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**Working Paper**

## Financial cycles and co-movements between the real economy, finance and asset price dynamics in large-scale crises

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# FinMaP-Working Paper No.61



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FINMAP –

FINANCIAL DISTORTIONS AND MACROECONOMIC  
PERFORMANCE: EXPECTATIONS, CONSTRAINTS AND  
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TITLE

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## ABSTRACT

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Keywords: Housing Prices, Stock Prices, Business Cycle, Co-movements, Large-Scale Dataset.  
JEL-Codes: C23 E32, E44, E52, G10, G21

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# Financial cycles and comovements between the real economy, finance and asset price dynamics in large-scale crises.

Maria Teresa Punzi\*

## Abstract

We empirically analyze asset price boom-bust cycles over a long-run period of 1896-2014 for the U.S., the Netherlands, Norway and Sweden. We focus on macro-financial linkages to understand if these are common phenomena during financial crises, or if the linkage was simply amplified during the last financial crisis in 2007. In particular, we ask if economic recessions are usually followed by asset price and credit bursts, and find that housing and stock prices tend to lead real economic activities, while developments in credit and money markets typically lag developments in the real economy. The dynamic of assets' portfolio allocation effects in times of crises has been the same.

We also study the cyclical behaviour of real GDP per capita, asset prices (housing or stocks) and lending. In particular, we test for the existence of comovements with asset prices during periods of crisis. We find that the correlations between real GDP per capita and real housing prices and between lending and real housing prices have increased since World War II, and that the increase is much more pronounced if we compare the Great Recession with the Great Depression. Monetary policy shocks also become more important in explaining the comovements in the Great Recession, compared with the Great Depression. Furthermore, inflation shocks have played an important role in explaining the correlation between house prices and lending for Scandinavian countries.

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# 1. Introduction

Housing and stock prices showed a strong run-up in the years preceding the Great Recession, but their downturns at the beginning of the recession contributed to the substantial drop in macroeconomic activity.<sup>1</sup>

The recessions triggered by the financial crisis tended to be deeper in countries that experience strong housing boom-bust cycles. Consequently, there has been great interest in understanding the linkages between housing, macroeconomic activity and financial stability.

During boom periods, rising house prices benefit households through a sharper amplification of their net worth. But when house prices decline, the level of indebtedness may exceed the value of the house, thus wiping net worth. Indeed, with the financial crisis, many households experienced a shrink of their wealth relative to their debt, finding it hard to meet their mortgage repayments and other financial obligations despite very low policy interest rates.<sup>2</sup>

In this paper we investigate if this macro-financial linkage is specific to the recent global crisis or if it is common to all previous crises. Figure 2 shows that in the U.S. since 1896, house prices have always peaked before a banking crisis, and a recession has always followed the crisis, meaning that the housing boom-bust cycle is a phenomenon that is common to each financial crisis.

We focus on a large-scale dataset covering four advanced economies (U.S., Netherlands, Norway and Sweden) over the period 1896-2014 and ask the following questions: Do economic recessions always follow asset price and credit bursts in advanced economies? Have the cyclical behaviors changed over time? How are changes in the comovement with asset prices related to structural shocks?

This paper has a threefold structure. First we use the concordance index (CI) developed by Harding and Pagan (2002) to study the linkages between downturns in financial markets and the real economy. GDP, housing prices and lending activities are highly procyclical, but it is not clear which variables lag or lead the business cycle. The concordance index provides a measure of the fraction of time the two time series are in the same phase (expansion or downturn) of their respective cycles. In particular, we compute CIs of real GDP per capita with lags and leads of the financial variables to test if the phases of the real economy are more related to the past or to the future phases of financial variables. We construct individual country indices and an index for all four countries pooled together. We find that the concordance of real GDP per capita with the past phases of real house prices and real stock prices is somewhat higher than the concordance with the contemporaneous phases, while the index with the future phases of the loan-to-GDP, money-to-GDP and loan-to-money ratios is higher than with the contemporaneous phases. These findings indicate that asset prices tend to lead real activity,

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<sup>1</sup>See Figure 1.

<sup>2</sup>The huge declines in housing prices and housing net worth were one of the shocks that pulled the economy into recession. See Iacoviello and Guerrieri (2015).

while developments in credit and money markets typically lag developments in the real economy.

Second, we estimate a time-varying parameter structural vector autoregression (TVP-VAR) model with stochastic volatility. The TVP-VAR allows us to capture when gradual change or a structural break has occurred in the economy. Given the large-scale sample size, from 1896 to 2014, potential time-varying structures in the estimation of macroeconomic variables are found. The model determines what shocks replicate responses of macroeconomic variables according to data and theory. We find that overall, monetary and technology (TFP) shocks are the main shocks replicating asset price booms in all countries.

Third, we document the changes that have occurred in the cyclical behaviour of real GDP per capita, assets prices (housing or stocks) and lending. In particular, we test the existence of comovement with asset prices in the U.S., the Netherlands, Norway and Sweden since 1896 and we evaluate if the correlations during crisis periods have changed over time and if the same shocks have affected such correlations. We find that the correlations between real GDP per capita and real housing prices and between lending and real housing prices has increased since World War II (WWII), and the increase is much more pronounced if we compare the periods of the Great Recession and the Great Depression. While asset prices have always experienced a boom before a recession, the macro-financial linkage has become more important during recent decades. Monetary policy shocks have also been much more important in explaining the comovements in the Great Recession, rather than the Great Depression. With a different approach, Jordà, Schularick and Taylor (2015a) show that an accommodating monetary policy lead to housing price booms.<sup>3</sup> Furthermore, inflation shocks have played an important role in explaining the correlation between house prices and lending for Scandinavian countries.

A growing literature has investigated the link between monetary policy and house prices and the implications of house price fluctuations for monetary policy; see Del Negro and Otrok (2007), Goodhart and Hofmann (2008), Jarocinski and Smets (2008), Allen and Rogoff (2011), Glaeser, Gottlieb et al. (2012), Williams (2011), Kuttner (2012), Mian and Sufi (2015). Most of these papers found that productivity shocks, accommodative monetary policy and housing demand shocks are the main drivers of the fluctuations of real and financial variables when looking only at data going back to 1980.<sup>4</sup> This study makes a clear contribute to a growing literature drawing on large-scale datasets. Jordà, Schularick and Taylor (2016) construct a long-run dataset covering disaggregated bank credit for 17 advanced economies from 1870 to 2008. They show that in the second half of the 20th century, banks and households have been heavily leveraging up through mortgages, and that this great mortgaging has had a major influence on financial fragility in advanced economies, and has also increasingly left its mark on business cycle dynamics. Knoll, Schularick and Steger (2014) present new historical house

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<sup>3</sup>Jordà, Schularick and Taylor (2015a) implement an instrumental variable local projection methods.

<sup>4</sup>Den Haan and Sterk (2011) estimate a structural VAR model to prove that financial innovation is a weak driver of the great moderation.

price indices for 14 advanced economies since 1870. They find that house prices remained constant from the 19th to the mid-20th century, but rose sharply in the second half of the 20th century. Booming land prices, not construction costs, were the key driver of this trend. Jordà, Schularick and Taylor (2015b), drawing on a long-run dataset going back to 1870, distinguish different types of bubbles in terms of the extent of their impact and how their economic costs differ. When credit growth fuels asset price bubbles, the dangers for the financial sector and the real economy are much more substantial, and the damage done to the economy by the bursting of credit boom bubbles is significant and long lasting. Simo-Kengne, Miller, Gupta and Aye (2015) apply a time-varying parameter vector autoregressive model to estimate the effects of housing and stock prices on U.S. consumption growth rate, using data from 1890 until 2012. We expand on previous work by comparing four economies in terms of asset price cycles. We concentrate on the comovements of asset prices with GDP and lending activities to analyze if the comovements increase around periods of crisis, and if they have changed over time. We also contribute to the literature by studying the contribution of shocks during periods of crisis.

The paper is organized as follows. Section 2 describes the data and provide evidences of asset price leading cycle through the concordance index. Section 3 presents the time-varying parameter VAR model and reports the main results of the impulse response functions. Section 4 describes the comovements and what shocks are more important in explaining the correlation across macro-financial variables. Finally, the last Section concludes.

## 2. Data Description and Concordance Index

In this section, we study the co-movements between asset prices, real activity and financial variables over the business cycle for a sample period from 1896 until 2014. Data are at an annual frequency. The sample combine data from Schulraick et al. (2012), Eitrheim and Erlandsen (2004), Shiller (2005), Bank of International Settlement, National Central Banks and National Statistics.<sup>5</sup> We particularly focus on the behavior of house prices in the business cycle over the large-scale dataset, with the aim of detecting whether house prices have played an important role not only before the financial crisis in 2007, but also during previous crises. Figure 1 reports the real house price index for the U.S., the Netherlands, Norway and Sweden over the period of 1896-2014. Disregarding the exceptional periods around the World Wars and the financial crisis in 1929, the real house price index shows itself to be quite stable until the 1990s, at which time there is a strong run-up evident for all countries. However, over the business cycle, all countries show a strong pro-cyclical behaviour and quite often a banking crisis coincides with a peak in house prices.<sup>6</sup> See Figure 2. We can also notice international spillover

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<sup>5</sup>Appendix 1 reports details on sources of the data.

<sup>6</sup>Banking crises are defined by a dummy variable and are taken from Schularick and Taylor (2012).

effects of crises: a banking crisis first occurred in Norway during 1899, followed by contemporaneous banking crises in the U.S., the Netherlands and Sweden in 1907. Nordic countries experienced another banking crisis during 1921-1922, right after WWI, with the Netherlands being the first country to enter the crisis in 1921. Around 1931 another banking crisis affected Norway and Sweden, as a reflection of the Great Depression of the U.S. in 1929. The Netherlands are somewhat immune from banking crises, even if house prices experience a strong boom-bust cycle, but the crisis arrived some years later in 1939. Again, the crisis in Nordic countries clearly spilled over to the Netherlands, after a period of lag. Since WWII, these countries have been more successful in avoiding banking and financial crises. These years of calmness reflected the effort of the Bretton Woods system of monetary management to establish the rules for commercial and financial relations among advanced economies in the mid-20th century. The Bretton Woods system promoted the adoption of a monetary policy to peg the exchange rate to gold and the ability of the IMF to fill up temporary imbalances of payments. The Bretton Woods system also encouraged the cooperation among countries to prevent competitive devaluation of currencies. The Bretton Woods system ended in March 1973, when a system of generalized floating exchange rates was adopted for the major international currencies. The 1970s and early 1980s were characterized by protracted inflation, record-setting interest rates, and higher than normal rates of market volatility. By early 1979 the annual rate of inflation in the U.S. doubled, coupled with a strong rise in oil prices. To combat inflation, the Federal Reserve launched a strong anti-inflationary monetary policy in the period 1979 to 1982, eventually raising nominal and real interest rates to unprecedented levels for the postwar period. In the early 1980s, the U.S. experienced its first recession since the 1929s, entering into a deep banking crisis with the bankruptcy of the Continental Illinois Bank in May 1984.<sup>7</sup> The U.S. crisis spilled over to Nordic countries years later, during 1988 and 1991. Since then, several countries have started targeting inflation, opening the era of the Great Moderation, until the collapse of the housing market in the U.S. in 2006, followed by a deep recession in most advanced countries.

