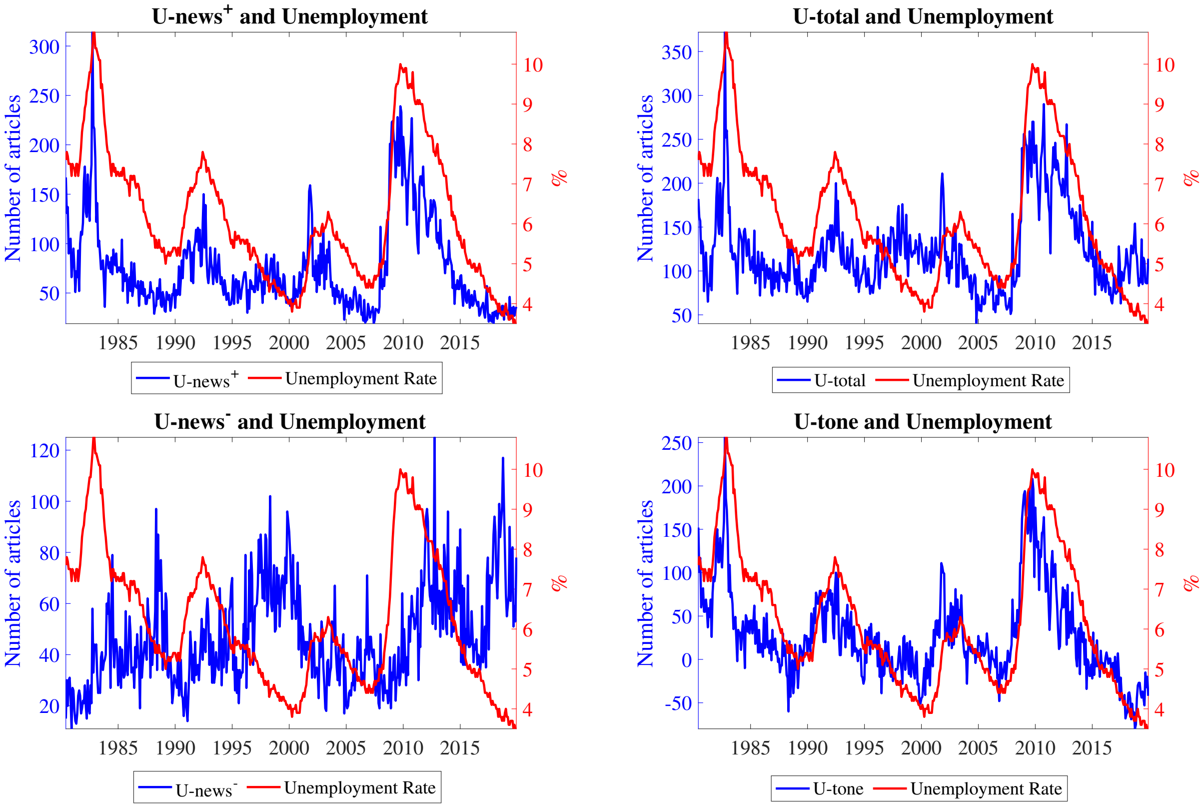


FIGURE 2.1: Bad news, good news and unemployment

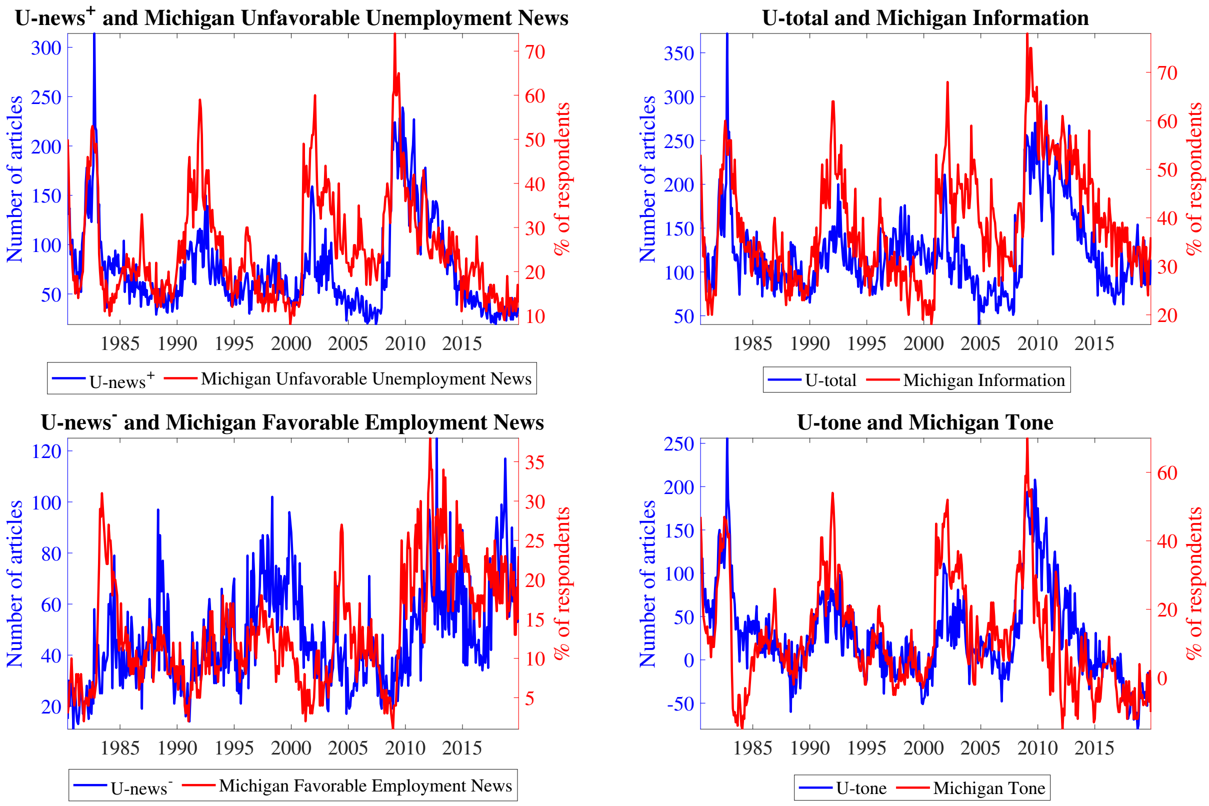


FIGURE 2.2: Bad news, good news and Michigan news

FIGURE 2.3: Response of news coverage to unemployment changes - U-tone

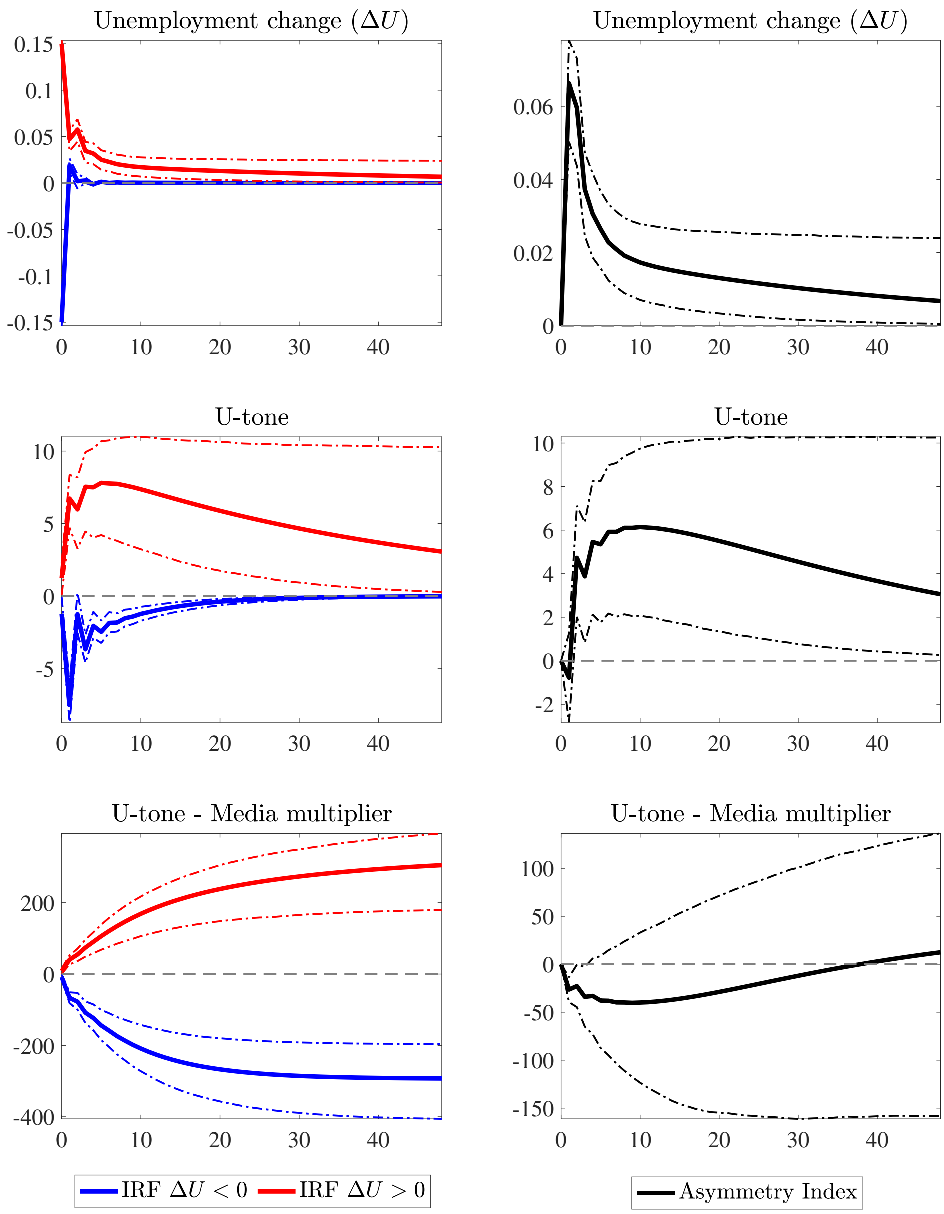
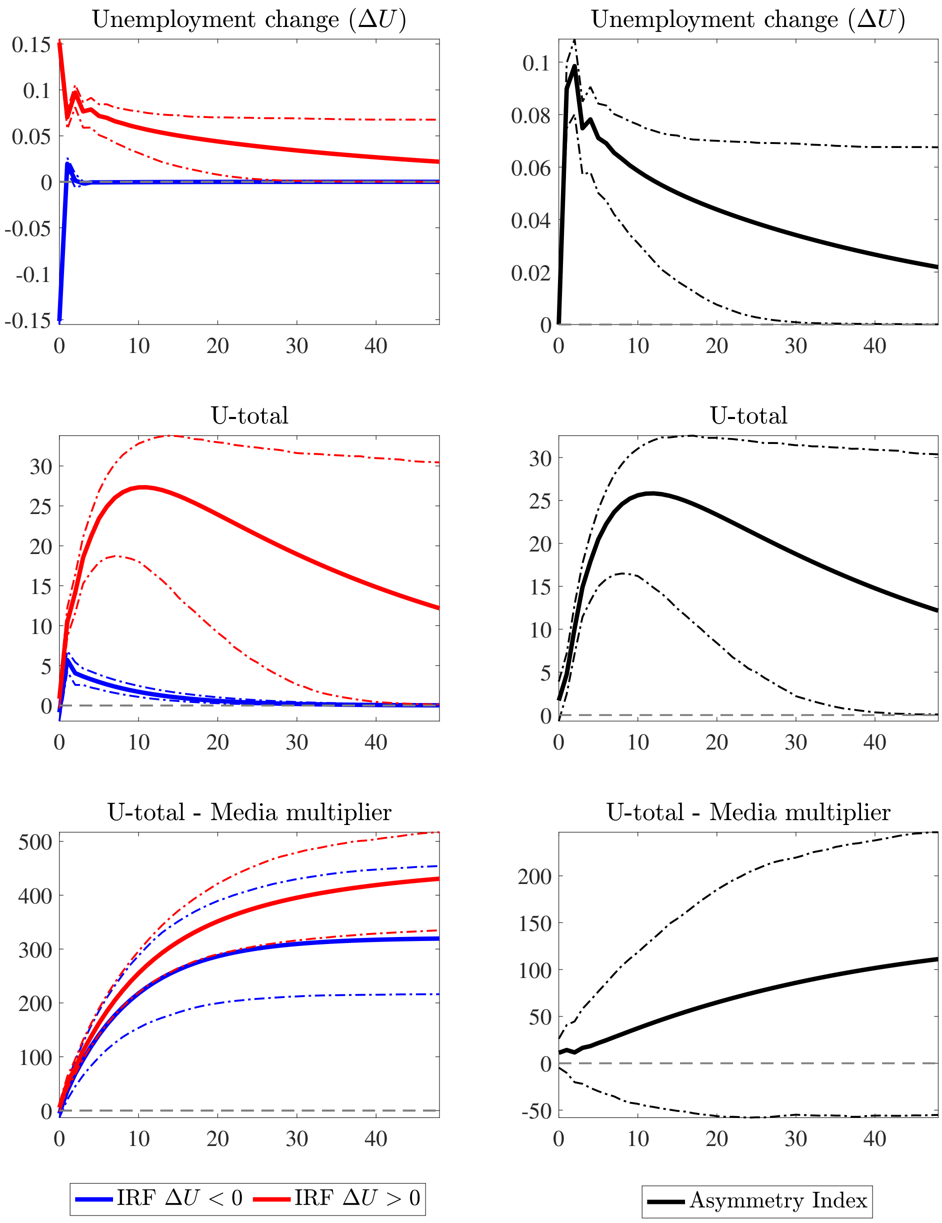


