On the Sources of Business Cycles: Implications for DSGE Models

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Abstract

What are the drivers of business cycle fluctuations? And how many are there? By documenting a strong and predictable co-movement of real variables during the business cycle in a sample of advanced economies, we argue that most business cycle fluctuations are driven by one major factor. The positive co-movement of real output and inflation convincingly argues for a demand story. This feature – robust across time and space – provides a simple smell test for structural macroeconomic models. We propose a simple statistics that can compare data and models. Based on this statistics, we show that recent vintage of structural economic models has difficulties replicating the stylized facts we document.

JEL Codes: C10, E32, E50.

Keywords: Business cycle, demand shocks, dynamic principal component analysis, DSGE models.

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This paper was prepared as part of Czech National Bank Research Project B4/13. The support is gratefully acknowledged. We thank Jan Babecký, James Costain, Ben Hunt, Mika Kortelainen, Junior Maih, Michael Reiter, Antti Ripatti, Daniel Thorton, and Jan Vlček. The authors are solely responsible for all errors and omissions. The views expressed herein are those of the authors and should not be attributed to the Czech National Bank, the World Bank, or the International Monetary Fund, its Executive Board, or its management.

Nontechnical Summary

In this paper we investigate sources of economic fluctuations – their number, their nature, and their implications for economic modeling. Our empirical approach allows us to reach strong conclusions with relatively modest identification assumptions: we apply a dimension reduction technique—dynamic principal component analysis—on data of advanced economies. We focus exclusively on business cycle frequencies, without intentions to explain long-run trends in the data or high frequency fluctuations.

We consider the real GDP, real consumption, real investment, real exports, real imports, unemployment rate and core inflation. We use the median inflation as our preferred measure of inflation. Median inflation eliminates outliers and diminishes high-frequency variation without ex-ante eliminating particular components of the consumer basket. We present the results for the U.S. and the summary statistics for the cross section of advanced countries.

We carry out our analysis both in time and in frequency domain. In the time domain, we use statistical filters to isolate the part of the time series that corresponds to frequencies of interest and then the common component is identified using the standard dynamic principal component filter. The results in time domain can be transparently illustrated using intuitive graphs. In the frequency domain, we create the dynamic principal components using frequency-domain filtering directly and ask how much the first or second dynamic principal components fit the spectral density. The analysis in the frequency domain is immune to criticism of pre-filtering of the time series by statistical filters. Both exercises carry the same message.

There are three main messages of our analysis. First, we document great regularities in business-cycle co-movements of key macroeconomic variables across multiple economies. Our dynamic principal component analysis of the data identifies that there is one dominant source of real co-movements, typically explaining more than two thirds of cyclical fluctuations. We conclude that business cycle dynamics of key macroeconomic data can be largely, although not completely, explained by a single source of variation.

Second, the analysis of both real variables and inflation confirms their tight co-movement and allows us to venture an interpretation of the dominant principal component as a ‘demand factor’. Attention to treatment of inflation dynamics is essential to our results on output-inflation co-movement. Low-frequency developments of inflation linked to changes in long-term inflation expectations are complemented with cyclical dynamics by and large due to demand shocks. Using the log of price level or inflation itself would not acknowledge the often time-varying nature of the long-run inflation expectations or inflation targets and might elicit concerns about the stationarity of the series. Using a first difference of inflation in the analysis, however, leads in our view to a misspecification which prevents uncovering the Phillips curve relationship in the data, as the cyclical frequencies are suppressed and the high frequencies emphasized.

Third, the results of our agnostic analysis carry implications for theoretical economic models regarding the number of shocks and properties of a dominant structural shock. Independent of all structural interpretations of our finding, it is clear that any structural economic or econometric model of business cycles must be able to generate the principal component structure that we present. In this sense the principal component space of the data is a very strong testable restriction. We argue that the recent vintage of structural economic models fails this test – these models cannot explain business cycle dynamics.

1. Introduction

What are the drivers of business cycle fluctuations, how many are there, and what are the implications for structural models? This paper attempts to shed more light on these perennial and profoundly difficult questions. It illustrates that most business cycle fluctuations in advanced and some emerging economies are driven by a single major source. We label it 'the demand shock,' due to its properties. We document that a strong and predictable co-movement of real variables during the business cycle is well explained by a single unobserved principal component. The positive co-movement of real output and inflation, reminiscent of the 'Phillips correlation,' convincingly argues for a demand story, not for the technology-driven fluctuations of the Real Business Cycle (RBC) theory. While both demand and technology-shock-driven business cycle hypotheses may be consistent with one dominant source of co-movement of real variables, the strong co-movement of the dominant component with inflation is a decisive piece of evidence that argues for a demand-driven explanation.

The results of our analysis bear important consequences for structural macroeconomic models in terms of the nature and number of driving forces needed to reconcile the models with observed data. Our results suggest that the structure of empirical macro-models, notably of Dynamic Stochastic General Equilibrium (DSGE) models, should imply that only a few structural shocks drive the dynamics of the model at business cycle frequencies, with one shock being the dominant one. Of course, many other shocks contribute to the overall dynamics and specific episodes. Essentially, stochastic singularity of many macro models seems to be a virtue, if handled appropriately, though currently often considered a vice. Further, the response of the economy to the dominant shock must result in a very tight positive co-movement between most GDP components, employment, and inflation. In this paper, we document that most prominent DSGE models today are not compatible with our empirical findings on the number of factors and the nature of co-movement in the macroeconomic data. Our findings thus constitute a powerful smell test for DSGE model misspecification and should prove useful in further model development.

The co-movement of macroeconomic variables is surprisingly strong and stable across the countries and in time. As most practitioners and policymakers know, it simply does not happen that investment plummets while private consumption remains resilient or rallies during a recession. Again, it does not happen that the unemployment rate drops when the output slumps. It just does not happen, except in many DSGE models. Yet, what may not be clear from the outset—given all the buzz about the great moderation, the great turbulence, stochastic volatility, or regime switches—is the surprising degree of business cycle fluctuation stability in time and across economies that we document in this paper. In short, we confirm Cochrane (1994)'s argument that business cycles are "all alike" in many important ways. As Kindleberger and Aliber (2005) also suggest, despite each individual crisis or cycle being a product of a unique set of circumstances, the more things change, the more they stay the same.

Our empirical approach boils down to multi-country dynamic principal component analysis of data at business cycle frequencies. We focus exclusively on business cycle frequencies, with no intention to explain long-run trends in the data, or every high-frequency wiggle. We use non-parametric spectral analysis to estimate dynamic principal components or—with a slight abuse of terminology—factors present in the data.[1] We demonstrate that the first dynamic principal component itself can explain up to 80% of business cycle variation in real macroeconomics aggregates across a variety of countries. Despite the frequency-domain nature of the analysis, we present most of our results in

[1] Henceforth, we use the terms 'factor' and 'component' interchangeably unless stated otherwise.

the time domain, using simple and intuitive charts. Our empirical strategy is most closely related to the index (factor) model by Sargent and Sims (1977) and investigations of Burns and Mitchell (1946) on the nature of the 'reference cycle.'

There are three original contributions of this paper in our view. First, we document great regularities in Post-War business-cycle co-movements of key macroeconomic variables across multiple economies. Going beyond cross-correlations, our dynamic principal component analysis of the appropriately transformed data identifies that there is usually one dominant source of real co-movements, typically explaining more than two thirds of cyclical fluctuations. Second, the analysis of both real variables and inflation reveals their tight co-movement—often doubted in the literature—and allows us to venture structural identification of the dominant principal component as a 'demand factor.' The use of inflation—instead of the price level—and its deviations from the trend or long-term inflation expectations is a key ingredient for our results. Third, the results of our agnostic analysis carry important implications for theoretical economic models regarding the number of shocks and properties of a dominant structural shock in a way that, to our best knowledge, has not yet been demonstrated.

We anticipate three major possible objections to our analysis. First, one may dismiss the results as obvious, trivial and known to everybody. Second, one could view our results as spurious, a result of creative statistical analysis, and continue to believe there is little co-movement of output and inflation, since the Phillips curve's slope is deemed flat or varying in time. And third, we expect a claim that our tools are too simple and we should use a parametric, estimated—and why not a DSGE—model. We do our best to dispel all these objections through the paper. For readers with a view that an argument in favor of demand-driven business cycles is redundant since it is all obvious, the heavy focus of the literature on various flavors of technology shocks and models incapable of producing a positive co-movement of consumption and investment may come as a surprise. For instance, a prominent textbook by Gali (2008) does not feature a single model with an impulse-response function resembling aggregate demand fluctuations. For those who believe that demonstrating a positive co-movement of output and inflation is impossible, we demonstrate what assumptions and data analysis is needed to avoid the impression that the Phillips curve is in flux. To convince the reader that our results are not just a statistical fluke or data mining, we provide sensitivity analysis of our computations. Finally, this paper does not employ an explicit estimated DSGE model or the like, since our goal is to use data and a minimal set of assumptions to obtain strong implications for testing and falsification of structural models themselves.

The structure of the paper is the following: in the next section 2 we place our investigation into the context of economic research. In Section 3 we introduce and discuss methods used in the paper. In Section 4 we describe the results for the U.S. and summarize evidence for the rest of the countries in our sample. In Section 5 we assessment the implications of our results for macroeconomic modeling and in Section 6 we conclude. Additional materials, such as non-core graphs, sensitivity, or robustness checks are included in the Appendix.

There is a related paper to this research: Andrle et al. (2016). The difference between the two papers is that in this paper we give more emphasis on the implications of our findings for structural macroeconomic models. On the other hand, Andrle et al. (2016) is more exploratory and the reader is referred to it for the detailed description of more countries and for various sensitivity analyses.

2. Related Literature

Our paper is related both to the literature that seeks to identify the source of business fluctuations and also to the research on empirical testing of structural macroeconomic models. This section places our paper in the context of both streams of literature.

2.1 Related Literature on the Source of Business Cycles

Despite the voluminous literature focused on the sources of business cycles, there seems to be no clear consensus. There is no clear consensus on number of drivers of business cycles or their nature, namely whether these are more in line with the real business cycle (RBC) tradition or aggregate demand and expectations shocks. Cochrane (1994) carried out an extensive exercise and concluded that there is not enough evidence that economic fluctuations are caused by popular candidates (technology, money, oil, credit). Similarly, Rebelo (2005) overviews a list of possible causes of business cycle fluctuations, centered around the RBC theory. Shapiro and Watson (1988) carry out a thorough empirical investigation concluding that 'aggregate demand accounts for between 20 and 30 percent of the variation in output at business cycle horizons'. After the Great Recession events of 2008 and onwards there has been a revival of theories linking cyclical fluctuations to financial or risk shocks, and credit creation, see Christiano et al. (2014), for instance. Recently, the excess optimism, changes in agents confidence or self-fulfilling prophecies have been proposed as sources of fluctuations, see Angeletos et al. (2014) as an example.

Empirical literature often points towards a real-nominal 'dichotomy,' meaning that real shocks mostly drive real variables and nominal shocks the nominal ones. This is quite a frequent finding of DSGE models, see for instance Smets and Wouters (2007b) or Justiniano et al. (2010), where inflation is dominated by cost and wage-push shocks. There are three important papers that are inspecting a similar question that we ask and thus we build on their methodology—Sargent and Sims (1977), Giannone et al. (2005), and Kydland and Prescott (1990). In the two first papers the authors estimate dynamic factor models in frequency domain and investigate co-movement among a subset of real and nominal variables. In both papers the authors reach the conclusion that there are two major sources of economic dynamics—a real shock driving real variables and a nominal shock, orthogonal to the real one, driving nominal variables. (Sargent and Sims, 1977, pp. 68) reach a conclusion that "one index [factor] model . . . delivers high coherences for all of the real variables except business formation . . . and low coherences for the price indexes. . . . But adding the second index results in high multiple coherences for the two prices . . . [such that] the coherences for the other real variables remain about as they were with one-index [model]'. Giannone et al. (2005) conclude that the U.S. macroeconomic dynamics are driven by two shocks. GDP and other real variables are driven by the real shock, output deflator is driven mainly by the nominal shock, and the Phillips curve relation is weak, according to the paper. We are inspired by, and revisit some of the analysis in Kydland and Prescott (1990). The crucial difference is the treatment of nominal variables, of price level versus inflation. The authors focus on cyclical dynamics of price level, not inflation, and use the fact that price level is counter-cyclical as an argument in favor of the their real business cycle theory. However, pro-cyclical inflation, lagging activity cycle, is consistent with counter-cyclical price level.

We believe that the results of our analysis have implications both for the number of shocks driving the business cycles and for the real-nominal dichotomy. We present the evidence for one dominant shock that drives the business cycles and this shocks move real variables and inflation in the same direction. Our results therefore do not confirm a real-nominal dichotomy and support a short-run Phillips' correlation. Two of the reasons for our different results are the transformation of variables—we use inflation instead of the price level, for instance—and the focus on business cycle frequencies. In an inflation-targeting economy, output should be related to the inflation deviation from its target, or from long-term inflation expectations, if there is a 'Phillips correlation' in the economy. This would be so for demand shocks in a New-Keynesian DSGE models. Our analysis acknowledges that low-frequency dynamics of inflation, due to an explicit or implicit inflation target, are a factor of their own and inflation in relation to its trend or inflation target is the variable of interest. Both inflation and interest rates are tied to the explicit inflation target and long-term inflation expectations.

2.2 Related Literature on Testing Structural Macroeconomic Models

Given the prominence of macroeconomic structural models in contemporaneous macroeconomics, it is not surprising that there is a huge amount of papers that aim at evaluating and testing structural macroeconomic models, such as DSGE models. These papers differ in features being tested and they differ also in the underlying metrics. The examined features can range from testing assumptions of trends, to forecast accuracy relative to simple statistical benchmarks, and to selected features of data. There are various metrics used: from very abstract, such as Bayes factors, to very transparent metrics that can be easily summarized and that directly reveal where a potential problem with a particular model is.

In this paper, we concentrate on a particular feature – the co-movement along business cycles: we aim at evaluation of whether structural models are capable of generating strong co-movements on cyclical frequencies. Although, we do not question that for practical forecasting the correct specification of the trend component is important, DSGE models are primary models of business fluctuations, not models of long run growth determinants, and therefore the cyclical frequencies should be of the main interest.

We are also close to papers that summarize their findings using transparent statistics. We would like to highlight the potential problems with recent vintage of DSGE models and therefore, we present our conclusions using pictures and simple summary numbers. We believe that this is more informative than abstract metrics like likelihood ratio statistics or Bayes factors.

Two papers are therefore especially close to our paper. Herbst and Schorfheide (2012) propose a method for evaluating DSGE models using co-movements of macroeconomic variables. Similarly to us, they also consider an application of statistics of interest both to actual data and to model-simulated data. The difference is that they concentrate on forecast densities and more importantly, they are interested in growth rates. We instead are interested in cyclical implications of the structural models and therefore, our statistics is directly targeted to frequencies of interest.

Faust and Gupta (2012) is another paper close to ours. They use the posterior predictive analysis to check implied properties of estimated DSGE models. Similarly to us, they conclude that canonical DSGE models have problems of generating strong co-movements in real variables. Contrary to us, they investigate the implied correlations of growth rates; in our research we show that using the proper transformation of variables is even more revealing about the co-movement.