We seek to analyze how financial cycles are synchronized with business cycles in order to identify if the co-movement is specific to the recent financial crisis, or whether it is a common feature to all such events. Traditional approaches identify the business cycle with phases of expansion and contraction in which time periods move from peak to trough. Harding and Pagan (2002) proposed the concordance index between macroeconomic variables to identify turning points, i.e. the average number of periods in which two variables move from a high point (peak) to a low point (trough) in the same phase of the cycle. The turning points define a binary variable  $w_{z,t}$  as follows:

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<sup>7</sup>In 1982, Mexico, Argentina, Brazil, Chile, Peru, Venezuela, the Philippines and Yugoslavia also experienced a financial collapse.



$$w_{z,t} = \begin{cases} 1, & \text{if } z \text{ is in expansion at time } t \\ 0, & \text{otherwise} \end{cases}$$

where  $w = x, y$  is a vector containing the two variables for which we want to calculate the concordance index. One variable in  $z$  is going to be the country's GDP, since we are interested in the synchronization of business and financial cycles.

The concordance index is a measure of the fraction of time the two variables  $w_{x,t}$  and  $w_{y,t}$  are in expansion or in downturn during the same phase, as follows:

$$C_{x,y} = \frac{1}{T} \sum_{t=1}^T [w_{x,t}w_{y,t} + (1 - w_{x,t})(1 - w_{y,t})]$$

If the concordance index takes values close to 1, then the two variables are always in the same phase (i.e. pro-cyclical), otherwise, for values close to 0 they are in opposite phases (i.e. countercyclical).

In this respect, we construct the concordance index taking into consideration leads and lags over the business cycle in order to evaluate if the current phase of the business cycle is related to previous or future financial cycles.

Figure 3 computes the concordance index relative to GDP for real house prices, real stock prices, interest rate spread, loan-to-GDP, loan-to-money and money-to-GDP. The sample includes the U.S., Norway, Sweden and the Netherlands over the period from 1896 until 2014, at yearly frequency. House and stock prices are indicators of asset prices; loans measure total lending activities, including credit by banks to non-financial corporations and households; money corresponds to the stock of M2; spread rates are calculated as the difference between 10-year government bonds and policy rates; loan-to-money is a proxy for financial and banking dependency. The vertical line at time 0 indicates the average of real GDP per capita peaks. Therefore, periods between -4 and 0 indicate phases of GDP expansion, while periods between 0 and 4 indicate phases of contraction. Every interval indicates a change in year. Real house prices peak exactly at time 0, meaning that development in the housing variable coincides with developments in real variables. Past phases of real stock prices and spread rates are higher than current or future phases, indicating that real stock prices lead real activities. However, co-movements with stock prices are lower, at their peaks, than that of housing prices at their peaks. Different behaviour is found on credit and money markets. Loan-to-GDP and money-to-GDP show an higher concordance index after GDP peaks, meaning that those variables lag real activities.<sup>8</sup> Loan-to-money peaks exactly at the GDP peak, similar to house prices. This last result shows how financial-banking cycles are related to business cycles, and how such dependency increases with house prices. Jordà, Schularick and Taylor (2015) documents that booming asset price increase the risk of financial crises risks and are usually followed by deep recessions and slow recoveries. In contrast to

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<sup>8</sup>Jordà, Schularick and Taylor (2011) document that credit growth emerges is a good predictor of financial instability.

Jordà, Schularick and Taylor (2016), we find that lending activities follow economic recessions and make the recovery slow.

Figure 4 shows the concordance index for individual countries. Real house prices are more synchronized to the business cycle, relative to stock prices. As can be already detected in Figure 2 and Figure 3, real house prices always have a peak at 0, with the exception of Sweden, where house prices peak 3 years before the recession. Similar to the pooled sample, asset prices lead economic activities, while financial variables lag the business cycle, with the exception of the Netherlands where financial variables peak together with the GDP peak.

Those results confirm the importance of including asset prices when studying business cycles. House prices are clearly synchronized with the business cycle, peaking at the same time or even leading the business cycle. This is not only a factor in the global financial crisis in 2007; it is a common factor in previous boom-bust cycles.

### 3. The time-varying parameter VAR with stochastic volatility

Vector autoregression (VAR) have been largely used in modelling and forecasting macroeconomic variables. Sims (1980) advocated VAR models as providing a simple method to estimate economic relationships through the estimation of impulse response functions that describe the effects of a specific structural shocks on key economic variables. Since then, many studies have been developed with the use of VAR models, such as Leeper et al. (1996) and Christiano, Eichenbaum, and Evans (1999). Those studies have assumed an homoskedastic error covariance matrix. However, in recent years, the literature has explored and incorporated time-varying components into traditional constant coefficient models, where the VAR coefficients are allowed to gradually change over time. See Uhlig (1997), Cogley and Sargent (2005), Cogley, Primiceri and Sargent (2010), Koop, Leon-Gonzalez and Strachan (2011) and Koop and Korobilis (2013).<sup>9</sup>

Cogley and Sargent (2005) estimate the interaction of inflation, unemployment, and nominal short-term interest rates with a VAR model which incorporates drifting coefficients and stochastic volatility. Primiceri (2005) estimate a three-variable TVP-VAR model that allows parameters to vary over time. Relative to Cogley and Sargent (2005), Primiceri (2005) finds that the responses of short-term interest rates to inflation and unemployment exhibit a stronger trend in recent decades, relative to a negligible effect on the rest of the economy. Benati and Mumtaz (2005) estimate the TVP-VAR model by imposing sign restrictions to identify uncertainty shocks and the source of the Great Stability in the United Kingdom. Baumeister, Durinck, and Peersman (2008) estimate the TVP-VAR model to assess

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<sup>9</sup>Uhlig (1997) incorporates a stochastic volatility component into a vector autoregressive (VAR) model, but its application is relatively limited due to the need to apply Monte Carlo simulation-based estimation techniques.

the effects of excess liquidity shocks on the Euro-area. DAgostino, Gambetti and Giannone (2013) explore the advantages of using the TVP-VAR models in forecasting macroeconomic variables.

Let's consider a simple TPV-VAR model in the spirit of Cogley and Sargent (2005) and Primiceri (2005):

$$y_t = c_t + B_{1,t}y_{t-1} + \dots + B_{k,t}y_{t-k} + \varepsilon_t, \quad (1)$$

where  $y_t$  is an  $n \times 1$  vector of endogenous variables;  $c_t$  is an  $n \times 1$  vector of time varying coefficients that multiply constant terms;  $B_{i,t}$ , with  $i = 1, \dots, k$ , are  $n \times n$  matrices of time varying coefficients;  $\varepsilon_t \sim \mathcal{N}(0, \Sigma_t)$  is a normally distributed vector white noise error term with time-varying variance-covariance matrix  $\Sigma_t$ .

We can rewrite 1 in the following simple way:

$$y_t = (I_N \otimes x_t')\alpha_t + \varepsilon_t, \quad (2)$$

with  $x_t = (y'_{t-1}, \dots, y'_{t-k})'$  and  $\alpha_t = (B_{1,t}, \dots, B_{k,t})$ .

The time-varying coefficients,  $\alpha_t$ , evolve according to

$$\alpha_{t+1} = \alpha_t + u_t, t = 0 \dots, n-1, \quad (3)$$

where  $u_t \sim \mathcal{N}(0, \Omega_t)$  is a vector of white noise innovations.  $\varepsilon_t$  and  $u_s$  are independent of one another for all  $s$  and  $t$ .

The stochastic volatility evolves according to

$$\sigma_t^2 = \gamma \exp(h_t) \quad (4)$$

$$h_{t+1} = \phi h_t + \eta_t \quad (5)$$

$$\eta_t \sim N(0, \sigma_\eta^2), t = 0 \dots, n-1 \quad (6)$$

The time-varying coefficients  $\alpha_t$  in equation (3) are defined as a random walk process of order 1, in order to consider temporary and permanent shifts in the coefficients. This allows the model to capture a possible nonlinearity due to possible structural break. The log-volatility,  $h_t = \log \frac{\sigma_t^2}{\gamma}$  in equation (4) follows an autoregressive process of order 1. We assume that  $|\phi| < 1$  and  $\eta_0 \sim N(0, \frac{\sigma_\eta^2}{(1-\phi^2)})$  in order to guarantee for stationarity. For values  $\phi = 1$ , the log-volatility follows the random walk process.

We estimate the state variables  $\alpha_t$  and  $h_t$  with a Bayesian approach using the Markov chain Monte Carlo (MCMC) method for a precise and efficient estimation of the TVP regression model.<sup>10</sup> The MCMC method aims to assess the joint posterior distribution of parameters of interest at a given prior probability density,  $\pi(\theta)$ . The posterior distribution is then obtained by the Bayes' theorem:

$$\pi(\theta|y) = \frac{f(y|\theta)\pi(\theta)}{\int f(y|\theta)\pi(\theta)d\theta} \quad (7)$$

Following Primiceri (2005), we derive mean and variance from an pre-sample period estimates of constant parameter VAR model in setting a prior of normal distribution. To compute the posterior estimates, we draw about 10,000 samples out of 1,000 discarded.

### 3.1 Identification

To identify the shocks, we rely on the Cholesky's decomposition of the covariance matrix, which assumes a recursive exogeneity structure. See Giuliadori (2005), Adalid and Detken (2007), Goodhart and Hofmann (2008), Assenmacher-Wesche and Gerlach (2008), Abildgren (2010) and Musso et al. (2010). Therefore the first variable in the VAR is only affected contemporaneously by the shock to itself, the second variable in the VAR is affected contemporaneously by the shocks to the first variable and the shock to itself, and so on. The orthogonalized shocks should not be interpreted as structural shocks, but rather as orthogonalized reduced-form shocks. Alternative identification of structural shocks can be derived through a combination of long-run and short-run restrictions or sign restrictions. Musso et al. (2010), Walentin (2014) and Huber and Punzi (2016) identify a monetary VAR model with housing market through sign restrictions and their results are robust to the use of a recursive ordering scheme.

In our estimation we include the following variables: real GDP per capita, price level, short-term interest rate, spread rate (difference between long-term and short-term interest rates), real house prices, nominal debt and nominal broad money. All variables are taken in log terms, with the exception of interest rates and GDP per capita.

According to the monetary transmission literature, the ordering of the economic activity, inflation and interest rates are standard. The financial variables are placed lower in the ordering. Assenmacher-Wesche and Gerlach (2008) argue that they should follow interest rates, because monetary policy only reacts to asset price movements if these are prolonged, while asset prices react immediately to changes in monetary policy. The ordering of credit and house prices is arbitrary. Goodhart and Hofmann

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<sup>10</sup>Cogley and Sargent (2005) and Primiceri (2005) sample stochastic volatility in the spirit of Kim, Shephard, and Chib (1998) and convert the original model into a linear Gaussian state space form by approximating the nonlinear and non-Gaussian state space model by the normal mixture distribution. Alternatively, Shephard and Pitt (1997) and Watanabe and Omori (2004) draw samples from the exact posterior distribution of the original model.

(2008) suggest that house prices should appear before financial variables, because prices are probably stickier. By contrast, Musso, Neri and Stacca (2011) order house prices before credit, because they interpret credit as a mortgage loan demand function. Christiano et al. (1999) and Assenmacher-Wesche and Gerlach (2008) order credit before housing prices, arguing that a shock to credit affects output and the price level with a lag, while housing prices can react within a quarter to the shock. Money shocks are identified with an increase in broad money which is independent of changes in real GDP per capita, inflation, policy rates and housing prices. Therefore this is ordered as the last variable in the system. By inverting the order of housing prices and mortgage loans, our results appear robust.