FIGURE 2.4: Response of news coverage to unemployment changes - U-total



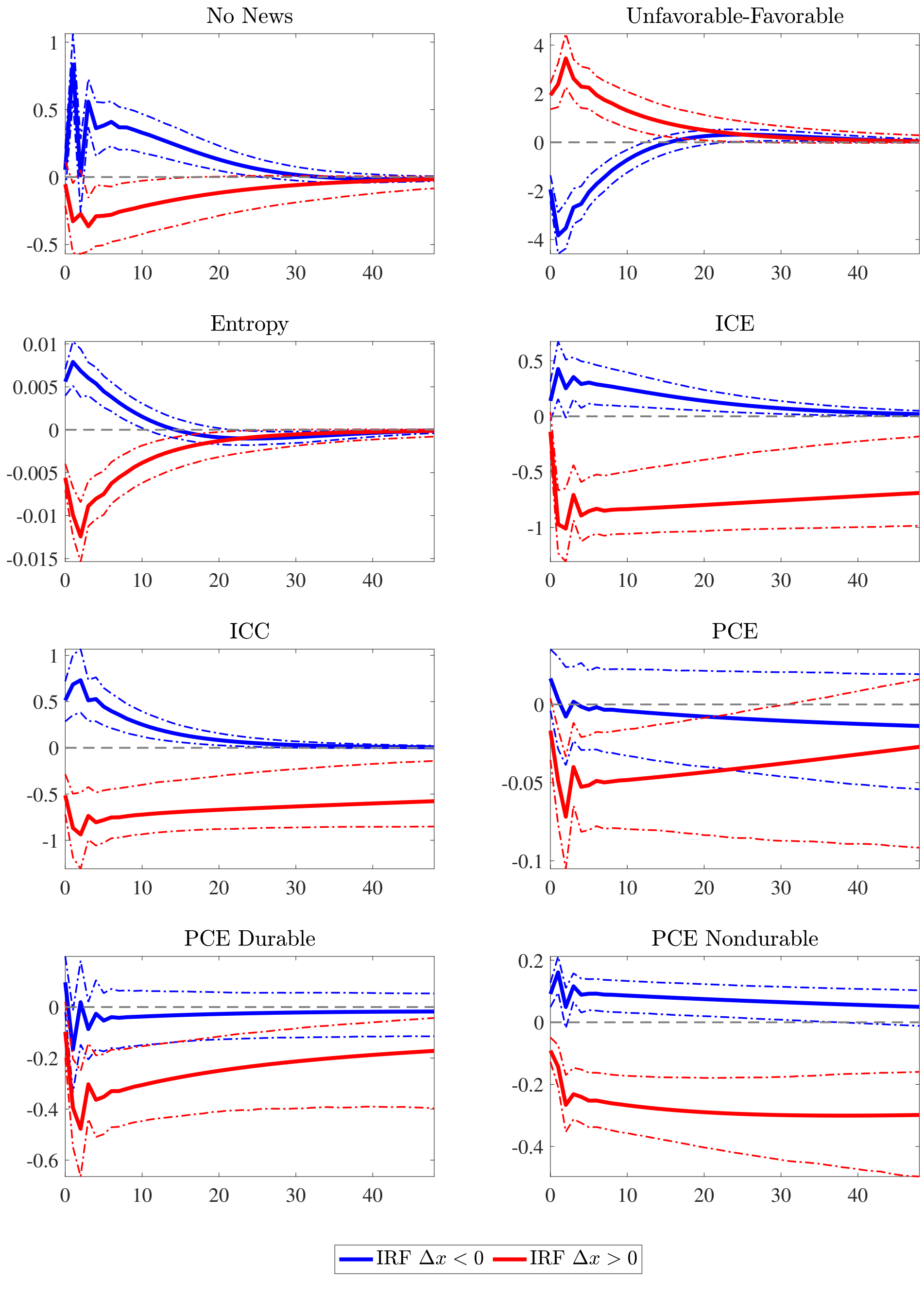


FIGURE 2.5: Asymmetric effects of news - IRFs

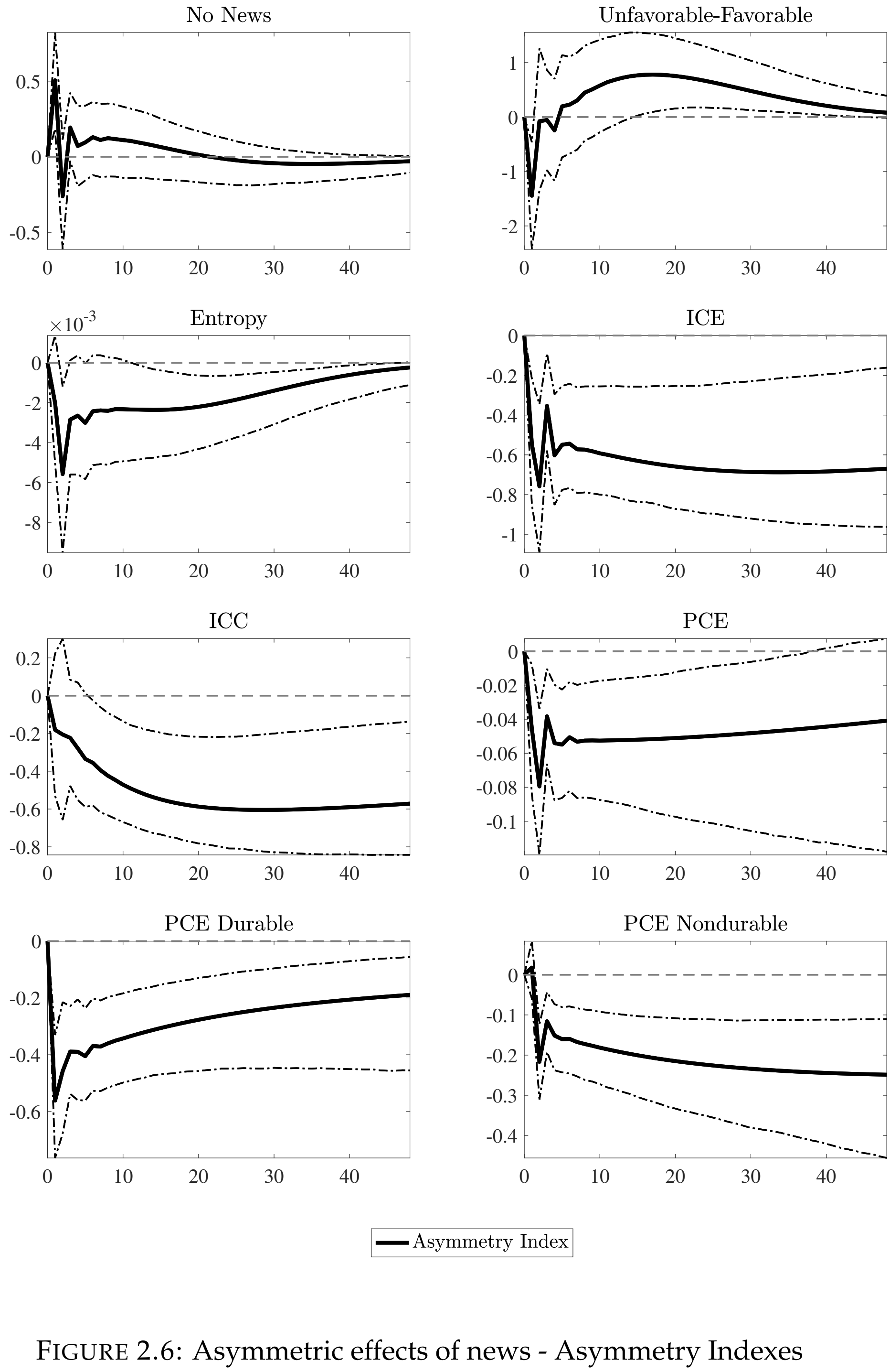


FIGURE 2.6: Asymmetric effects of news - Asymmetry Indexes

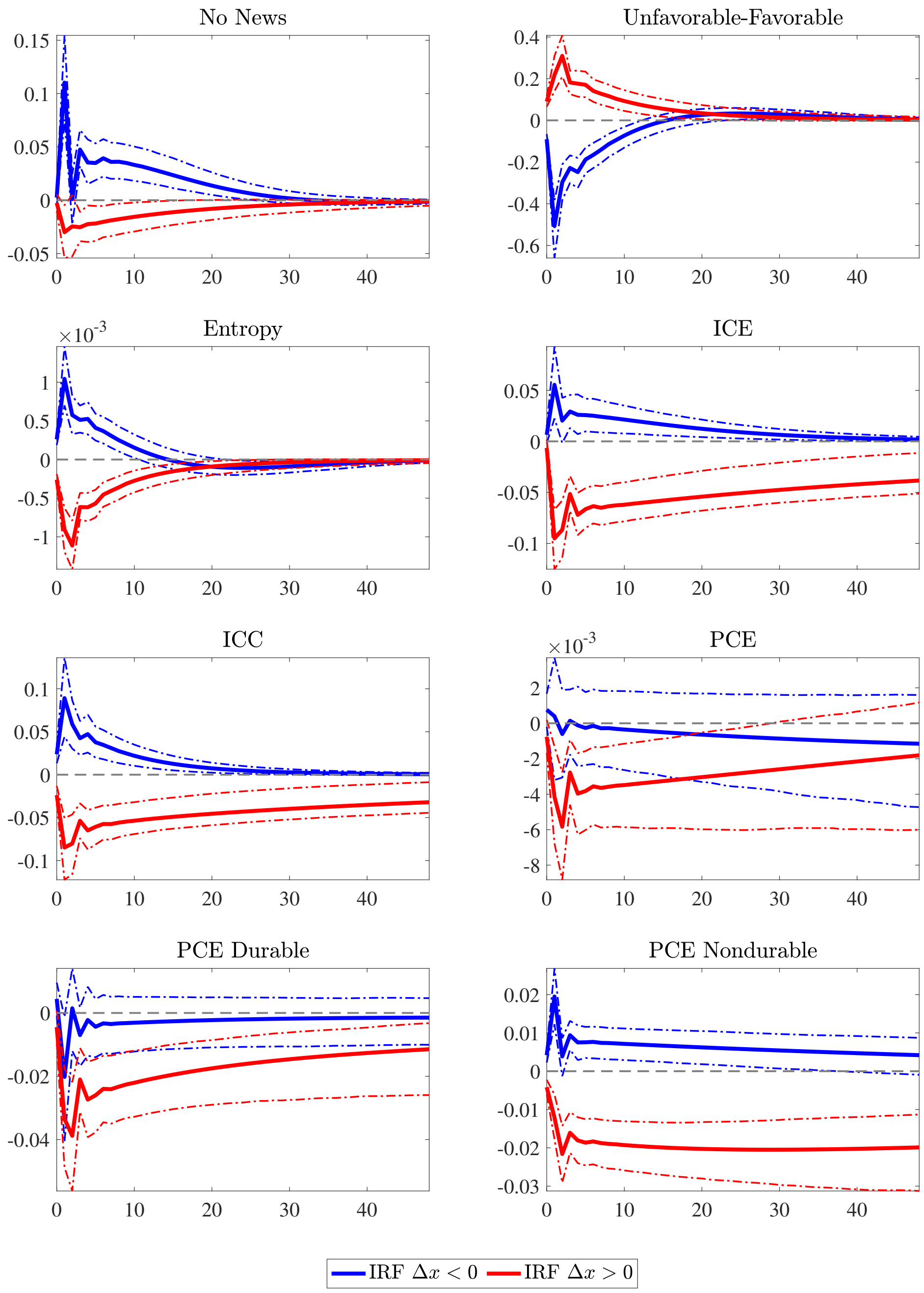


FIGURE 2.7: Asymmetric effects of news - Normalized

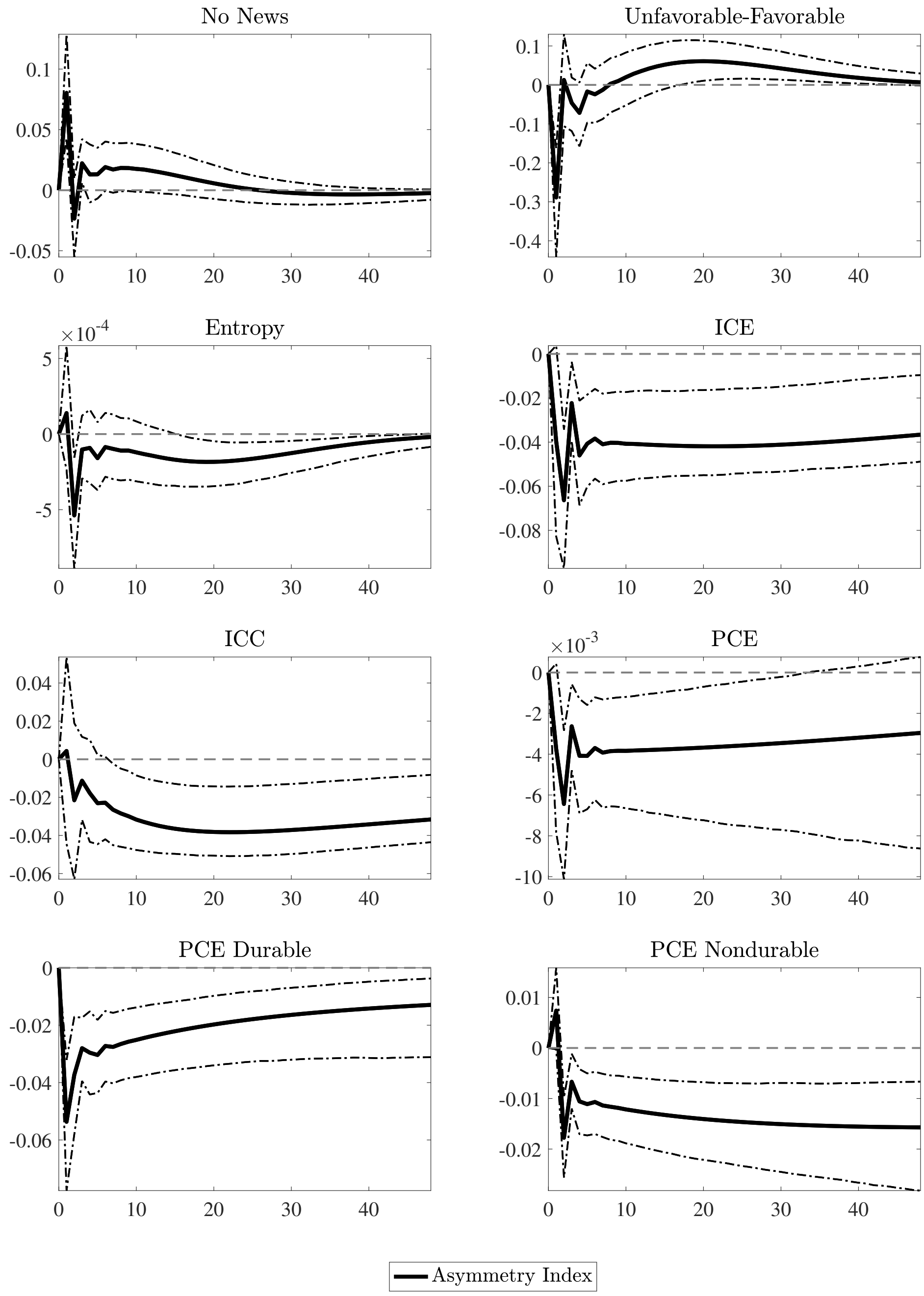


FIGURE 2.8: Asymmetric effects of news - Normalized - Asymmetry Indexes

Chapter 3

Heterogeneous effects of the ECB Asset Purchase Programs

Sarah Zoi

I study the effects of the ECB Asset Purchase Program (APP) and Panedemic Asset Purchase Program (PEPP) announcements on the four largest European economies and on the aggregate of the Euro Area. Using a proxy variable of surprises for the size of announced purchases, I identify the APP shock in a TVP-SV-FAVAR using zero and sign restrictions. I document substantial heterogeneity in the responses of European countries to the policy: i) Southern European economies experienced the largest decrease in government bond yields but the smallest decrease in the cost of credit to households and non-financial corporations; ii) the response of inflation has been stronger in Germany and Spain than in Italy and France; iii) Most of the observed cross-country differences reduced significantly over time and with later packages of the policy. Results on the aggregate of the Euro Area show that most of the channels of transmission of Quantitative Easing were active at the European level.

3.1 Introduction

In the aftermath of the 2008 financial crisis, slow economic growth and declining inflation expectations induced many Central Banks to dramatically ease their policy stances bringing their reference rates to record lows and adopting unconventional measures. The European Central Bank reduced its policy rate to negative levels in June 2014 and announced its Expanded Asset Purchase Program (EAPP or APP), in January 2015 with the precise objective of driving inflation back to its long term target. After the first announcement, asset purchases by the ECB were adjusted several times, suspended at the end of 2018, launched again in 2019 and significantly expanded in 2020 through the Pandemic Emergency Purchase Program (PEPP). Under the two programs the ECB bought a total amount of around 4.9 trillion euros, around 40% of the Euro Area GDP.

To understand how the set of policies adopted under the APP and the PEPP have transmitted to the economy is of first order importance for policy makers. On the one hand, and given the still high degree of institutional and economic heterogeneity among European economies, answering this question requires an assessment of the effects of these policies on the aggregate of the Euro Area, but also an exploration of its transmission across countries. On the other hand, the institutional and economic framework in which different packages of purchases were adopted changed considerably from the first announcement of the APP, challenging the assessment of the overall policy under a unified econometric framework. The purpose of this work is to shed light on how the Asset Purchase Programs (both the APP and the PEPP) affected the aggregate of the Euro Area and the four largest European economies and to test whether their effects have been significantly different across countries.

In the framework of a time-varying parameters Factor Augmented Vector Autoregressive model with stochastic volatility (TVP-SV-FAVAR), I identify the APP shock building on the methodology proposed by (Gambetti & Musso, 2020). Specifically, I extend their analysis on the effects of the APP announcements in two important dimensions. First, I employ a large scale multi-country setup to explore possible heterogeneities in the transmission of the APP among European countries. Second, I extend and adapt their identification strategy to evaluate the effects of the more recent PEPP. In particular, the PEPP differs from the previous Program in key institutional aspects on which their identification strategy was relying (e.g. the absence of a delay between the announcement and the implementation of purchases). Even more importantly, the PEPP was a timely response to the economic and financial consequences related to the spread of the COVID19. Its first announcement, in March 2020, coincided with the implementation of lockdown policies and with a generalized shutdown in economic activity. These characteristics make the previous identification of the APP insufficient to isolate the effect of the policy from the effect of the pandemic. To overcome these issues, I exploit the positive effect of purchases on the Stock Market as predicted by the *Portfolio Re-balancing Channel* and documented by most event studies to identify the PEPP shock and the Covid shock separately using sign restrictions.

In order to study to which extent the responses of European countries to the policy have been significantly different, I compute their impulse response functions in deviations from Germany. I find that Asset Purchase Programs generated quite heterogeneous responses among European countries. In particular, they significantly contributed to reduce government credit cost for all countries, but with stronger effects for Spain and Italy. Nonetheless, lower refinancing costs for the government in these countries didn't translate in a proportional decrease in lending rates to households and non financial corporations. This piece of evidence points in the direction of existing financial frictions that may have impaired the transmission mechanisms of the policy in Southern European economies. Second, inflation dynamics in response to the shock have been quite subdued in Italy and France with respect to Germany and Spain, suggesting certain weakness of the *Inflation Anchoring Channel* in the two countries. Third, at the aggregate Euro Area level most of the channels of transmissions of Quantitative Easing policies were active, with strong evidence of exchange rate depreciation and anchoring of inflation expectations. Fourth, there is scarce and mixed evidence of short term effects on real activity, both at aggregate and at country-level. Finally, heterogeneity in cross-country responses have been declining since the first announcement of the policy while some of the aggregate channels of transmission have been strengthening. This possibly suggests a positive contribution of the policy in reducing cross country heterogeneities which deserves further investigation.

A large empirical literature quantified the effects of Quantitative Easing policies for the US and the UK and tested the effectiveness of different channels through which asset purchases transmit to the economy (see (Borio & Zabai, 2018) for a review). In the case of the Euro Area, most of the existing studies of the APP or PEPP focus on the short term effects on financial markets relying on event studies using high frequency data, see for example (Altavilla et al., 2015), (De Santis, 2016), (Eser et al., 2019) and (Moessner & de Haan, 2022). Only few papers assess the macroeconomic effects of the Asset Purchase Program. (Wieladek & Garcia Pascual, 2016)) use four alternative identification schemes based on zero and sign restrictions imposed according to the transmission channels of Quantitative Easing policies as suggested by the theory. (Gambetti & Musso, 2020) derive a proxy of unexpected amount of announced monthly purchases to identify the APP shock using institutional characteristics of the Program. As mentioned above, I share with these authors the same strategy to identify shocks related to the APP and I build on that to extend the analysis to the PEPP. Another close literature focused on the effects of unconventional monetary policies preceding the APP or the PEPP (TLTROs, OMTs, SMP) (see for example (Altavilla et al., 2016), (Markmann & Zietz, 2017) and (Giannone et al., 2012)) or on the broader class of all them. In general, these works find significant reductions in interest rates, especially at the long end of the yield curve, and positive effects on real activity and prices. However, these preceding policies differ substantially from the Asset Purchase Programs in that they didn't implied an expansion of the Central Bank balancesheet.

With respect to this literature the contribution of this paper is twofold. First, it provides new empirical evidence on the effects of the Quantitative Easing policies on the aggregate of the Euro Area and tests potential heterogeneities in its transmission mechanisms across European countries. Second, to the best of my knowledge, it is the first paper in quantifying the macroeconomic effects of the PEPP.

Finally, this works relates to the literature that measures the effect of monetary policy shocks on European countries using Dynamic Factor Models (DFM). (Barigozzi et al., 2014) study pre and post-euro differences in transmission mechanisms of monetary policy across countries, Corsetti *et al.* (2018), study heterogeneities in the transmission of monetary policy in the Euro Area, using an high frequency identification of monetary shocks. Similarly to what I find, all these authors document substantial heterogeneity in the transmission mechanisms of monetary policy shocks.

The remind of the paper is organized as follows. Section 2 reviews the timeline of ECB announcements related to the APP and the PEPP and the main characteristics of these policies and their channels of transmission. Section 3 describes the statistical model, the estimation strategy and the dataset. Section 4 discusses the results. Section 6 concludes.

3.2 The ECB Asset Purchase Programs (APP and PEPP)

The European Central Bank announced its first Quantitative Easing, the Expanded Asset Purchase Program (EAPP or APP), in January 2015 with the specific objective of contrasting a scenario of declining inflation expectations and and increasing risk of inflation remaining too low for a prolonged period of time[1]With the first announcement of the APP, the 22 of January 2015, the ECB delivered an initial envelope

[1]The APP was not the first Unconventional Monetary Policy adopted by the ECB. Starting from July 2009, the ECB had adopted other assets purchase measures targeting different types of securities: two covered bonds purchase programs, CBPP1 and CBPP2, of 60 and 40 billions euros respectively; three Targeted Long Term Refinancing Operations (TLTRO) with the aim of providing credit to financing institutions at attractive conditions; a public sector securities purchase program, the SMP(Securities Market Purchases), that reached 210 billions euros at its peak but differed substantially from the APP in that it didn't imply an expansion of ECB balance sheet and was implemented through a *sterilization* mechanism instead.

of 1.14 tn euros, approximately 11% of the annualized European GDP of the fourth quarter of 2014, to be carried out in 60 billions euros of monthly purchases during 18 months starting from March 2015.

The initial package was re-adjusted in five subsequent re-calibrations. In December 2015 the the program was extended for 6 additional months, until March 2017, adding other 360 billions euros to the total Program. In March 2016, the Governing Council decided to increase both the size and the duration of the program. The APP was extended to non-financial corporate bonds (CSPP) starting from June 2016 and monthly purchases were increased to 80 billions per month starting from April. In December 2016, monthly purchases were reduced to 60 billions euros but the program was extended for 9 additional months, until December 2017, adding 540 billions euros more to the Program. In October 2017, the ECB announced a reduction in monthly purchases to 30 billions starting from January 2018 and an extension of APP until September 2018, or beyond if necessary. In June 2018 it was announced that monthly purchases would have run until December 2018 and were reduced to 15 billions starting from October 2018. In December 2018, when the APP was terminated the ECB announced that it would continue to fully reinvest the principal payments from maturing securities until after the first raise in policy rates, or beyond. By that time the ECB had bought 2.6 trillions euros in assets, around 25% of the Euro Area GDP.

In September 2019, motivated by a still very weak inflation and growth outlook, the Governing Council restarted the purchases under the APP by delivering an open-ended program[2] to be implemented at a monthly pace of 20 billions starting from November 2019.

In March 2020, the European economy experienced a severe and sudden contraction due to the lock-down measures adopted by most governments to contrast the spread of coronavirus. Most production activities were suspended, stock markets slumped and Southern European countries started experiencing an increasing financial pressure with soaring spreads over German bonds. Against this disruptive outlook, on the 12th of March the ECB undertook a package of measures including more favorable condition of financing through TLTROs and additional LTROs. Purchases under the APP were increased by additional 120 billions until the end of the year. Few days later, on the 18th of March, due to a worsening economic outlook and increasing volatility volatility in financial markets, the Governing Council approved the Pandemic Emergency Program (PEPP), a package of 750 billions of purchases to be conducted flexibly at least until the end of the year. Two main features differentiate the March 2020 announcements from previous announcements regarding the APP. First, the ECB didn't commit to a specific amount of target monthly purchases for the PEPP and the additional package of 120 billions for the APP like it used to

[2]Purchases were expected to be protracted *"as long as necessary to reinforce the accommodative impact of policy rates"*, and to end shortly before the ECB started raising interest rates

since 2015. Second, announced purchases started immediately in March to allow the ECB to intervene promptly to contrast the effects of the pandemic. As I will discuss more in detail later on, these differences are relevant for the identification strategy. The PEPP was expanded in two subsequent meetings, in June 2020, when 600 billions were added to the overall package, and in December 2020, when additional 500 billions of purchases were announced, bringing the total size of the program to 1.85 trillions.

In December 2021 the Governing Council re-calibrated the pace of monthly purchases under the APP to €40 bln in the second quarter of 2022, €30 billion in the third quarter of 2022 and €20 billion per month from October 2022 onwards. Figure(3.1) reports the composition of monthly purchases under the APP and the PEPP and summarizes the main announcements and re-balancing of the two policies.

3.2.1 The Asset Purchase Program Announcement Proxy

As explained by (Gambetti & Musso, 2020), one of the main challenges in identify the Asset Purchase Program shock lies in isolating the unexpected component of the total purchases from the expected one. Indeed, most of the times, the market correctly anticipated when the ECB was going to announce a Purchase Program or to re-calibrate it. However, expectations on the size of the policy have not always be in line with the announced amounts. For example, the launch of the EAPP in January 2015 was greatly anticipated by financial markets. From June 2014, and in expectation of the first announcement, interest started compressing and the euro largely depreciated against all major currencies[3]. However, the size of the announced Program doubled market expectations.

In order to identify policy surprises related to the Purchase Programs, consider the announced size of the policy at time t, a_t, as the sum of two components

$$a_t = E_t(a_t) + \psi_t \tag{3.1}$$

where $E_t(a_t)$ is a measure of market expectations on the size of the policy and ψ_t is the surprise component of the announcement.

The interest here is in retrieving the unexpected component ψ_t. (Gambetti & Musso, 2020) take a_t to be the amount of monthly purchases announced and $E_t(a_t)$ to be the median response of the Bloomberg survey of financial analysts.

With respect to their methodology, I make two important changes. First, I take a_t to be the total amount of announced purchases (monthly purchases multiplied by the number of months during which the ECB commits to target the specified amount, if announced). This is dictated by the fact that APP surprises can be related not only

[3]Yields on italian BTPs and Spanish Bonos decreased by 130 and 140 bps respectively between June 2014 and January 2015 and the exchange rate against the dollar depreciated 14.5% during the same period.

to changes in the amount of monthly purchases, but also to extensions in the duration of the Programs. Moreover, starting from the launch of the PEPP in March 2020, the ECB stopped targeting a specified amount of monthly purchases and announced exclusively the size of the overall package allowing for certain flexibility on the distribution of the purchases over time. Second, to construct $E_{t-1}(a_t)$ I use the information about market expectations as reported in articles issued by the Financial Times from one week before the announcement to few hours before. For example, on January the 21st, 2015, the day before the first announcement on APP, in the article "ECB eyes € 50 billions monthly bond purchases" the FT was writing "*Monthly purchases of €50 billions would be at the higher end of market expectations...[...]The ECB is expected to buy €550 billions of government debt, analysts polled by Bloomberg earlier this week said.*"According to this information, $E_t(a_t)$ takes value 550 billions euros in January 2015. However, the policy announcement on the 22nd of January 2015 was for an overall package of purchases of 1.1 tn euros to be carried out at the pace of 60 billions euros per month for 18 months. Therefore, the value of a_t is 1.1 tn and the size of the unexpected component ψ_t in January 2015 is of 550 billions.

Following this methodology I identify four surprises related to policy announcements on Asset Purchase Programs from January 2015 to June 2020.

$$\begin{aligned}
\psi_t &= 550 \quad billions \quad if \quad t = 2015:01 \\
\psi_t &= 120 \quad billions \quad if \quad t = 2016:03 \\
\psi_t &= 570 \quad billions \quad if \quad t = 2020:03 \\
\psi_t &= 100 \quad billions \quad if \quad t = 2020:06
\end{aligned}$$

For all $t \neq 2015:01, 2016:03, 2020:03, 2020:06$, $\psi_t = 0$. The first two realizations for the surprise variable coincide in time with the proxy derived by (Gambetti & Musso, 2020) for the APP ended in December 2018, while the last two relates to the first announcement and the first re-calibration of the PEPP. A detailed motivation for the values of the surprise variable is reported in the Appendix. Figure (3.2) graphs the proxy ψ_t.

3.2.2 Channels of Transmission of APP

By now there is quite a large consensus on the channels through which an Asset Purchase program transmits to the financial system and, to a larger extent, to real economy and prices.

According to the *Portfolio Re-balancing Channel* ((Vayanos & Vila, 2021)), in the presence of investors with preferences for specific maturities, the increase in Central Bank demand for bonds reduces bonds duration and term premia and translates in

a decline in government yields with two main effects. First, lower yields will induce investors to change their portfolio composition increasing their appetite for different type of assets (i.e. equity). The increase in demand for equity pushes its price upward and boost equity financing for corporations. Second, through the banking sector, lower government credit costs translates in lower financing costs for households and corporations and, henceforth, in an increase in the stock of loans.
The increase in liquidity in the banking system due to Central Bank's purchases is predicted to have two main effects. First, it depreciates the exchange rates boosting external demand for domestic goods and exports (*Exchange Rate Channel*). Second, high supply of liquidity pushes the lending sector to increase loans to households and corporations by loosening credit conditions (*Credit Channel*)[4].
Through the *Signaling Channel* ((Eggertsson & Woodford, 2003)) and (Bernanke et al., 2004) the Central Bank signals its commitment to keep its expansionary stance for a prolonged period of time, inducing a downward revision in expectations around future policy rates. The *Inflation Anchoring Channel* can be included in the broader category of *Signaling*. According to this channel, the liquidity injection through CB purchases lifts inflation expectations and translates in a positive effect on future inflation.
According to the *Reduction in Uncertainty* ((Weale & Wieladek, 2016)), communication about future path of monetary policy and the setting of a precise schedule for asset purchases tend to reduce uncertainty around future financial developments and pushes market volatility down.