3. Empirical Models and Methods

Our main tool is the dynamic principal component analysis (DPCA), which can be applied both to data and to a model (either directly on the model's reduced form or indirectly on simulated data). The DPCA is based on the seminal work of Brillinger (1981), which was popularized in empirical macroeconomics by Forni et al. (2000). The DPCA is a dimensionality reduction technique, which is essentially based on the eigenvalue decomposition of the spectral density. At the same time, it can be reverted back to the time domain, which results in a two-sided filter that can be used to filter the common component. Somewhat more formally, the DPCA aims at a decomposition of observed time series $x_{i,t}$ using the following representation:

$$x_{i,t} = \chi_t + \xi_{i,t},$$

where $x_{i,t}$ is the observed series, χ_t is the low-dimensional common component, and $\xi_{i,t}$ is the idiosyncratic noise, which is uncorrelated with the common component χ_t, and only 'weak' correlation among elements of ξ_t is allowed. A set of K time series is fully explained by K principal components, with potentially a small number of principal components explaining most of the dynamics.

Frequency domain DPCA starts with the estimation of the multivariate spectral density $\Sigma^x(\omega)$ of the observed process x_t, from which the spectral density of the common component χ_t is obtained by selecting dominant eigenvalues. By selecting the dominant eigenvalues at each frequency, one estimates the spectral density $\Sigma^\chi(\omega)$ of the common component. This is essentially a frequency domain filter. This frequency domain filter can be inverted back to time domain to obtain a two-sided filter that relates the observed series to the common component:

$$\chi_t = \sum_{l=-L}^{L} \Lambda_l x_{t+l}, \tag{3.1}$$

where $\{\Lambda_l\}_{l=-L}^{L}$ are weights of the time-domain filter.[2] For $L > 0$, the resulting time-domain filter can easily account for lead-lag relationship among variables (such as is the case for unemployment and output cycles).

$L > 0$ implies that the filter is two-sided and that the common component cannot be inferred at the beginning and at the end of the sample. Nevertheless, the two-sided nature of the filter for the common component in time domain is not a big issue for us since we are not interested in real-time forecasting but in ex-post analysis of the data. Therefore, we stick the two-sided formulation as in Forni et al. (2000).[3].

We present the results for DPCA both in the time and in frequency domain. In the *time domain*, we isolate cycles using the band-pass filter (Fitzgerald-Christiano) and high-pass Hodrick-Prescott filter and then, we apply the time-domain filter (3.1) on such isolated cycles. We chose $L = 2$ as the filter can account for lead-lag relationships in the data. The lead-lag relationships of the DPCA increase the fit of the model,[4] although for our data the gain in fit is not dramatic: if we

[2] Ideally, one would choose $L = \infty$, which is obviously infeasible in practice. However, for a typical example, filter weights with a finite and 'small' L give a very accurate approximation to $\{\Lambda_l\}_{l=-\infty}^{\infty}$.
[3] In fact, in our empirical analysis we use exactly the same approach in estimating the multivariate spectral matrix (the Bartlett non-parametric approach with the same setting of smoothing window) as described by Forni et al. (2000).
[4] This is obviously true in large samples. In small samples, it can happen that the static principal component analysis could fit data better than the DPCA because of an imprecise estimation of the spectral density.

applied the static principal component analysis to our data, the results and implications would be qualitatively unchanged with slightly lower fit. The main reason for dynamic PCA is a time shift of unemployment with respect to output (Okun's law) and of inflation and interest rates if included in the computations.

To measure the co-movement in time domain, we use the statistics introduced by Stock and Watson (2002). In particular, let χ_{it}^k be the common component for the series x_{it} estimated using k first dynamic principal components based on the time domain filter (3.1). Our preferred statistics is the analogy of $\mathfrak{R}^2$ statistics of linear regression:

$$\mathfrak{R}^2(k) = 1 - \frac{\sum_{t=1}^{T}(x_{it} - \chi_{it}^k)^2}{\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2}, \tag{3.2}$$

where $\bar{x}_i$ is the sample mean of x_{it}.

The *frequency-domain representation*—as already mentioned—is centered on the multivariate spectral density $\Sigma^x(\omega)$. Let $\{\lambda_{(i)}(\omega)\}_{i=1}^n$ be ordered eigenvalues of $\Sigma(\omega)$ at frequency ω. Since $\Sigma(\omega)$ is positive semi-definite for each frequency ω, all eigenvalues are non-negative. Therefore, for a stationary time series, Y, we consider the following statistics:

$$\mathscr{S}_Y(\omega,k) \equiv \frac{\sum_{i=1}^{k}\lambda_{(i)}(\omega)}{\sum_{i=1}^{n}\lambda_{(i)}(\omega)}, \tag{3.3}$$

which intuitively tells the percentage of variability explained by k principal components at frequency ω.

The computation of the spectral density estimate using raw, unfiltered data is a subtle issue, since some of our macro variables are non-stationary. When working with non-stationary data, spectral estimates cannot be carried out without some modification. We use the non-parametric Bartlett approach on first log differences (when meaningful), which renders the problem stationary. This does not pose a problem for the measure (3.3), as it is invariant with respect to first-differencing all series. Indeed, it can be shown that:

$$\mathscr{S}_Y(\omega,k) = \mathscr{S}_{\Delta Y}(\omega,k), \tag{3.4}$$

for all ω, such that both sides are defined.[5] It implies that for non-stationary $I(1)$ time series, the statistics (3.3) can be just estimated for first differences of series and this holds for all $\omega \neq \pm 2\pi n$, where $n \in \mathbb{N}_+ \cup 0$. Moreover, some other statistics of interest, such as coherence, also remain unchanged if both series are pre-processed by the difference filter. Formally, if $\mathscr{C}_{x,y}(\omega)$ is the coherence between series x and y, then, it holds that:

$$\mathscr{C}_{x,y}(\omega) = \mathscr{C}_{\Delta x,\Delta y}(\omega),$$

for all ω for which both expressions are defined.[6]

[5] This statement can be easily generalized: the equivalence would hold if each of the series is pre-filtered by the same linear filter. This follows from the easily seen fact that such filtering would scale up all eigenvalues of the spectral density matrix by the same number.
[6] See (Koopman, 1974, pp. 149).

The analysis turns out to be robust with respect to whether our computations are carried out in either the time or in the frequency domain. In the frequency domain, we create the dynamic principal component using frequency-domain filtering and ask how much first or second dynamic principal components fit the spectral density. This information can also be represented by revealing plots, though in the frequency domain. The analysis in the frequency domain is immune to criticism of pre-filtering of the time series by statistical filters. That being said, it is useful to note that the often-heard opinion that the use of statistical filters, say the Hodrick-Prescott filter, always causes spurious cycles is misguided; see Pollock (2013) who proves that “this idea is largely mistaken".

For each country in our sample, we consider the following set of variables: real GDP, real consumption, real investment, real exports, real imports, unemployment rate, and short-term interest rate. The common component based on the first principal component analysis is then projected on cyclical dynamics of inflation.

For our goals, it is crucial that we ask how the cyclical dynamics in real variables are related to the cyclical dynamics of inflation. We do it again in two ways. In the time domain, we compare the dynamics of the first dynamic component to the dynamics of inflation deviation from its trend (henceforth called *inflation cycle*). We compare the dynamics of the inflation cycle to the output cycle. In the frequency domain, we compute and report the coherence between inflation and output as well as between inflation and the isolated first dynamic component. We employ the median inflation as our preferred inflation. Median (or more generally trimmed-mean) inflation eliminates outliers and lowers high-frequency variation without ex-ante eliminating particular components of the consumer basket.[7] However, with the exception of the U.S. and Australia, we have to construct our own median inflation measures with data available only from early 90’s using the Haver Analytics database.

So, why don’t we put inflation directly into the dynamic principal component model? The only reason is that median inflation data for most countries span much smaller sample size than macroeconomic data on other variables, which would restrict our analysis too much. This is why we choose to compare inflation dynamics with the common component estimated on real variables instead. Inflation, therefore, does not affect the estimates of the unobserved principal components. Nevertheless, we can do this for the U.S. and we present the result, which supports our conclusions.

Our results do not confirm a real-nominal dichotomy and support Phillips’ correlation. Two of the reasons for our different results are the transformation of variables—we use inflation instead of the price level, for instance—and the focus on business cycle frequencies. In an inflation-targeting economy, output should be related to the inflation deviation from its target, or from long-term inflation expectations, if there is a ‘Phillips correlation’ in the economy. This would be so for demand shocks in a New-Keynesian DSGE models. Our analysis acknowledges that low-frequency dynamics of inflation, due to an explicit or implicit inflation target, are a factor of their own and inflation in relation to its trend or inflation target is the variable of interest. Both inflation and interest rates are tied to the explicit inflation target and long-term inflation expectations.

[7] Andrle et al. (2013) show this point using the euro-area data. Elimination of high-frequency variation using median inflation (i.e., the extreme case of trimmed means) has been suggested also by Meyer and Zaman (2013) in the forecasting context.

4. Main Empirical Results

In this section we document the strong co-movement among cyclical components of main macroeconomic variables and inflation. We show this for the United States and for the cross-section of advanced countries. The United States are an obvious choice for it's 'benchmark' status earned by the size of the economy and length and quality of the statistical data.In the accompanying paper (Andrle et al. (2016)), the interested reader may find the evidence also for Germany and Japan. Moreover, the accompanying paper contains a bulk of robustness tests related to the sample size or the method for extracting the cycles in time domain.

4.1 The United States

In the case of the U.S. economy, our empirical findings are the most robust ones. Figure 1 clearly demonstrates in time domain that the first dynamic principle component can explain a great portion of variation of the business cycle in the U.S. Virtually every cyclical component of GDP, with the exception of real exports, and short-term interest rates is explained by more than 80% using a single dynamic principal component. In the case of the short-term interest rate this is due to the fact that monetary policy is not easily described as following some sort of pro-active Taylor rule in late 1980's to early 1990's. The case of exports is different, since U.S. exports are the imports of their trading partners and thus should be well approximated by trade-weighted linear combination of explained import components of partner regions and in our analysis is put into second dynamic principal component mostly.[8]

In the frequency domain—without pre-filtering in the time domain—the results hold as well. Figure 4 shows the portion of the spectral density explained by first two dynamic principal components over the whole range of frequencies. Apparently, the fit of the spectral density using one principal component over the business cycle is great especially for imports and investment. For exports, one needs the second principal component, which makes the fit of the spectral density of exports almost perfect over business cycles.

We present the results for both Christiano-Fitzgerald and Hodrick-Prescott filters. The key difference is that the HP filter does not exclude high frequencies of the data and filter cutoff between low and cyclical frequencies is not as sharp as for the Christano-Fitzgerald band pass filter. The results for HP filter (both in time and frequency domain) show that the results holds also for data pre-filtered by this popular filter in both the shorter and full sample, see Figure 2 and Figure 12.

These results are not affected much by extending the sample to before the 'Great Moderation' episode. We estimated the DPCA model for data since 1955 and featuring two periods of what most economist agree on is a different volatility of macroeconomic aggregates in the U.S. – a period of volatile business cycles, followed after mid 1980's by a Great Moderation period, which was abruptly put to an end by the Great Recession starting in 2007. The relative explanatory power of the first principal component is changed a little bit, with an expected deterioration of the short-term interest rate fit before 1985 – an era of volatile policy rate, Gold-Exchange Standard, and two important oil price shocks. The first principal component changes its variance but the filter loadings (coefficients of the model) are constant. That means that relative variances among real

[8] To investigate this hypothesis we used data from IMF's Global Projection Model database and computed implied export gap using constant trade weights and imports of China, Eurozone, Emerging Asia, Japan, Latin America, and Remaining Countries. Fig. 21 presents the results and suggest that more formal and detailed investigation of co-movements and spillovers could explain the data in a more comprehensive way. A multi-country restricted factor model is left for our further research.

variables cycles have not changed significantly neither during the Great Moderation period nor during the recent Great Recession. The sample starts in 1955Q2 and ends in 2012Q4 (see Figure 11 in Appendix). This simple calculation has potential consequences for specification of models with time-varying coefficients, namely that the stochastic volatility can be relevant but the dynamics driving relative co-movement of variables may be kept constant.[9]

A thorough consideration of inflation dynamics is key to our analysis and an important piece of evidence in favor of demand shocks. It is the explicit use of inflation—instead of the price level—and considerations about the implicit and subsequently explicit inflation target of the FED, that allow us to demonstrate the close co-movement of output and deviation of inflation from the target. Central banks today do not operate in a price-level targeting but rather closer to an inflation targeting regime. Clearly, low-frequency movements of inflation are driven by perceptions of the inflation target, as embodied in the long-term inflation expectations, or long-term nominal bond yields. The cyclical component of inflation is obtained using a band-pass and HP filter for consistency with other countries in our baseline calculations, however. Using a measure of the ten-years-ahead long-term inflation expectations[10] though would lead to similar removal of the 'trend' process from inflation, see the Fig. 20 in Appendix. The high-frequency dynamics of the core inflation is lower than in the case of headline CPI, since our measure is Cleveland's FED median inflation.

Viewed through lens of our analysis, there is little evidence for nominal-real dichotomy in the U.S.: inflation lags the output cycle in a relatively stable and predictable way. The strength of output-inflation co-movement can be recognized from Fig. 3, which depicts the cyclical component of core inflation and the normalized first dynamic principal component (essentially the output cycle).[11] The figure also shows the estimated coherence along with 95 confidence intervals.[12] between median inflation and output (and between median inflation and the first estimated dynamic component). Figure 13 in Appendix then shows the results for the full sample. Unlike in the case of real variables, monetary policy conduct following the chairman Volcker lead to a lower variance of inflation around the long-term inflation expectations that we have adjusted by normalizing the series to Great Moderation mean variance. Yet, apart from the amplitude change, the co-movement between inflation and real variables is preserved.

Our results thus indicate a strong and stable co-movement between key real macro variables and inflation in the course of business cycle. The first dynamic component has such a dominant explanatory power that we do not venture identification of other type of macroeconomic disturbances. The positive co-movement of the dominant component (and output) with inflation cycle motivates the label of the component as a 'demand factor' or demand shock. We do not observe the demand shock directly and cannot link it to particular events. At the very detail all cycles will look as triggered by a different cause just to look more or less alike, echoing the conclusions of Cochrane (1994) or Kindleberger and Aliber (2005), among others.

[9] To check robustness to the chosen methodology, we also redone the calculations using the standard static PCA instead of the DPCA. The co-movement among real variables is clearly visible even for the static PCA that does not allow for lead-lag relationship among variables; see Figures 16 and 17.

[10] 10Y ahead long-term inflation expectations are obtained from Survey of Professional Forecasters (SPF) at Philadelphia FED. The FRB/US measure of implicit inflation target, variable PTR in the FRB/US model, can also be used as a proxy for the unobserved inflation target (thanks to Bob Tetlow for providing the data) as it reaches the sample before SPF 10Y expectations; see Andrle (2012) for empirical analysis and demonstration of consistency of New-Keynesian expectational Phillips curve with observed data dynamics. What our analysis also says is that while cyclical dynamics around long-term inflation expectations seems driven by economic cycle, the dynamics of long-term inflation expectations is a different issue altogether.

[11] The plot is phase-aligned, i.e. the inflation cycle is shifted by a mean lag.