## 3.2 Impulse Responses

In this section, we report impulse responses functions (IRFs) for each country. Given space restrictions, we report only IRFs for shocks that replicate a positive comovement between house prices, lending and GDP per capita. See Iacoviello (2002, 2005), Davis and Heathcote (2005), Goodhart and Hofmann (2008), Musso et al. (2011), Walentin (2014), Huber and Punzi (2016) and Cerutti et al. (2015). IRFs reports values over a 15 year forecast horizon (*axes x*) for the entire sample period, excluding WWII, (*axes y*).

### 3.2.1 The United States

Figure 5 reproduces standard IRFs to a technology (TFP) shock in the U.S.: all variables increase, with the exception of interest rate spread, which decreases. TFP shock reproduces a pure aggregate demand shock, which shows a lot of time variation throughout the sample period. We can see that inflation and broad money respond more in the period before WWII, while lesser impact is evident afterward. This reflects the inflation targeting strategy adopted by the Federal Reserve in order to maintain inflation stability. Moreover, at the beginning of the 19th century, productivity shocks have no impact on booming house prices (indeed the response is negative) but a positive response becomes evident just before the Great Depression in 1929. Figure 6 shows IRFs for a contraction in U.S. monetary policy; again, IRFs are standard, with all variables dropping in response to an increasing policy rate. In contrast with a TFP shock, there is no time variation on changes in macro-financial variables due to monetary policy. Results are in line with Iacoviello (2005), Goodhart and Hofmann (2008) and Musso et al. (2011). However, unlike Iacoviello (2005), Jarocinski and Smets (2008), Musso et al. (2011), housing demand shocks and credit supply shocks do not generate a comovement in house prices, lending and GDP when we estimate a large-scale dataset.

### **3.2.2 The Netherlands**

IRFs for the Netherlands cover only 60 years in total, because data omits the periods during WWI and WWII. TFP shocks in the Netherlands generate similar responses as in the U.S., except for inflation which now decreases. These shocks also generate significant time variation, with the exception of loans and broad money. The response of house prices is stable for a large portion of the sample period, but shows greater increases during the last 20 years, the period corresponding to the Great Moderation. Interest rate spread shows major variability over the sample period, reflecting in part the time variability of short-term rates. The decrease in spread is much more pronounced over the last 10 years. See Figure 7.

Monetary policy shocks reproduce the same results as in the U.S., but are not reported. Credit shocks lead to an increase in GDP, policy rate, broad money and asset prices. The Netherlands is the only country showing a strong relationship between monetary variables, housing prices and the macroeconomy due to credit and financial shocks. See Figure 8.

### **3.2.3 Norway**

Similar results can be seen in Norway's response to a TFP shock, and again we find major time variability. House price response was negative before WWI, and become positive afterwards with a greater response over time. However, the response to TFP shocks become less important during the Great Moderation. See Figure 9.

Relative to the other countries, money shocks are more important in Norway. An increase in money supply generates an increase in house prices on impact and a GDP increase over the entire forecast horizon. See Figure 10.

### **3.2.4 Sweden**

IRFs due to TFP shocks for Sweden show a certain time variation in house prices, which strongly increases during the Great Moderation period. Prior to this period, at the beginning of the sample and during the Great Depression, the impact on house prices for a TFP shock is less pronounced, or even negative. Spread decreases more before WWI, while short-term interest rate shows a deeper impact after the Great Depression. Broad money and loans show some time-variation and are both negative before WWI, but become positive afterward. However, their impact is very minor in absolute terms. See Figure 11.

## 4. Co-movement Decomposition

In this section, we test the existence of macro-financial linkage. In particular, we study the evolution of comovements over time between real GDP per capita, real house prices and lending. We also identify what shocks mainly drive the correlation over time. For this purpose, we follow Den Haan (2000) and Den Haan and Sterk (2011) in constructing comovement statistics using the estimated VAR. This is an alternative way to measure comovement with the correlation coefficients of HP-filtered time series. Den Haan (2000) proposes that the correlation between two variables can be decomposed into the contributions of the structural shocks of the model. The covariance between variable  $x_t$  and  $y_t$  at the  $K^{th}$ -period ahead forecast errors can be decomposed as follows:

$$COV(x_t, y_t; K) = \sum_{m=1}^M COV(x_t, y_t; K, m) \quad (8)$$

where  $x_k^{imp,m}$  and  $y_k^{imp,m}$  are the  $k^{th}$ -period responses of the two variables to one-standard-deviation innovations of the  $m^{th}$  structural shocks, and  $COV(x_t, y_t; K, m) = \sum_{k=1}^K x_k^{imp,m} y_k^{imp,m}$ . The total covariance is simply the sum of the accumulated cross products for all possible shocks and does not depend on how the shocks are identified. Then it follows that the correlation coefficient can be decomposed as:

$$CORR(x_t, y_t; K) = \sum_{m=1}^M CORR(x_t, y_t; K, m) = \sum_{m=1}^M \frac{\sum_{k=1}^K x_k^{imp,m} y_k^{imp,m}}{SD(x_t; K)SD(y_t; K)} \quad (9)$$

In the denominator, we use the total standard deviations of the  $K^{th}$ -period ahead forecast error (and not the standard deviations due to the  $m^{th}$ -shock) to ensure that the sum of all the scaled covariances is equal to the total correlation coefficient.

In order to study the change of correlation over time, and the contribution of shocks during each phase, we split the sample in two different periods around the two major crises in 1929 and 2006. Therefore we consider a period 1896-1954, which includes the Great Depression in 1929<sup>11</sup>, and a second period from 1955 until 2014, which includes the Great Moderation period and the Great Recession. Unfortunately, given the data as at annual frequency, we are unable to look at a shorter sample to consider other possible boom-bust cycles. Figure 12 reports comovements for the U.S. and shows that the correlation between real GDP per capita and house prices (Panel A) and the correlation between real GDP per capita and lending (Panel B) were both negative until 1954, and both turn positive during the second sample period. The correlation between house prices and lending activities has been always positive, however it is higher in the second period. During the first period, monetary

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<sup>11</sup>This sample excludes observations during WWII, simply because this data is missing for several variables.

policy has almost no role in explaining the correlations, whereas it becomes more important during the second period, in particular for the correlation of real house prices with real GDP per capita and lending. Similarly results are found in Jordà, Schularick and Taylor (2015a) who demonstrate that an accommodating monetary policy lead to housing price and mortgage lending booms. Instead, house price shocks were able to explain almost all the correlation between real house prices and total lending during the first period, while these lose any explanatory power during the second period (Panel C).

For the Netherlands, all correlation are very small, or even close to zero, during the first period, but they increase sharply after 1955. See Figure 13. TFP shocks explain most of the correlation of real GDP per capita with real house prices (Panel A) and total lending (Panel B), but little of the correlation between house prices and lending activities (Panel C), whereas house price shocks contribute more in explaining the latter comovement since 1955. Moreover, money supply shocks show some contribution to explaining the co-movements between GDP and house prices during the second period; indeed money supply shocks explain as much as TFP shocks over a long horizon.

In contrast, Norway shows an equal or higher correlation across the two sample periods. TFP shocks explain almost the entire correlation of real GDP per capita with real house prices and total lending, with a marginal improving contribution of monetary policy during the second period. However, inflation shocks were able to explain mostly of the co-movements between house prices and lending, while house prices become more important during the second period. See Figure 14.

Sweden presents more mixed results. See Figure 15. The correlation between real GDP and real house prices is mainly explained by TFP and inflation shocks, while monetary policy becomes more important after 1955. Inflation shocks are equally important in the second period as the first, but TFP becomes less important. See Panel A. The correlations of total lending with real GDP per capita and house prices were initially negative but then become positive. Again, monetary policy shocks becomes more important, while TFP were more important during the first sample. House price shocks also explain part of the correlation in Panel C.

## 5. Conclusion

We study the business cycle properties over a long-run period of 1896-2014 for the U.S., the Netherlands, Norway and Sweden. We focus on macro-financial linkages to understand if these are common to the entire period, or if the linkage was simply amplified during the last financial crisis in 2007. In particular, we ask if economic recessions are usually followed by asset price and credit bursts, and find that housing and stock prices tend to lead real economic activities, while developments in credit and money markets typically lag developments in the real economy.

We also study the cyclical behaviour of real GDP per capita, asset prices (housing or stocks) and lending. In particular, we test for the existence of comovements with asset prices during periods



of crisis. We find that the correlations between real GDP per capita and real housing prices and between lending and real housing prices have increased since World War II, and the increase is much more pronounced if we compare periods of the Great Recession with the Great Depression. Monetary policy shocks have also become more important in explaining the comovements in the Great Recession, in comparison with the Great Depression, but TFP shocks have always been the main source of fluctuations across the four countries. Furthermore, inflation shocks have played an important role in explaining the correlation between house prices and lending for Scandinavian countries.

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Figure 1: Real House Price Index.

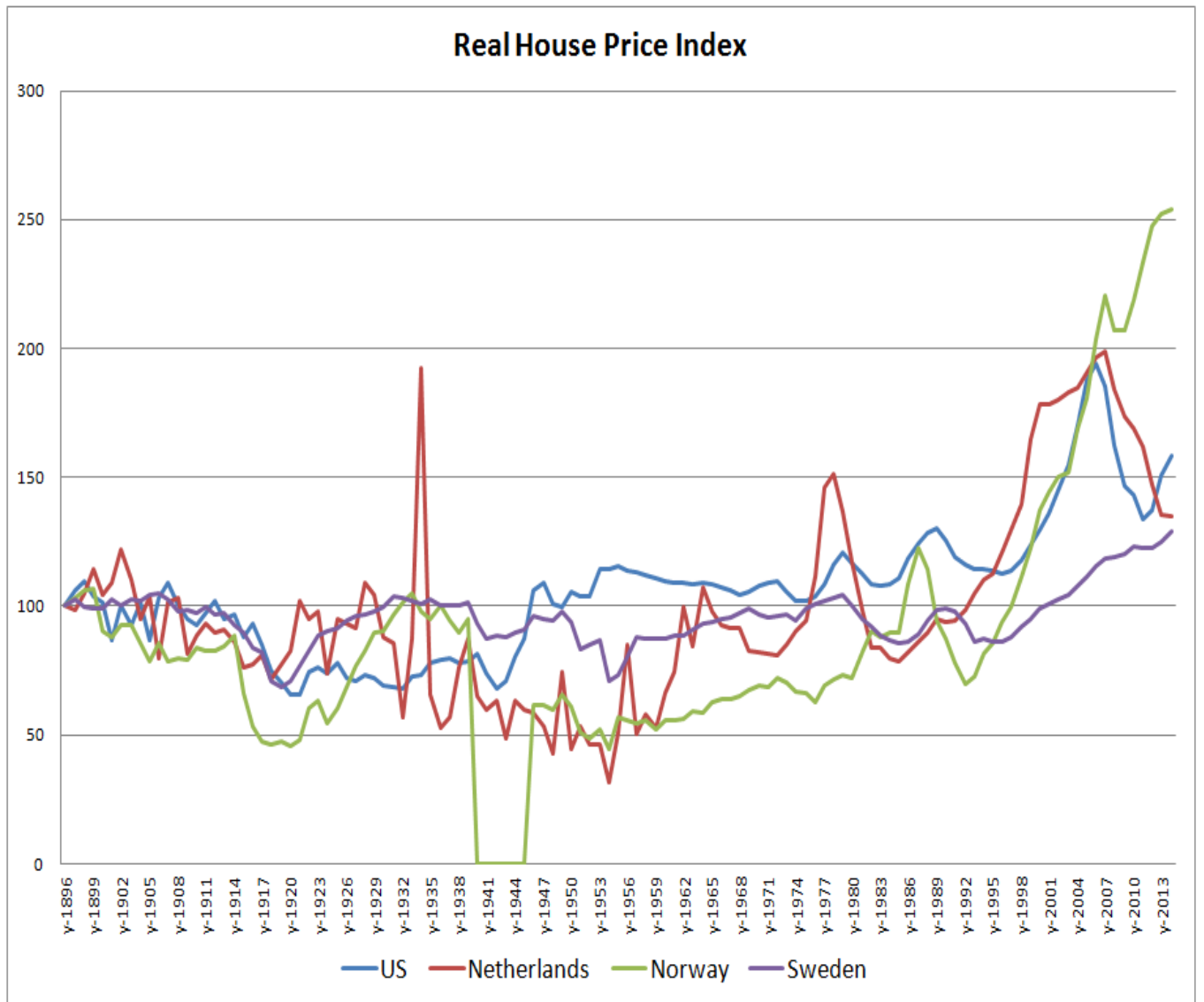


Figure 2: Cyclical behaviour of US Real GDP per capita (blue solid line) versus Real House Price Index (green starred line) during banking crisis (black vertical line).