3.3 Model, Identification and Estimation

In order to study the effects of ECB Asset Purchase Program on Euro Area and on the four largest economies I identify an Asset Purchase Shock in the framework of a Time Varying Parameters Structural Factor Augmented Vector Autoregressive Model with Stochastic Volatility (TVP-SV-SFAVAR).
Few facts justify the choice of the model. First, a factor model allows to conveniently handle a large number of time series and recover their responses to a unique, common shock using one single model. This makes the framework a suitable tool to study the effects of a monetary policy shock in the Euro Area on a panel of member countries. Second, since January 2015, both the composition of purchases by asset class and the way new packages were announced and implemented have changed substantially, leaving room to potential time-variation in the effects of the policy.

[4]Notice that this last effect can be also seen as a second order effect of the *Portfolio Rebalancing Channel*.

Third, the Asset Purchase Program shock is observed infrequently and this is reflected in the surprise variable ψ used for identification. Given that this variable takes value zero most of the time and displays large peaks corresponding to few announcements, assuming homosckedasticity of the error components can seriously impair inference. The shape of ψ represents an additional motivation to allow for time variation in coefficients and in volatilities.

3.3.1 Model

Let x_t be a vector of n variables observed at time t, f_t a vector of r latent common components (with $r < n$) and y_t a vector of m variables relevant for identification of one or more structural shocks. The TVP-SV-FAVAR model is described by the following equations:

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} I & 0 \\ \Lambda_y & \Lambda_f \end{bmatrix} \begin{bmatrix} y_t \\ f_t \end{bmatrix} + \begin{bmatrix} 0 \\ \eta_t \end{bmatrix} \tag{3.2}$$

$$\begin{bmatrix} y_t \\ f_t \end{bmatrix} = c_t + B_t(L) \begin{bmatrix} y_{t-1} \\ f_{t-1} \end{bmatrix} + \nu_t \tag{3.3}$$

$$\eta_t \sim N(0, \Sigma_\eta)$$

$$\nu_t \sim N(0, \Sigma_{\nu,t})$$

where Λ_y, Λ_y and $B_t(L)$ are matrices of coefficients, c_t is a vector of constants and η_t is vector of n idiosyncratic components. Matrix Σ_η is assumed to be diagonal, while $\Sigma_{\nu,t}$ is a full matrix of covariances at time t.

Equation (3.2) describes a factor shrinkage given by the projection of x_t on the lower dimensional space spanned by f_t. Equation (3.3) describes a VAR model for factors, f_t, and policy variables, y_t.

To close the model, I assume that the dynamics of time-varying coefficients is well described by a random walk process:

$$\beta_t = \beta_{t-1} + \epsilon_t \tag{3.4}$$

where $\beta_t = [c_t, vec(B_t), vec(B_{t-1}), ...vec(B_{t-p+1})]$ and $\epsilon_t \sim N(0, Q)$, with Q diagonal. Finally, for the stochastic volatility, consider the triangular reduction $A_t \Sigma_{\nu,t} A_t' = \Omega_t \, \Omega_t'$, with A_t being lower triangular with principal diagonal of numeraries and Ω_t being a diagonal matrix of standard deviations of residuals. Let α_t to be the vector of non-zero elements of A_t and σ_t the vector of diagonal elements of Ω_t. Standard assumptions, as in Primiceri (2005), imply α_t and σ_t to follow:

$$\mathbf{ff_t} = \mathbf{ff_{t-1}} + \zeta_t \tag{3.5}$$

$$log\mathbf{œ_t} = log\mathbf{œ_{t-1}} + \omega_t \tag{3.6}$$

where $\begin{bmatrix} \omega_t \\ \zeta_t \end{bmatrix} \sim N(0, V)$ with V block diagonal: $\begin{bmatrix} W & 0 \\ 0 & \Psi \end{bmatrix}$ and Ψ being block diagonal.

Like in a standard VAR, identification of structural shocks is obtained by orthogonal rotations of residuals ν_t:

$$\begin{bmatrix} y_t \\ f_t \end{bmatrix} = D(L)^{-1}Ru_t \tag{3.7}$$

where $u_t = (S_t H')^{-1}\nu_t$ is a vector of structural shocks and $R = S_t H$ with S_t is a lower triangular matrix such that $S_t S_t' = \Sigma_{\nu,t}$, and H is an orthogonal matrix. Identification implies choosing matrix H so to impose economic meaningful restrictions on $D(L)$. The representation of x_t and y_t in terms of structural shocks can be obtained by substituting 3.7 in 3.2:

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} I & 0 \\ \Lambda_y & \Lambda_f \end{bmatrix} D(L)^{-1}Ru_t + \begin{bmatrix} \eta_t \\ 0 \end{bmatrix}$$

where $x_t = \begin{bmatrix} \Lambda_y & \Lambda_f \end{bmatrix} D(L)^{-1}R$ are the impulse responses of x_t to the structural shocks u_t.

Estimation of the model is fully bayesian. I first draw the factors f_t using the Carter-Khon algorithm. Conditional on those, I draw coefficients Λ_f, Λ_y and the coefficients of Σ_η. Conditional on factors and non-time-varying coefficients, I draw β_t and, finally, the stochastic volatilities. The details of the MCMC adopted for estimation and prior choices are reported in the Appendix.

3.3.2 Identification

(Gambetti & Musso, 2020) use ψ_t as external instrument to proxy the unexpected component of asset purchases and use a parsimonious identification scheme based on institutional features of the announcements and on the statistical properties of ψ. Let z_t be the amount of ECB monthly purchases for monetary policy purposes. They identify the APP shock by ordering z_t first and ψ_t second followed by other variable of interest and apply a recursive identification scheme[5]. This identification implies

[5]They take S_t in equation 3.7to be the lower triangular matrix given by the choleski factorization of $\Sigma_{nu,t}$, and H to be the identity.

that a shock in ψ_t, an unexpected news on the size of the APP, affects ECB purchases for monetary policy purposes, z_t, only with some delay, but not contemporaneously.

Given the institutional characteristics of the announcements related to the first two surprises (January 2015 and March 2016), this parsimonious identification strategy is sufficient to identify the Purchase Program shock for these events. Indeed, all the policy announcements between January 2015 and December 2019 were providing a target for monthly purchases and a precise date in which the ECB would have started to buy the specified amount (usually one or two months after the announcement). However, when extending the analysis to the PEPP, there are at least three reasons why a simple recursive scheme becomes insufficient to identify the shock. First, announcements around the PEPP were not specifying a target for monthly purchases but only the overall amount that the Central Bank was committing to buy during the following months. Second, purchases under the PEPP were starting few days after the announcement making the non-contemporaneous response of ECB assets to the shock an implausible assumption. Third, the announcement of the PEPP in March 2020 coincides with the implementation of lockdown policies in most countries. Indeed, it is reasonable to think that both the PEPP and its subsequent re-calibration were mostly policy responses to the economic and financial consequences of the pandemic. In this case, identification through a simple recursive scheme would not be sufficient to disentangle the PEPP shock from the Covid shock.

To overcome these issues, I separately identify the PEPP shocks and the Covid shock in March and June 2020 by exploiting variations in the European Stock Market Index (Euro Stoxx 50) and using sign restrictions. Indeed, one of the most immediate and disruptive effects of Covid in March 2020 was the huge slump in Stock Market Indices all over the World [6]. Against this background, the PEPP was positively received by financial markets by stimulating a significant increase in the Euro Stoxx 50 and a compression of the spreads of Southern European bonds[7] immediately after the announcement. Motivated by this evidence of opposing effects of these two

[6]As mentioned by Ms Schnabel, Member of ECB Executive Board, during the press conference following the meeting of March 18th: *"The EURO STOXX 50 was down by nearly 40% since 20 February 2020, when the coronavirus epidemic had started to turn into a global pandemic."*

[7]By means of an event study (Aguilar et al., 2020) estimate the effects of the first announcement of the PEPP on the Euro Stoxx 50 to be around +3% and to be milder, around 0.5%, for the the first re-calibration. The Italian BTP- German Bund spread decreased by more than 80bps after the first announcement and around 25bps after the re-claibration.

	January 2015	March 2016	March 2020		June 2020	
	APP	APP	Covid	PEPP	Covid	PEPP
z_t	0	0	+	+	+	+
ψ_t			+	+	+	+
s_t			-	+	-	+

TABLE 3.1: Summary of identification of the APP, PEPP and Covid shocks - Contemporaneous effects.

shocks on the Stock Market, I consider the following system of variables:

$$\begin{bmatrix} z_t \\ \psi_t \\ s_t \\ f_t \end{bmatrix}$$

where s_t is the European Stock Price Index (Euro Stoxx 50) and f_t are the common components of model (3.2) but may also be interpreted as a vector of observable which can be affected contemporaneously by an Asset Purchase Program shock or by a Covid shock.

According to the above discussion, I identify a Covid shock in March and June 2020 as a shock with a positive impact effect on ψ_t and z_t and a negative impact effect on the Stock Market s_t. At the same time a PEPP shock is identified has having a positive impact effect on ψ_t, z_t and s_t.

Few remarks are in order. First, the identification of an asset purchase policy shock through a positive sign restriction on the Stock Market Index is not only justified by previous empirical evidence (see (De Santis, 2016), (Aguilar et al., 2020)) but it is also suggested by the *Portfolio Re-balancing Channel* and has been previously adopted by (Wieladek & Garcia Pascual, 2016). Second, the identification of the Covid shock is based on the fact that the PEPP announcement have been a policy response to the economic and financial consequences generated by the pandemic. This announcement, in turn, exceeded market expectations resulting in a PEPP shock.

Table (3.1) summarizes the identification of the shocks for the four events in which variable ψ takes positive values. For the first two events, identification is recursive as in (Gambetti & Musso, 2020).

3.3.3 Data and factors selection

The database includes 195 monthly series for the aggregate of the Euro Area (19 countries) and for the four largest European economies (Germany, France, Italy and Spain[8]). All the variables have been properly transformed to insure stationarity. A detailed description of the data and the transformations applied is provided in the Appendix. Figure(**??**) reports the percentage of variance explained as a function of factors for this dataset. The number of common components is fixed to $r = 5$. The (Bai & Ng, 2002) IC_1 and IC_2 criteria for the number of static factors suggest 7 and 5 factors, respectively. Five factors explain around 51% of the total variance of the dataset. The explained variance of the variables of interest (the ones for which I report impulse responses) is 54% in total. Three variables are used for identification of the APP shock, the surprise variable constructed according to the methodology reported in Section 2.1, the ECB monthly purchases for monetary policy purposes and the Euro Stoxx 50. The model is estimated using data from July 2009 to December 2021. For the TVP-SV-FAVAR, I choose three lags. Results are based on a MCMC with 60000 draws of which the first 30000 are discarded.

3.4 Results

Figure ((3.3)) reports the posterior mean and the 18th and 84th percentiles of the posterior distribution of the IRFs of the three variables used for identification for each of the four announcements. Impulse responses are resized by the size of the corresponding estimated shock. As imposed by the recursive identification scheme, in January 2015 and March 2016, the amount of monthly ECB purchases for monetary policy purposes doesn't react contemporaneously to the shock. After the first period, monthly purchases increase and, in the third period, reach approximately 20 billions in January 2015 and 20 billions in March 2016, suggesting that indeed a significant proportion of the increase in asset purchases corresponding to the first two announcements was not expected. The response of the Eurostoxx is positive, between 0.5% and 1.5%, for both episodes, as predicted by the *Portfolio Re-balancing Channel*. Notice that the response of the stock market was not imposed with identification which, for the first two shocks, is recursive. This piece of evidence provides additional support to the the identification strategy used for the PEPP shocks in March and June 2020. Turning to the effects of the announcements of the PEPP, the shock increases the surprise variable by a bit less than 500 billions, a bit less than the value of ψ for that period (570 billions). Interestingly, the covid shock is also generating a significantly large response of the announcement surprise variable ψ, which increases by around 100 billions in March and 100 in June. Even if this is

[8]Being the first four countries by *capital key*, these countries were the ones benefitting the most from the asset purchases

partly imposed through identification, the non-negligible size of the response suggests that more than one fifth of the surprise in the announcement is explained by covid. Additional results on the effect of the Covid shock are reported in the Appendix. The responses of purchases for monetary policy purposes are positive and reach 40 billions and 100 billions after three months in March and June respectively. The response of Stock Prices is also positive, even if much smaller than for the previous APP shocks.
The estimated stochastic volatility of residuals (Figure(3.5)) gives evidence of considerable time variations in the variance of the residuals of three variables used in identification. In particular the four peaks in the residuals of ψ corresponding to the four events discussed suggest that they represent true surprises which could not be forecasted given available information.

3.4.1 Macroeconomic effects on the Euro Area

Figures 3.6 to 3.8 reports the responses of variables related to the aggregate of the Euro Area. IRFs point to the evidence that the majority of the channel through which QE policies typically transmit to the economy were active. One exception is June 2020, when most of these channels seem to have reduced their relevance.
The *Reduction in Volatility Channel* was particularly strong in March 2020, when the shock had an effect of around 10% reduction in Stock Market volatility. The responses of the EA composite 10-year yield show a strong reduction in government credit costs, especially in January 2015 and March 2020. However, both interest rates on loans to non-financial corporations and households do not show significant responses. On the other hand, the stock of loans to non-financial corporations was boosted by the shock, pointing towards a positive effect through the *Credit Easing Channel*. Results suggest a quite strong *Inflation Anchoring Channel*, through positive effects of the shock on inflation and both short and long-term inflation expectations. These effects have been milder for the first announcement and have been gaining relevance in March 2016 and March 2020 until being almost insignificant in June 2020.
The *Exchange Rate Channel* have been also active through a depreciation of the Nominal Effective Exchange Rate (NEER) of the euro.
Effects on real activity are controversial. While most of the time the shock had no effect on Industrial Production, it contributed to a substantial decrease in unemployment until 2016. A positive effect on New Industrial Orders and Retail Sales is also estimated in January 2015 but vanished in the subsequent events. Finally, the policy has shown a positive effect on Consumer Confidence starting from the first announcement. This effect was especially strong in March 2020, signalling a positive assessment from the consumers' side of the ECB response to covid.

3.4.2 Heterogeneities in the transmission of APP

Figures (3.9) to (3.14) reports the responses of the four largest European economies to the shock. Responses for Italy, Spain and France are expressed in deviations to the response of Germany. Results reveal a substantial degree of heterogeneity in the transmission of the shock. First, the policy reduced government credit costs substantially more in Southern European Economies with respect to Germany. The extra effect in reducing bond yields is estimated to be between 10 and 50 basis points for Italy and Spain and between 5 and 10 for France. The strongest differences were in January 2015 and March 2020 and disappeared for the last announcement. Similar effects are documented by (Altavilla et al., 2015), (De Santis, 2016) and (Moessner & de Haan, 2022). Even if depressing effects on government yields were stronger for Italy and Spain with respect to Germany and France, this didn't translate in a larger decrease of borrowing costs for non-financial corporations and households in these countries. Figures (3.10) and (3.11) show a much stronger effect of the *Credit Easing Channel* on German lending rates with respect to other economies. A possible explanation for this is the presence of frictions in the lending market connected with a poor capitalization of the banking sector. This is also argued by (Elbourne, Ji, et al., n.d.),(Burriel & Galesi, 2018) and (Boeckx et al., 2014) who, analysing a broader class of unconventional monetary policies, find evidence of larger effects on real activity for North European economies.

The response of inflation displays also a large degree of heterogeneity across countries. The strongest positive effects are for Germany and Spain while Italy and France shows negative inflation dynamics in response to the shock. These maybe due, in turn, to subdued inflation expectations in these countries as opposed to Spain and Germany which deserve a further assessment. It is worth to notice that, as for other indicators, these differences in responses reduced over time until they became largely insignificant for the last shock in June 2020.

Finally, as for the aggregate of the Euro Area, responses of indicators of real activity and labor market are also quite heterogeneous and do not point toward a clear conclusion. The countries benefiting the most in terms of a reduction in unemployment were Italy and France followed by Germany. However, the response of Retail Sales, an indicator of industrial activity and demand was significantly stronger for Germany .

3.5 Conclusions

Heteregeneities in responses of countires to the policy have significant reduced over time This paper investigates the effects of announcements on the APP and the PEPP of the European Central Bank, on the aggregate of the Euro Area and on a panel of four European countries. In the framework of a TVP-SV-FAVAR, I identify the APP and PEPP shocks using a proxy of unexpected size of the announcements around shock I investigate these effects by adopting an identification strategy similar to Gambetti and Musso (2017). I evaluate cross-country differences by computing the responses in deviations from Germany. I find that Asset Purchase Programs generated quite heterogeneous responses among European countries. In particular, they significantly contributed to reduce government credit cost for all countries, but with stronger effects for Spain and Italy. Nonetheless, lower refinancing costs for the government in these countries didn't translate in a proportional decrease in lending rates to households and non financial corporations. This piece of evidence points in the direction of existing financial frictions that may have impaired the transmission mechanisms of the policy in Southern European economies. Second, inflation dynamics in response to the shock have been quite subdued in Italy and France with respect to Germany and Spain, suggesting certain weakness of the *Inflation Anchoring Channel* in the two countries. For the aggregate of the Euro Area, almost all the traditional channels of transmission of QE policies are activated. The policy had positive effects in decreasing governments bond yields and increased retail credit, boosted equity markets, reduced market volatility, depreciated the exchange rate, and stimulated inflation and inflation expectations. However, there is scarce and mixing evidence of short term effects on real activity, both at aggregate and at country-level. Finally, heterogeneity in cross-country responses have been declining since the first announcement of the policy while some of the aggregate channels of transmission have been strengthening. This possibly suggests a positive contribution of the policy in reducing cross country heterogeneities which deserves further investigation.

Figures

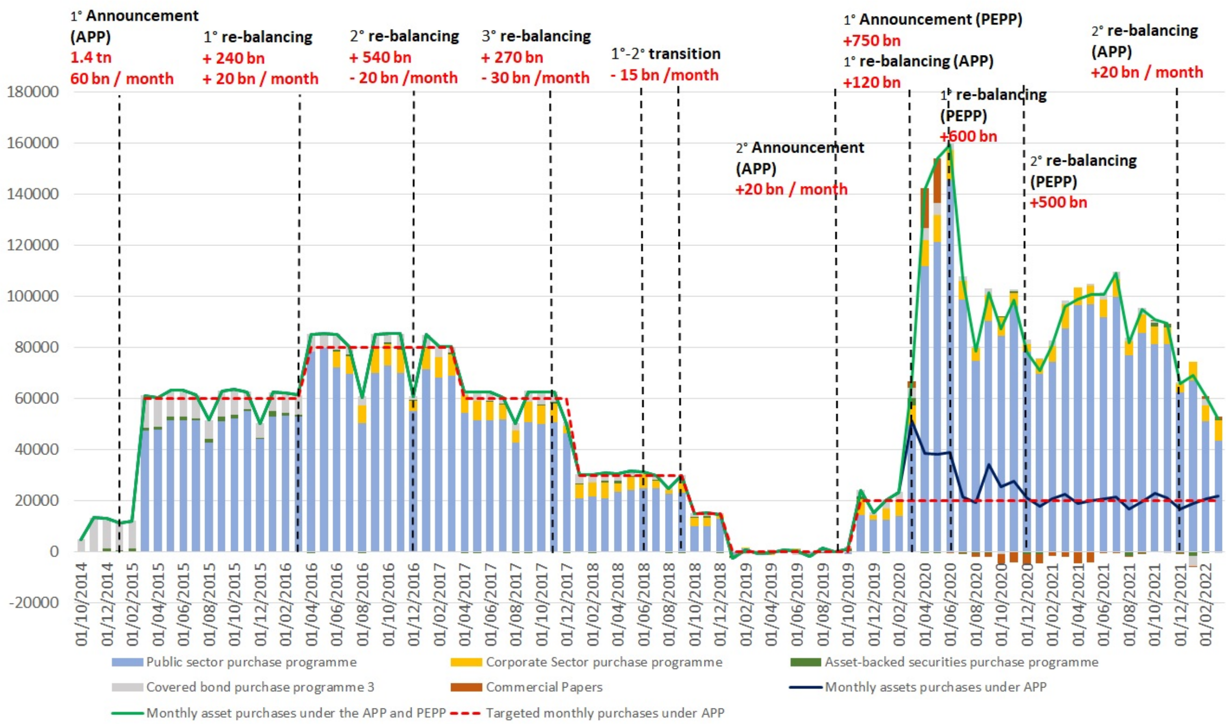


FIGURE 3.1: ECB Asset Purchases under the APP. Author's computation on ECB data. Data on composition of monthly purchase after March 2020 are bi-monthly. Monthly data are imputed based on monthly amounts of overall purchases

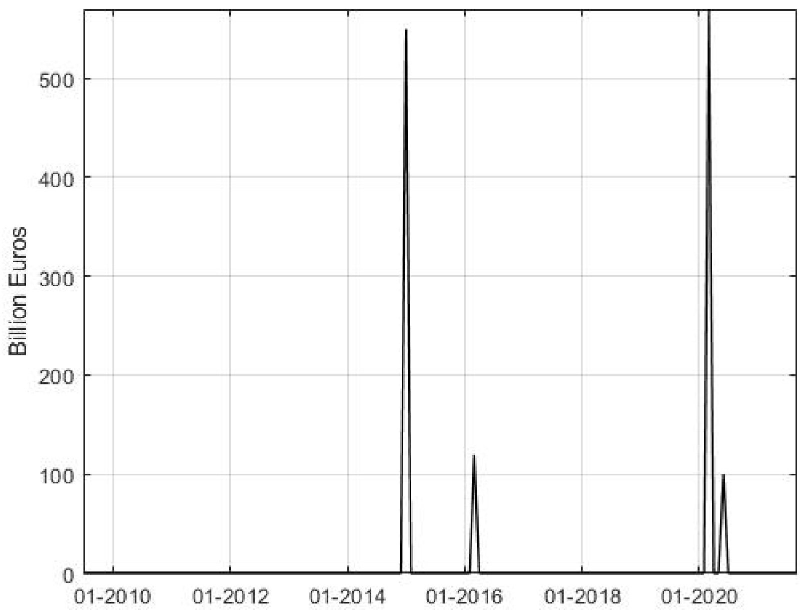


FIGURE 3.2: Unexpected component, ψ_t, of announcements related to the APP and the PEPP.