[12] Computed using wild bootstrap, see Wu (1986)

Let's not forget that data transformations are important for seeing clear results. If growth rates were used instead of a band-pass filter, the DPCA fit would deteriorate, which can be seen from Figure 5. The logic is clear as soon as one looks at the graph of the transfer function of the difference operator, $1-L$, which amplifies high frequencies relative to business-cycle and the low frequencies. Nevertheless, despite the deterioration of the fit, the co-movement among real variables is still there, although not as impressive as for cyclical components of real variables. Figure 18 in Appendix presents normalized growth rates of GDP components to highlight that strong co-movement is easily discernible. For inflation, we have already argued that the economic theory has a strong say in terms of data transformation–namely linking deviation of inflation from its target (and thus long-term expectations) to output dynamics. Often, the contributions to the literature, namely factor models, search for co-movement of the first difference of inflation with output growth or output gap. Such attempts necessarily fail, as those attempts that ignore inflation targets. This is especially easy to understand in the case of inflation-targeting countries that underwent a disinflation process, like Canada, the Czech Republic, or Poland.

Finally, the length of the U.S. data enables us to plug the median mean inflation directly to the DPCA analysis. We did it and the results are available at Figure 14 showing the fit in the time domain for HP cycles (results for the band-pass cycles look like similar). For the output, consumption, investment, and unemployment, the one principal component produces an excellent fit. The common component based on the first principal component for the exports, short-term interest rate, and median inflation explains about 50% of volatility. The relatively low explanatory power of the first principal component is due to large volatility of these series during the 1960s and the 1970s, nevertheless, filter loadings have the same sign. We conclude that this exercise confirms our finding that the relative variance of some variables may change, but the co-movement is stable.

4.2 Summary Statistics

In this subsection, we report summary statistics for all countries in our dataset. We have collected data for a list of advanced and several emerging market countries at quarterly frequency. The lists consists of: Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, the U.K., and the U.S. Our benchmark analysis starts from the year 1985 (or later according to data availability). The choice of this year is motivated by the change in relative volatilities of inflation and real activity (Great Moderation) in developed countries around the mid 1980s. Nevertheless, we carry out our exercise with a longer sample for countries where a larger sample is available. The co-movement among real variables remains stable, even after the larger sample has been used. We also find a cyclical similarity of inflation and real activity when the change in their relative volatilities is taken into the account.

First, we report the boxplots[13] of how our model fits the co-movement in cyclical parts of real variables. Figure 6 shows the fit for sample post 1985 for the first three dynamic components (organized by rows) and for the two popular filters used (Christiano-Fitzgerald band-pass filter and HP filter – organized by columns). Apparently, for most countries, already the first dynamic principal compo-

[13] Boxplots are organized as follows: on each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme datapoints that are not outliers, and the outliers are plotted individually. Observations are defined as outliers if they are larger than $Q_{75}+1.5(Q_{75}-Q_{25})$ or smaller than $Q_{25}-1.5(Q_{75}-Q_{25})$, where Q_{25} and Q_{75} are the 25th and 75th percentiles.

nent explains the most dynamics in output, investments, imports and unemployment.[14] The first two dynamic principal components then explain the high share of the dynamics in all variables. Figure 15 in Appendix depicts the same exercise for all data in our sample. Apparently, the fit is robust for the inclusion of the period before 1985, for countries where available. The analysis reveals that for all countries the larger dispersion of percentage explained is for exports, short-term real rate, and consumption as indicated in the discussion above.

The co-movement of inflation and real variables seems also quite strong for all countries in the sample. Figure 7 reports the summary results on the co-movement between the inflation cycle and cycles in real variables for all countries in the sample. It reports the coherence and cross-correlation of inflation cycle with output and of inflation with the first dynamic principal component. Apparently, the results argue for a relatively high co-movement between inflation and the real economy over the business cycle.[15]

[14] The exact figures on the fit using the first principal component (both based on the two-sided DPCA and on static PCA) for all countries in our sample are given in Tables 2 and 3 in Appendix.

[15] Interestingly, for each country in our sample, there is a lag $k \in (0,\ldots,4)$ for which correlation between cyclical inflation and the cyclical component of output is positive and significantly different from zero at 5% level.

Figure 1: Cyclical components (Christiano-Fitzgerald filter): data and fit with the DPCA – the U.S.

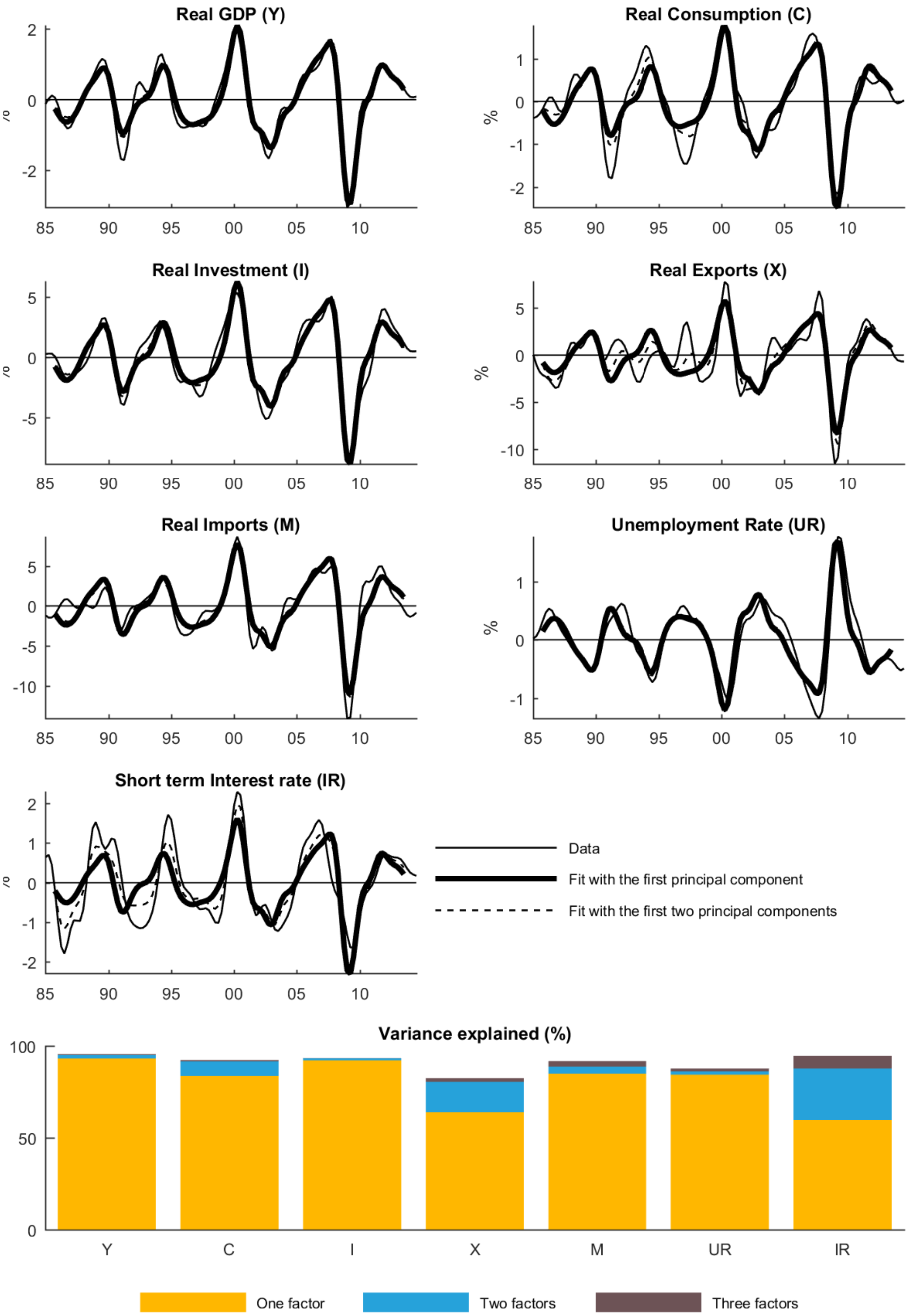


Figure 2: Cyclical components (Hodrick-Prescott filter): data and fit with the DPCA – the U.S.

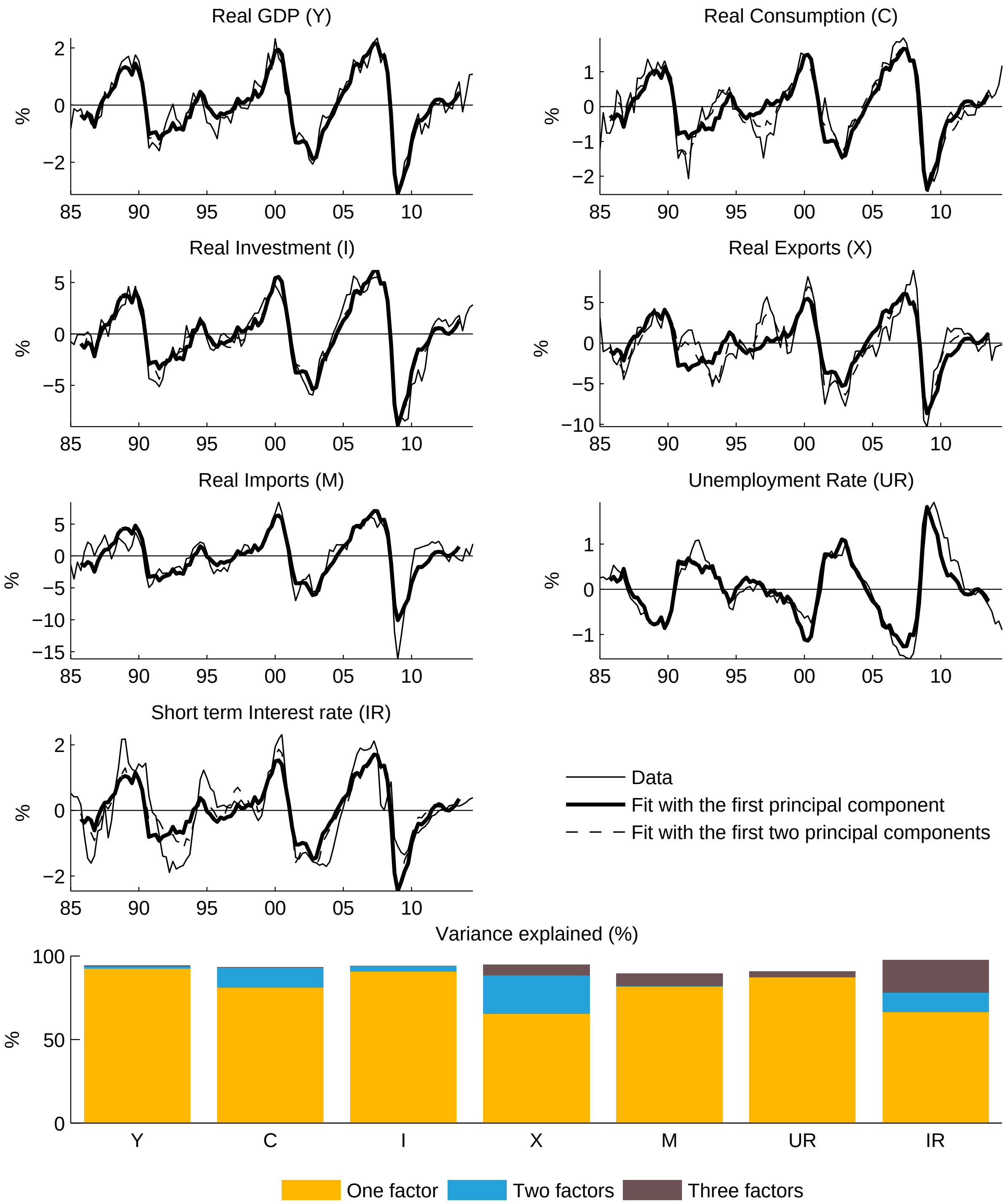


Figure 3: Inflation and real economy – the U.S. (post 1985)

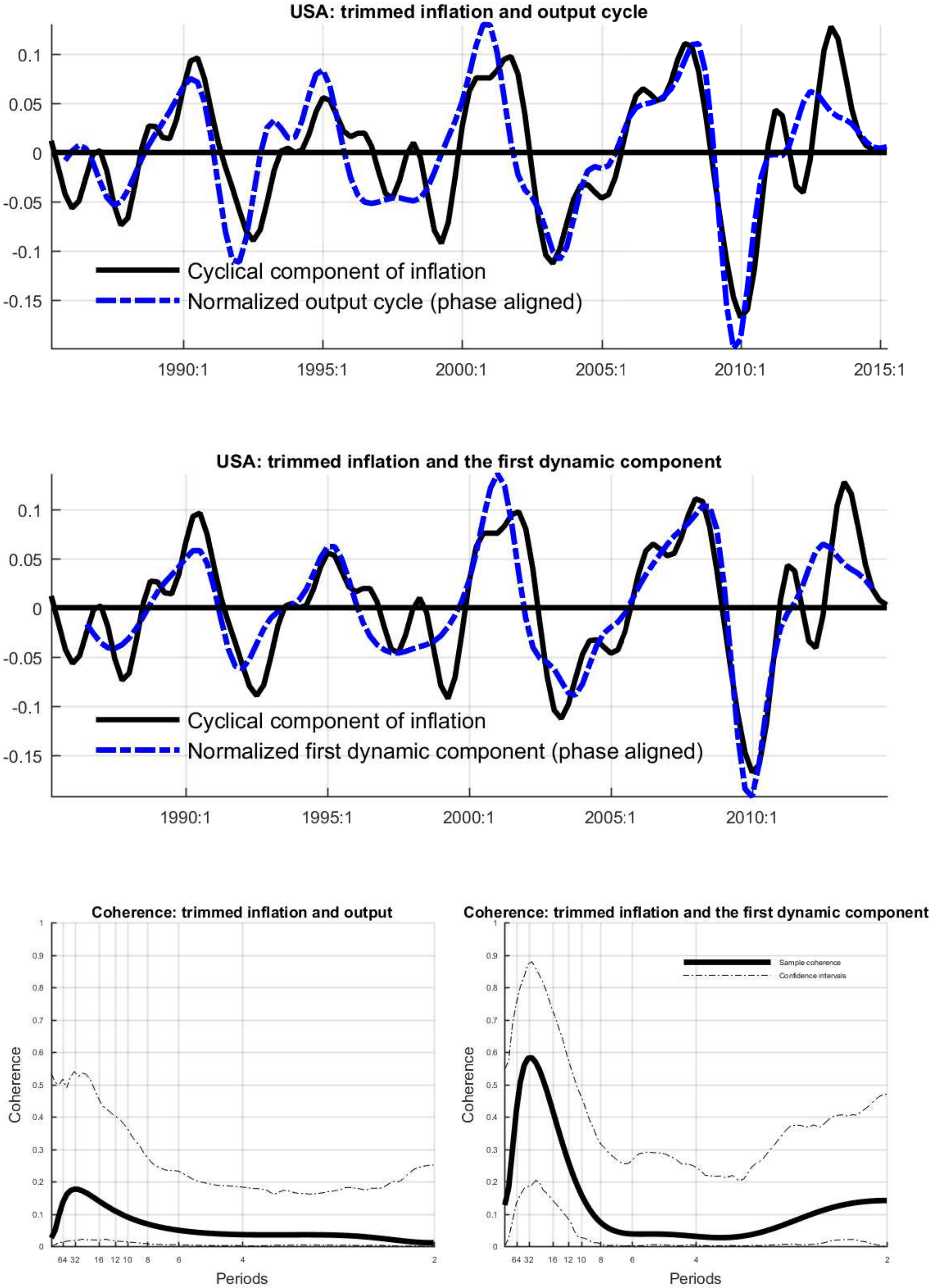


Figure 4: The share of spectral density explained by first two dynamic components – the U.S.