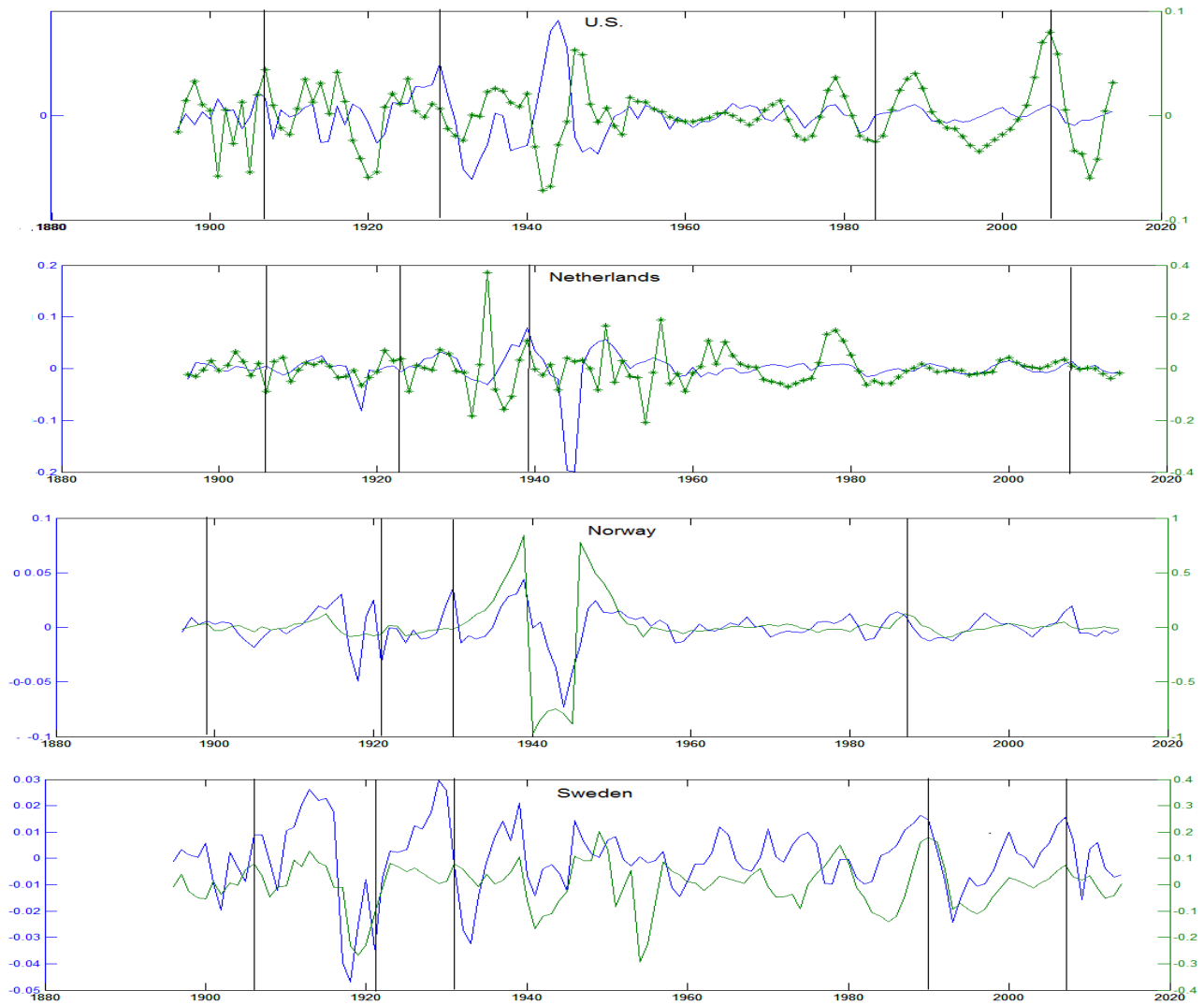


Figure 3: Concordance Index for the US, the Netherlands, Norway and Sweden, all pooled together.

Concordance of Real GDP per Capita with past and future phase of Financial Cycle

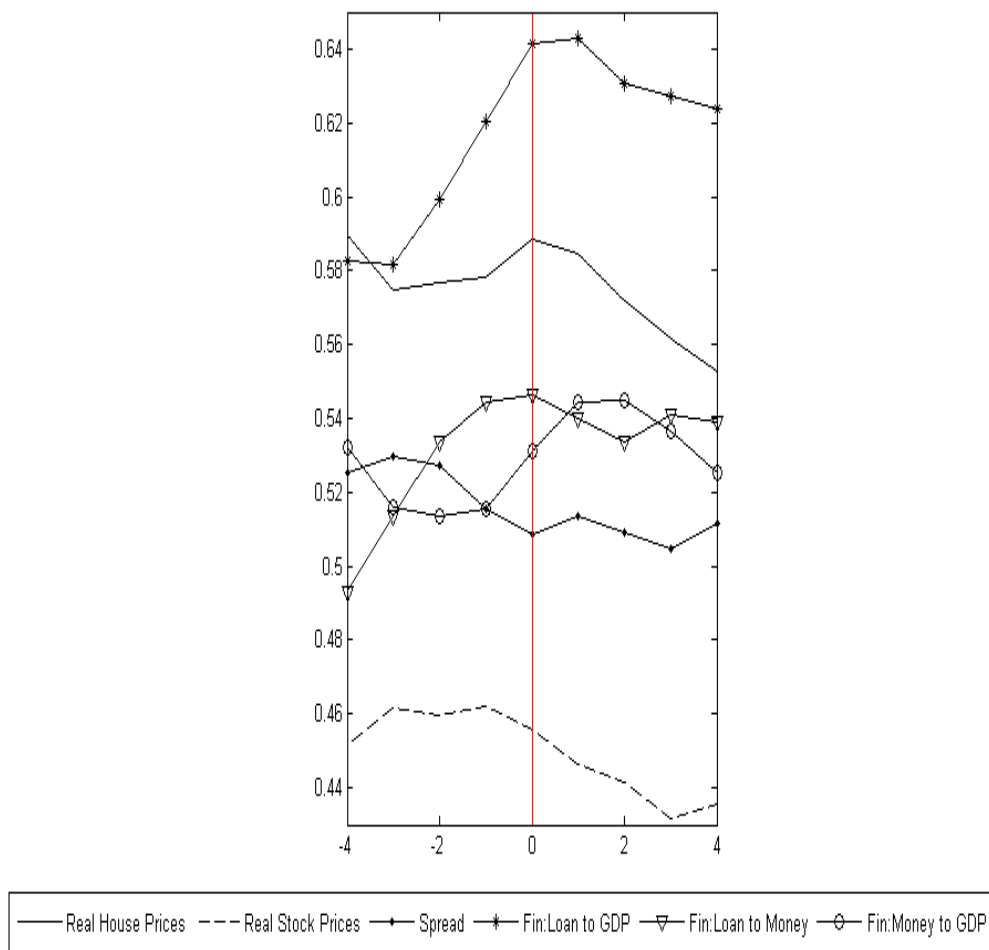


Figure 4: Concordance Index for the US (top, left), the Netherlands (top, right), Norway (bottom, left) and Sweden (bottom, right).