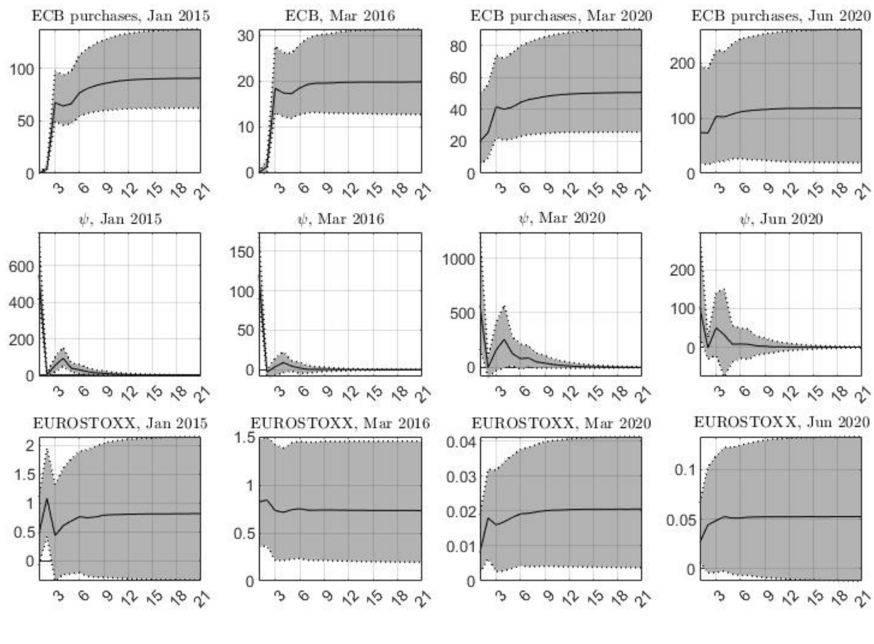


FIGURE 3.3: IRFs to an APP shock - Mean and 16-84 percentiles of posterior distribution.

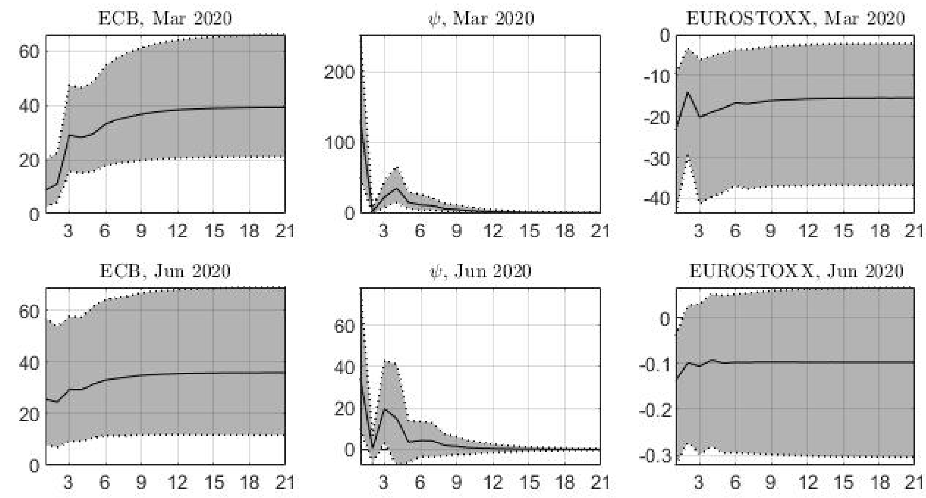


FIGURE 3.4: IRFs to a Covid shock - Mean and 16-84 percentiles of posterior distribution.

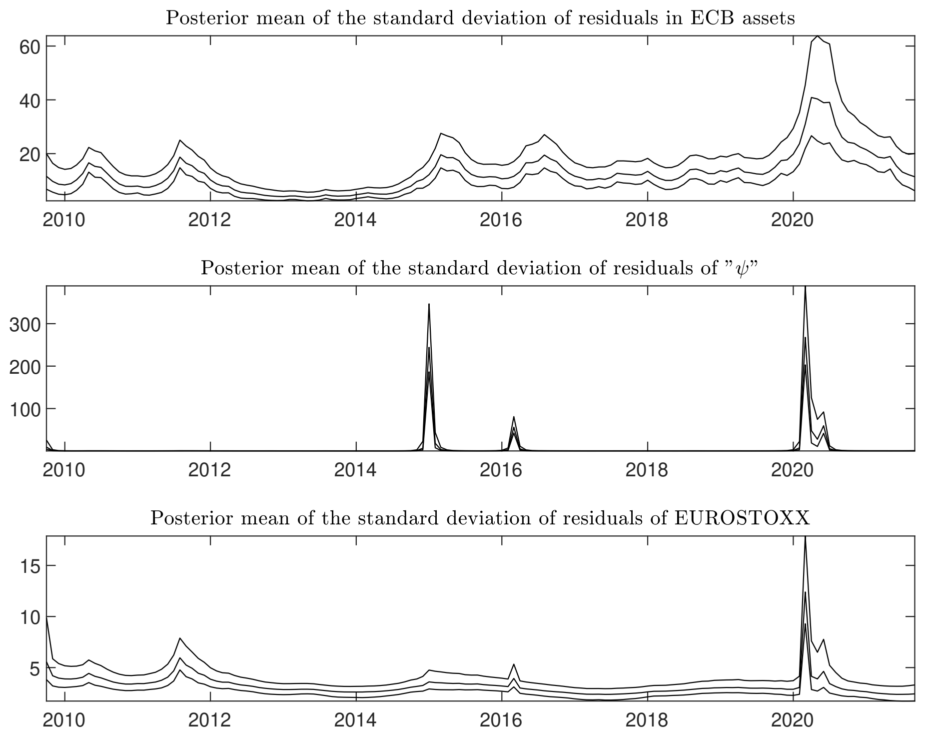


FIGURE 3.5: Posterior mean and 16-84 percentiles of the standard deviations in monthly ECB securities held for monetary policy purposes, surprise ψ and Euro Stoxx 50

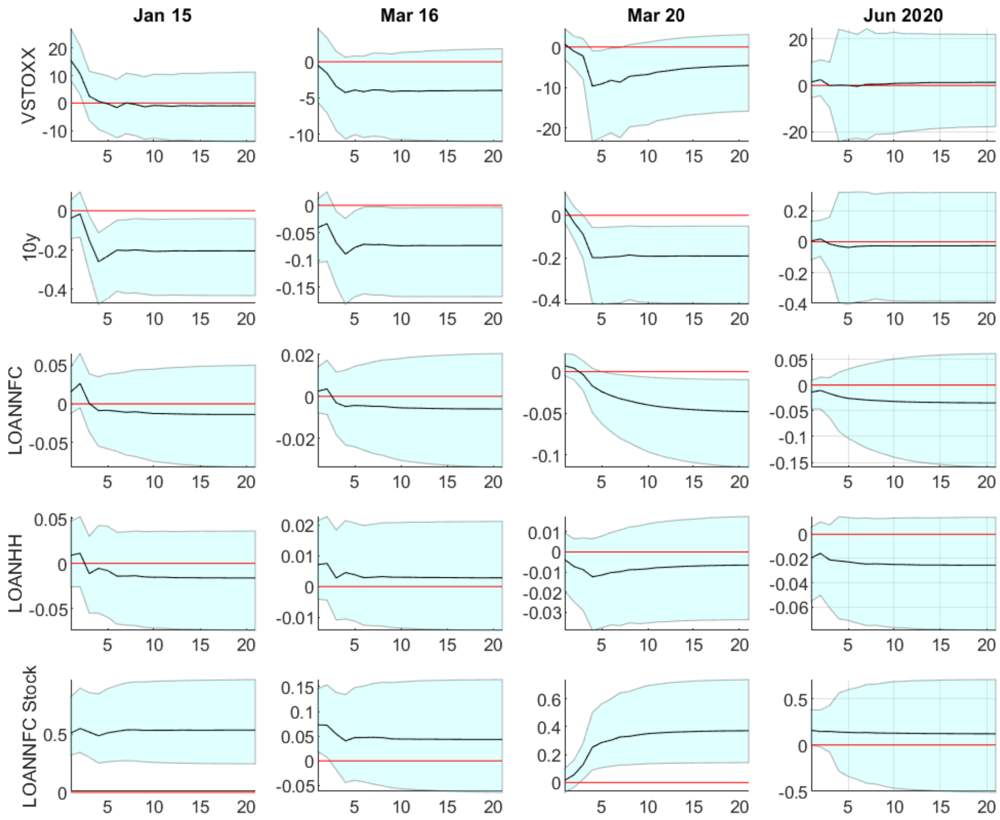


FIGURE 3.6: IRFs to an APP shock. Euro Area. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

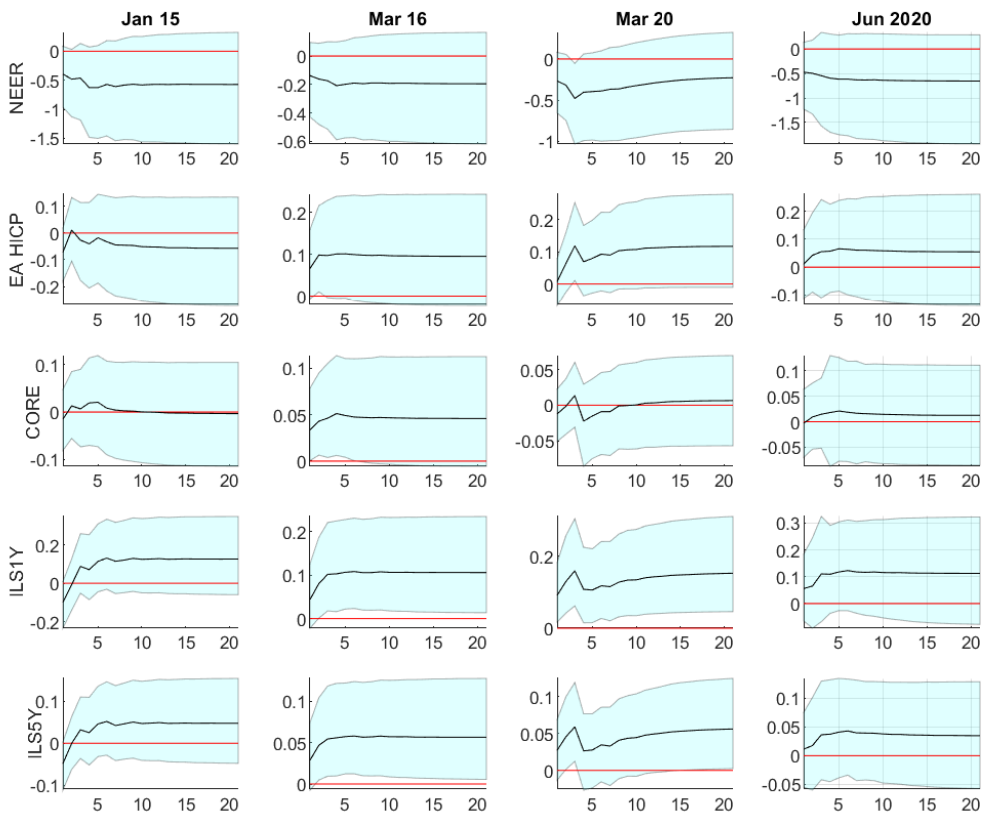


FIGURE 3.7: IRFs to an APP shock. Euro Area. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

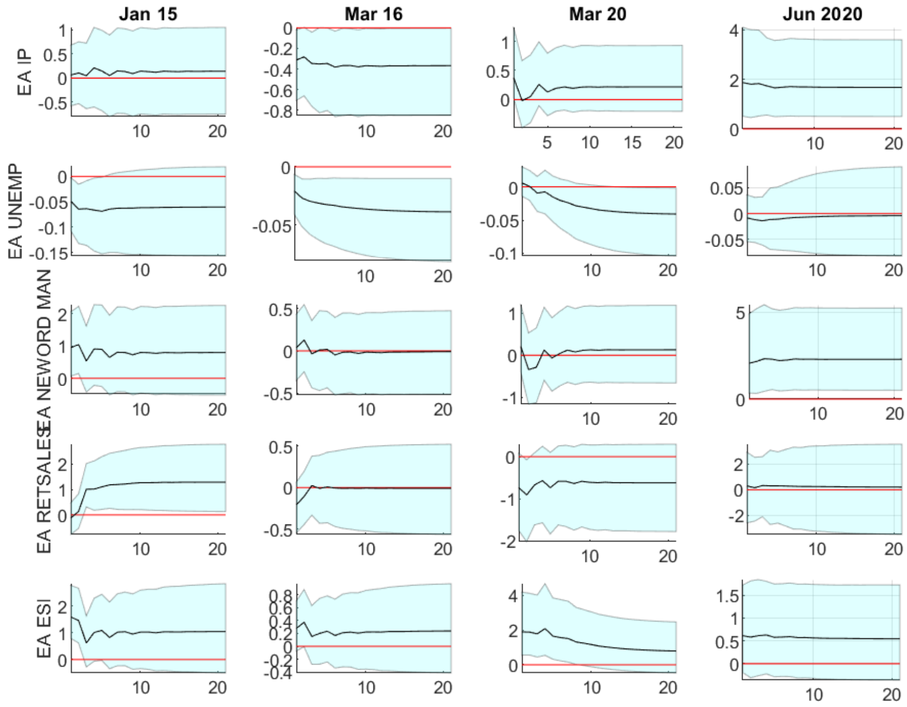


FIGURE 3.8: IRFs to an APP shock. Euro Area. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

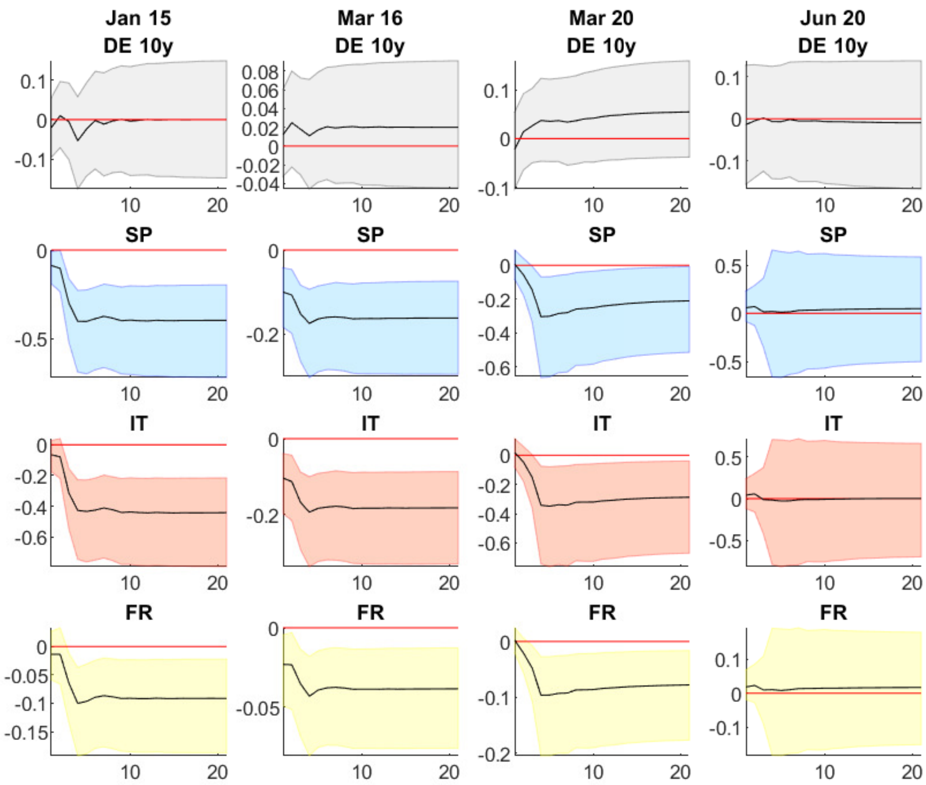


FIGURE 3.9: IRFs to an APP shock. Germany and countries differences with respect to Germany - 10-year government bond yield. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

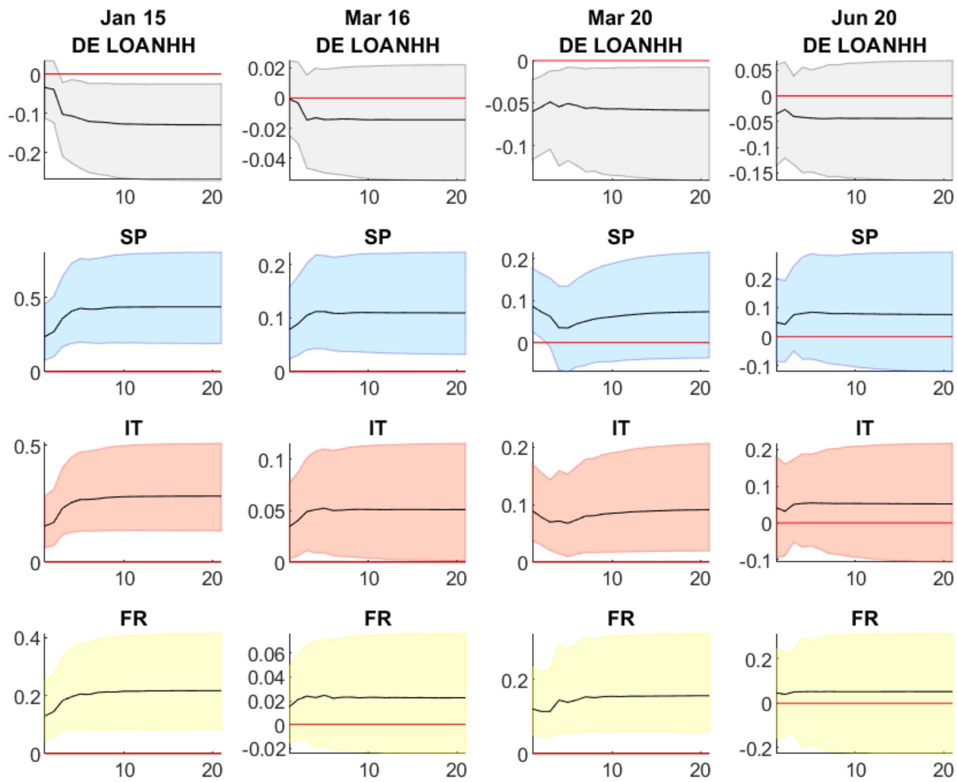


FIGURE 3.10: IRFs to an APP shock. Germany and countries differences with respect to Germany - Lending to Households for consumption, Composite interest rate. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

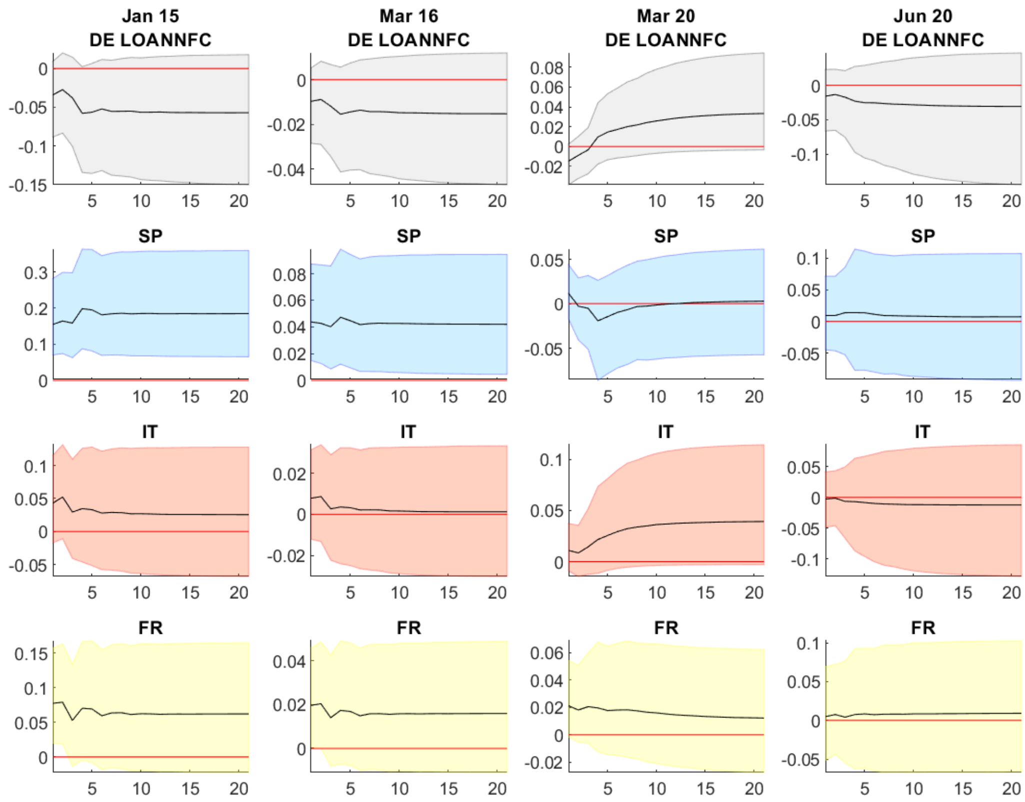


FIGURE 3.11: IRFs to an APP shock. Germany and countries differences with respect to Germany - Lending to Non-financial corporations. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

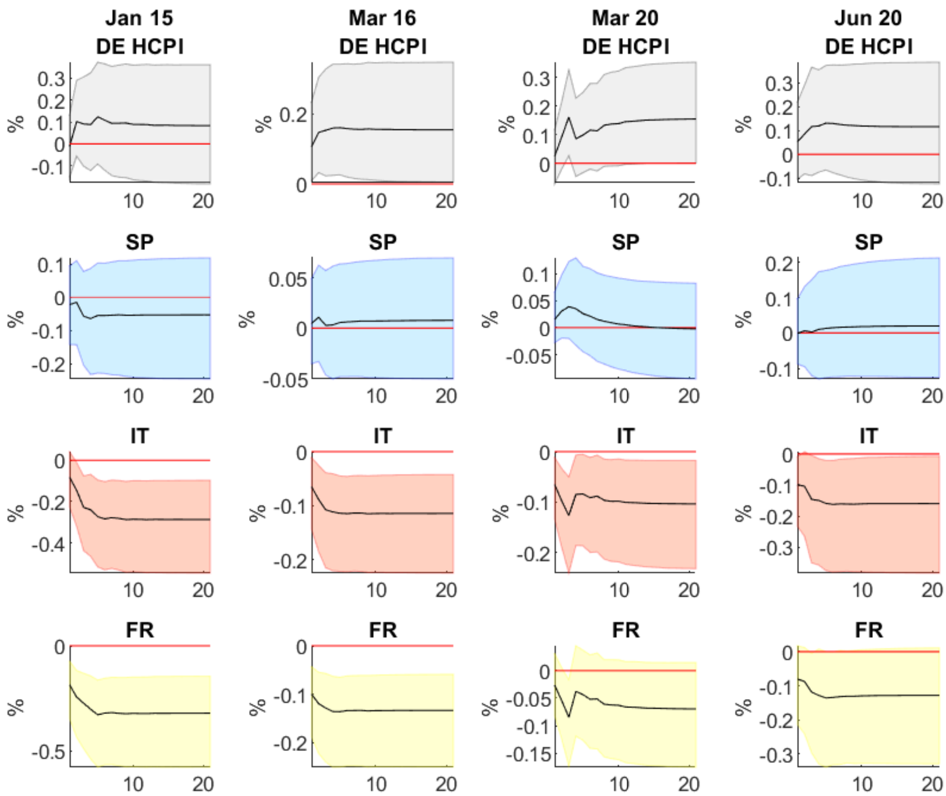


FIGURE 3.12: IRFs to an APP shock. Germany and countries differences with respect to Germany - HCPI. Mean and 16-84 percentiles of posterior distribution. Percentage changes.