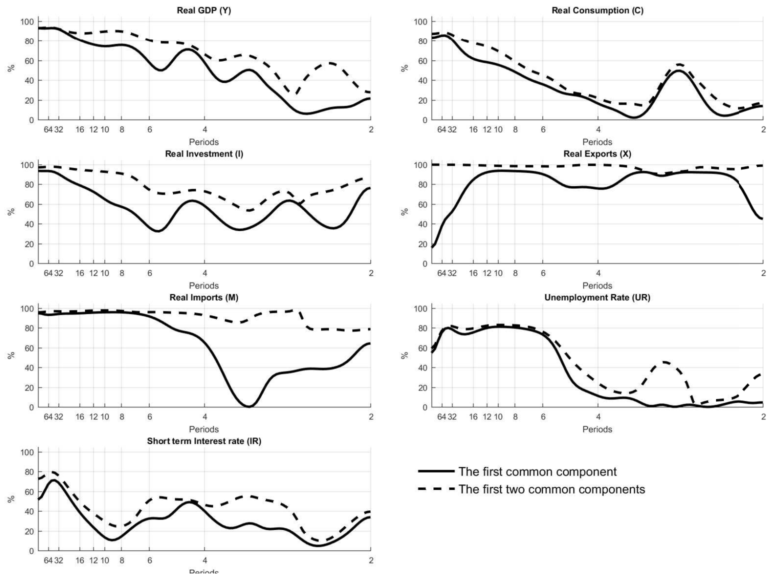


Figure 5: Growth rates: data and fit with the DPCA – the U.S.

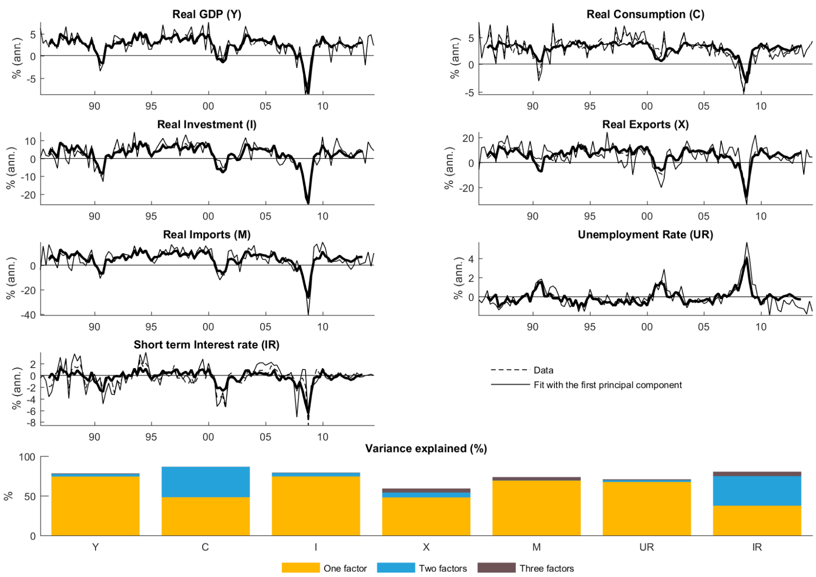


Figure 6: The boxplot summary statistics

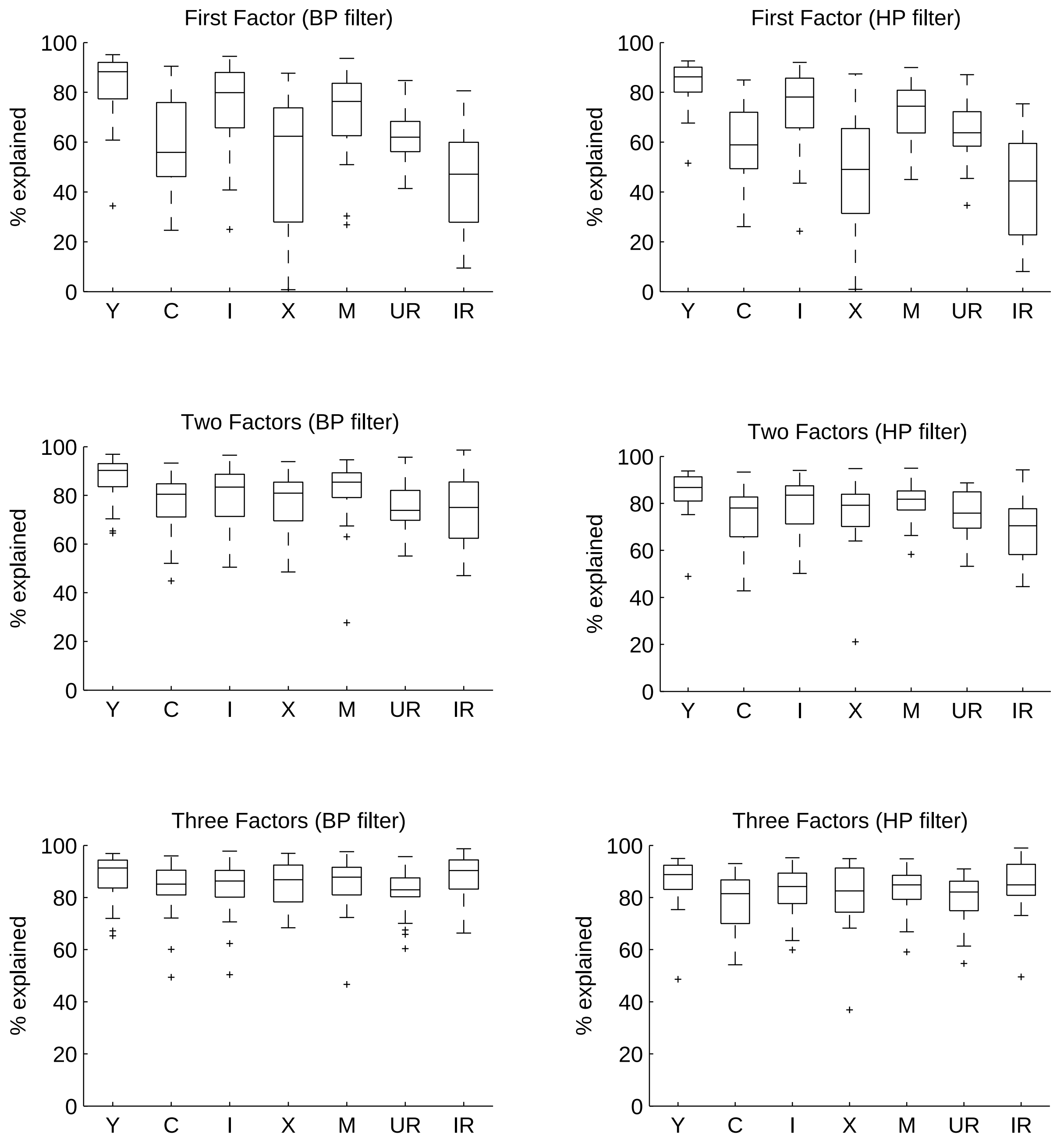
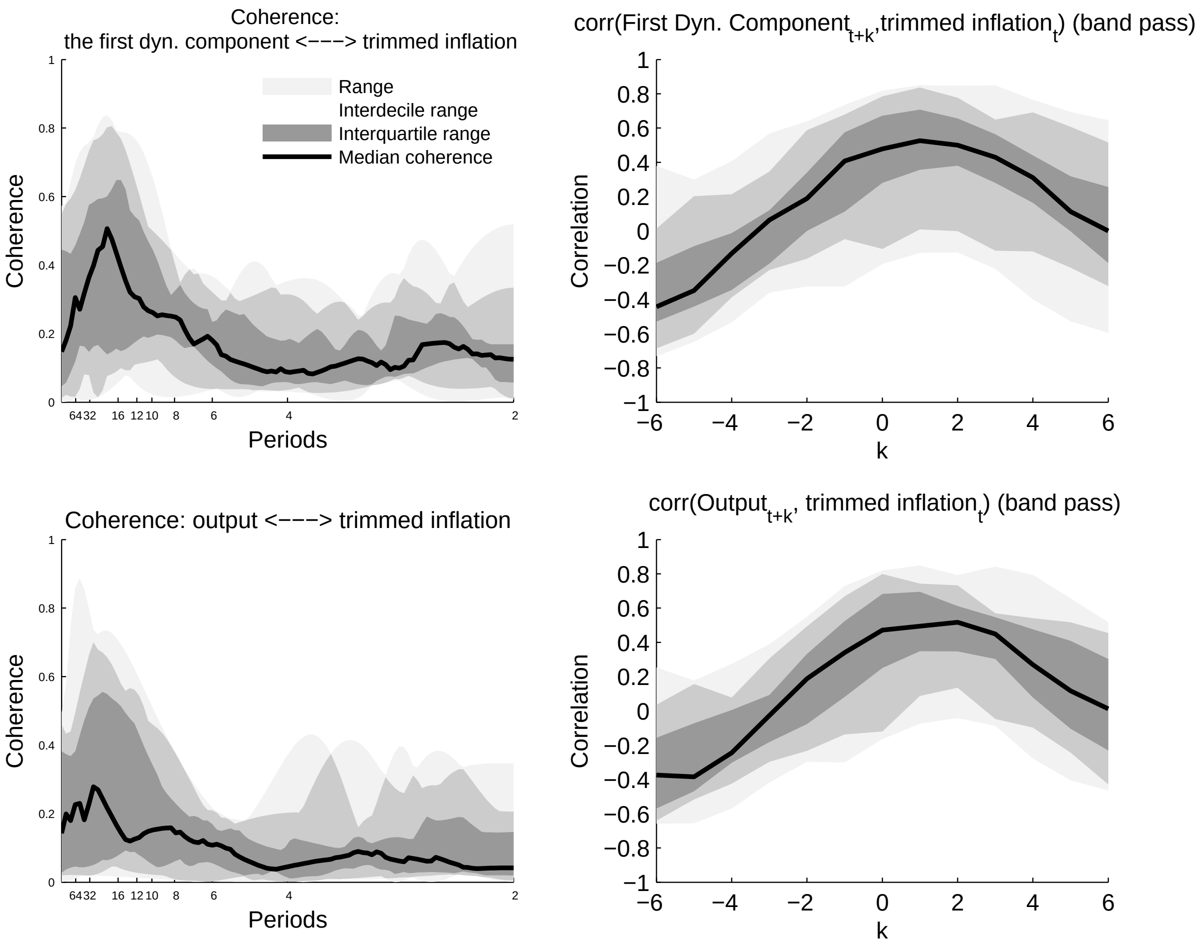


Figure 7: The summary statistics: coherence and correlations between inflation and real activity



5. Implications for Macroeconomic Models

5.1 Economics of Co-Movement

Our findings that macroeconomic cycles of both real and nominal variables are well-explained by a single dominant dynamic principal component bear important implications for structural economic modeling. More specifically, an economic model, for instance a DSGE model, that does not feature a structural shock that dominates the cyclical frequencies of consumption, investment, output, hours worked, and inflation is very likely to be misspecified. This amounts to both (i) variance contribution of the shock and (ii) direction of co-movement of relevant variables. To the best of our knowledge, no DSGE model in the literature has so far demonstrated the ability to explain the principal-component space of the data in a satisfactory manner. We do not propose a solution either but offer a testing procedure. In a companion work, Andrle (2014) elaborates on the issue in more rigorous terms and suggests some remedies for estimating structural shocks with misspecified or singular DSGE models.

When a DSGE model lacks a dominant structural factor with the above-mentioned properties, the misspecification will lead remaining structural shocks or measurement errors to be correlated. The requirements on models are rather strict. At business cycle frequency, not only should a single shock be dominant and result in a positive co-movement of real variables with inflation but little leeway is also for the shape of the impulse-response function to such a shock.[16] A misspecified structural shock inevitably leads to cross-correlation of other shocks and disturbances.

Leading DSGE models in the literature fail to satisfy the restrictions on co-movement argued for in this paper and are therefore misspecified and easily falsified. Standard RBC-like TFP shocks are ruled out, mostly due to their implausible effects on inflation. The literature has thus proposed other types of shocks. For instance, a state-of-the-art model by Justiniano et al. (2010) proposes investment-specific shocks as an explanation of the business cycle.[17] Their model explains a large portion of output, investment, and hours worked but fails to explain private consumption or inflation. The reason is that after an expansionary investment-specific shock, private consumption actually drops and increases only after about five quarters, see Fig. 19. In light of the evidence elaborated in this paper, we believe that the likelihood of finding such a structural shock is small and a correlated shock explaining the close positive co-movement of consumption and investment is necessary to explain the data with the model. Andrle (2014) replicates the analysis by Justiniano et al. (2010) and confirms the cross-correlation patterns in the structural shocks, namely between the consumption shock and investment-specific shock. We believe that correlated structural shocks are not truly structural shocks.

The line of research using financial sector disturbances and risk shocks seems also not to fit the bill. For instance, a prominent study by Christiano et al. (2014) fails to invoke a robust co-movement of consumption and investment as robustly observed in the data. After a negative risk shock, with output and investment falling, private consumption drops marginally and only very gradually continues its decline, see (Christiano et al., 2014, Fig. 4, Panel A). Such co-movement is rather inconsistent with the risk shock being a dominant source of business cycle fluctuations. The risk shock in the model explains almost none of business cycle dynamics of consumption and consumption-specific

[16] Andrle (2014) illustrates that these strong regularities in terms of principal-component space of the data hold for redefinition of investment including consumer durables and consumption being understood only as non-durables. See Figure 18 in the Appendix with data definitions and transformations identical to Justiniano et al. (2010).

[17] We choose Justiniano et al. (2010) and Christiano et al. (2014) as illustration mainly due to their major influence on empirical modeling, quality of execution, and exemplary scholarship and transparency of their research.

