The Role of Financial Factors in Estimating the Output Gap

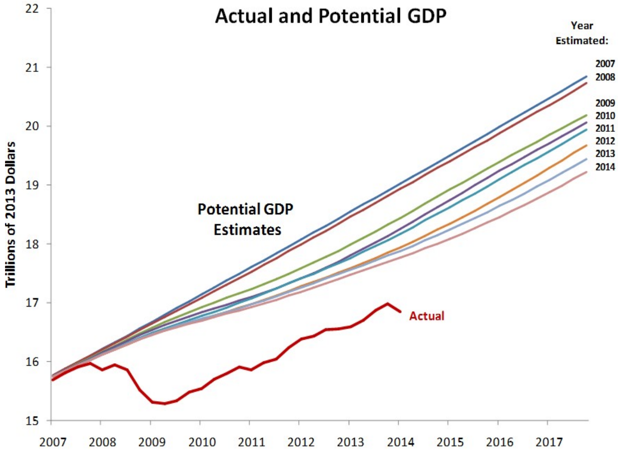
Mihnea Constantinescu[1] and Anh D.M. Nguyen[2]

National Bank of Ukraine
February 14th, 2019

[1] PrepayWay AG

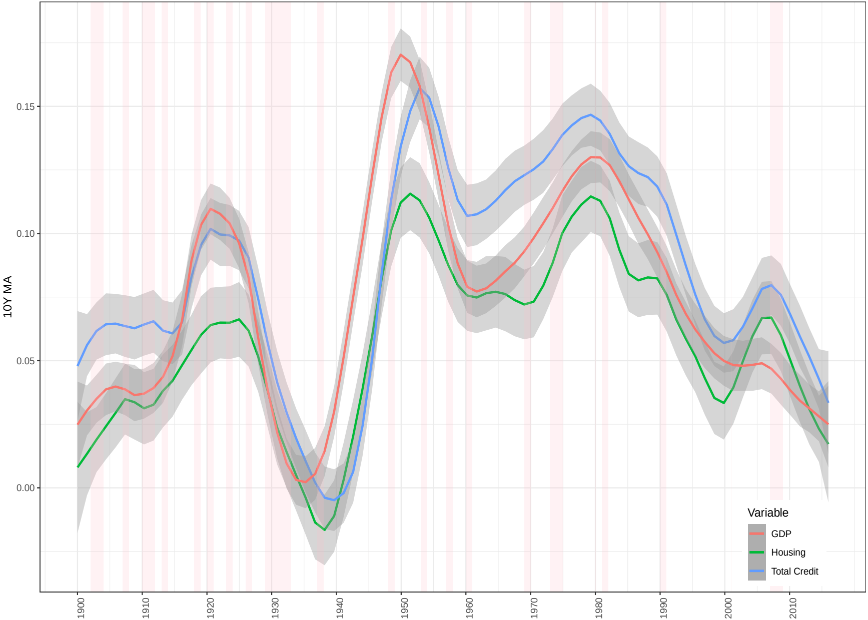
[2] Bank of Lithuania. Disclaimer: Author's views, do not necessarily reflect those of the Bank of Lithuania or the ESCB.

The Motivation



The Motivation

The Global Component



Today's Talk

Propose a new methodology for the estimation of real and financial gaps:

- "A Century of Gaps", WP (2018)
- "Unemployment or Credit: Which One Holds the Potential? Results for a Small-Open Economy with a Low Degree of Financialization", Economic Systems (2018)
- A few speculations on a global model of the real-financial gap

Introduction: A review

- Potential output and output gap: important notions for policy analysis (Stabilization Policy, Fiscal policy surveillance, Macroprudential policy, etc)
- Not observed directly $\Rightarrow$ imperfect measures of level and dynamics. Broad categories of models:

Introduction: A review

- Potential output and output gap: important notions for policy analysis (Stabilization Policy, Fiscal policy surveillance, Macroprudential policy, etc)
- Not observed directly $\Rightarrow$ imperfect measures of level and dynamics. Broad categories of models:

1. Statistical filters: most popular Hodrick-Prescott (HP) filter.
    - Advantage: Simplicity and transparency, requiring only GDP data
    - Drawbacks: lack of economic structure, subject to end-of-sample instability (see, e.g., Baxter and King, 1999)

Introduction: A review

- Potential output and output gap: important notions for policy analysis (Stabilization Policy, Fiscal policy surveillance, Macroprudential policy, etc)
- Not observed directly ⇒ imperfect measures of level and dynamics. Broad categories of models:

1. Statistical filters: most popular Hodrick-Prescott (HP) filter.
   - Advantage: Simplicity and transparency, requiring only GDP data
   - Drawbacks: lack of economic structure, subject to end-of-sample instability (see, e.g., Baxter and King, 1999)
2. Production function approach
   - (S1) Specifying a functional form of the production function and (S2) substituting inputs by their corresponding full-employment values (see, e.g, Havik et al., 2014; Fernald, 2014). For instance, Cobb-Douglas: $Y = AK^{\alpha}L^{1-\alpha}$

Introduction: A review

- Potential output and output gap: important notions for policy analysis (Stabilization Policy, Fiscal policy surveillance, Macroprudential policy, etc)
- Not observed directly ⇒ imperfect measures of level and dynamics. Broad categories of models:

1. Statistical filters: most popular Hodrick-Prescott (HP) filter.
    - Advantage: Simplicity and transparency, requiring only GDP data
    - Drawbacks: lack of economic structure, subject to end-of-sample instability (see, e.g., Baxter and King, 1999)
2. Production function approach
    - (S1) Specifying a functional form of the production function and (S2) substituting inputs by their corresponding full-employment values (see, e.g, Havik et al., 2014; Fernald, 2014). For instance, Cobb-Douglas: $Y = AK^{\alpha}L^{1-\alpha}$
    - Advantage: economic theory taken into account.

Introduction: A review

- Potential output and output gap: important notions for policy analysis (Stabilization Policy, Fiscal policy surveillance, Macroprudential policy, etc)
- Not observed directly $\Rightarrow$ imperfect measures of level and dynamics. Broad categories of models:

1. Statistical filters: most popular Hodrick-Prescott (HP) filter.
    - Advantage: Simplicity and transparency, requiring only GDP data
    - Drawbacks: lack of economic structure, subject to end-of-sample instability (see, e.g., Baxter and King, 1999)

2. Production function approach
    - (S1) Specifying a functional form of the production function and (S2) substituting inputs by their corresponding full-employment values (see, e.g, Havik et al., 2014; Fernald, 2014). For instance, Cobb-Douglas: $Y = AK^{\alpha}L^{1-\alpha}$
    - Advantage: economic theory taken into account.
    - Disadvantages: Reliable capital-stock data (K) can be hard to obtain, constructing the cyclically adjusted measures of inputs (K and L) is not trivial.

Introduction: A review

- Potential output and output gap: important notions for policy analysis (Stabilization Policy, Fiscal policy surveillance, Macroprudential policy, etc)
- Not observed directly ⇒ imperfect measures of level and dynamics. Broad categories of models:

1. Statistical filters: most popular Hodrick-Prescott (HP) filter.
    - Advantage: Simplicity and transparency, requiring only GDP data
    - Drawbacks: lack of economic structure, subject to end-of-sample instability (see, e.g., Baxter and King, 1999)
2. Production function approach
    - (S1) Specifying a functional form of the production function and (S2) substituting inputs by their corresponding full-employment values (see, e.g, Havik et al., 2014; Fernald, 2014). For instance, Cobb-Douglas: $Y = AK^{\alpha}L^{1-\alpha}$
    - Advantage: economic theory taken into account.
    - Disadvantages: Reliable capital-stock data (K) can be hard to obtain, constructing the cyclically adjusted measures of inputs (K and L) is not trivial.
3. Multivariate unobserved component (MUC) model: Kuttner (1994), Blagrave et al. (2015), Alichi (2015) and Melolinna and Toth (2016), Borio, Disyatat and Juselius (2014, 2016) - **BDJ**

Introduction: A review

- Renewed interest in the estimation of the output gap and the implicit impact different measures have in policy design and implementation.

Introduction: A review

- Renewed interest in the estimation of the output gap and the implicit impact different measures have in policy design and implementation.
- Main factors concurrently contributing to the rebirth of this literature are
  1. Summers' *Secular Stagnation Hypothesis* (2014) - a nice application of anchoring and adjustment bias
  2. Borio's *Financial Cycle Drag* along with his argument that *non-inflationary* potential output is **not** a synonym for *sustainable* potential output

Introduction: A review

- Renewed interest in the estimation of the output gap and the implicit impact different measures have in policy design and implementation.