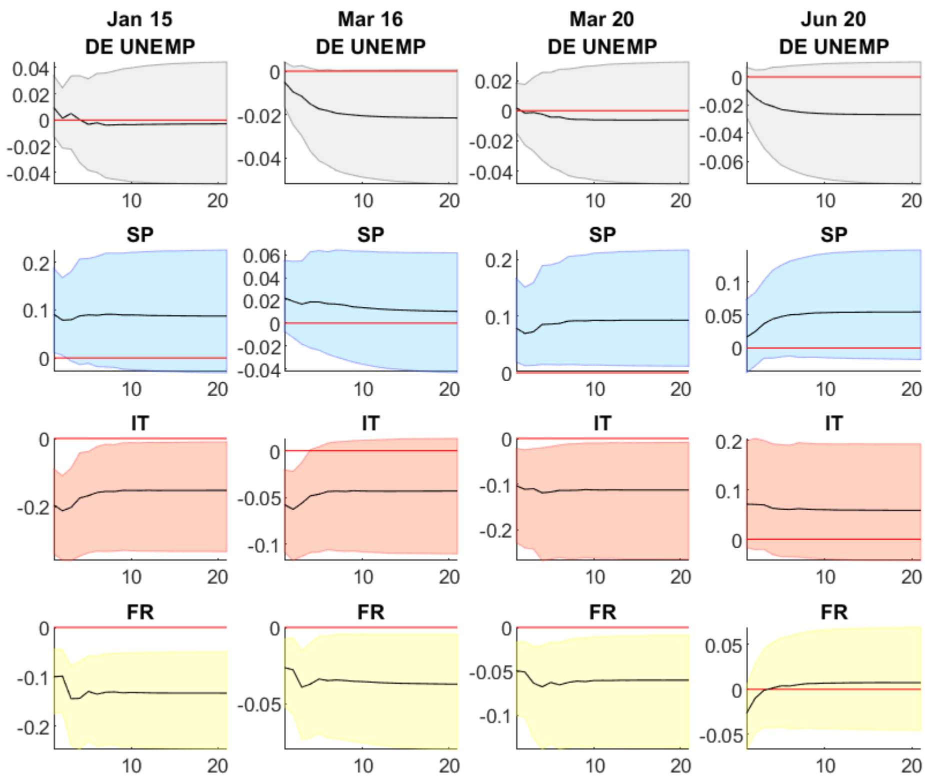


FIGURE 3.13: IRFs to an APP shock. Germany and countries differences with respect to Germany - Unemployment. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

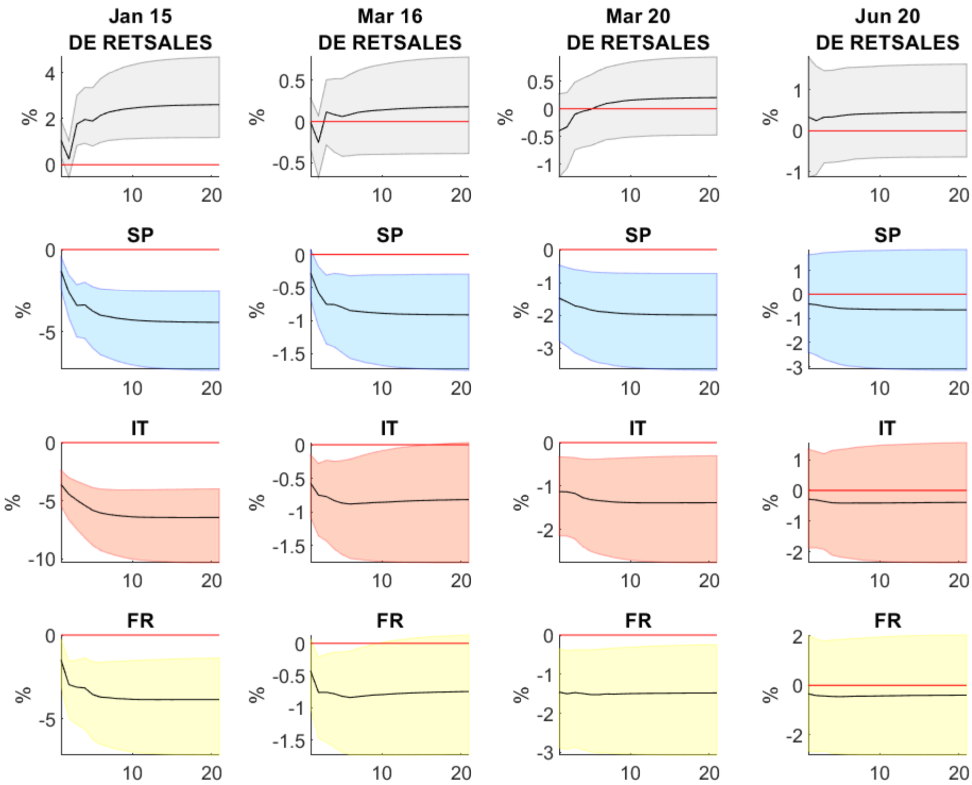


FIGURE 3.14: IRFs to an APP shock. Germany and countries differences with respect to Germany - Retail Sales. Mean and 16-84 percentiles of posterior distribution. All changes in percentage points.

Appendix A

Appendix - Chapter 1

A.1 Historical estimate of labor income risk

To estimate a time series of labor income risk I use survey data from PSID for the years 1968-1996 on males head of households aged between 20 and 64. I closely follow ? (?) on the selection criteria of observations and restrict the sample to individuals who satisfy the following conditions for twenty years (not necessarly consecutive): i) reported positive labor earnings and hours; ii) worked more than 10 hours a week and less than 14 hours per day (everyday) in a given year; iii) had an average hourly earnings between 2$ and 400$[1]; iv) do not belong to the poverty (SEO) subsample in 1968. Let $y_{i,t}$ be the logarithm of earnings of individual i for year t, I estimate the regression:

$$y_{i,t} = d_t + \alpha_i + \mathbf{fiX_{i,t}} + u_{i,t}$$

where d_t are year dummies, α_i are individual fixed effects and $X_{i,t}$ is a vector of regressors including education, age, experience, their squared terms and number of family members. I model the dynamic component of income $u_{i,t}$ as an AR(1) process augmented with a purely transitory component:

$$u_{i,t} = \rho u_{i,t-1} + \xi_{i,t} \tag{A.1}$$

where $\xi_{i,t}$ is an i.i.d. transitory shock with variance σ^2_ξ. Given the i.i.d. assumption, which implies $E[(u_{i,t-1}\xi_{i,t})] = 0$, (A.1) can be estimated using pooled OLS. To get the time series of σ^2_ξ, I compute the predicted values $\hat{\xi_{i,t}}$ and estimate their cross-sectional variance for every year. The estimated series of σ^2_ξ is reported in the left panel of figure (A.1) together with TFP. The right panel illustrates the two series linearly de-trended. Their correlation coefficient is -0.18.

[1]Dollar amounts for the year 1993. For the remaining years, I make an adjustment for inflation

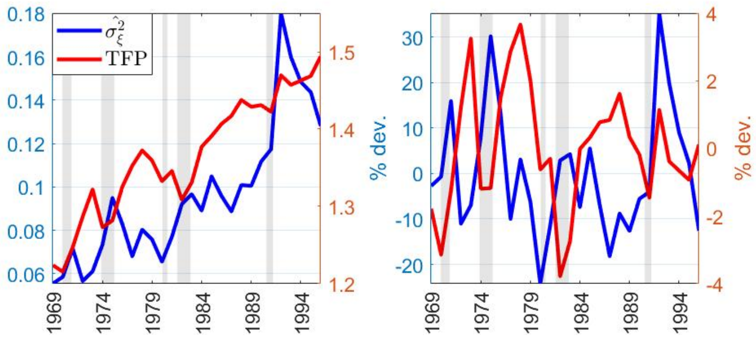


FIGURE A.1: TFP (red line) and labor income risk σ^2_ξ (blu line). Left Panel: levels. Right panel: percentage deviation from a linear trend. Author's computation on PSID data for 1968-1996

A.2 Responses of earnings and unemployment risk to a TFP shock

This Section reports the details on the estimation of the responses of earning risk σ^2_ξ, non-employment and average duration of unemployment to a 1% TFP shock. For the purpose of calibrating the model, I estimate three separate VARs with two lags ordering TFP first and applying Cholesky decompisition. Given that the time series of σ^2_ξ is at annual frequency, I estimate a Mixed-Frequency VAR (MF-VAR). The IRFs obtained from the three models are reported in figure (A.2). In figure (A.3) I report the responses to a TFP shock obtained using a MF-VAR for the four regressors together as a robustness check.

Let $y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix}$ be a vector containing two observable time series: an high-frequency variable y_{1t} and a low frequency variable y_{2t}. Define $y^*_t = \begin{pmatrix} y_{1t} \\ y^*_{2t} \end{pmatrix}$ to be a vector containing y_{1t} and the unobserved high frequency series y^*_{2t} underlying y_{2t}. The mapping between y_{2t} and y^*_{2t} is a one-sided filter of order m in the lag operator such that, for every low frequency t, $y_{2t} = C(L)y^*_{2t}$ holds.
The model to estimate is:

$$D(L)y^*_t = \varepsilon_t \tag{A.2}$$

where $D(L)$ is a polynomial in the lag operator of order p and $\varepsilon_t \sim N(0, \sigma_\varepsilon)$. Also, at every low frequency t, the following relation has to hold:

$$y_t = H(L)y^*_t \tag{A.3}$$

where: $H(L) = \begin{bmatrix} 1 & \mathbf{0_{1xm}} \\ 0 & C(L)_{1xm} \end{bmatrix}$

Equations (A.1) and (A.2) describe a State Space model in the form:

$$y_t = As_t \tag{A.4}$$

$$s_t = Fs_{t-1} + \varepsilon_t \tag{A.5}$$

with $_t \sim N(0, Q)$. Conditional on the choice of a time aggregator $C(L)$, matrices of coefficients F, Q and the unobserved component y^*_{2t} can be estimated using the Kalman Filter after replacing the missing observations with zeros or random numbers.

To choose $C(L)$, I follow ? (?) and approximate the annual deviation from the trend as the weighted average of seven consecutive quarterly growth rates:

$$y^y_{2t} = \frac{3}{4}y^q_{2t} + \frac{1}{2}y^q_{2t-1} + \frac{1}{4}y^q_{2t-2} + y^q_{2t-3} + \frac{1}{4}y^q_{2t-4} + \frac{1}{2}y^q_{2t-5} + \frac{3}{4}y^q_{2t-6}$$

but results are robust to applying the simple arithmetic sum.

After obtaining estimates of F, Q and the unobserved component y^*_{2t}, standard impulse response analysis can be applied. As for the MF-VAR the BIC criteria cannot be computed, I assume the same numbers of lags as in the annual VAR but results are robust to including more than one lag. I apply Cholesky decomposition and take the first shock. The third column of figure(A.2) reports quarterly IRFs of income risk to a 1% TFP shock.

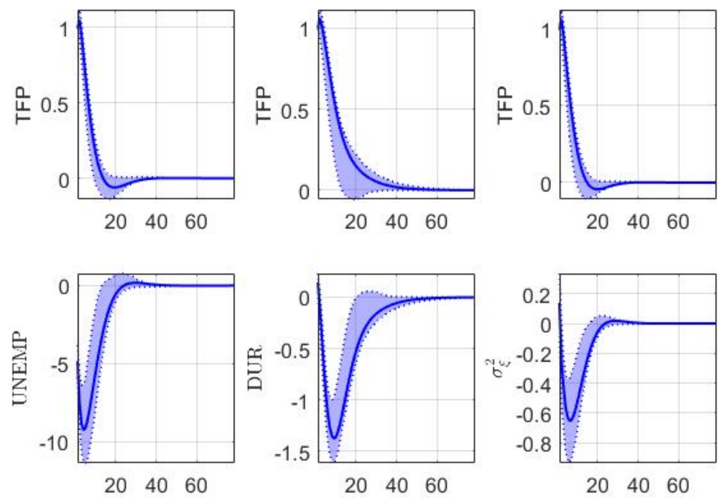


FIGURE A.2: IRFs of TFP and income risk to a 1% shock in TFP. Results from a MF-VAR(1) model with annual and quarterly data. Percentage deviations from a linear trend.

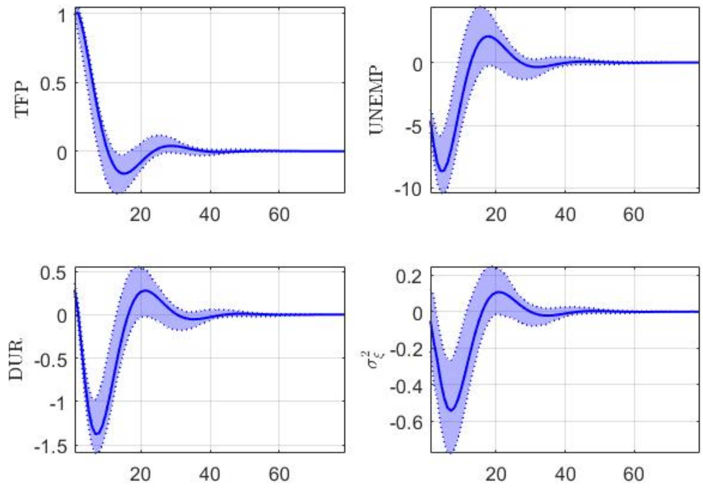


FIGURE A.3: IRFs of TFP, earning risk, unemployment and average unemployment duration to a 1% shock in TFP. Results from a MF-VAR(3) model with annual and quarterly data. Percentage deviations from a linear trend.

A.3 Solution Algorithms

A.3.1 Stationary Recursive Competitive Equilibrium

To solve for the stationary recursive equilibrium I implement the following steps:

1. Guess prices $\{r, \lambda\}$, call this initial guess $\{r^0, \lambda^0\}$

2. Given $\{r^0, \lambda^0\}$, I solve for the policy functions of the employed and the unemployed using the Endogenous Grid Method (? (?)). For the model in Section 3 this implies:

   (a) Define a grid over (a', ε') for the employed and over $(a', \varepsilon', h^{-'})$ for the unemployed

   (b) guess $c'_e(a', \varepsilon')^0$, $h'(a', \varepsilon')^0$ and $c'_u(a', \varepsilon', h^{-'})^0$, where the superscript 0 indicates the initial guess

   (c) For the employed, given $c'_e(a', \varepsilon')^0$ and $h'(a', \varepsilon')^0$, solve the system of three non-linear equations given by the two FOCS, (1.4) and (1.5), and the budget constraint. This gives $\{c_e(a', \varepsilon), a_e(a', \varepsilon), h(a', \varepsilon)\}$ for each point in the grid (a', ε)

   (d) For the unemployed, given $h'(a', \varepsilon')^0$ and $c'_u(a', \varepsilon', h^{-'})^0$, solve for $c_u(a', \varepsilon, h^{-'})$ using (1.6) and for $a_u(a', \varepsilon, h^{-'})$ using the non-linear equation defined by the budget constraint.

   (e) For the employed, interpolate over (a, ε) to get $\{c_e(a, \varepsilon), h(a, \varepsilon)\}$. For the unemployed, interpolate over $(a, \varepsilon, h^{-'})$ to get $c_u(a, \varepsilon, h^{-'})$

(f) Check if:

$$max(|c_u(a',\varepsilon',h^{-'}) - c_u'(a',\varepsilon',h^{-'})|) \leq \varepsilon$$
$$max(|c_e(a',\varepsilon') - c_e'(a',\varepsilon')|) \leq \varepsilon$$
$$max(|h(a',\varepsilon') - h'(a',\varepsilon')|) \leq \varepsilon$$

If these conditions are satisfied, stop. If otherwise, update the guesses on $c_e'(a',\varepsilon')^0$, $h'(a',\varepsilon')^0$ and $c_u'(a',\varepsilon',h^{-'})^0$ as follows:

$$c_e'(a',\varepsilon')^1 = \delta c_e(a',\varepsilon') + (1-\delta)c_e'(a',\varepsilon')^0$$

and in the same way for $c_u'(a',\varepsilon',h^{-'})^1$ and $h'(a',\varepsilon')^1$ and go back to c). I choose $\delta = 0.9$ and $\varepsilon = 10^{-5}$.

3. Solve for the stationary distribution Ω using a Montecarlo simulation with 150 thousands individuals and T= 500

4. I iterate over $\{r, \lambda\}$ using a Newton-Raphson algorithm performed by Matlab function `fsolve` in order to solve for the zeros of the system of equations defined by the asset market clearing condition and the government budget

A.3.2 Recursive Competitive Equilibrium

To solve for the transition, I choose the maximum number of periods T in which the economy reverts back to the stationary economy equal to 300 and proceed as follows:

1. Guess two sequences for prices $\{\lambda^0\}_{t=1}^T$, $\{r^0\}_{t=1}^T$

2. Given prices, solve backwards for policy functions $\{c_t^e(a,\varepsilon)\}_{t=1}^T$, $\{h_t^e(a,\varepsilon)\}_{t=1}^T$, $\{a_t^{e\prime}(a,\varepsilon)\}_{t=1}^T$, $\{c_t^u(a,\varepsilon,h^{-'})\}_{t=1}^T$ and $\{a_t^{u\prime}(a,\varepsilon,h^{-'})\}_{t=1}^T$ using the Endogenoues Grid Method (? (?)). This consists in repeating the steps described for the stationary equilibrium for each t starting from T. The difference is that now, instead of guessing on c_e', c_u' and h', these elements are given by $c_{e,t+1}$, $c_{u,t+1}$ and h_{t+1}

3. Solve for the distribution $\{\Omega\}_{t=1}^T$ forward using a Montecarlo method

4. Compute the sequences of $\{\lambda\}_{t=1}^T$ and $\{r\}_{t=1}^T$ implied by the guesses in the first step $\{\lambda^0\}_{t=1}^T$, $\{r^0\}_{t=1}^T$

5. Check if the following conditions are satisfied:

$$max(|\{\lambda^0\}_{t=1}^T - \{\lambda\}_{t=1}^T|) \leq \varepsilon_1 \tag{A.6}$$

$$max(|\{r^0\}_{t=1}^T - \{r\}_{t=1}^T|) \leq \varepsilon_2 \tag{A.7}$$

6. If (A.6) and (A.7) are both satisfied, stop. If otherwise, update the guesses taking convex combinations between $\{r^0\}_{t=1}^T$, $\{\lambda^0\}_{t=1}^T$ and $\{r\}_{t=1}^T$, $\{\lambda\}_{t=1}^T$

$$\{\lambda^1\}_{t=1}^T = \delta_1\{\lambda^0\}_{t=1}^T + (1-\delta_1)\{\lambda\}_{t=1}^T$$
$$\{r^1\}_{t=1}^T = \delta_2\{r^0\}_{t=1}^T + (1-\delta_2)\{2\}_{t=1}^T$$

   and go back to 2. Iterate over 2-6 until conditions (A.6) and (A.7) are both satisfied.

   For the results of the transition presented in Sections 5 and 6, I choose $\delta_1 = \delta_2 = 0.8$ and $\varepsilon_1 = \varepsilon_2 = 10^{-6}$

A.3.3 Optimal policy along the transition

Solving for the optimal policy along the transition implies solving for the entire sequence $\{\phi(t)\}_{t=1}^T$ which maximizes the objective in (1.8). In order to find $\{\phi^*(t)\}_{t=1}^T$, I proceed as follows:

1. Guess an initial candidate for $\{\phi(t)\}_{t=1}^T$, say $\{\phi^0(t)\}_{t=1}^T$

2. Starting from the first period, maximize (1.8) w.r.t. $\phi(1)$ taking the rest of the sequence as given. This implies solving for the recursive equilibrium described above for each possible candidate of $\phi(1)$.

3. Replace the corresponding element in $\{\phi^0(t)\}_{t=1}^T$ with the solution $\phi^1(1)$, where the superscript indicates that element $\phi(1)$ is the result of the maximization in the first iteration.

4. Go to the next element in the sequence and maximize (1.8) w.r.t. $\phi(2)$ taking the rest of the sequence as given and where $\phi^0(1) = \phi^1(1)$. More generally, repeat steps 2 and 3 for all the $\phi(t)$ in $\{\phi^0(t)\}_{t=1}^T$. This will give a new candidate sequence $\{\phi^1(t)\}_{t=1}^T$

5. Check if:

$$max(|\{\phi^1(t)\}_{t=1}^T - \{\phi^0(t)\}_{t=1}^T|) \leq \epsilon \tag{A.8}$$

   with ϵ small. If (5) is satisfied, stop. If otherwise, go back to 2 and iterate until condition (5) is satisfied.