Table 1: Variance Decomposition at Business-Cycle Frequency, Justiniano et al. (2010)

Series / Shock	Policy	Neutral	Government	Investment	Price mark-up	Wage mark-up	Preference
Output	0.05	0.25	0.02	**0.50**	0.05	0.05	0.07
	[0.03, 0.08]	[0.19, 0.33]	[0.01, 0.02]	[0.42, 0.59]	[0.03, 0.07]	[0.03, 0.08]	[0.05, 0.10]
Consumption	0.02	0.26	0.02	**0.09**	0.01	0.07	**0.52**
	[0.01, 0.04]	[0.20, 0.32]	[0.02, 0.03]	[0.04, 0.16]	[0.00, 0.01]	[0.04, 0.12]	[0.42, 0.61]
Investment	0.03	0.06	0.00	**0.83**	0.04	0.01	0.02
	[0.02, 0.04]	[0.04, 0.10]	[0.00, 0.00]	[0.76, 0.89]	[0.02, 0.06]	[0.01, 0.02]	[0.01, 0.04]
Hours	0.07	0.10	0.02	**0.59**	0.06	0.07	0.08
	[0.04, 0.10]	[0.08, 0.13]	[0.02, 0.03]	[0.52, 0.66]	[0.04, 0.09]	[0.04, 0.11]	[0.06, 0.12]
Wages	0.00	**0.40**	0.00	0.04	0.31	0.23	0.00
	[0.00, 0.01]	[0.30, 0.52]	[0.00, 0.00]	[0.02, 0.07]	[0.23, 0.41]	[0.16, 0.32]	[0.00, 0.01]
Inflation	0.03	0.14	0.00	**0.06**	**0.39**	0.34	0.02
	[0.02, 0.06]	[0.09, 0.21]	[0.00, 0.00]	[0.02, 0.13]	[0.29, 0.50]	[0.26, 0.42]	[0.01, 0.04]
Interest Rates	0.17	0.09	0.01	**0.47**	0.05	0.04	0.16
	[0.13, 0.22]	[0.06, 0.12]	[0.00, 0.01]	[0.37, 0.56]	[0.03, 0.07]	[0.03, 0.07]	[0.11, 0.23]

'demand' shocks must step in. The estimated demand shock thus must be correlated with the risk-shock in order to explain the strong co-movement of real variables present in the data. In other renditions of financial premium shocks, e.g. Christiano et al. (2011), the problem is compounded by unrealistic response of investment relative to output. Investment is implied to be roughly eight to ten times more volatile than output, contrary to a stylized fact of investment variance being roughly four times the one of output.

Variance decompositions strongly support our argument for model misspecification in the literature. As our discussion above indicates, the business cycle frequency dynamics of the main GDP components, unemployment, or inflation are dominated by one source of variation in the data across many countries. The modeling analogue of the analysis is the variance decomposition of model variables by source of structural shocks. Both Justiniano et al. (2010) and Christiano et al. (2014) are transparent in presenting the statistics with the identical definition of cyclical frequencies as in this paper. In variance decomposition by Justiniano et al. (2010), restated here for convenience, it is clear that the investment shock cannot explain even 10% of consumption dynamics and preference shock fills the void. It can also be seen that inflation is driven by cost and wage-push shocks and not by investment-specific shocks, further undermining the investment shock as a plausible explanation of the business cycle. In Christiano et al. (2014), Table 5, one can see that business cycle dynamics of consumption are essentially unaffected by the risk shock, amounting to 3% of total, with almost half of the variance driven by the 'demand' shock, which, on the other hand, hardly affects any other variable. Although some 11% of the consumption dynamics is driven by investment shock, yet the IRF has the wrong sign, which is not reflected in a variance decomposition.

Misspecification of a structural model is easy to recognize from the correlation patterns of shocks and shock decompositions. Once the model falls short of a dominant shock with a robust co-movement of real and nominal variables at business cycle frequencies, the estimated shocks must be correlated. Inspecting the auto-covariance function of the shocks is thus an easy and useful test for misspecification of the model and fits within the best tradition of econometrics where 'residuals' matter and are inspected closely. The cross-correlation of shocks is visually apparent in shock decomposition of the observed data, where one gets 'fish graphs' with one shock's contribution almost perfectly offsetting another shock's contribution, see Andrle (2014). For instance, a positive investment shock often increases output and investment but depresses private consumption, while a 'consumption' preference shock expands consumption and lower investment. To fit the observed profile of consumption and investment, the shocks must be negatively correlated and their individual contributions are offseting. Correlated estimated 'structural' shocks are problematic, since most of the model properties assumes they are independent, namely impulse-responses, variance decompositions, or counterfactual simulations. All these properties are invalidated by misspecification manifested in correlated shocks.

Our analysis suggests several intuitive 'smell tests' to asses model performance and misspecification. Maximum-likelihood or other estimators will converge to some extrema and models can be compared in relative terms to each other using more or less sophisticated measures, posterior odds for instance. We can device two additional tests – one *ex-ante*, based on the principal-component space of the model, and the other *ex-post*, based on cross-correlation of estimated shocks.

Before a thorough analysis of shocks and measurement errors it is critical to check if the model can explain business cycle dynamics with one dominant source of variance; more formally, if the model-induced principal-component space is close to the principal-component space of the data and if the impulse-responses 'make sense' in light of robust stylized facts on co-movement that most practitioners are aware of. This check can help preventing the structural macroeconomic modeling from becoming a degenerative research program -as Farmer (2012) puts it- that is characterized by adding additional 'structural' shocks to explain the dynamics of the expanding set of observable variables.

5.2 Specification Testing

Based on our findings, we believe that any structural economic model must at least be able to generate the principal component structure of the data it is supposed to represent. Note that this requirement is void of any structural interpretation of the data-based factors or the theory of the model. It is not enough to explain real variables and fail to explain inflation, or explain output and investment dynamics and miss consumption dynamics. In this sense the principal component space of the data is a very strong restriction on every model and can become a useful device for testing and falsifying hypotheses. As we discuss below, recent vintage of structural economic models fails this to match the factor structure observed in macroeconomic data– the models cannot explain the essential business cycle dynamics.[18] The requirement that models approximate well the dynamic-principal-component space of the data does not exclude models with stochastic singularity, on contrary, as long as the sources of dynamics capture the dominant eigenvalues closely enough.

It is possible to construct a simple test statistics based on principal component space. Let $F(Y_T)$ be a suitable function of data Y_T of length T, such as (3.3) or (3.2), which can be compared to the implication of a model $\mathscr{M}$ or to the distribution of the same statistics, applied to the simulated series of the length T, Y_T^s, from the model $\mathscr{M}$. While the share of the dominant eigenvalue of the spectral density can be computed exactly (i.e. without simulation) for a model having a linear state space form, the comparison of $F(Y)$ to the empirical distribution of $\{Y_T^s\}_{s=1}^S$ has the advantage to addressing finite sample issues in the sense that, for 'reasonable' statistics, the empirical distribution of $\{Y_T^s\}_{s=1}^S$ will estimate consistently (as $S \to \infty$) the implied distribution of $F(Y_T)$ under the null that the model $\mathscr{M}$ is true one.

Further, the mapping from structural shocks to principal components (factors) can be easily investigated. In time domain, it follows trivially from the fact that factors are function of data and its

[18] Recall also that many DSGE models target specifically business cycle frequencies and report variance decomposition at these frequencies, which are directly comparable to our computations.

covariance structure. The principal factor then is the results of all the independent structural shocks, with appropriate weighting.

We carried out the test for two prominent models Justiniano et al. (2010) and Smets and Wouters (2007a). In both cases, we took data used in estimation of each respective model[19] $\mathscr{D}$ and applied the time-domain statistics (3.2). Then, we simulated a large number (500) of the series from the model[20] of the same length as original data and compare the empirical distribution of this statistics on simulated series with those on data.

Figure 8 shows the results for the Smets and Wouters model. We show the results in time domain for three data transformation: HP filter, band-pass filter and growth rates. Evidently, the model underestimates the co-movement for investment and hours worked (especially if cyclical frequencies are isolated), while overestimates the co-movement for real wage. It would seem that the model gets the inflation-output co-movement right, but this impression vanishes at when factor loadings signs are inspected. Figure 9 displays PCA factor loadings.[21] Apparently, the mean of the loadings for inflation has the opposite sign that that in data: in data the loading for inflation has the same sign as the loading for consumption (and the rest of the real variables), while the most simulations with the model would imply the opposite sign. Apparently, the shocks that dominate in the Smets and Wouters (2007a)'s model move inflation and output in the opposite direction. Given the nature of the monetary policy reaction function, the same holds also for interest rate.

Figure 10 shows the results for the Justiniano et al. (2010) model. Again for the three data transformations and, consistently with the previous section, the most pronounced results are obtained when growth rates are not used. The Justiniano et al. (2010) model is not able generate the cyclical co-movement of private consumption with the rest of real macro variables, and also employment is not fully synchronized. This should not be surprising, since the dominant shock in the model–the investment-specific shock–is producing a negative response of consumption to boom in investment and output, see Fig. 19.

[19] Smets and Wouters (2007a)'s data were downloaded from the article website of the American Economic Review. Justiniano et al. (2010) data come from Haver Analytics, following the appendix to the paper on the Journal of Monetary Economics website.

[20] For the simulation of the Smets and Wouters (2007a)'s model, we use the Dynare implementation by Volker et al. (2011). For the Justiniano et al. (2010) model, we use Gensys code by Christopher Sims.

[21] If χ_t is the first dominant factor (principal component), the fitted series can be written as $\hat{x}_{it} = \lambda_i \chi_t$ (in the static case). Since the factor and its loadings are not identified, we normalize them on output weight and report $\lambda_i / \lambda_{\text{output}}$. The positive (negative) value of this ratio means that the variable is cyclical (counter-cyclical). For the case of the dynamic model, the fitted series are given as $\hat{x}_{it} = \sum_{k=-K}^{K} \lambda_{ik} \chi_{t-k}$. In that case, we report $\tilde{\lambda}_i \equiv \sum_k \lambda_{ik}$ as the factor loading.

Figure 8: R^2 ***fit of DPCA for various transformations: data versus Smets and Wouters (2007)'s model***

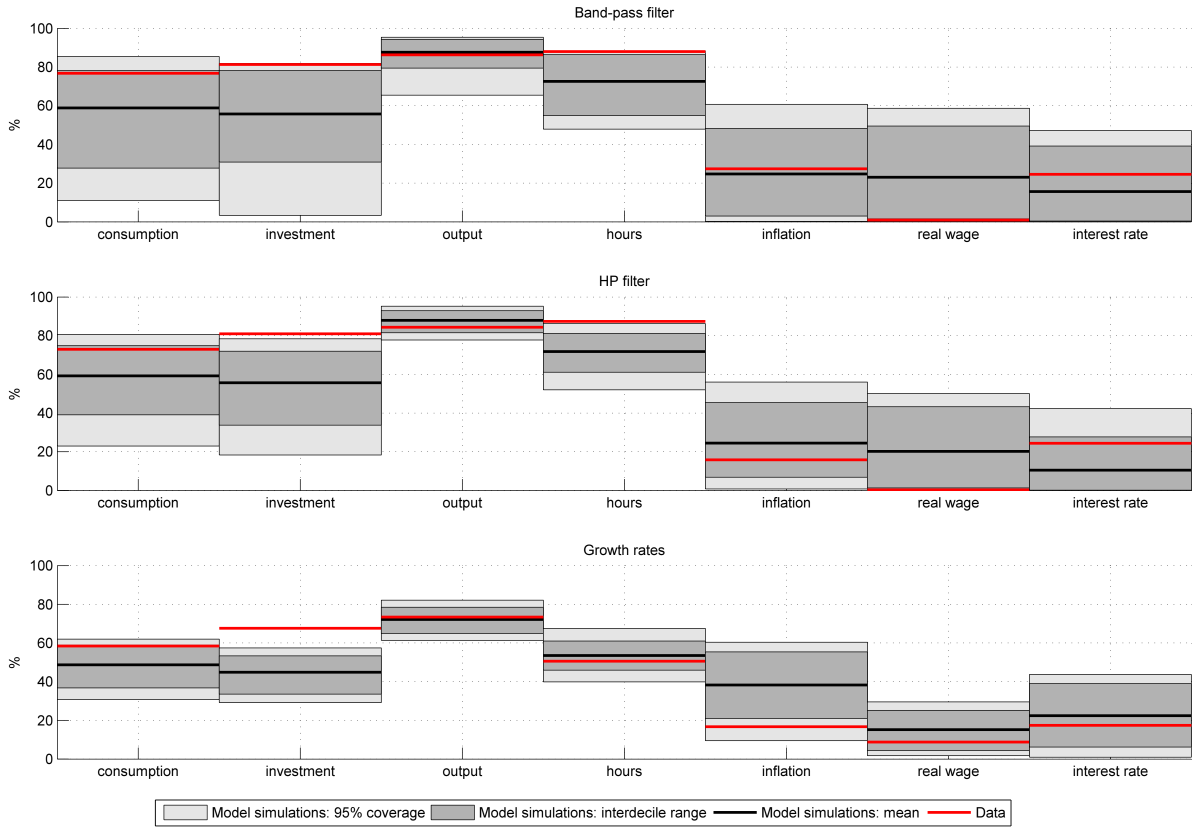


Figure 9: PCA weights based on Smets and Wouters (2007): data versus model

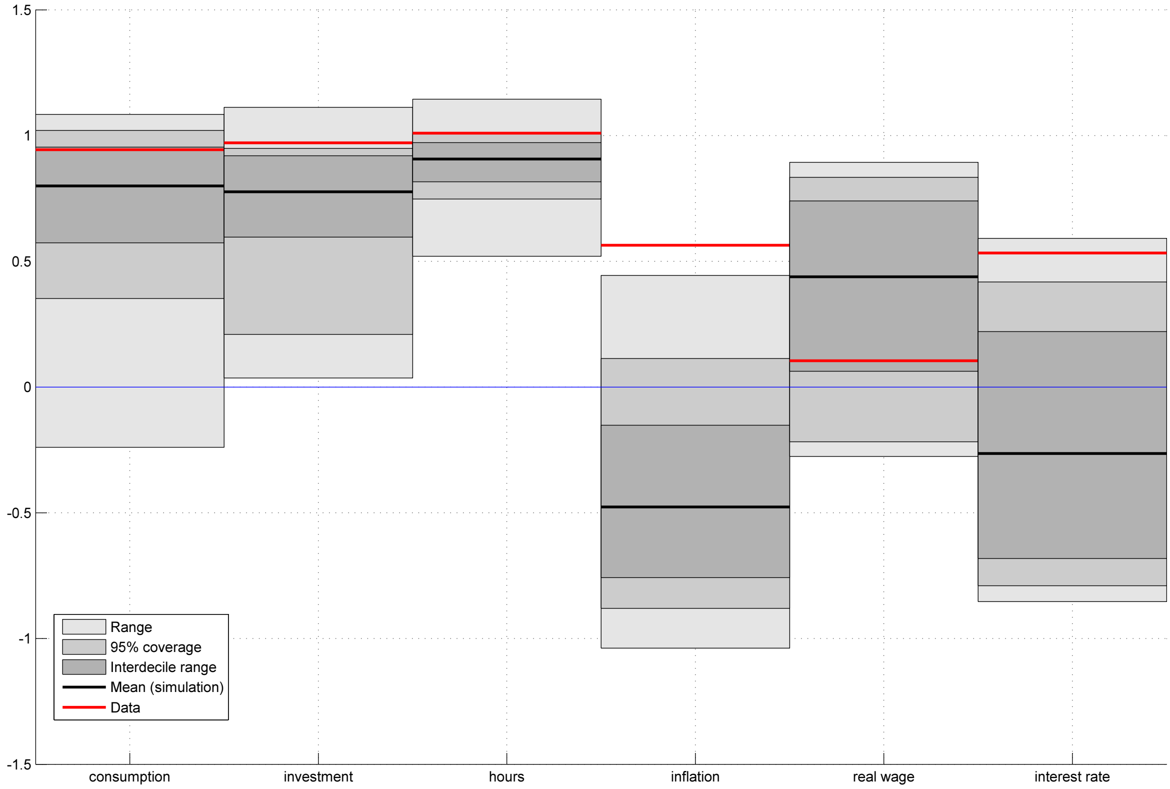
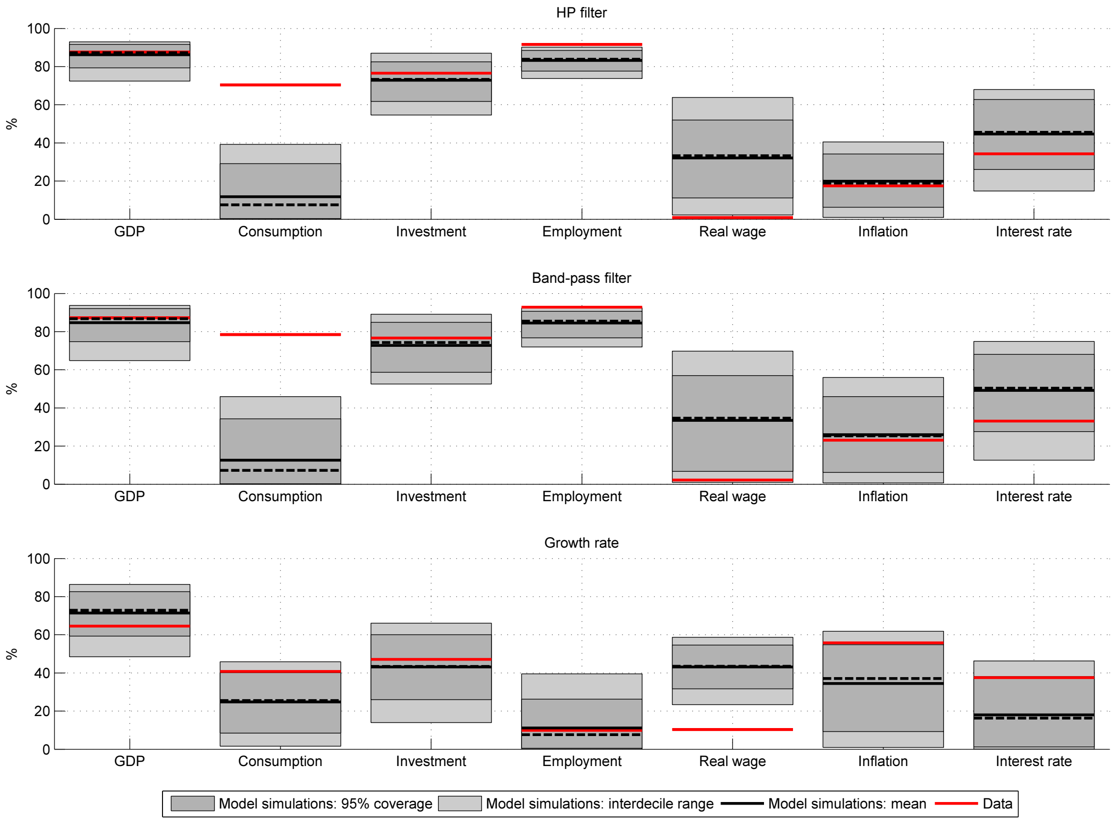