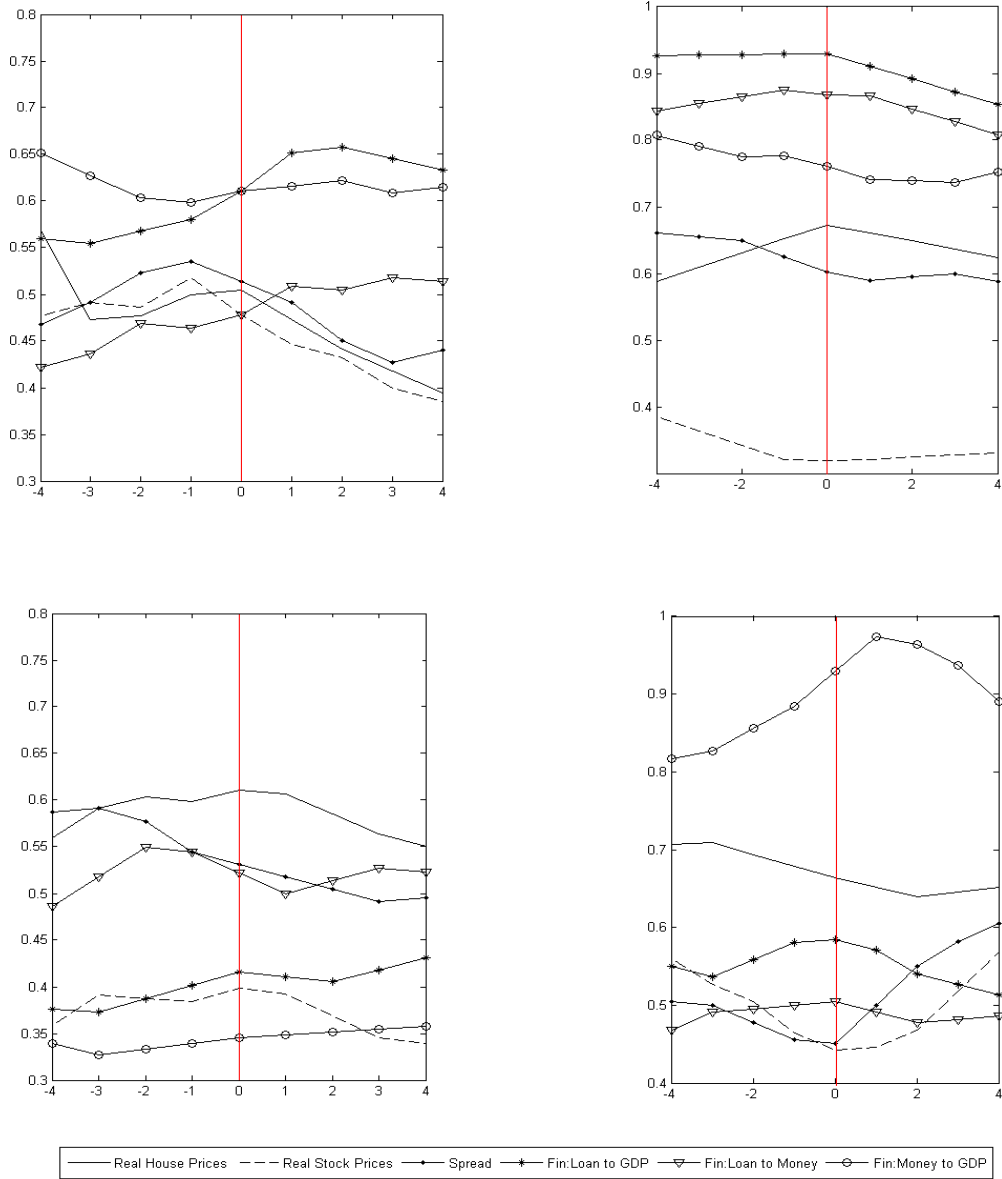




Figure 5: U.S. IRFs from TPV-VAR: TFP Shock

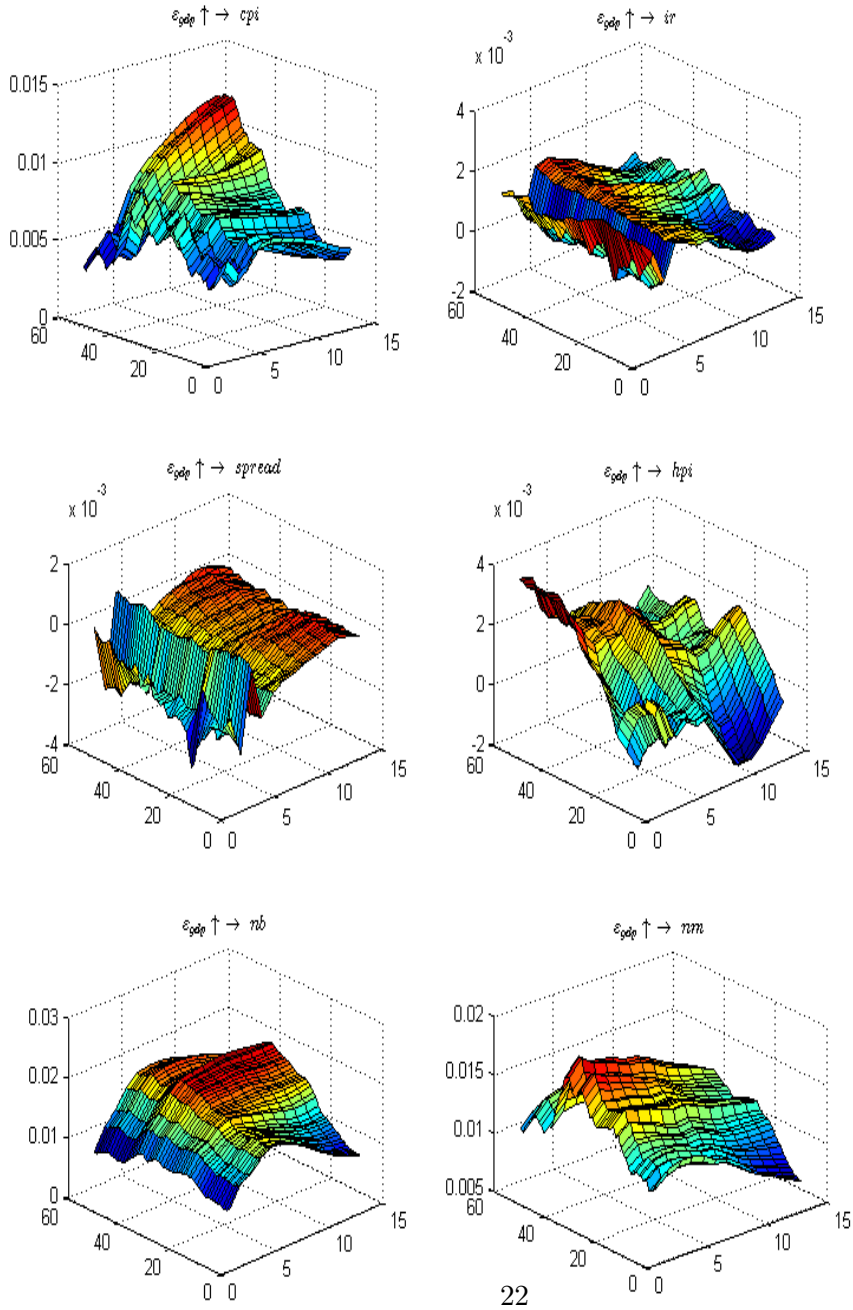


Figure 6: U.S. IRFs from TPV-VAR: Monetary Policy Shock

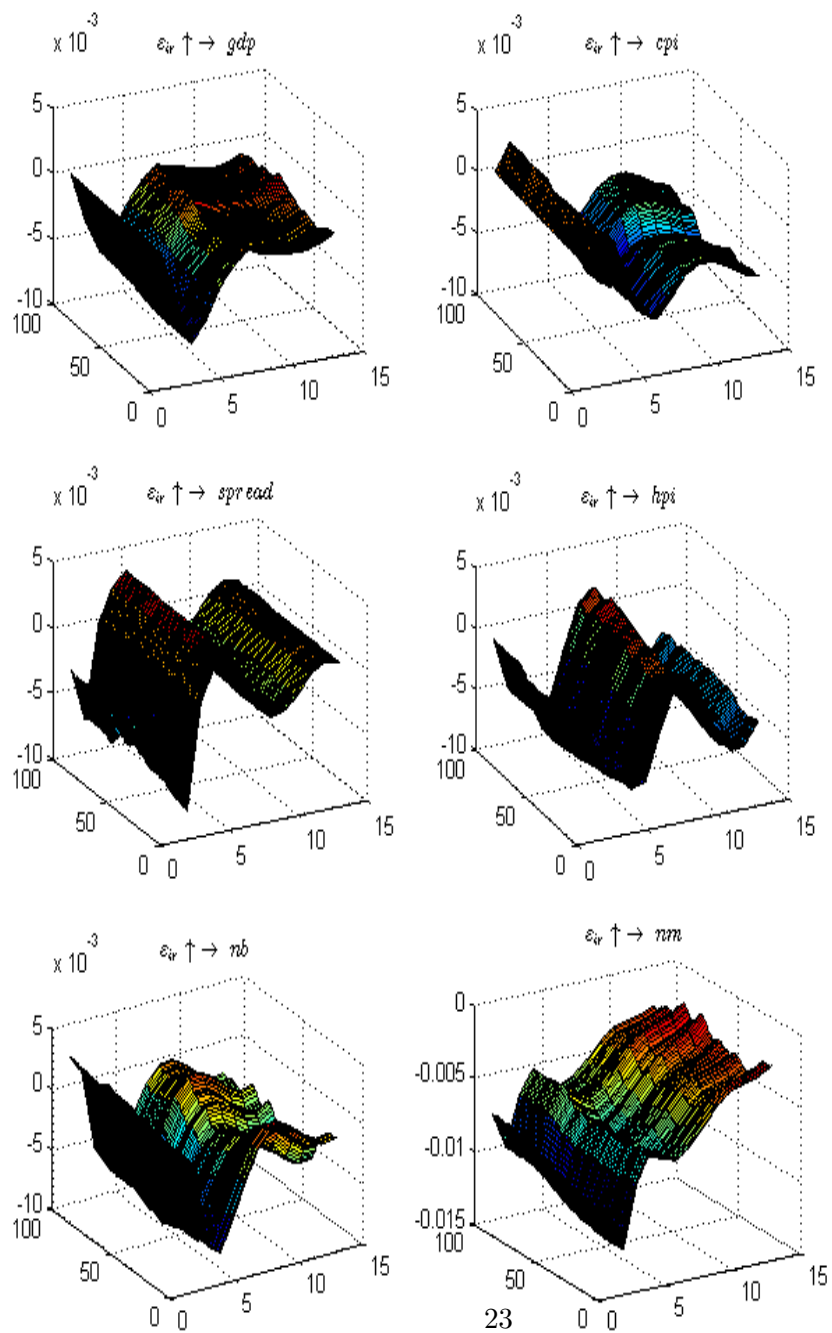


Figure 7: Netherlands IRFs from TPV-VAR: TFP Shock

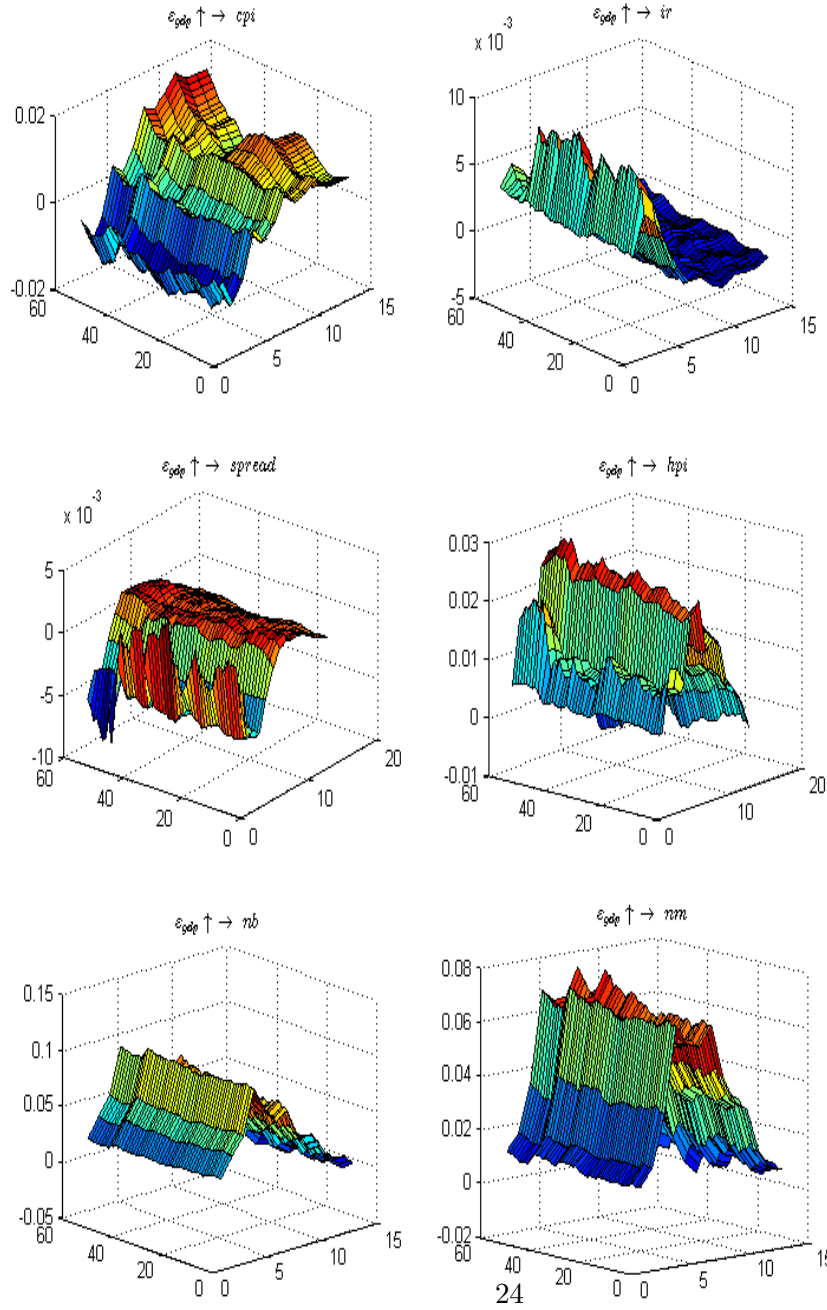


Figure 8: Netherlands IRFs from TPV-VAR: Credit Shock

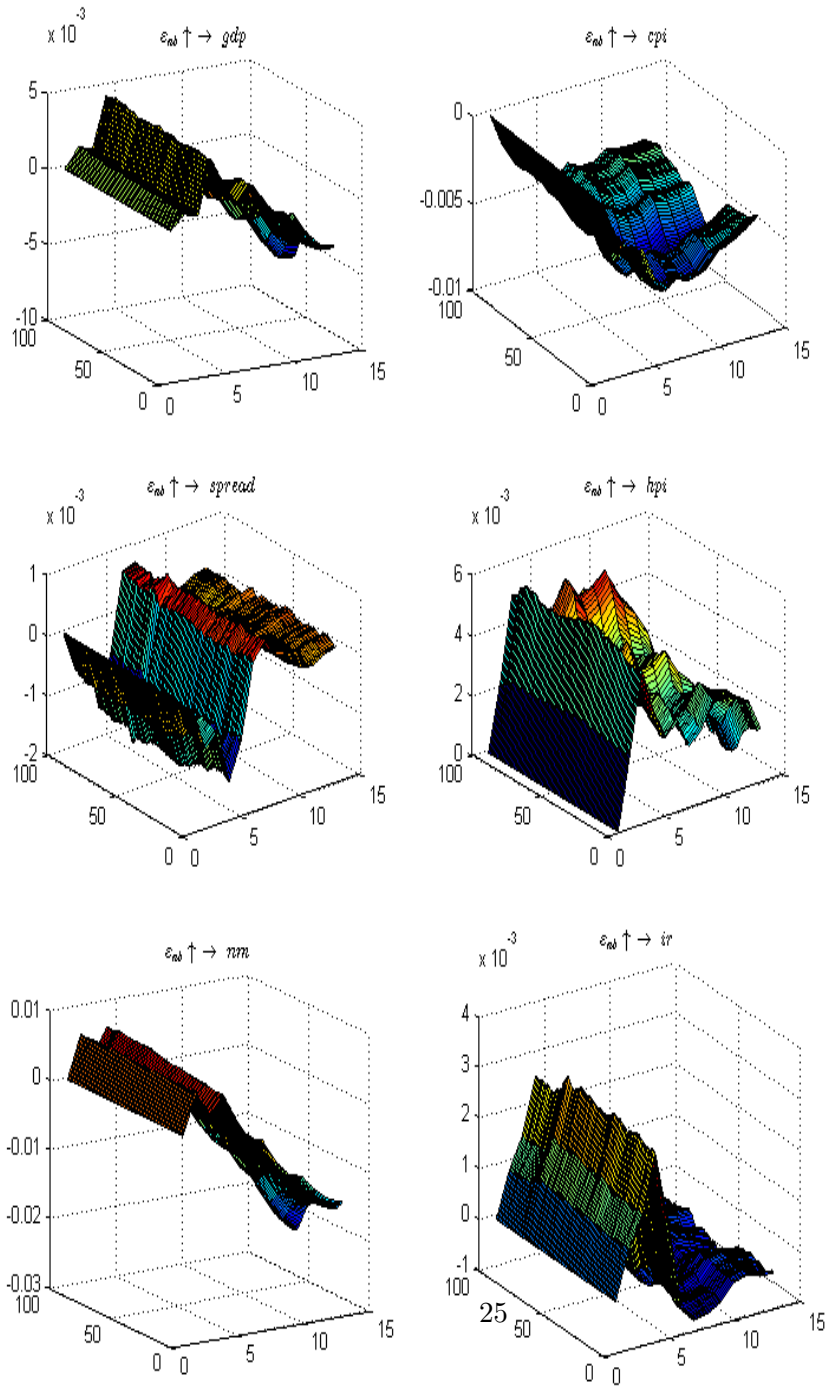


Figure 9: Norway IRFs from TPV-VAR: TFP Shock