   For the optimal policy result of Section 6 I choose $\epsilon = 10^{-4}$

A.4 Optimal Progressivity at the Steady State

Table (A.1) sums up the characteristics of the four groups of economies considered in the sensitivity analysis of Section 5.1. All the parameters not specified in the table below are set equal to the ones in the calibration of Section 4. Across different groups, Economy A represents the lower risk and/or higher TFP economy. Economy B is the benchmark economy used in the exercise in the next Section and doesn't vary across groups. This economy has a intermediate level of TFP and risk. Economy C is the riskiest and/or lower productive economy. The highest and lowest values of earning risk correspond to the estimates in ? (?) for the recessionary and expansionary states, while the benchmark value corresponds to their frequency weighted estimate of σ_{ξ}.

Few remarks related to the economies in groups iii) and iv) are in order. While in the benchmark economy the probabilities of transitioning from employment to unemployment and vice-versa are assumed to be uniform across different productivity realizations, when moving to economies with higher or lower unemployment risk, I assume that the changes in the transition probabilities depend on the idiosyncratic productivity. In particular, in economies with higher unemployment and unemployment duration (C economies in groups iii) and iv)), lower productive agents experience a larger increase in the probability of entering unemployment and a smaller decrease in the probability of exiting unemployment with respect to higher productive agents. The opposite happens in economies with lower unemployment and unemployment duration (A economies in groups iii) and iv)), where the decrease in unemployment probability and unemployment duration is assumed to be larger for lower than for higher productivity types. This is consistent with what we observe in the data: both the unemployment rate and the duration of unemployment tend to be higher and to increase more during recessions for agents with lower hourly wage. The idiosyncratic transition probabilities are set so that, on aggregate, the changes in the unemployment rate and the average duration of unemployment for recession and expansions match the data. These moments are specified in the third and fourth column of table (A.1).

A.4.1 CEV Decomposition of Welfare for the Benchmark Stationary Economy

Figure(A.4) reports the consumption equivalent variations (CEV) of moving from the optimal progressivity ϕ^* to each ϕ in the grid for the benchmark stationary economy. Moving from values of progressivity smaller than ϕ^* to the optimal level implies gains coming from a reduction and redistribution of hours worked and net

		z	σ_ξ	D_u	U	ϕ^*	label
i)	A	1	**0.061**	1.5	6.2%	0.07	$\sigma_{\xi,L}$
	B		**0.086**			0.22	$\sigma_{\xi,M}$
	C		**0.107**			0.33	$\sigma_{\xi,H}$
ii)	A	**1.05**	0.086	1.5	6.2%	0.22	z_H
	B	**1**					z_M
	C	**0.95**					z_L
iii)	A	1	0.086	**1.1**	**4.0%**	0.21	U_L
	B			**1.5**	**6.2%**	0.22	U_M
	C			**2.2**	**9.5%**	0.23	U_H
iv)	A	**1.05**	**0.061**	**1.1**	**4.0%**	0.07	$z_H, \sigma_{\xi,L}, U_L$
	B	**1**	**0.086**	**1.5**	**6.2%**	0.22	$z_M, \sigma_{\xi,M}, U_M$
	C	**0.95**	**0.107**	**2.2**	**9.5%**	0.34	$z_L, \sigma_{\xi,H}, U_H$

TABLE A.1: Parametrization of four groups of economies: i) economies with the same level of TFP and unemployment risk but different levels of earning risk; ii) economies with the same level of unemployment and earning risk but different levels of TFP; iii) economies with the same level of TFP and earning risk but different unemployment risk; iv) economies with different levels of TFP, earning and unemployment risk. Economy B correspond to the benchmark economy and it is the same across different groups. The last column refers to the corresponding label in graph(A.9). Bold characters highlight changes with respect to the benchmark economy. Unemployment duration, D_u is expressed in quarters.

losses deriving from a reduction and redistribution of consumption. When progressivity is lower than its optimal level, agents are induced to work more to be able to finance a larger capital buffer in order to self-insure against risk. This generates a utility cost which is only partly compensated by higher output and consumption (first panel). As progressivity increases, agents become better insured and their incentives to work and save decrease. This translates in lower welfare deriving from lower aggregate consumption and larger gains from a reduction in hours. At the optimal ϕ^*, these two forces perfectly compensate each other. Decomposing the total gains deriving from consumption and hours in distributional and level effects (second and third panel) highlights how increases in progressivity guarantee a more efficient allocation of resources through redistribution. Quantitatively, these re-distributive effects are almost as important as level effects in accounting for the total change in welfare due to consumption. However, they account only for a small variations in welfare due to changes in hours.

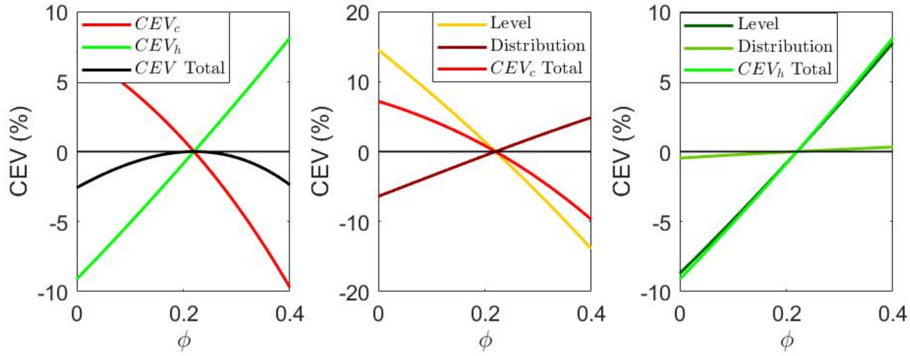


FIGURE A.4: Consumption equivalent variations of moving from ϕ^* to the the corresponding ϕ in the grid for the benchmark economy. First panel: decomposition of CEV welfare gains in consumption and hours. Second panel: decomposition of welfare gains deriving from consumption in level and distributional effects. Third panel: decomposition of welfare gains deriving from hours in level and distributional effects.

A.4.2 Comparative Statics - Aggregates and Prices

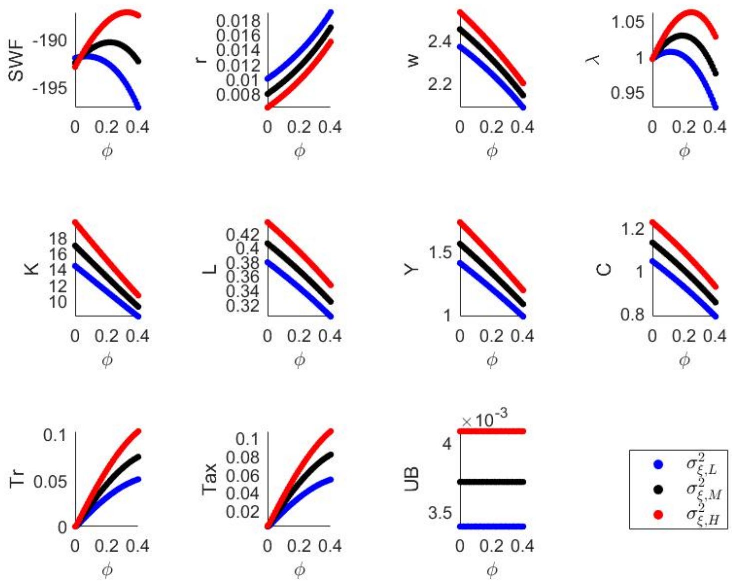


FIGURE A.5: Main aggregates and prices for the economies in group i). Economies differ in their earning risk σ_ξ at the steady state

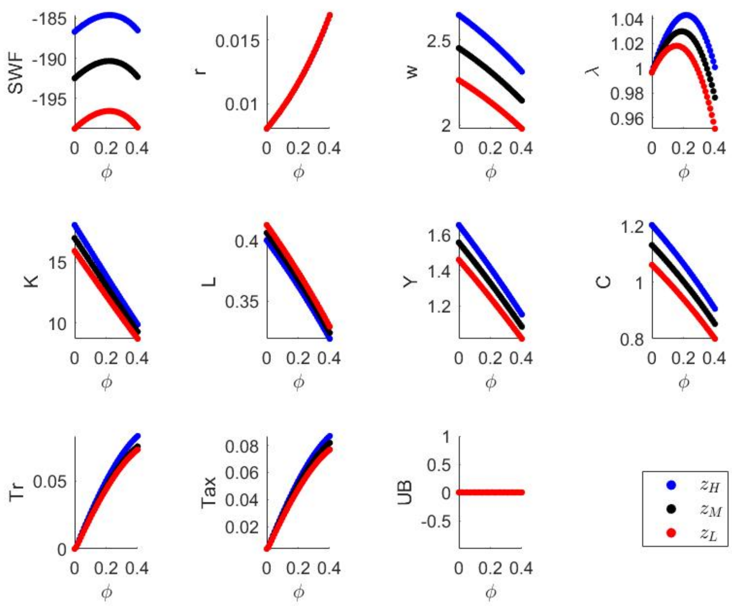


FIGURE A.6: Main aggregates and prices for economies in group ii) at the steady state. Economies differ in their TFP level, z.

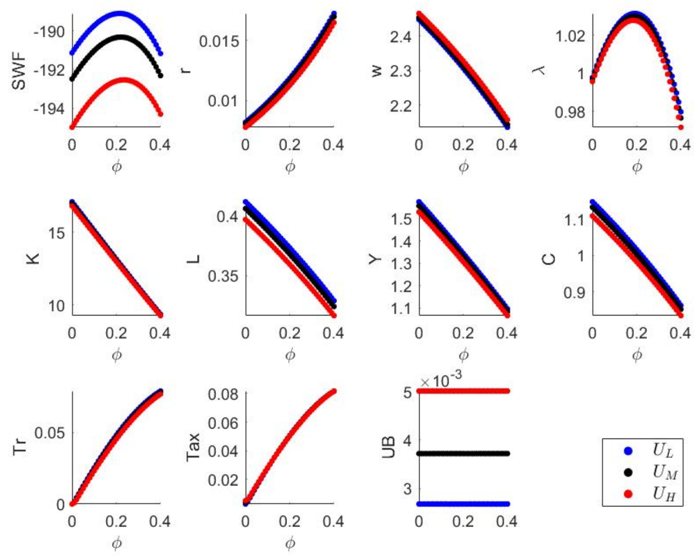


FIGURE A.7: Main aggregates and prices for economies in group iii) at the steady state. Economies differ in their unemployment risk

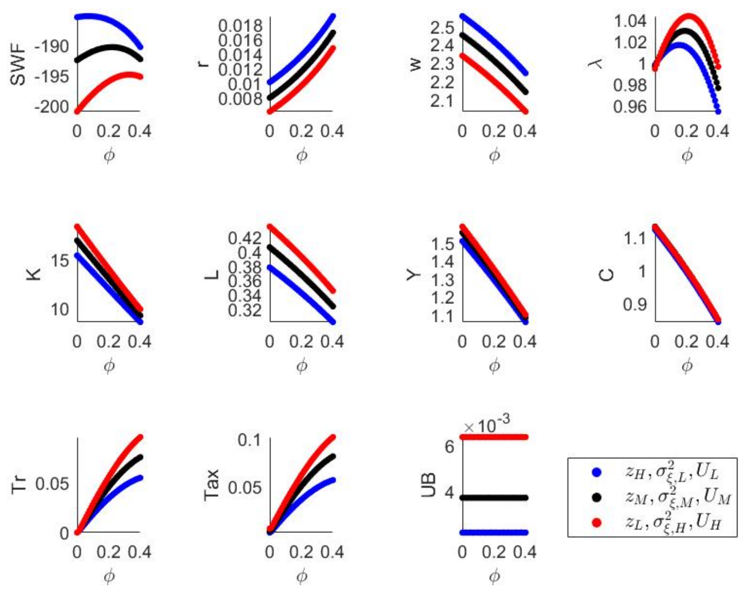


FIGURE A.8: Main aggregates and prices for economies in group iv) at the steady state. Economies differ in their TFP, unemployment and earning risk, σ^2_ξ.

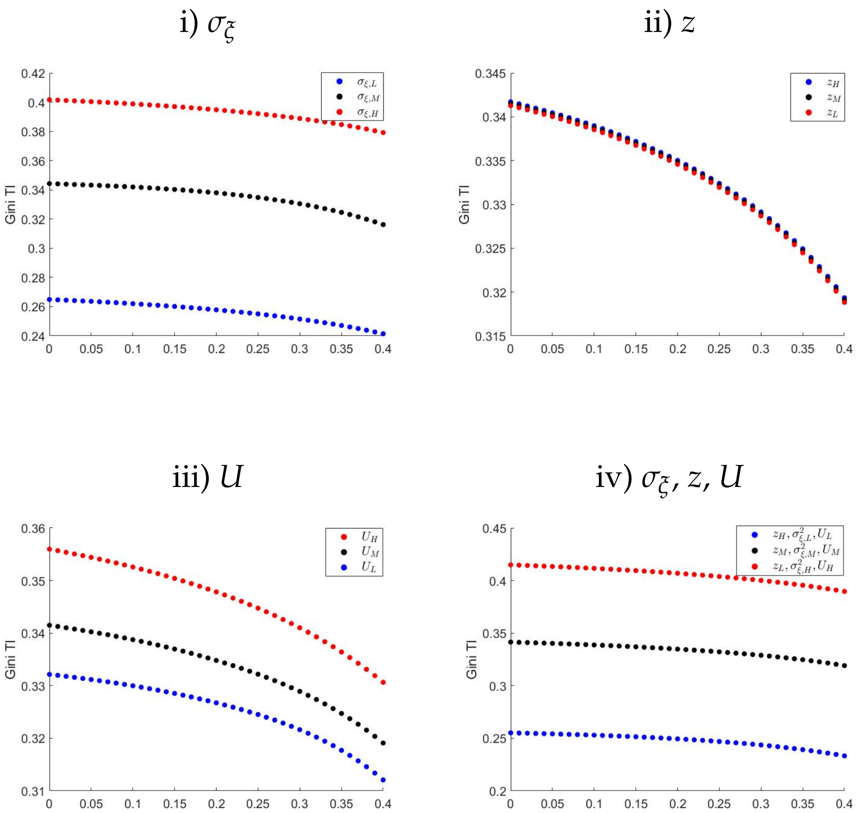


FIGURE A.9: Gini of total income as a function of progressivity parameter ϕ for the four groups of economies in table(A.1)

Appendix B

Appendix - Chapter 2

B.1 U-news indexes

We construct our U-news$^+$ and U-news$^-$ indexes using newspaper articles from *Dow Jones Factiva*. We focus our search to three major US newspapers, in terms of circulation, namely *The Wall Street Journal*, *The New York Times* and *The Washington Post*, and to news related to the US economy over the time period from June 1980 to December 2019. For each newspaper, we look for all the articles, in a given month, in which the word "unemployment" appears within a predetermined distance, in any order, to another word that denotes a negative or positive development. More specifically, we first define two semantic groups, one containing words which share a root denoting an increase or high level (*group 1*) and another containing words which share a root denoting a decrease or low level (*group 2*):

- *group 1*. The words included in this group have one of the following roots: "high-"■, "increas-", "ris-", "rose-", "soar-", "rais-" or "up-".

  group 2. The words included in this group have one of the following roots: "down-" or "low-" or "slow-" or "decreas-", "drop-", "fall-", "fell-", "slip-", "declin-".

We classify an article as a *bad news* item if the word "unemployment" appears within a 5-word distance to a word belonging to semantic *group 1*, but not within a 1-word distance to a word in semantic *group 2*. Symmetrically, we define an article as a *good news* item if the word "unemployment" appears within a 5-word distance to a word belonging to semantic *group 2*, but not within a 1-word distance to a word in semantic *group 1*. We choose the 5-word distance criteria to maximize the probability that the corresponding word in *group 1* (bad news) or in *group 2* (good news) is related to the word "unemployment" and not to other words. We obtain very similar results if we restrict this criteria to 4-word or 3-word distance. Given this first classification, we then clean our two measures of bad and good news by substracting, for both measures, the number of articles that can be classified as belonging to both groups according to our criteria. In fact, this class of articles cannot be clearly classified as positive or negative, either because these articles deliver mixed signals about unemployment,[1] so that their resulting tone is *neutral*, or because the word "unemployment" is incidentally mentioned close to a word in *group 1* and *group 2*, even if the article does not include direct information about unemployment (e.g. articles reporting presidential talks close to the elections). The articles belonging to this last category represent on average 6% of total articles over the period considered. After cleaning the measures, the number of all *bad news* in a given month is the value of the U-news^{+} index for that month, while the number of all *good news* in a given month is the value of the U-news^{-} index for that month.

B.2 Alternative search

An alternative measure of good news can be derived based on the word "employment" as opposed to "unemployment". We define the variable E-news^{+} as the total number of articles, in each month, in which the word "employment" appears within a distance of 5 words to a word denoting an increase or high level, i.e. to a word belonging to semantic *group 1*, according to the definition in Appendix A.1. As before, we clean this measure by removing all the articles that are selected under both good and bad search criteria.

[1]For example, on the 12th of March 2010, *The Wall Street Journal* writes "[...] initial claims for unemployment insurance dropped to 462,000 in the week ended March 6th, down 6,000 from the week before. Meanwhile, the number of people collecting unemployment checks rose 37,000 to 4.6 million in the week ending Feb. 27■.

B.3 Additional Results

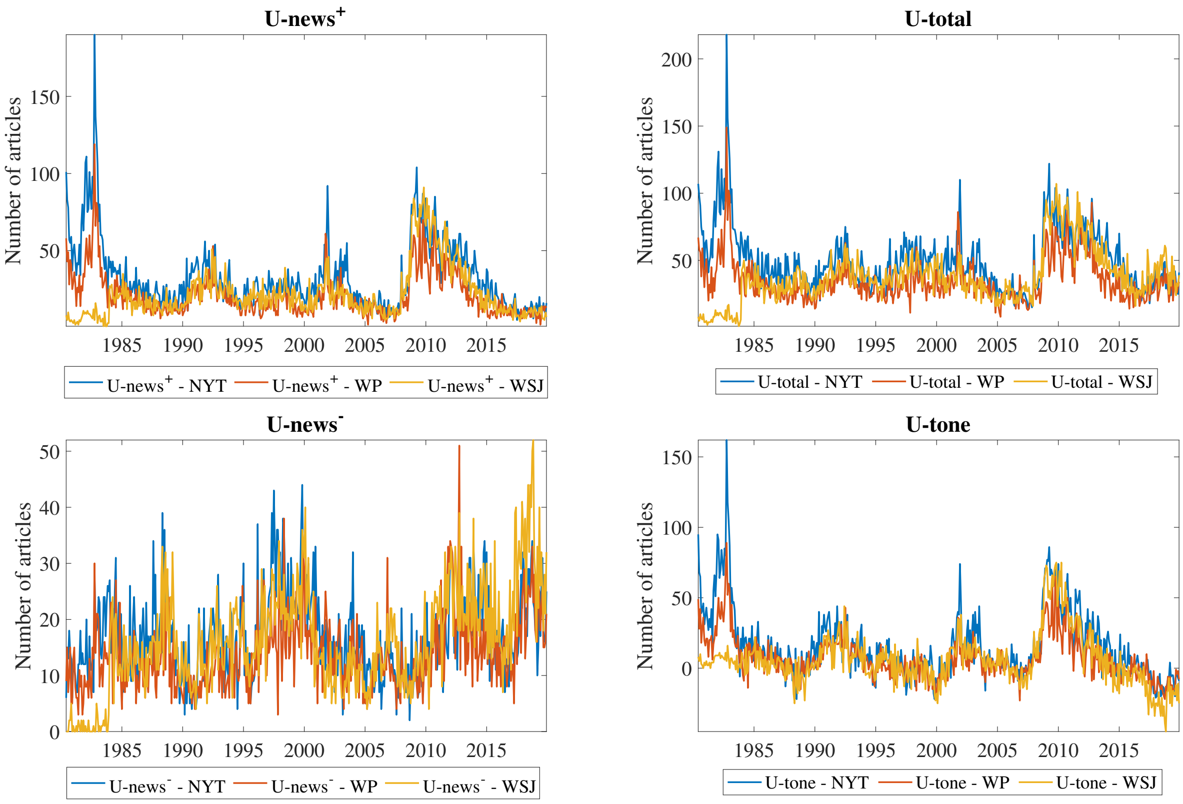


FIGURE B.1: Bad news and good news by newspaper

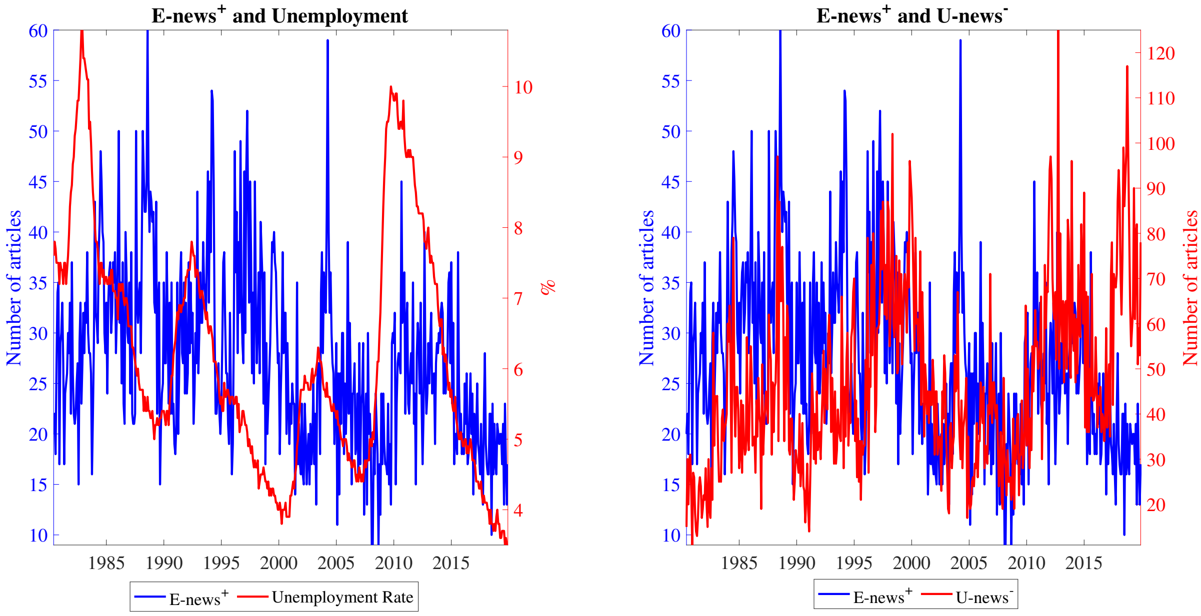


FIGURE B.2: Alternative measure of good news - E-news^{+}

FIGURE B.3: Response of news coverage to unemployment changes - U-tone - Sample excluding the Great Recession (1980:06 - 2007:12)