Figure 10: R^2 ***fit of DPCA for various transformations: data versus Justiniano et al. (2010) model***



6. Conclusions

In this paper we provide an empirical investigation of the sources of economic fluctuations – their number, their nature, and their implications for economic modeling and policy analysis. We reach a conclusion that business cycle dynamics of key macroeconomic data can be largely explained by a single source of variation. Since this dominant unobserved principal component behind the business cycle explains a positive co-movement of output cycle and inflation, we label the principal component as a 'demand factor.' We describe the properties of the demand factor and argue that structural economic models have great difficulties to deliver structural shocks resembling our robustly estimated dominant principal component.

Our analytical approach allows us to reach strong conclusions with relatively modest identification assumptions. We employ a straightforward dynamic principal component analysis to analyze key real and nominal macroeconomic data for OECD countries. The analysis decomposes data into a set of orthogonal contributions of a number of components. The first dynamic principal component clearly dominates in terms of explained variance, so other components are not explicitly analyzed or identified. The effects of the dominant component also satisfy the sign restriction one would expect from an intuitively understood demand, namely a positive co-movement of output and inflation, which renders the factor its label—a demand factor. We document that the set of stylized facts leading to a demand factor continues to hold for a set of OECD countries and in time. Further, our findings are invariant to use of both time- and frequency-domain techniques, which do not rely on time domain filtering.

The absence of a real-nominal dichotomy is an important result, highlighting the importance of variable definitions in the analysis as a shield to misspecification. We have illustrated that there is positive co-movement of output and inflation at business cycle frequencies, a key result allowing us to argue for a demand-like explanation of business cycles. Why do the Phillips curve estimates or dynamic factor model analysis usually fail to find a stable relationship, claiming a real-nominal dichotomy, while our results do find it? The key is our focus at business cycle frequency and thus data transformation. Cyclical dynamics of inflation is akin to a deviation of inflation from an inflation target or long-term inflation expectations and theory predicts this 'inflation gap' should positively co-move with cyclical component of output. We do find this positive relationship. If we were to follow the literature and use a first difference of inflation (to render it stationary) with demeaned GDP growth the task of finding a positive relationship would be much harder due to a transformation that amplifies high-frequency disturbances in the data and has weaker theoretical support.

The existence of a dominant 'demand' factor behind the business cycle dynamics of the data has strong implications for structural economic models. To sum up, we argue that the current vintage of DSGE models lacks a dominant demand shock that would explain the business cycle dynamics. This is no ado about nothing—most models fail to coherently explain up to 80% of key macroeconomic variables. Also, our analysis creates a shopping list for model builders in terms of the nature of the behavior a shock must exhibit in order to be considered as a plausible source of business cycles. No model known to us can explain positive co-movement of consumption, investment, and inflation to the degree and with the duration implied by the data and the estimated demand factor. Our analysis is tractable and powerful in testing and falsifying economic models and driving forces, while relying on a minimal set of assumptions.

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Appendix A: Additional Graphs and Tables

Figure 11: Cyclical components: data and fit with the DPCA (Christiano-Fitzgerald filter) – the U.S. (full sample)

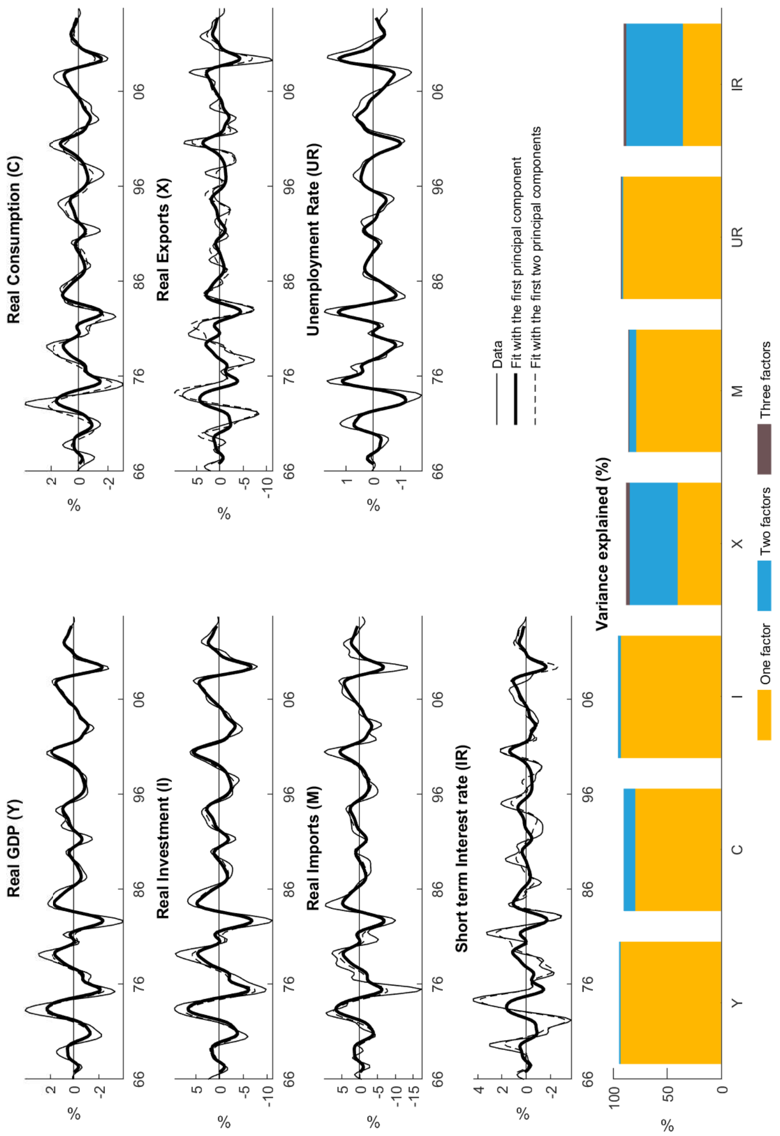


Figure 12: Cyclical components (Hodrick-Prescott filter): data and fit with the DPCA – the U.S. (full sample)

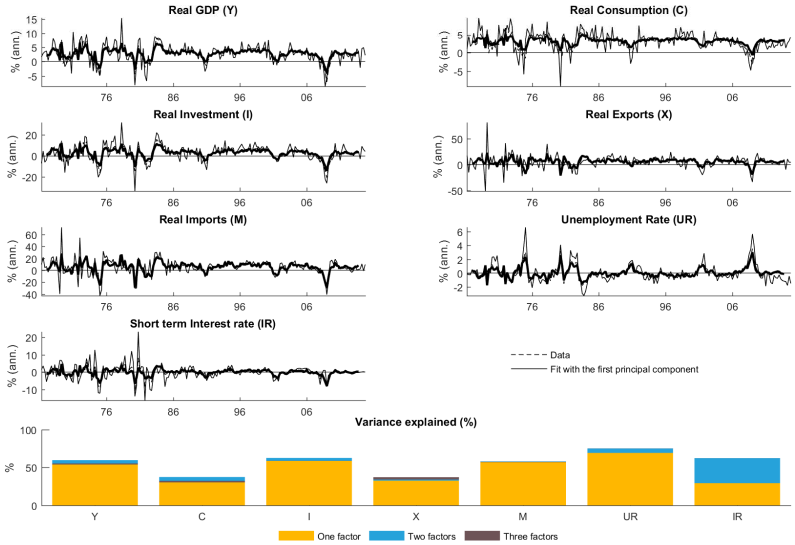


Figure 13: Inflation and real economy – the U.S. (full sample)

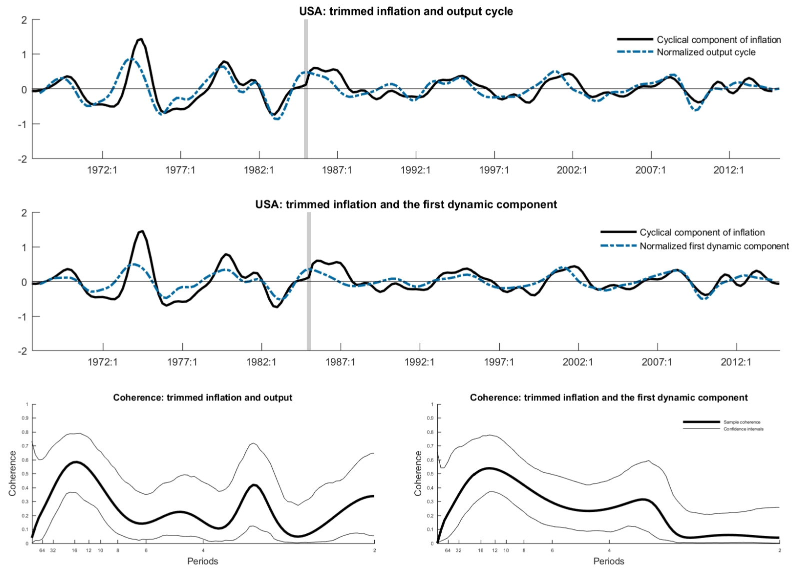


Figure 14: The DPCA in time domain for all variables together (HP cycles) – the U.S.

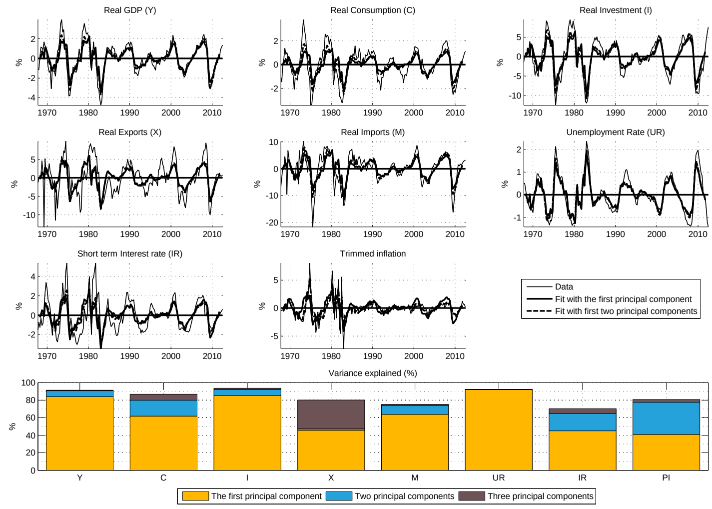


Figure 15: The boxplot summary statistics (the whole sample)

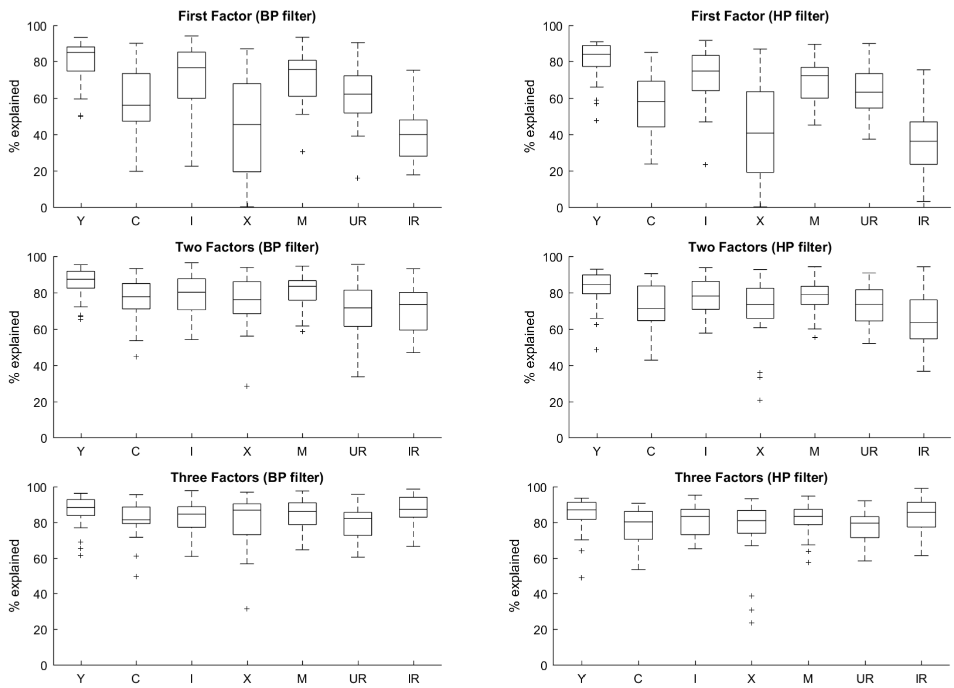


Figure 16: Cyclical components: data and fit with the static PCA (Christiano-Fitzgerald filter) – the U.S.