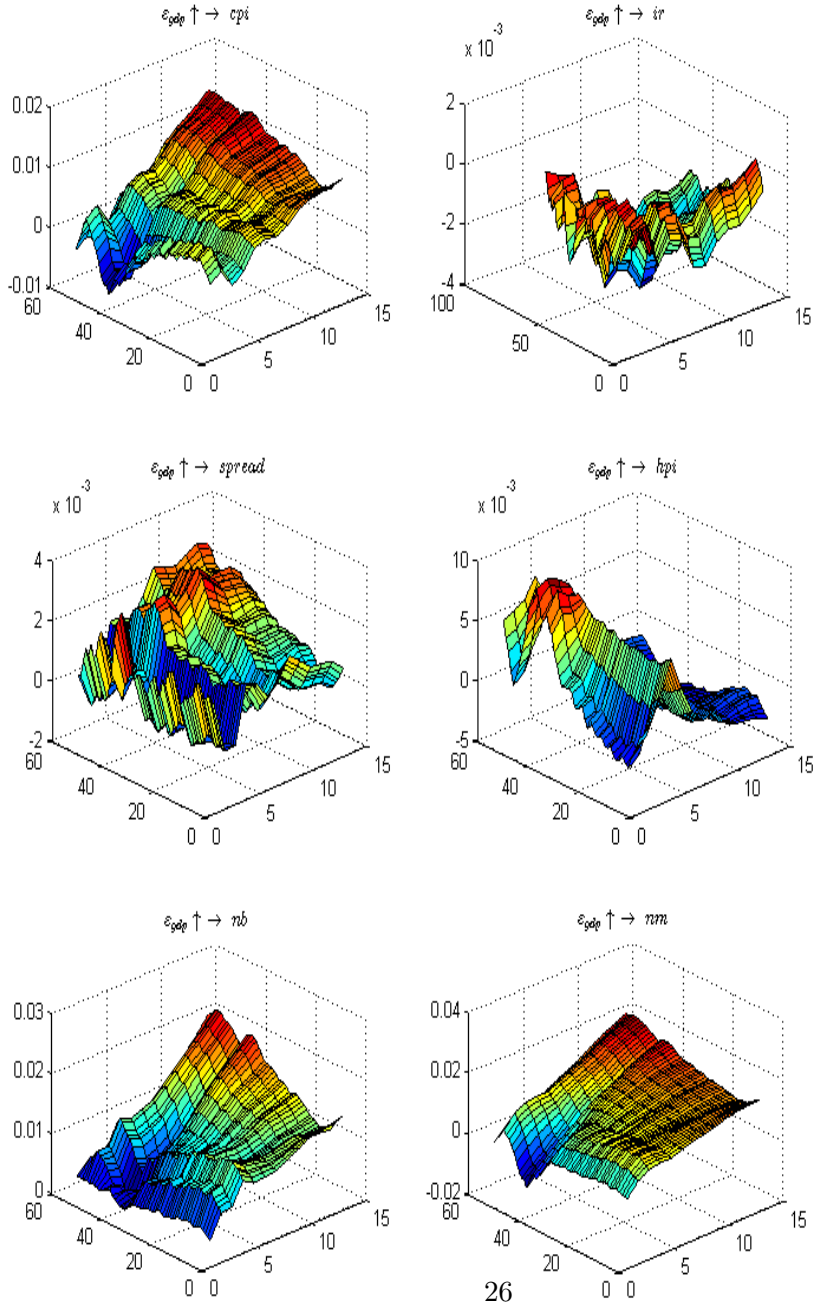


Figure 10: Norway IRFs from TPV-VAR: Money Shock

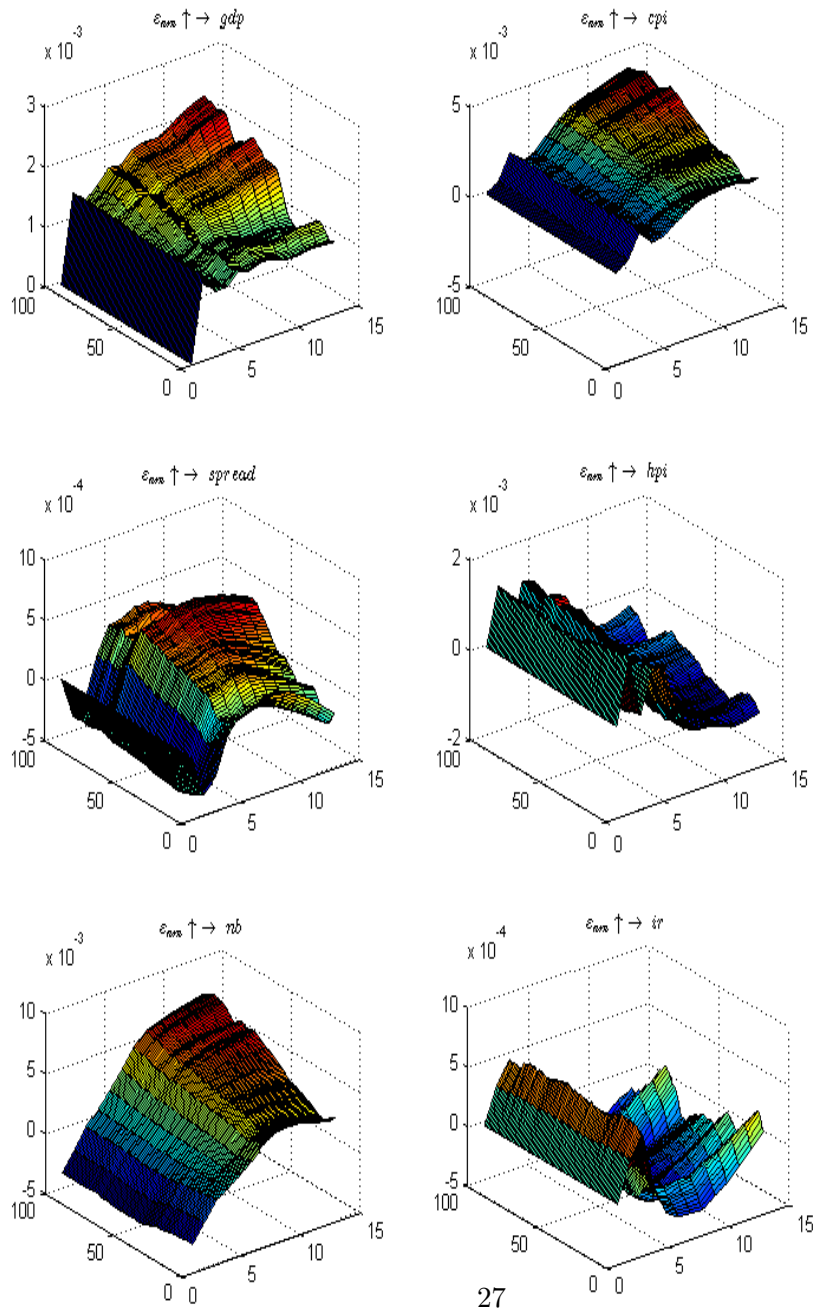


Figure 11: Sweden IRFs from TPV-VAR: TFP Shock

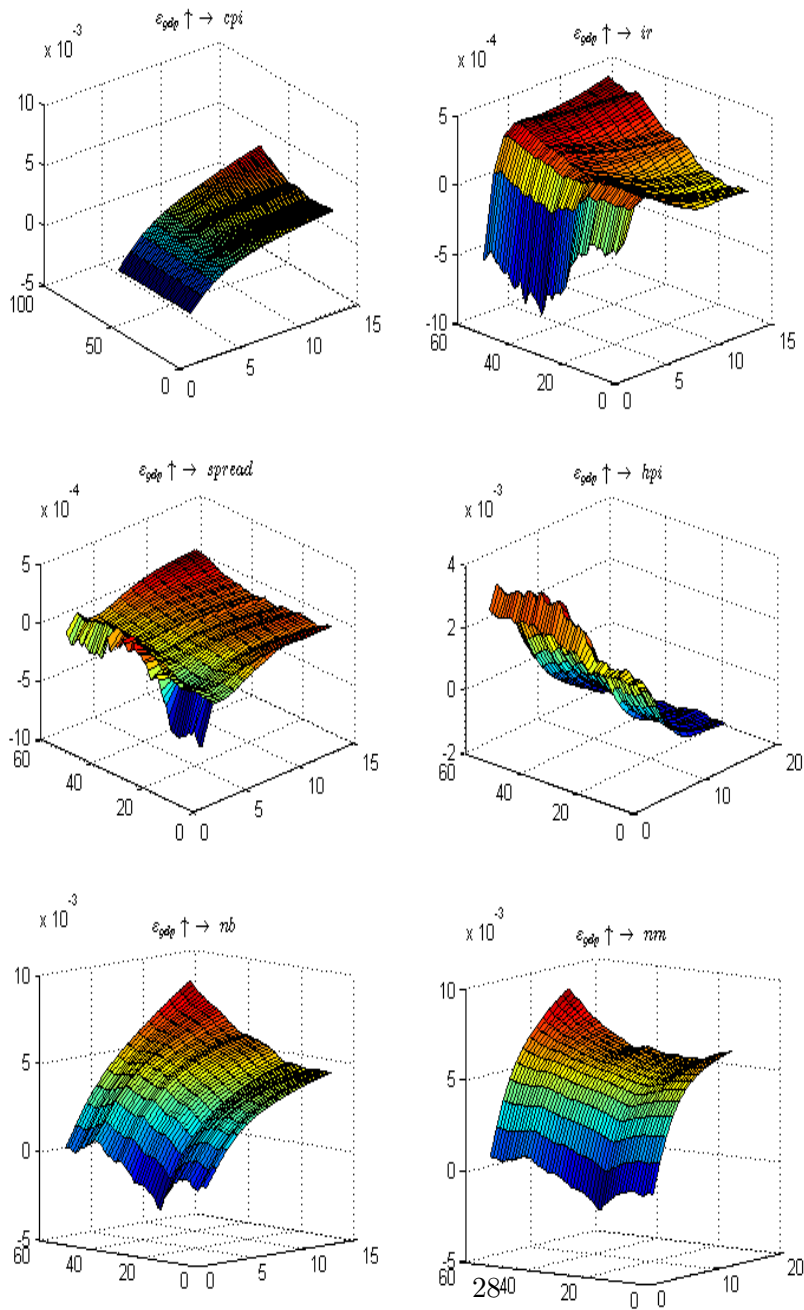


Figure 12: US Comovements: Total Correlation (solid line) due to Technology Shocks (starred line), Monetary Policy Shocks (dash-dotted line), House Price Shock (circular line).

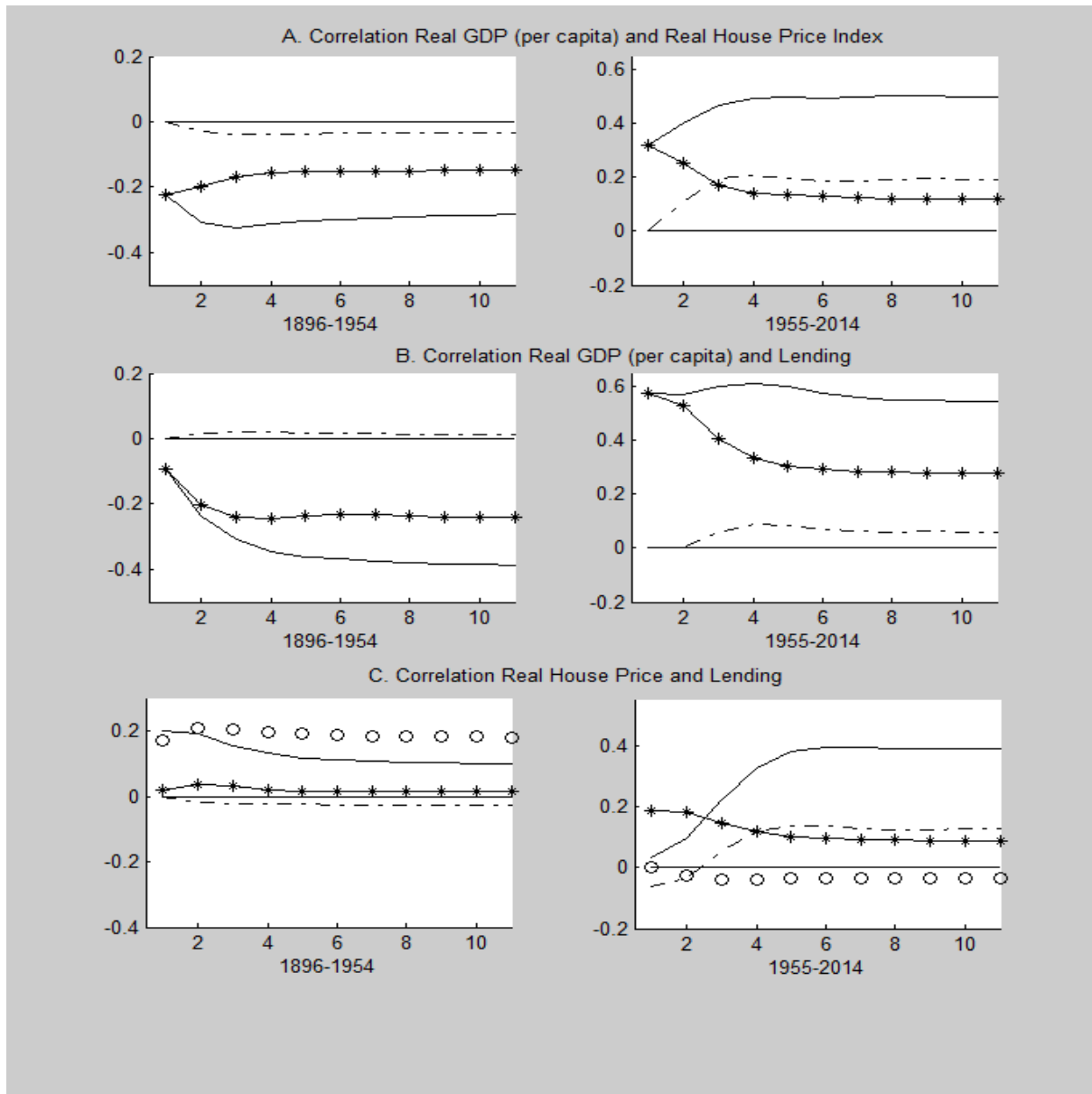