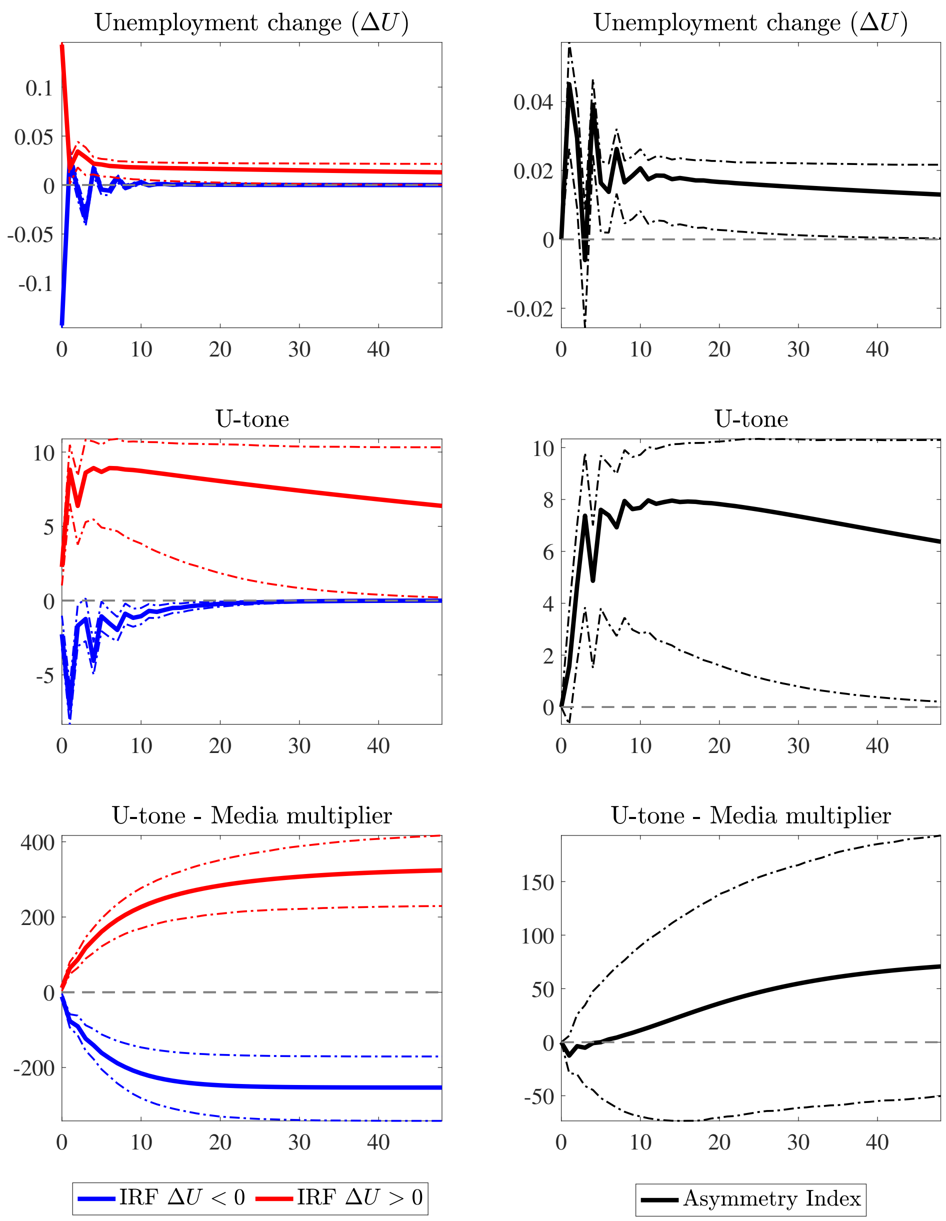
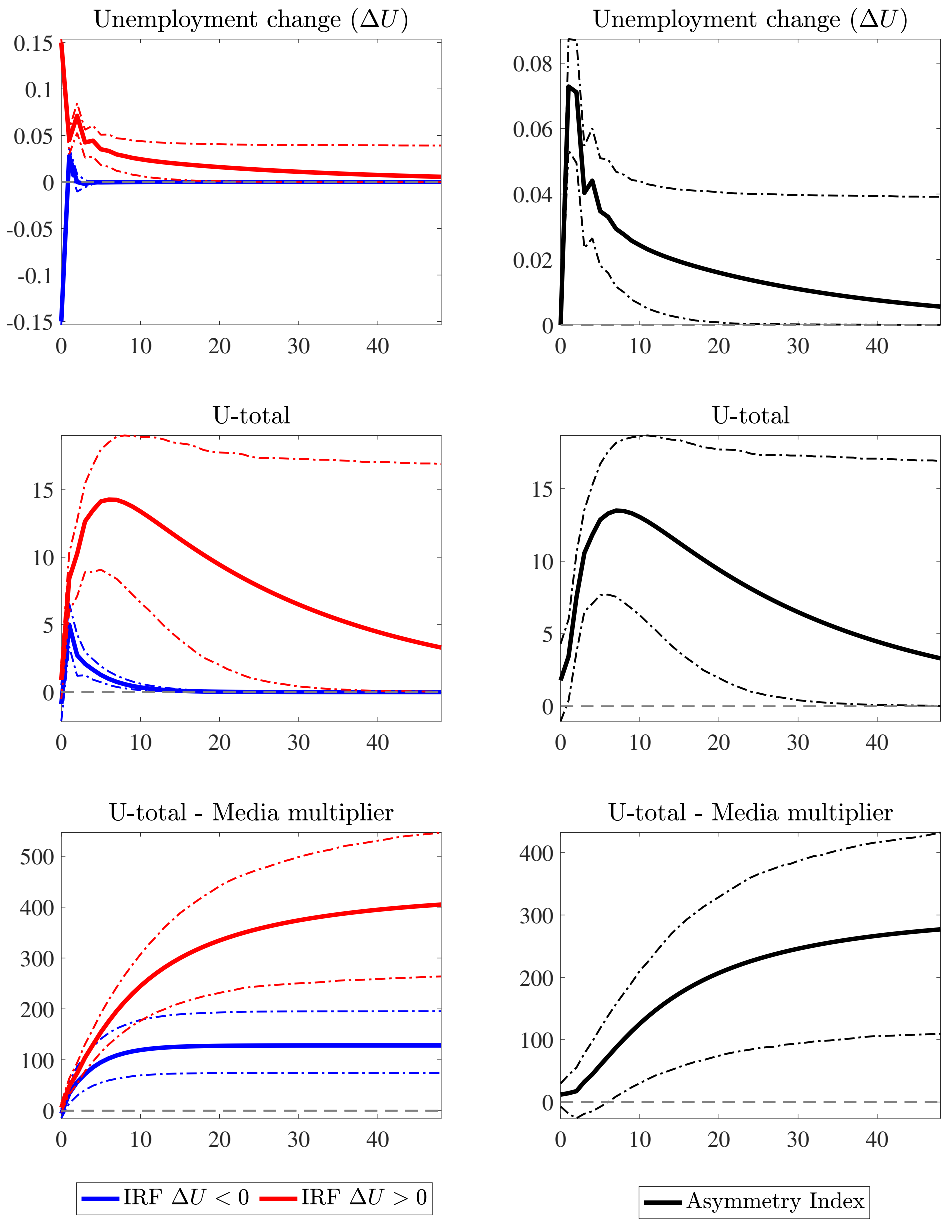


FIGURE B.4: Response of news coverage to unemployment changes - U-total - Sample excluding the Great Recession (1980:06 - 2007:12)



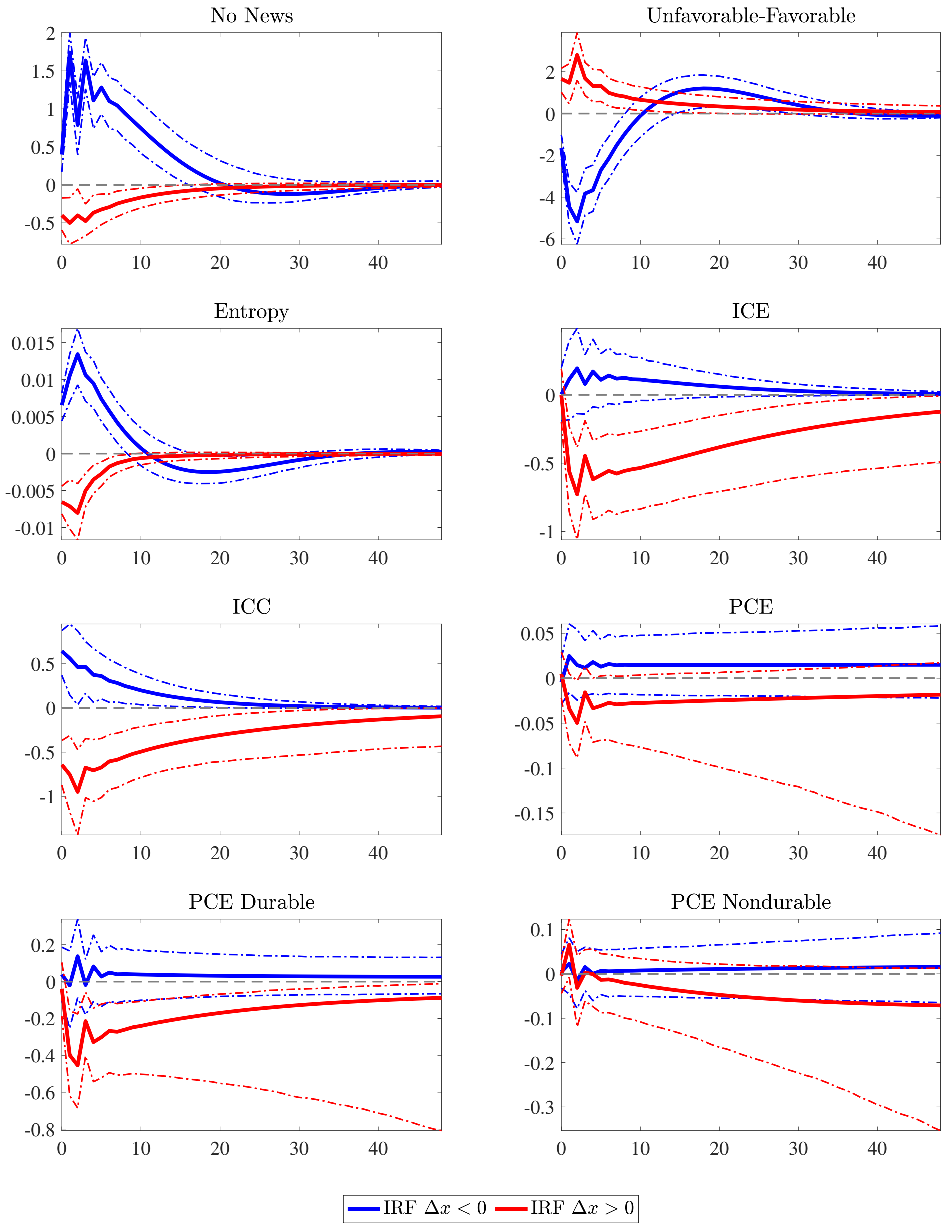


FIGURE B.5: Asymmetric effects of news - IRFs - Sample excluding the Great Recession (1980:06 - 2007:12)

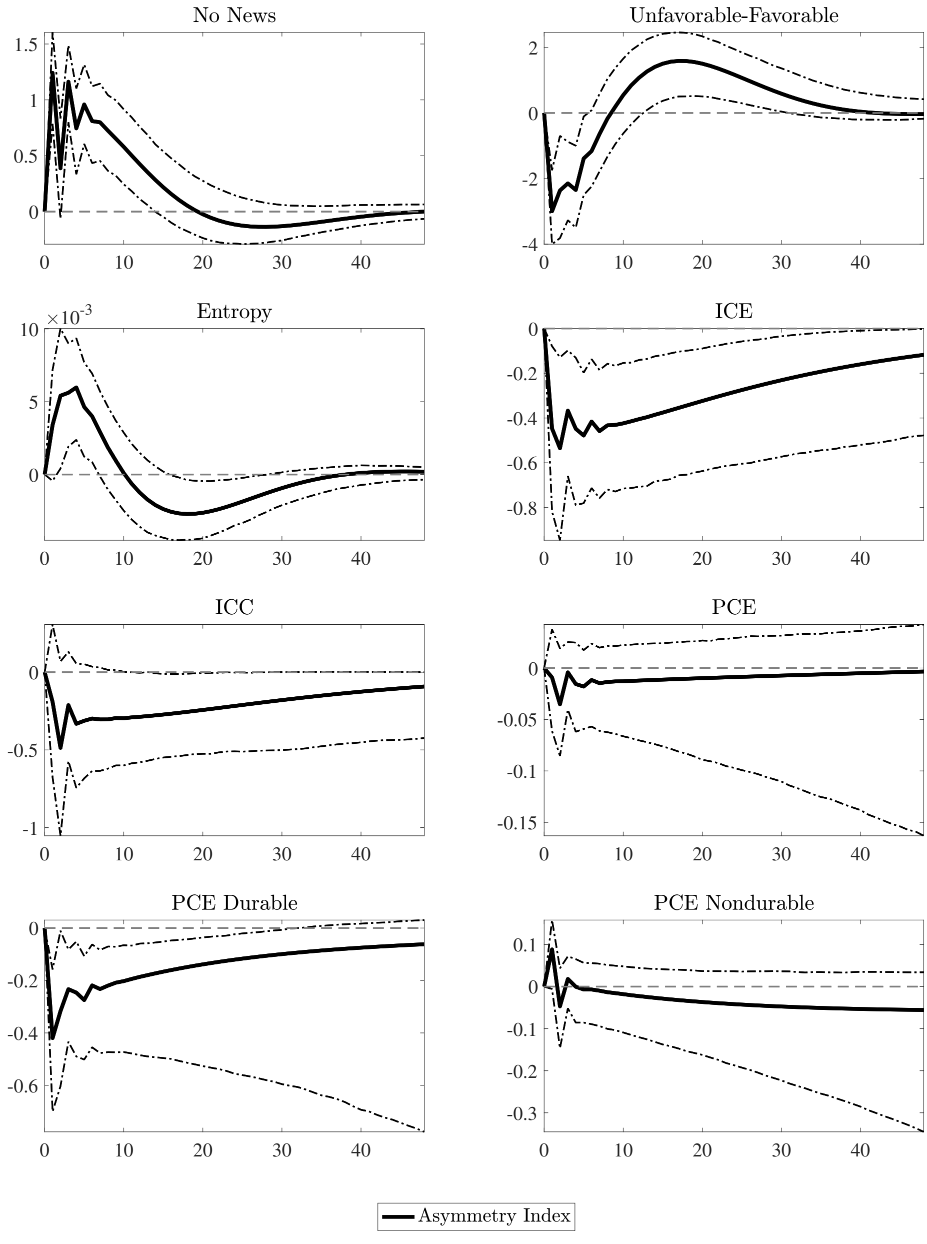


FIGURE B.6: Asymmetric effects of news - Asymmetry Indexes - Sample excluding the Great Recession (1980:06 - 2007:12)

FIGURE B.7: Response of news coverage to unemployment changes - U-tone - Including Industrial Production growth and PCE Inflation

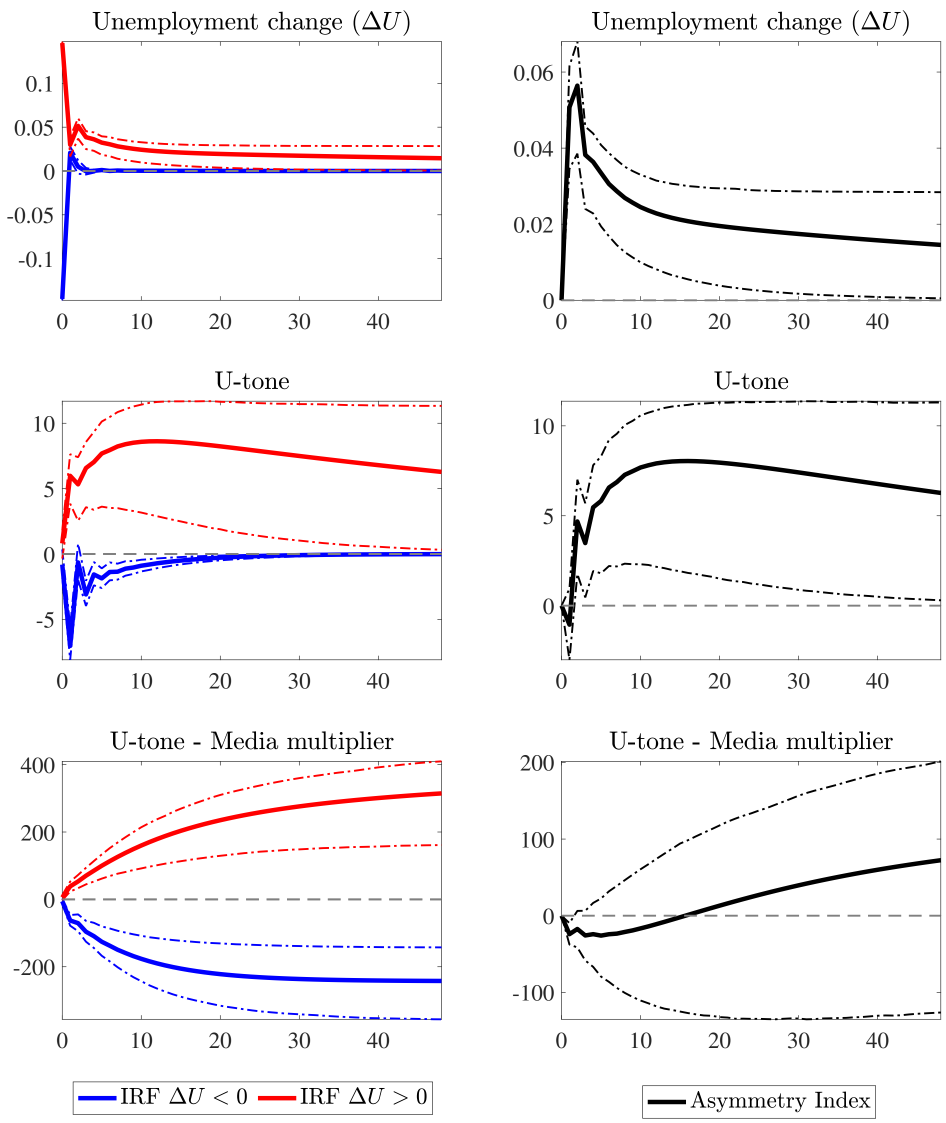
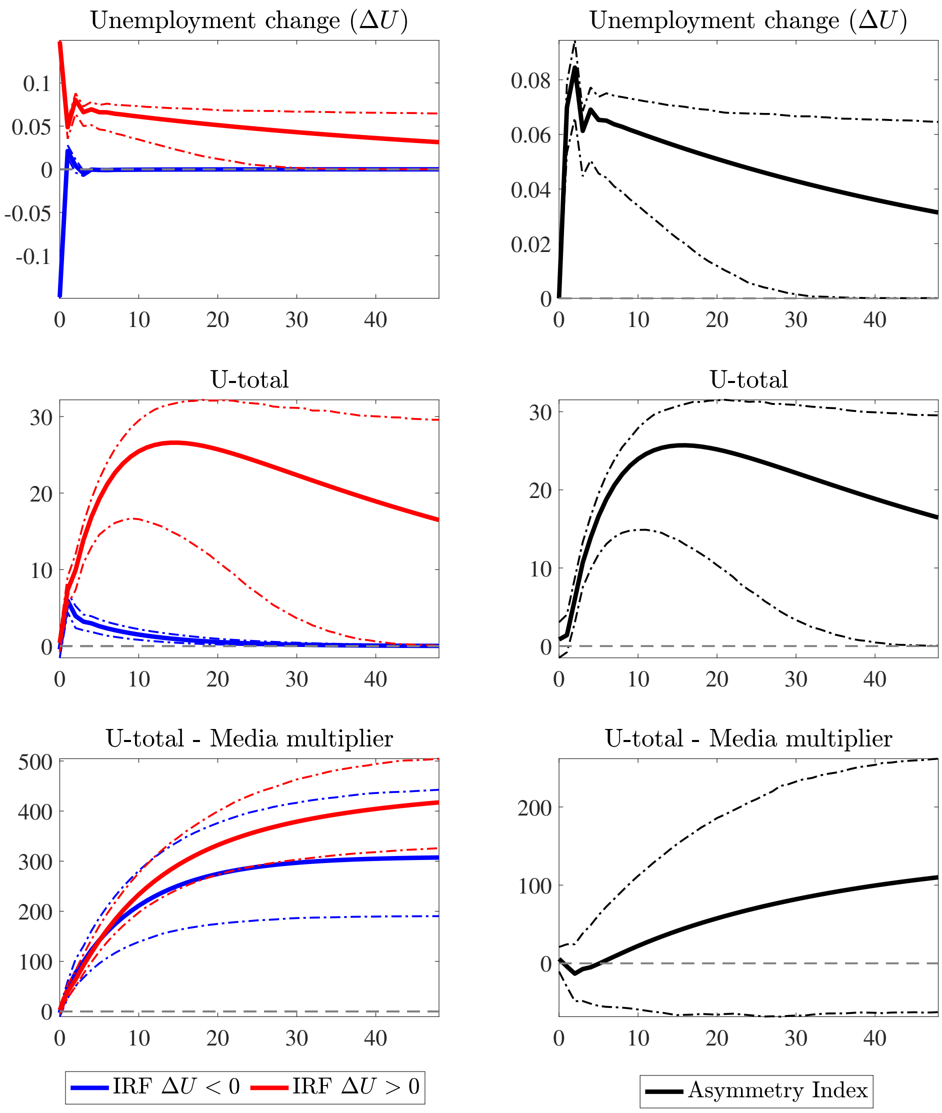


FIGURE B.8: Response of news coverage to unemployment changes - U-total - Including Industrial Production growth and PCE Inflation