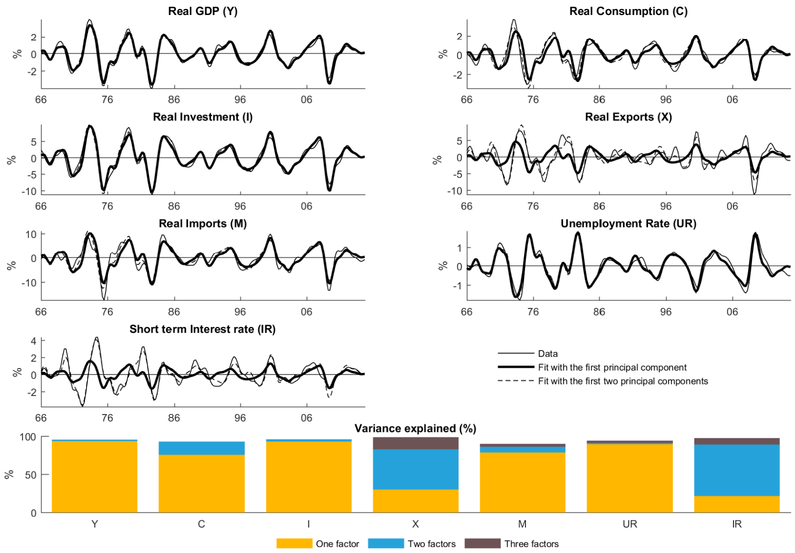


Figure 17: Cyclical components (Hodrick-Prescott filter): data and fit with the static PCA – the U.S.

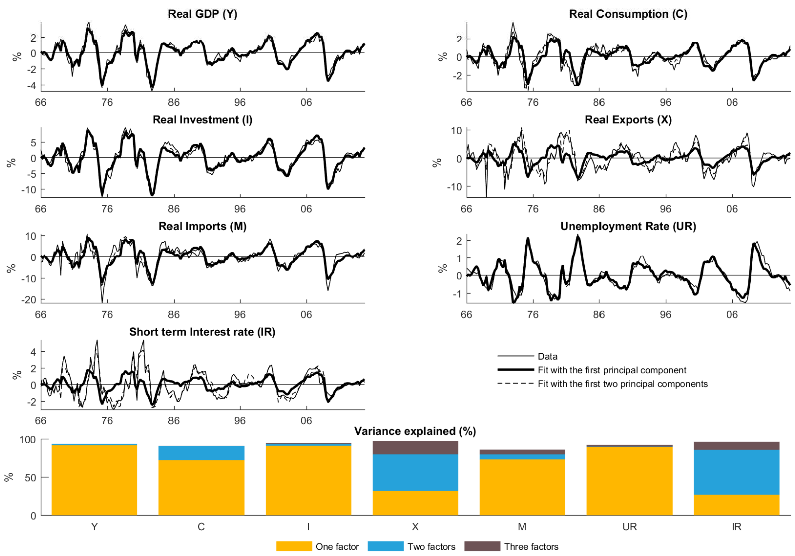
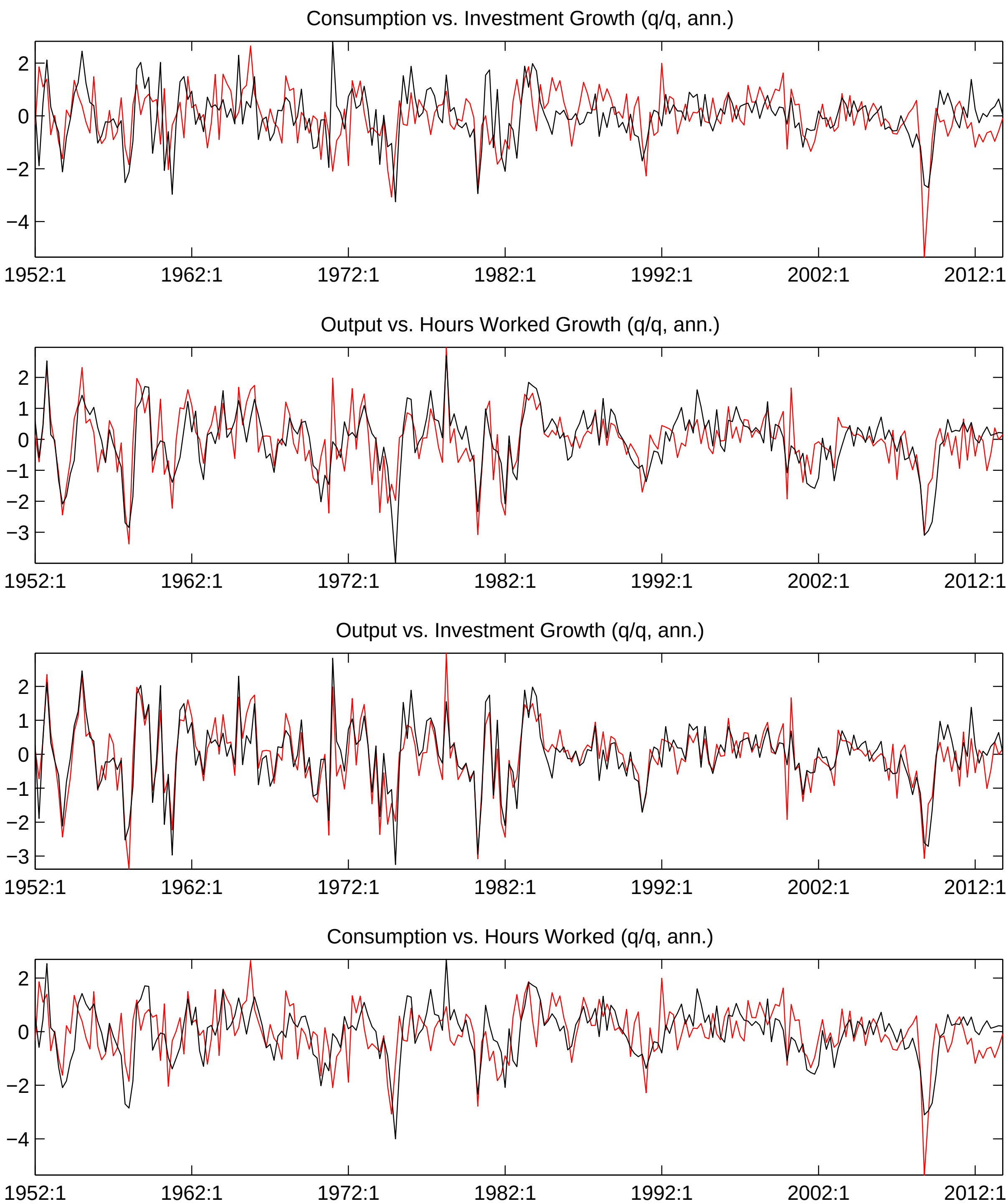


Figure 18: Growth Rates of Macroeconomic Data Consistent with Justiniano et al. (2010)



Note: Investment contain durable consumption; consumption consists of non-durable consumption only. The series are normalized to equal variance. Source: Haver Analytics

Figure 19: IRF to Investment-Specific Shock in Justiniano et al. (2010)

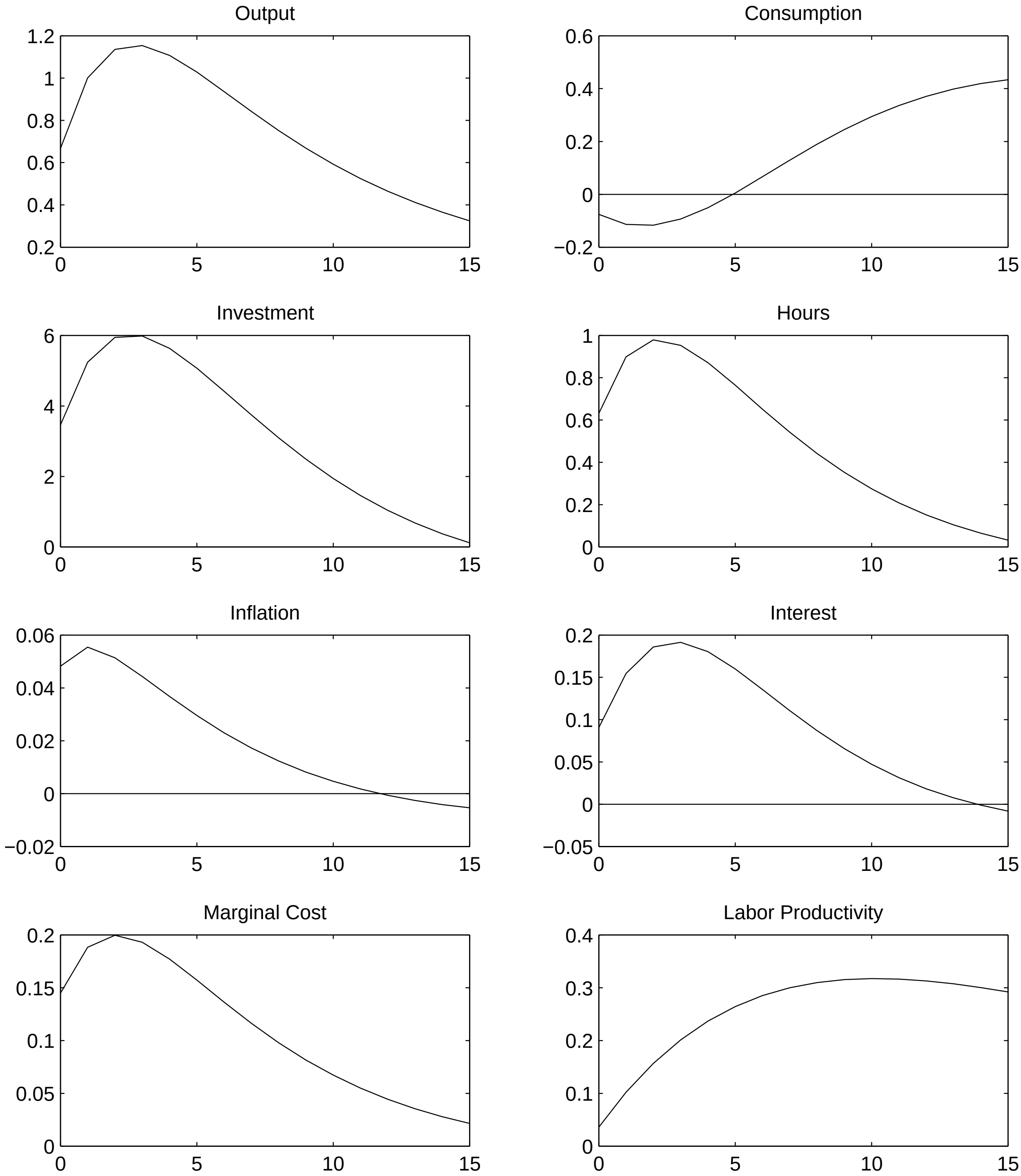
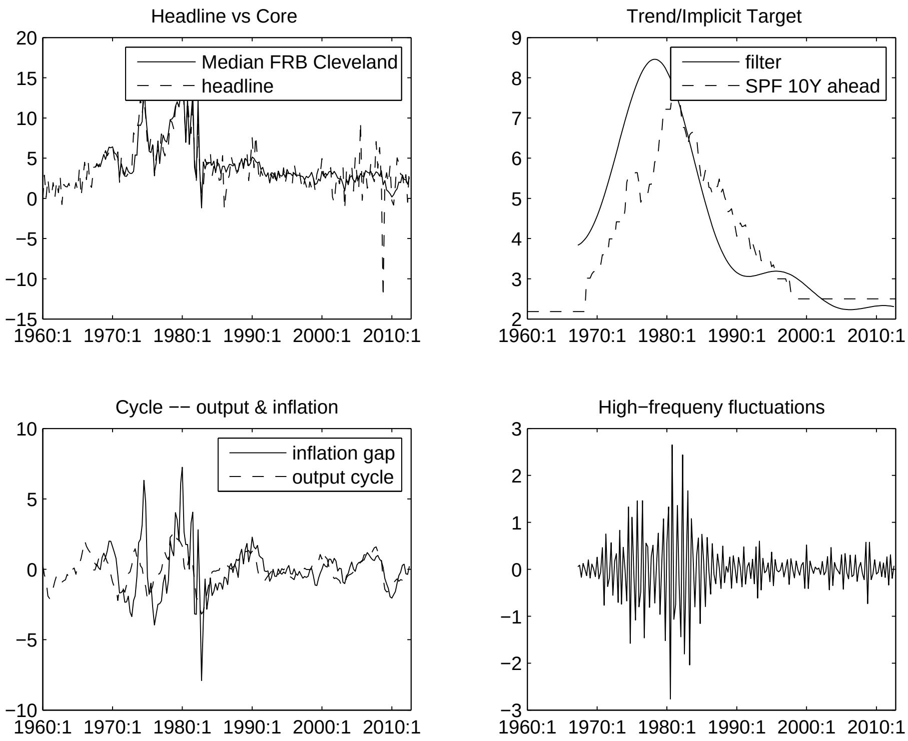
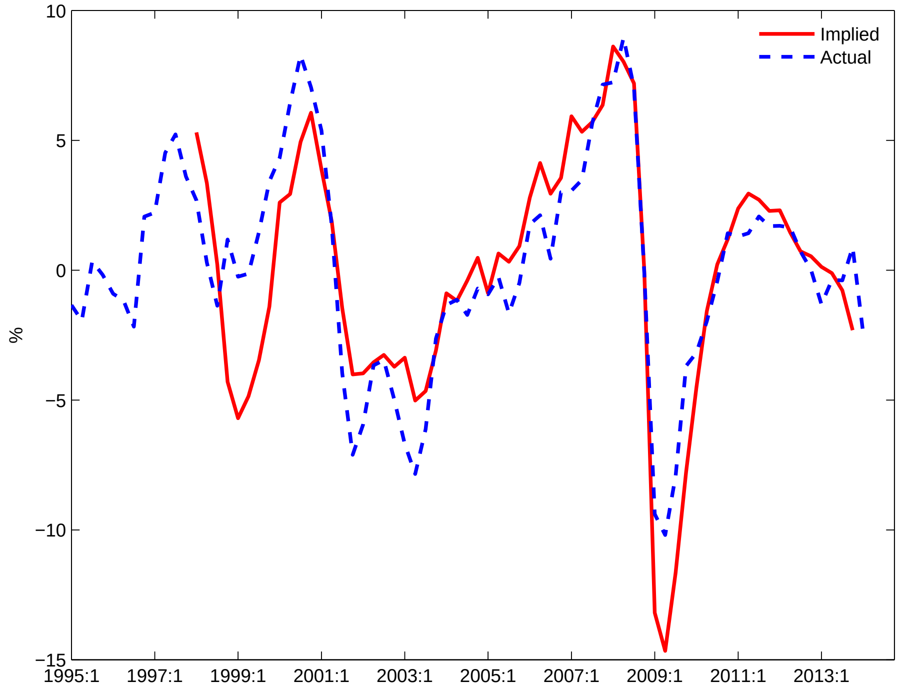