Figure 13: Netherlands Comovements: Total Correlation (solid line) due to Technology Shocks (starred line), Monetary Policy Shocks (dash-dotted line), House Price Shock (circular line), Money Supply Shock (triangle line).

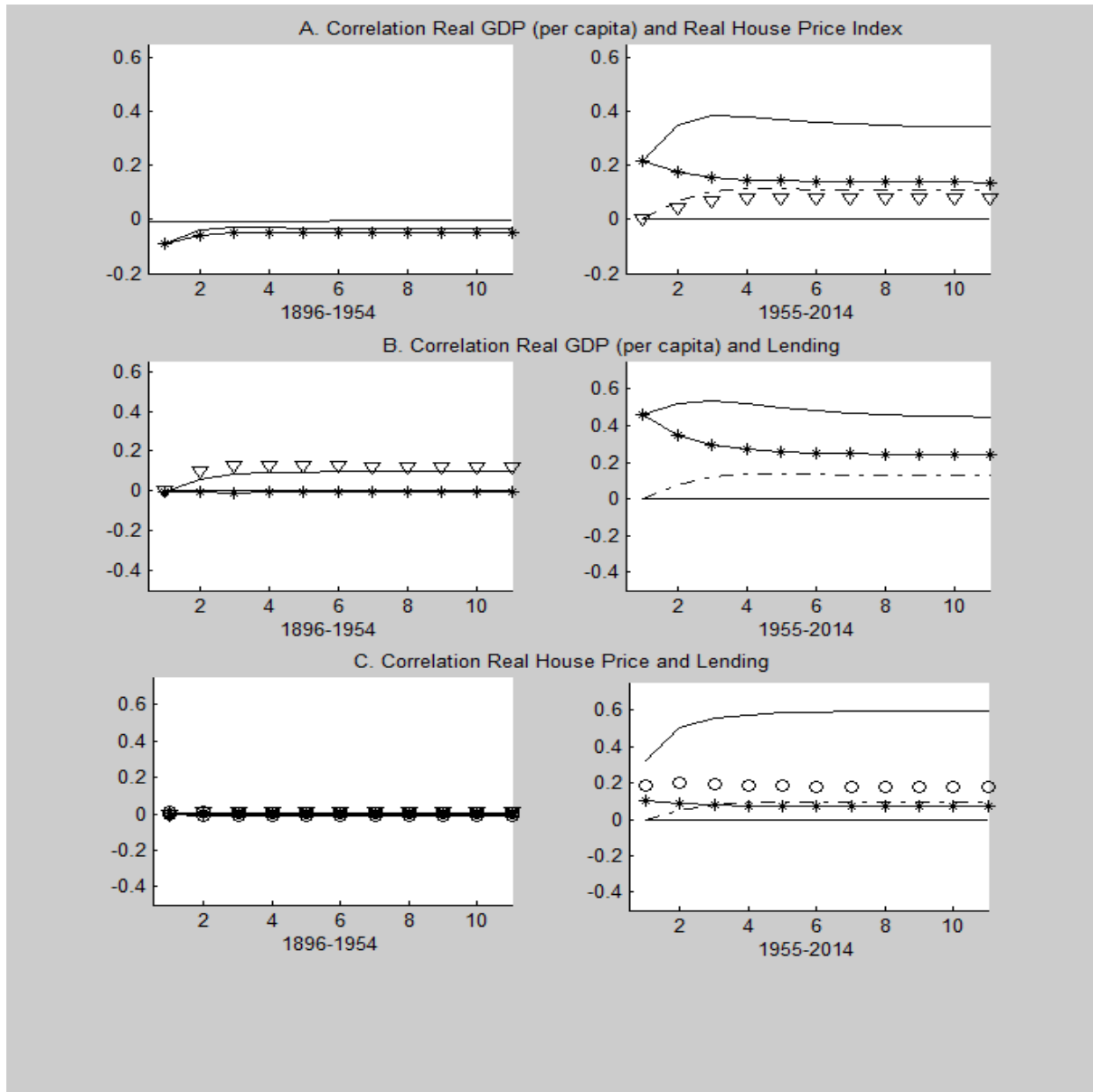


Figure 14: Norway Comovements: Total Correlation (solid line) due to Technology Shocks (starred line), Monetary Policy Shocks (dash-dotted line), House Price Shock (circular line), Inflation Shocks (dotted line).