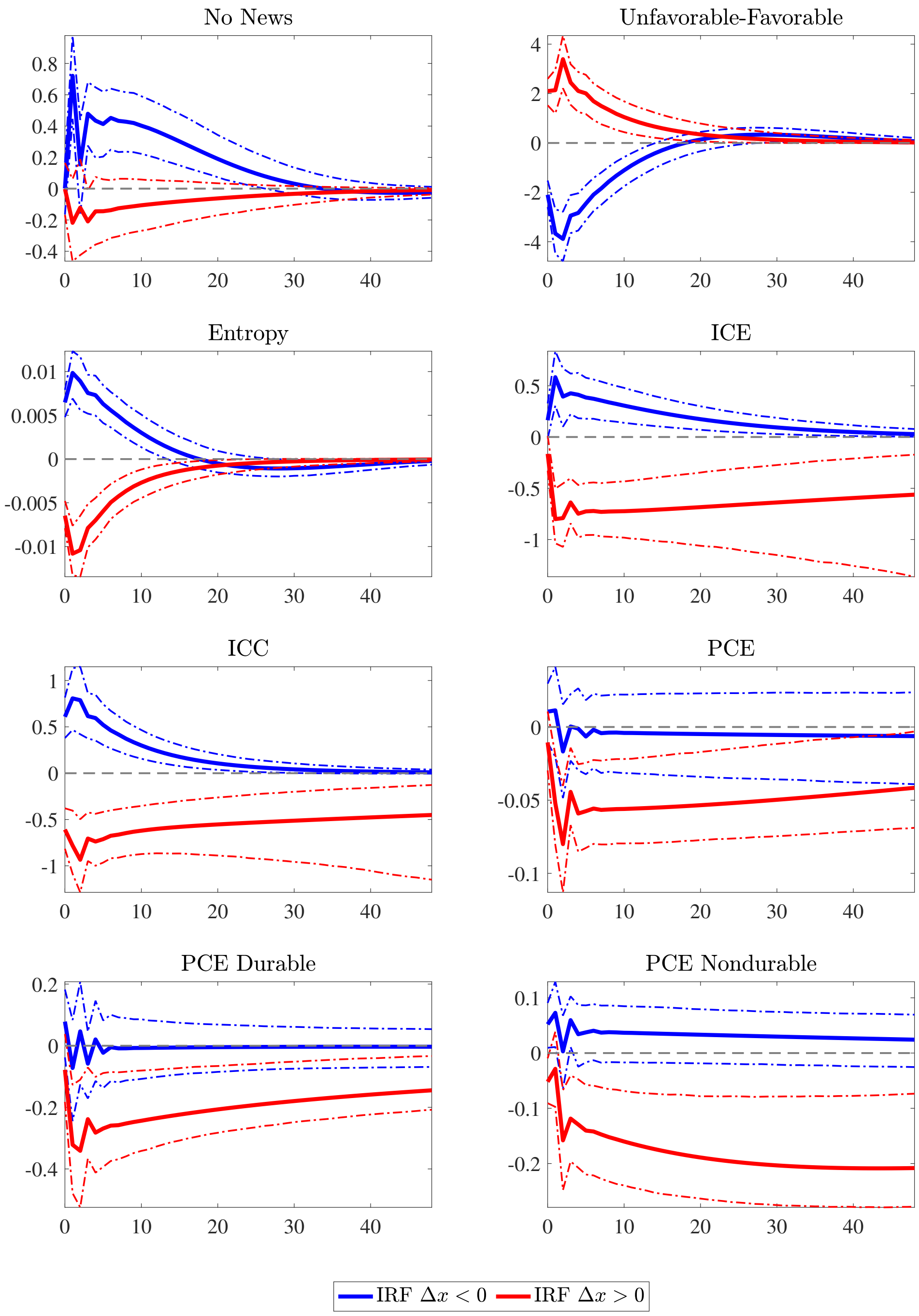


FIGURE B.9: Asymmetric effects of news - IRFs - Including Industrial Production growth and PCE Inflation

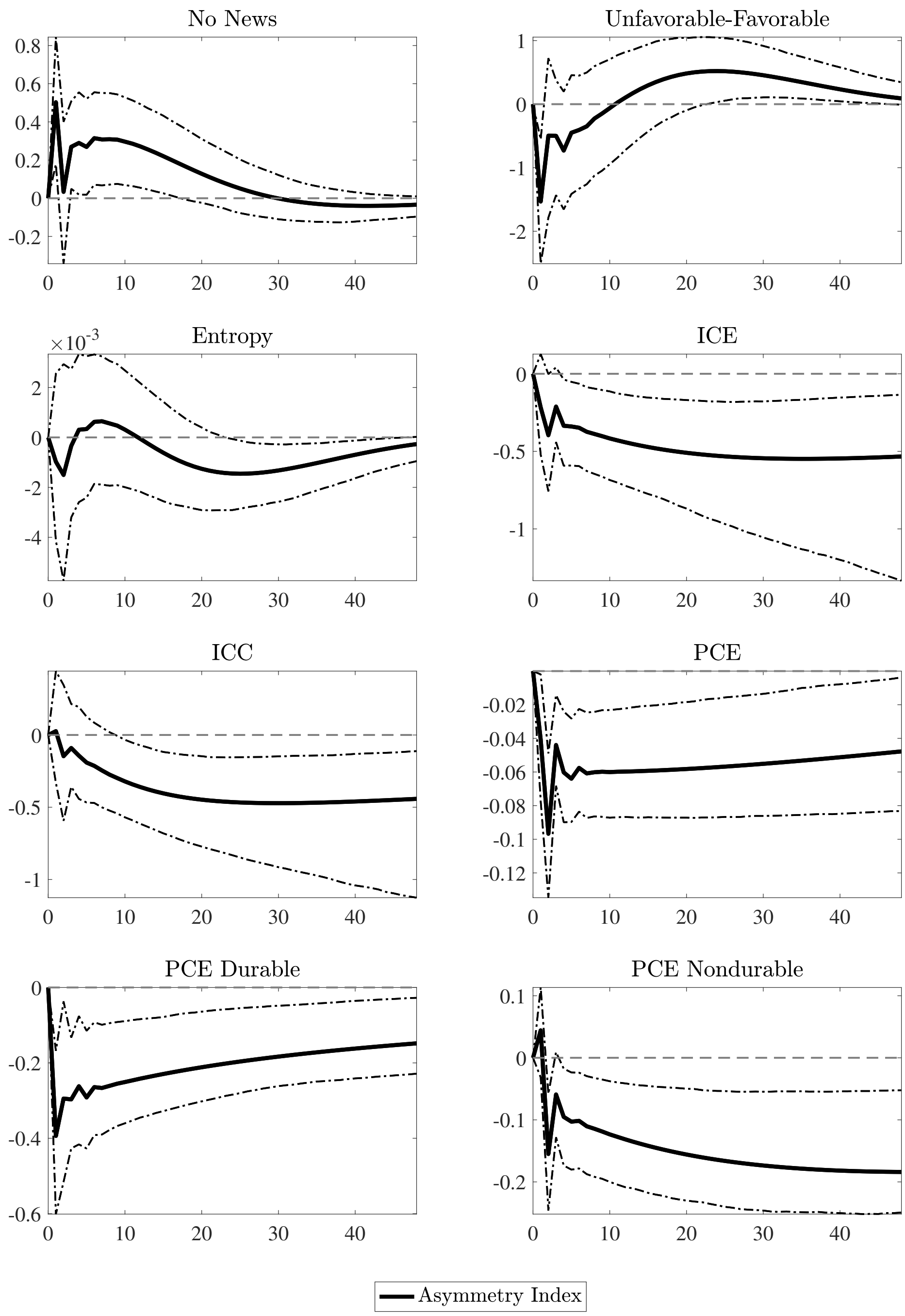


FIGURE B.10: Asymmetric effects of news - Asymmetry Indexes - Including Industrial Production growth and PCE Inflation

FIGURE B.11: Response of news coverage to unemployment changes - U-tone - Including Stock Prices growth

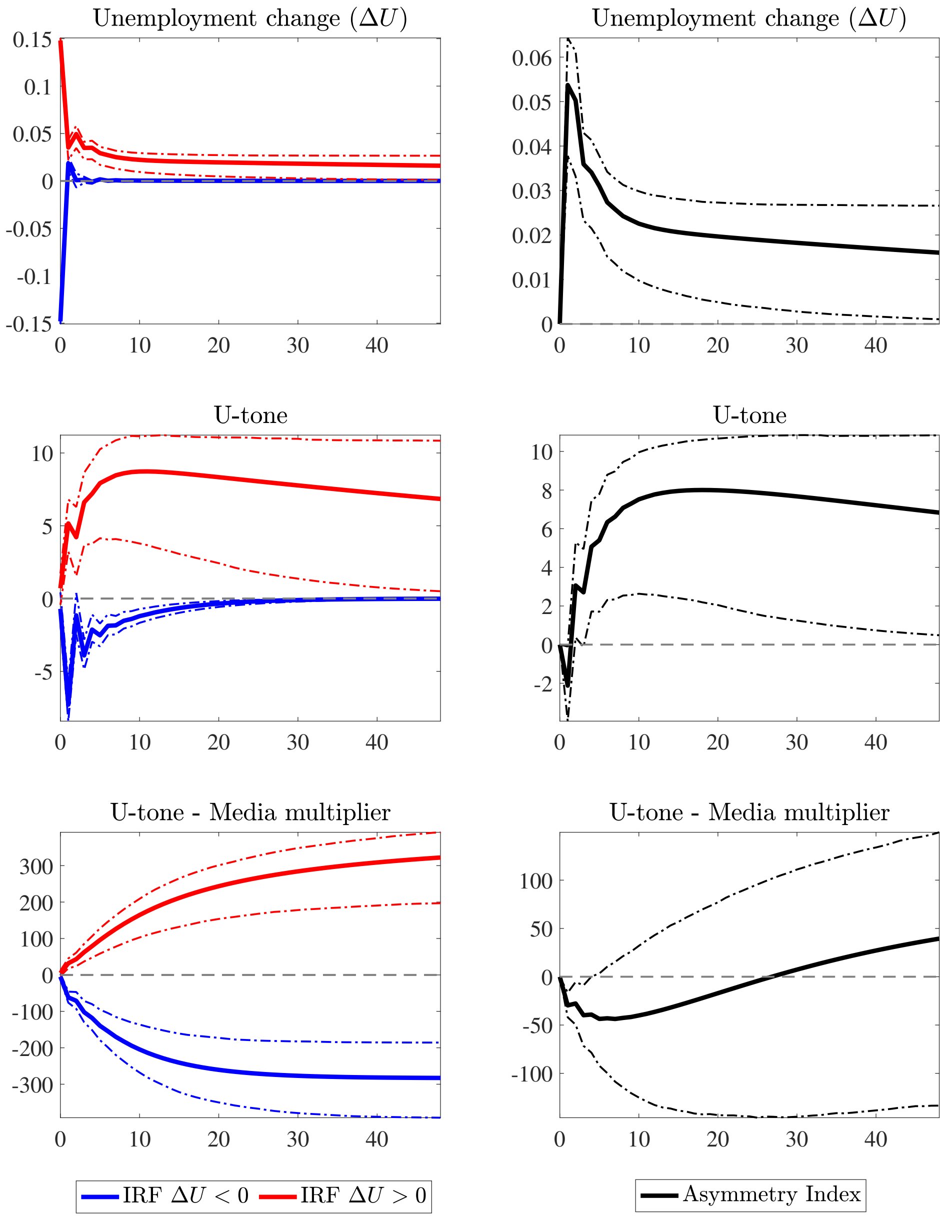
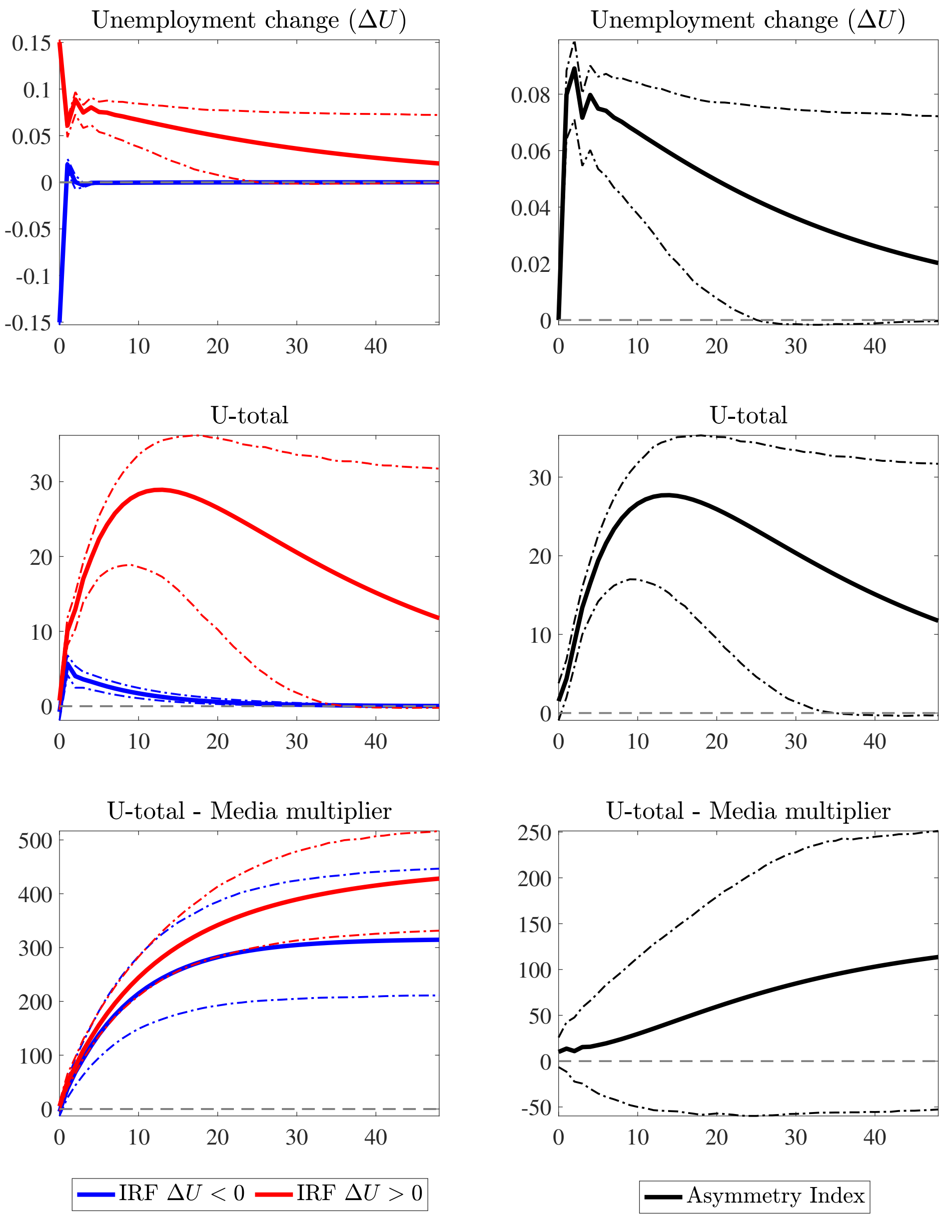


FIGURE B.12: Response of news coverage to unemployment changes - U-total - Including Stock Prices growth



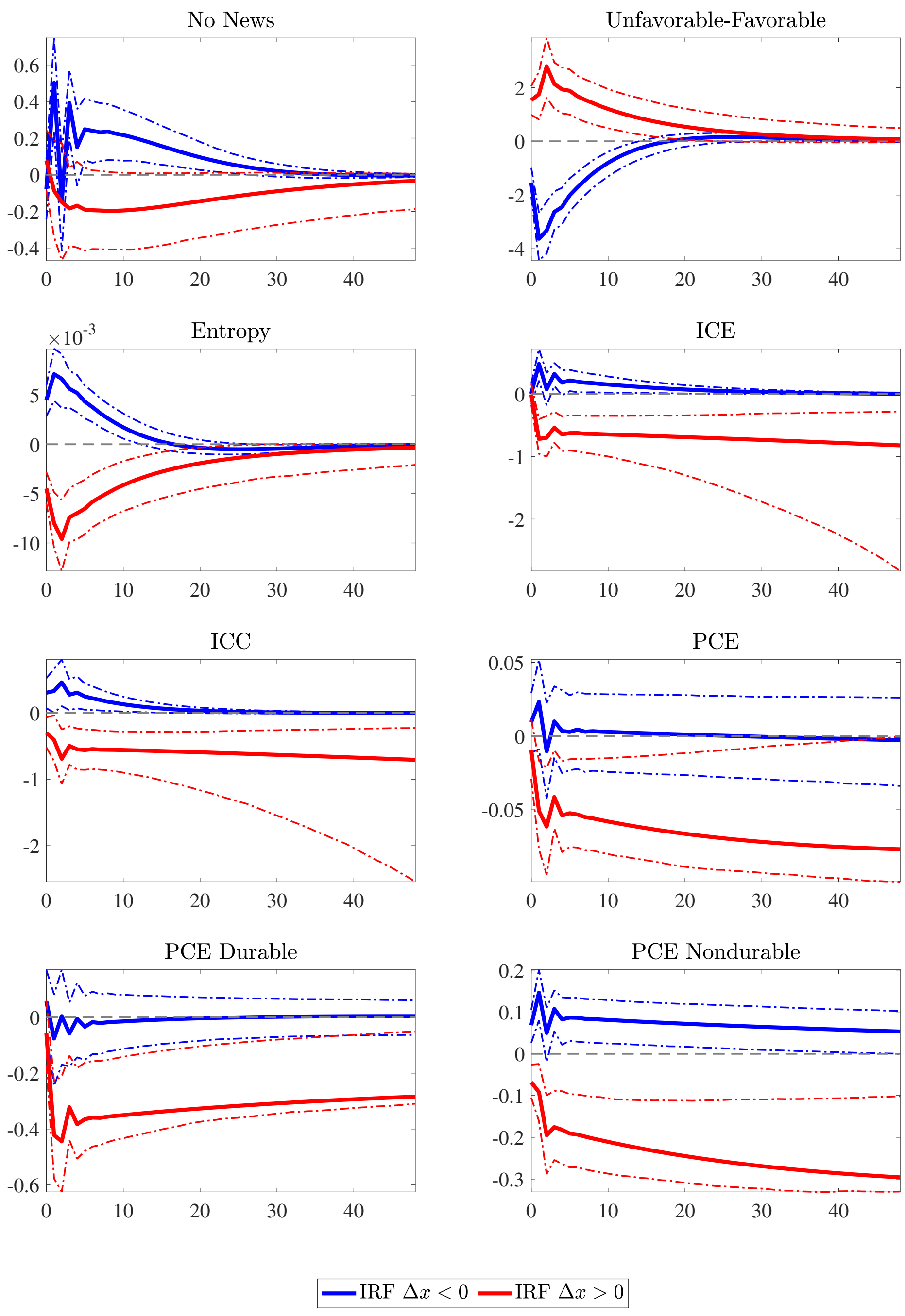


FIGURE B.13: Asymmetric effects of news - IRFs - Including Stock Prices growth

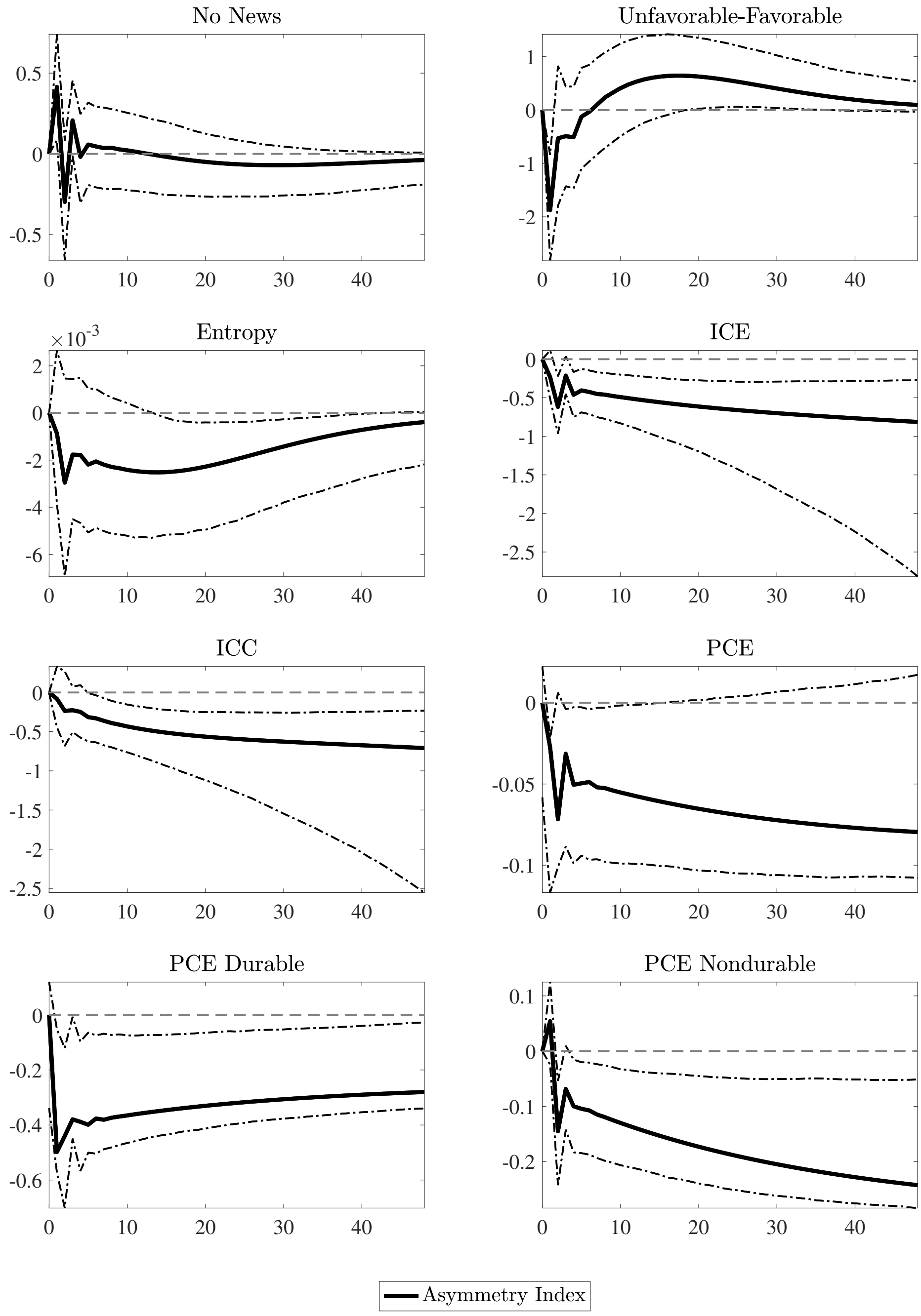


FIGURE B.14: Asymmetric effects of news - Asymmetry Indexes - Including Stock Prices growth

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