Figure 20: Inflation Components – Decomposition



Source: own computations

Figure 21: US Export Cycle – Actual and Implied



Source: own computations based on IMF Global Projection Model database

Table 2: The fit of the first dynamic principal component: band-pass cycle

Country / Variable	Y	C	I	X	M	UR	IR
Australia	60.8	66.4	70.2	29.8	81.1	83.2	61.3
Austria	90.3	35.4	65.8	84.9	81.8	41.4	73.0
Belgium	86.4	44.9	68.7	87.7	89.4	59.5	54.6
Canada	91.2	65.1	69.8	74.0	74.2	84.7	52.7
The Czech Republic	88.4	26.5	87.9	45.4	64.6	65.8	24.2
Denmark	88.8	47.7	81.7	71.1	85.4	67.3	22.9
Finland	91.9	77.0	88.0	34.0	81.2	59.0	38.8
France	92.1	49.5	88.3	78.8	89.2	60.3	63.8
Germany	92.4	60.8	92.3	78.8	78.6	62.0	75.2
Greece	64.2	46.6	51.0	12.1	30.4	43.7	17.7
Hungary	72.8	50.7	40.8	27.9	59.1	67.7	35.9
Ireland	75.3	78.7	65.6	73.7	75.0	70.2	22.4
Italy	88.2	55.1	80.4	60.2	85.5	55.0	53.5
Japan	92.9	60.6	86.9	62.3	75.6	63.8	27.5
Korea	84.9	85.3	88.4	0.8	76.6	83.3	69.2
Luxembourg	78.1	25.4	24.9	87.1	85.7	59.8	59.2
Mexico	92.8	87.6	90.0	17.2	93.7	63.4	47.1
Netherlands	91.9	51.4	64.4	66.3	76.3	52.4	80.6
New Zealand	69.5	55.9	84.7	7.0	61.9	55.1	43.3
Norway	67.3	75.5	43.6	27.9	61.2	67.0	53.7
Poland	85.9	24.6	87.3	68.7	62.8	58.9	41.0
Portugal	34.4	43.5	45.5	4.5	26.9	48.2	9.5
Slovakia	82.6	58.8	79.5	26.6	59.5	56.6	39.6
Spain	81.6	78.9	77.3	70.1	80.2	77.0	25.9
Sweden	95.1	47.6	80.6	72.8	83.3	67.4	57.7
Switzerland	84.2	38.0	72.9	59.5	69.1	52.9	71.1
Turkey	93.0	90.5	94.4	87.5	50.9	81.6	28.0
The UK	88.7	68.0	79.9	33.9	66.6	57.9	35.4
The USA	92.9	83.4	91.9	63.7	84.7	84.1	59.5

Table 3: The fit of the first static principal component: band-pass cycle

Country / Variable	Y	C	I	X	M	UR	IR
Australia	59.0	66.2	69.8	30.6	81.0	82.5	59.3
Austria	90.3	36.2	65.8	85.0	81.9	37.4	72.6
Belgium	86.0	45.5	68.3	87.5	89.1	60.5	53.2
Canada	90.9	65.5	69.1	73.7	74.6	84.0	51.7
The Czech Republic	87.7	15.5	86.5	37.2	68.1	46.1	4.90
Denmark	84.2	45.4	83.9	68.4	88.1	72.1	18.6
Finland	90.8	75.1	87.8	35.6	82.1	57.9	32.8
France	91.3	46.1	88.0	78.1	89.1	57.2	59.6
Germany	92.0	58.0	91.5	78.5	78.1	62.0	73.6
Greece	91.3	65.9	71.3	0.10	26.4	72.4	2.10
Hungary	80.7	28.6	43.6	21.8	57.7	49.2	6.20
Ireland	74.9	75.7	64.8	74.3	75.5	70.4	17.8
Italy	87.1	54.3	79.8	59.8	86.1	52.9	48.4
Japan	92.7	55.0	85.9	61.3	73.6	61.6	27.0
Korea	97.5	90.9	92.4	2.10	83.8	85.2	0.20
Luxembourg	76.4	24.7	19.2	86.8	85.0	59.3	58.2
Mexico	92.5	86.9	89.4	15.8	93.5	58.6	45.9
Netherlands	91.7	50.8	62.1	64.3	75.0	50.2	79.1
New Zealand	69.4	55.3	85.0	7.60	62.2	52.7	33.7
Norway	70.5	71.3	36.8	0.00	57.5	61.8	46.2
Poland	84.6	17.7	87.6	67.9	56.6	61.3	46.7
Portugal	46.6	73.6	81.0	6.3	76.2	54.2	0.30
Slovakia	83.0	58.9	80.2	23.5	58.1	54.1	42.8
Spain	81.7	79.4	77.5	68.4	78.0	74.7	22.1
Sweden	94.2	42.2	79.6	71.9	84.5	65.1	48.1
Switzerland	82.4	37.0	72.4	55.7	62.9	53.1	69.4
Turkey	94.2	90.9	94.4	87.6	44.9	76.1	15.3
The UK	87.3	66.7	78.2	34.9	67.6	54.1	24.2
The USA	92.8	83.2	91.9	63.0	83.6	83.1	58.9

Appendix B: Data Sources and Specification

Below the specification of the data is described. All computations were performed in Matlab by MathWorks. Data and codes for the paper are available upon request.

Weighted median inflation for EU countries was computed using the data from the EUROSTAT as represented in the Haver Analytics database, Level 3. In the case of the United States the weighted median inflation is from FRB Cleveland. Core inflation for Australia was obtained from the Reserve Bank of Australia website. Ten-years-ahead inflation expectations obtained from the Survey of Professional Forecasters (SPF) by FRB of Philadelphia. The 'PTR' variable (proxy for inflation target) of FRB/US model has been kindly provided by Bob Tetlow.

Seasonal data adjustment provided by the source authority, otherwise default Bureau of Census X12/ARIMA algorithm was applied in its default setting.

Table 4: OECD Data

Countries	Variables Collected per Country	Data Source
Euro Area15	Private final consumption expenditure, value, GDP expenditure approach	
Australia, Austria,	Private final consumption expenditure, volume	
Belgium, Canada,	Gross domestic product, value, market prices	
Finland, France,	Gross domestic product, volume, market prices	
Germany, Ireland,	Gross fixed capital formation, total, value	
Italy, Japan,	Gross fixed capital formation, total, volume	
Korea, Luxembourg,	Imports of goods and services, value, National Accounts basis	OECD Economic Outlook
Mexico, Netherland,	Imports of goods and services, volume, National Accounts basis	No. 94
New Zealand, Norway ,	Exports of goods and services, value, National Accounts basis	
Poland, Portugal,	Exports of goods and services, volume, National Accounts basis	
Spain, Sweden,	Core inflation index	
Switzerland, United Kingdom,	Unemployment rate	
United States of America	Short-term interest rate	

Table 5: National Source Data

Czech Rep: GDP: Final Consumption Expenditure: Households (SWDA, Mil.CZK)	Czech Statistical Office
Czech Rep: GDP: Final Consumption Exp: Households (SWDA, Mil.Chn.2005.CZK)	Czech Statistical Office
Czech Republic: Gross Domestic Product (SWDA, Mil.CZK)	Czech Statistical Office
Czech Republic: Gross Domestic Product (SWDA, Mil.Chn.2005.CZK)	Czech Statistical Office
Czech Republic: GDP: Gross Fixed Capital Formation (SWDA, Mil.CZK)	Czech Statistical Office
Czech Republic: GDP: Gross Fixed Capital Formation (SWDA, Mil.Chn.2005.CZK)	Czech Statistical Office
Czech Republic: GDP: Imports of Goods and Services (SA, Mil.CZK)	Czech Statistical Office
Czech Republic: GDP: Imports of Goods and Services (SA, Mil.Chn.2005.CZK)	Czech Statistical Office
Czech Republic: GDP: Exports of Goods and Services (SA, Mil.CZK)	Czech Statistical Office
Czech Republic: GDP: Exports of Goods and Services (SA, Mil.Chn.2005.CZK)	Czech Statistical Office
Czech Republic: Unemployment Rate, % of Labor Force (SA, %)	Czech Statistical Office
Czech Republic: PRIBOR: 3 Month (Avg, %)	Czech National Bank
Denmark: Private Consumption Expenditure (SA, Mil.Kroner)	Danmarks Statistik
Denmark: Private Consumption Expenditure (SA, Mil.Chn.2005.Kroner)	Danmarks Statistik
Denmark: Gross Domestic Product (SA, Mil.Kroner)	Danmarks Statistik
Denmark: Gross Domestic Product (SA, Mil.Chn.2005.Kroner)	Danmarks Statistik
Denmark: Gross Fixed Capital Formation (SA, Mil.Kroner)	Danmarks Statistik
Denmark: Gross Fixed Capital Formation (SA, Mil.Chn.2005.Kroner)	Danmarks Statistik
Denmark: GDP: Imports of Goods and Services (SA, Mil.Kroner)	Danmarks Statistik
Denmark: GDP: Imports of Goods and Services (SA, Mil.Chn.2005.Kroner)	Danmarks Statistik
Denmark: GDP: Exports of Goods and Services (SA, Mil.Kroner)	Danmarks Statistik
Denmark: GDP: Exports of Goods and Services (SA, Mil.Chn.2005.Kroner)	Danmarks Statistik
Denmark: Harmonized Unemployment Rate (SA, %)	Statistical Office of the European Communities
Denmark: Interbank Offered Rate: 3-months (AVG, %)	Danmarks Nationalbank
Greece: GDP: Private Consumption (NSA, Mil.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: GDP: Private Consumption (NSA, Mil.Chained.2005.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: Gross Domestic Product (NSA, Mil.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: Gross Domestic Product (NSA, Mil.Chained.2005.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: GDP: Gross Fixed Capital Formation (NSA, Mil.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: GDP: Gross Fixed Capital Formation (NSA, Mil.Chained.2005.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: GDP: Imports of Goods & Services (NSA, Mil.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: GDP: Imports of Goods & Services (NSA, Mil.Chained.2005.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: GDP: Exports of Goods & Services (NSA, Mil.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: GDP: Exports of Goods & Services (NSA, Mil.Chained.2005.Euros)	Hellenic Statistical Authority (ELSTAT)
Greece: Labor Force Survey: Unemployment Rate (SA, %)	Hellenic Statistical Authority (ELSTAT)
Hungary: Final Consumption Expenditure: Private (SA, Bil.Forints)	Central Statistical Office
Hungary: GDP: Final Consumption Expenditure: Private (SWDA,Bil.Ch.2005.Forints)	Central Statistical Office
Hungary: Gross Domestic Product (SA, Bil.Forints)	Central Statistical Office
Hungary: Gross Domestic Product (SWDA, Bil.Ch.2005.Forints)	Central Statistical Office
Hungary: Gross Fixed Capital Formation (SA, Bil.Forints)	Central Statistical Office
Hungary: GDP: Gross Fixed Capital Formation (SWDA,Bil.Ch.2005.Forints)	Central Statistical Office
Hungary: Imports of Goods & Services (SA, Bil.Forints)	Central Statistical Office
Hungary: GDP: Imports of Goods & Services (SWDA,Bil.Ch.2005.Forints)	Central Statistical Office
Hungary: Exports of Goods & Services (SA, Bil.Forints)	Central Statistical Office
Hungary: GDP: Exports of Goods & Services (SWDA,Bil.Ch.2005.Forints)	Central Statistical Office
Hungary: Unemployment Rate (SA, %)	Central Statistical Office
Hungary: Yield on 3-Month Government Debt Securities (EOP, % per annum)	National Bank of Hungary

Table 6: National Source Data

Slovakia: GDP: Final Consumption of Households (SA, Mil.EUR)	Statistical Office of the Slovak Republic
Slovakia: GDP: Final Consumption of Households (SA, Mil.Chn.2005.EUR)	Statistical Office of the Slovak Republic
Slovakia: Gross Domestic Product (SA, Mil.EUR)	Statistical Office of the Slovak Republic
Slovakia: Gross Domestic Product (SA, Mil.Chn.2005.EUR)	Statistical Office of the Slovak Republic
Slovakia: GDP: Gross Fixed Capital Formation (SA, Mil.EUR)	Statistical Office of the Slovak Republic
Slovakia: GDP: Gross Fixed Capital Formation (SA, Mil.Chn.2005.EUR)	Statistical Office of the Slovak Republic
Slovakia: GDP: Import of Goods and Services (SA, Mil.EUR)	Statistical Office of the Slovak Republic
Slovakia: GDP: Import of Goods and Services (SA, Mil.Chn.2005.EUR)	Statistical Office of the Slovak Republic
Slovakia: GDP: Export of Goods and Services (SA, Mil.EUR)	Statistical Office of the Slovak Republic
Slovakia: GDP: Export of Goods and Services (SA, Mil.Chn.2005.EUR)	Statistical Office of the Slovak Republic
Slovakia: Unemployment Rate [Registered] (SA, %)	Central Office of Labour, Social Affairs and Family
Slovakia: New Household Deposits: Redeemable at Notice: Up to 3 Months (%)	National Bank of Slovakia
Slovenia: GDP: Final Consumption: Households (SWDA, Mil.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: GDP: Final Consumption: Households (SWDA, Mil.Chn.2000.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: Gross Domestic Product (SWDA, Mil.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: Gross Domestic Product (SWDA, Mil.Chn.2000.EUR)	Statistical Office of the Rep of Slovenia
Slovenia: GDP: Gross Fixed Capital Formation (SWDA, Mil.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: GDP: Gross Fixed Capital Formation (SWDA, Mil.Chn.2000.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: GDP: Imports of Goods and Services (SWDA, Mil.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: GDP: Imports of Goods and Services (SWDA, Mil.Chn.2000.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: GDP: Exports of Goods and Services (SWDA, Mil.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: GDP: Exports of Goods and Services (SWDA, Mil.Chn.2000.EUR)	Statistical Office of the Republic of Slovenia
Slovenia: Unemployment Rate (%)	International Monetary Fund / IFS
Slovenia: Money Market Rate (% per annum)	International Monetary Fund / IFS
Turkey: Res/Nonresident HHs Final Consump Exp on Economic Territory(SA,Thous.TL)	Turkish Statistical Institute
Turkey: Res/Nonres HHs Final Consump Exp on Economic Territory (SA, Thous.98.TL)	Turkish Statistical Institute
Turkey: Gross Domestic Product (SA, Thous.TL)	Turkish Statistical Institute
Turkey: Gross Domestic Product (SA, Thous.98.TL)	Turkish Statistical Institute
Turkey: Gross Fixed Capital Formation (SA, Thous.TL)	Turkish Statistical Institute
Turkey: Gross Fixed Capital Formation (SA, Thous.98.TL)	Turkish Statistical Institute
Turkey: Exports of Goods & Services (SA, Thous.TL)	Turkish Statistical Institute
Turkey: Exports of Goods & Services (SA, Thous.98.TL)	Turkish Statistical Institute
Turkey: Imports of Goods & Services (SA, Thous.TL)	Turkish Statistical Institute
Turkey: Imports of Goods & Services (SA, Thous.98.TL)	Turkish Statistical Institute
Turkey: Unemployment Rate (SA, % of Labor Force)	Turkish Statistical Institute
Turkey: Weighted Average Interest Rates for TL Deposits: Up to 3 Months(% p.a.)	Central Bank of the Republic of Turkey