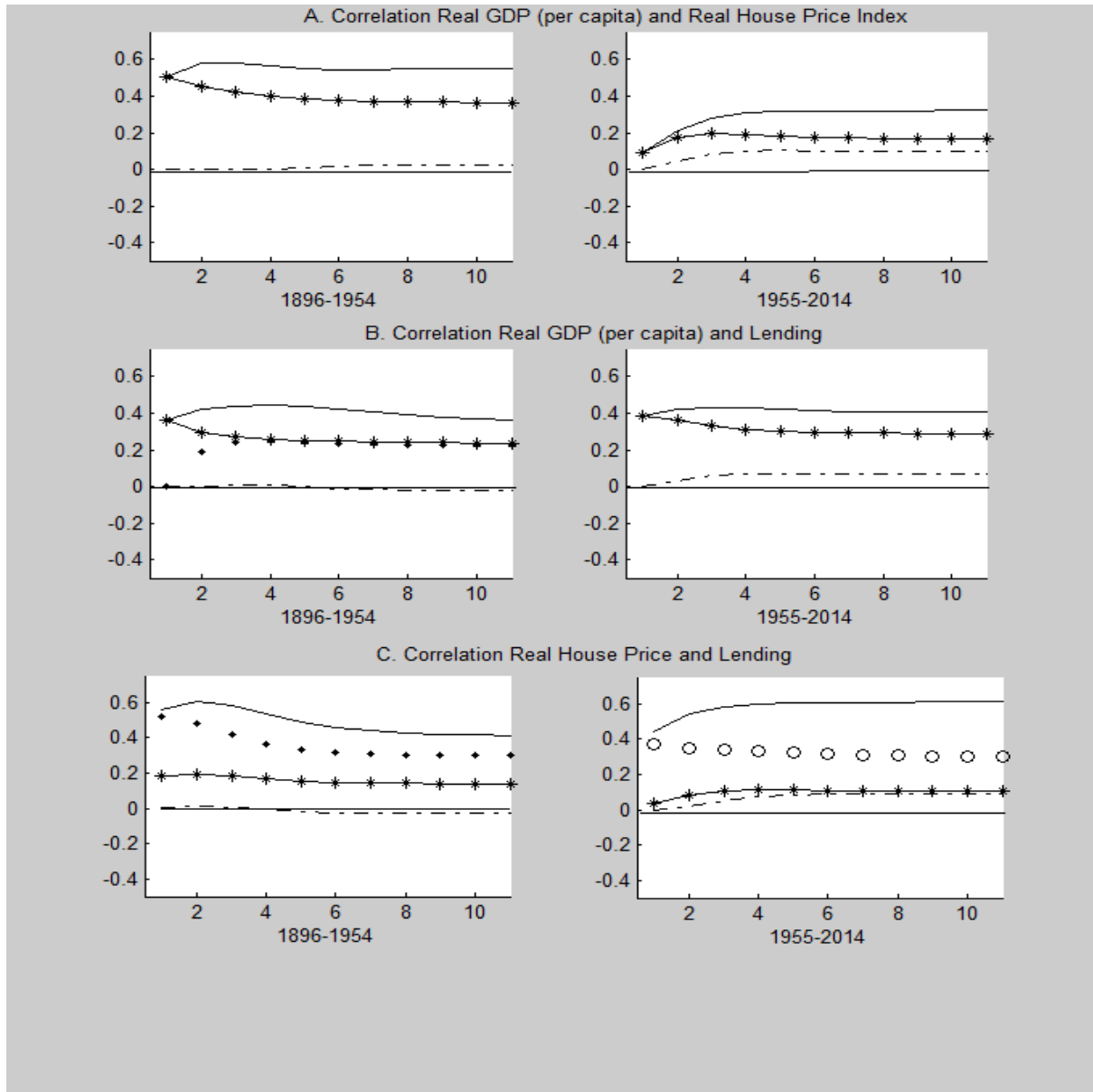
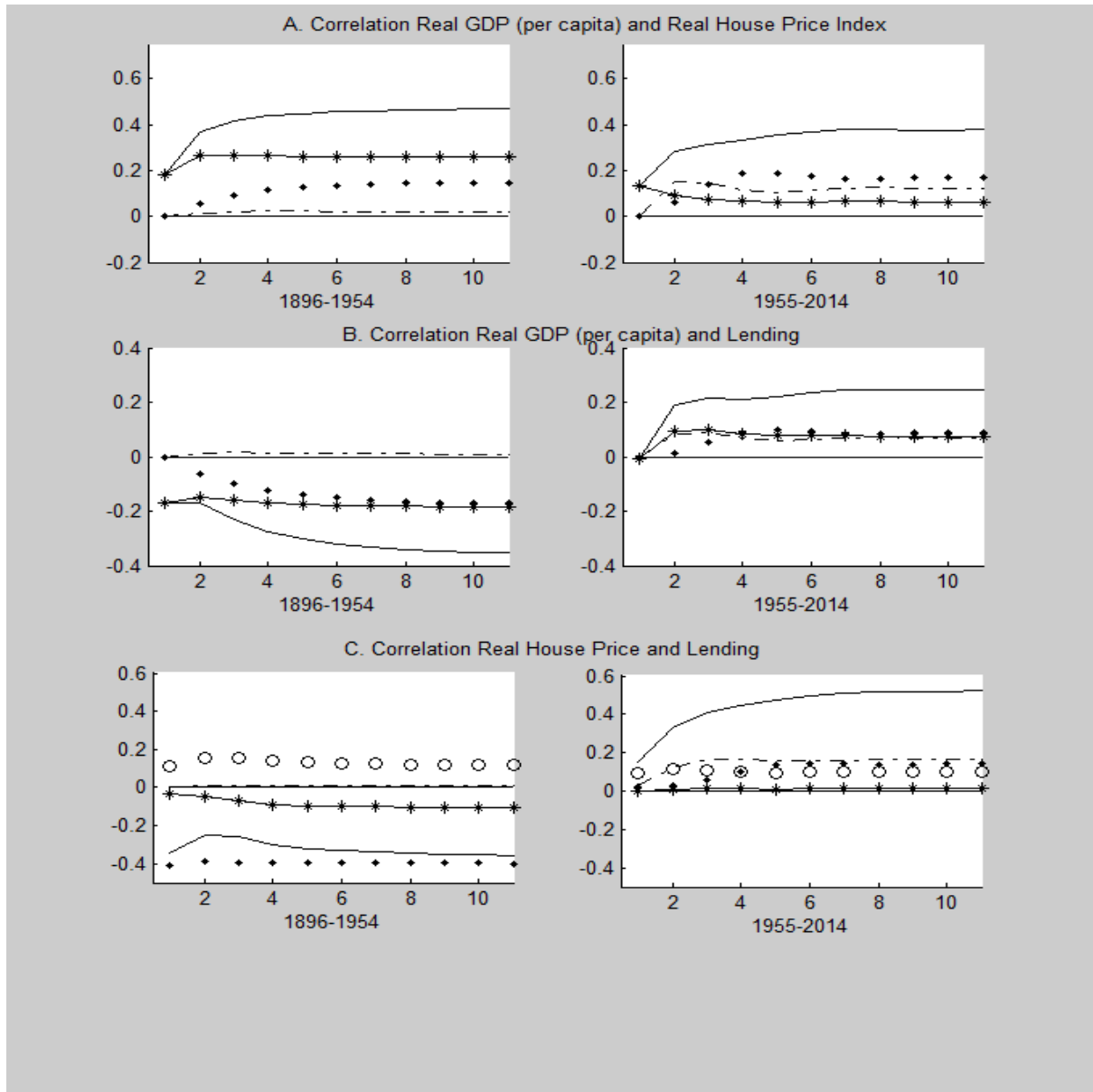


Figure 15: Sweden Comovements: Total Correlation (solid line) due to Technology Shocks (starred line), Monetary Policy Shocks (dash-dotted line), House Price Shock (circular line), Inflation Shocks (dotted line).



## APPENDIX

Table 1: Data Source

Variable	Countries	Year	Source	Title
Real gdp per capita	USA - Europe	1896 - 2010 2011-2014	Maddison Project OECD	Historic GDP
Loans	USA NLD NOR SWE	1896 - 2008 2009 - 2014 1896 - 2008 2009 - 2014 1896 - 1969 1970 - 1994 1995 - 2014 1896 - 1998 1999 - 2014	Schulraick et al. (2012) Board of Governors of the Federal Reserve System (US) Schulraick et al. (2012) ECB Schulraick et al. (2012) Norge National Bank Norge National Bank Schulraick et al. (2012) Statistics Sweden	Dataset Loans and Leases in Bank Credit, All Commercial Banks Dataset Outstanding Loans, Total maturity, All currencies combined - Domestic counterpart Dataset Historical Monetary Statistics for Norway - Growth Rates Loan by Banks to Non-Financial Corporations and Households Dataset Banking companies and Saving Banks lending to NFC and households
Money M2	USA NOR - SWE NLD	1896 - 2008 2009 - 2014 1896 - 2008 2009 - 2013 1896 - 2008 2009 - 2014	Schulraick et al. (2012) Board of Governors of the Federal Reserve System (US) Schulraick et al. (2012) Organization for Economic Co-operation and Development Schulraick et al. (2012) The World Bank	Dataset M2 Money Stock Dataset M2 Money Stock Dataset Money and quasi money growth
CPI	USA - Europe	1896 - 2008 2009 - 2014	Schulraick et al. (2012) OECD	Dataset Percentage change from previous period
Short-term rate	USA Europe	1896 - 2014 1896 - 2014	Board of Governors of the Federal Reserve System (US) OECD	Effective Federal Funds Rate 3-month interbank offer rate
Long-term rate	USA Europe	1896 - 2014 1896 - 2014	Board of Governors of the Federal Reserve System (US) Monthly Monetary and Financial Statistics (MEI)	10-Year Treasury Constant Maturity Rate 10-year government bonds
Stocks	USA NLD NOR SWE	1896 - 2014 1896 - 1992 1993 - 2014 1896 - 2008 2009 - 2014 1896 - 1991 1992 - 2014	Schulraick et al. (2012) - Standard & Poor's Schulraick et al. (2012) Euronext Amsterdam - AEX Schulraick et al. (2012) Oslo Stock Exchange - OBX Schulraick et al. (2012) Stockholm Stock Exchange - OMX 30	S&P 500 (1941-1943 = 10) Dataset December Closing Price - Growth Rate Dataset December Closing Price - Growth Rate Dataset December Closing Price - Growth Rate
Real house prices	USA NLD NOR SWE	1896 - 2015 1896 - 1999 2000 - 2014 1896 - 1969 1970 - 2014 1896 - 1985 1986 - 2004 2005 - 2014	Shiller (2015) Tweehonderd jaar statistiek in tijdreeksen Bank of International Settlement Eitheim and Erlandsen (2004) Bank of International Settlement Statistics Sweden Bank of International Settlement Bank of International Settlement	Real Home Price Index Home Price Index Real Home Price Index House price indices for Norway Residential property prices, all (only existing from 2012) dwellings, pure price, NSA Stockholm Residential Property Price Index Residential property prices, all owner-occupied All types of dwellings in the country as a whole