- Main factors concurrently contributing to the rebirth of this literature are
  1. Summers' *Secular Stagnation Hypothesis* (2014) - a nice application of anchoring and adjustment bias
  2. Borio's *Financial Cycle Drag* along with his argument that *non-inflationary* potential output is **not** a synonym for *sustainable* potential output

- A parallel stream of literature initiated by Schularick and Taylor (2012) provides substantial evidence of the role credit plays in driving boom and bust episodes (across time and space) - credit is a primary source of macroeconomic shocks not only a channel of shock propagation (usual implicit assumption in many financial-accelerator models)

Introduction: What we do

1. Investigate the **real-time performance** of output gap estimation using the Jorda, Schularick and Taylor 1870-2013 yearly US data.

Introduction: What we do

1. Investigate the **real-time performance** of output gap estimation using the Jorda, Schularick and Taylor 1870-2013 yearly US data.
2. Analyze the **role of financial variables** in measuring the output gap
    - Borio et al. (2016, 2014) and Melolinna and Toth (2016) have argued that the inclusion of financial variables improve the real-time performance of measuring output gap.
    - We explore the role of various financial factors in the estimation of output gap and potential output for the US, investigating the changing role of real credit growth over more than 100 years.

Introduction: What we do

1. Investigate the **real-time performance** of output gap estimation using the Jorda, Schularick and Taylor 1870-2013 yearly US data.

2. Analyze the **role of financial variables** in measuring the output gap
   - Borio et al. (2016, 2014) and Melolinna and Toth (2016) have argued that the inclusion of financial variables improve the real-time performance of measuring output gap.
   - We explore the role of various financial factors in the estimation of output gap and potential output for the US, investigating the changing role of real credit growth over more than 100 years.

3. Expand the original BDJ framowork to allow financial variables to have a **time-varying impact** in the estimation of potential output and the associated gap. JST (2016) Macrofinancial History and the "New Business Cycle Facts" point to two distinct finance eras:
   - Pre-1940 features a stable relationship between money and credit, business driven credit creation process and a modestly varying credit-to-gdp ratio/
   - Post-1940 gives way to the "financial hockey stick": increasing aggregate leverage ratios with most credit going to mortgages.

1. Growth in real credit to non-financial private sector is the financial variable carrying most information necessary for the timely estimation of the output gap.

Introduction: What we find

1. Growth in real credit to non-financial private sector is the financial variable carrying most information necessary for the timely estimation of the output gap.

2. Real equity growth plays a similar role to real credit in the Great Depression but not during the Great Recession; real housing growth indicates a similar information content to that provided by credit.

Introduction: What we find

1. Growth in real credit to non-financial private sector is the financial variable carrying most information necessary for the timely estimation of the output gap.
2. Real equity growth plays a similar role to real credit in the Great Depression but not during the Great Recession; real housing growth indicates a similar information content to that provided by credit.
3. The sensitivity of output gap to real credit growth is time-varying; the parameter is increasing since the beginning of 1990s

Introduction: What we find

1. Growth in real credit to non-financial private sector is the financial variable carrying most information necessary for the timely estimation of the output gap.

2. Real equity growth plays a similar role to real credit in the Great Depression but not during the Great Recession; real housing growth indicates a similar information content to that provided by credit.

3. The sensitivity of output gap to real credit growth is time-varying; the parameter is increasing since the beginning of 1990s

4. The finance-neutral potential output has been constant at 2% since the beginning of the 1980s. Ignoring the financial variables severely distorts its level post-2007 crisis - Financial Drag Hypothesis seems more likely than the Secular Stagnation Hypothesis.

Baseline BDJ Model

Let $\bar{y}_t$ denote the unobserved trend component of log real GDP and $\hat{y}_t$ its cycle (or output gap). Following Harvey and Todd (1983), Harvey (1985) and Harvey et al. (2007), the decomposition of y_t is written as follows:

$$y_t = \bar{y}_t + \hat{y}_t \tag{1}$$

The trend component is modelled as a BM

$$\Delta\bar{y}_{t+1} = \Delta\bar{y}_t + \varepsilon_t^{\bar{y}}, \text{where } \varepsilon_t^{\bar{y}} \sim N(0, \sigma^2_{\varepsilon^{\bar{y}}}) \tag{2}$$

The output gap will depend on its own lag as well as on the evolution of a financial variable, here denoted f_t

$$\hat{y}_t = \rho\hat{y}_{t-1} + \gamma\mathrm{f}_t + \varepsilon_t^{\hat{y}}, \text{where } \varepsilon_t^{\hat{y}} \sim N(0, \sigma^2_{\varepsilon^{\hat{y}}}) \tag{3}$$

TVP-OG Model

The output gap will depend on its own lag as well as on the evolution of a financial variable, here denoted f_t but now γ will be time-varying

$$\hat{y}_t = \rho\hat{y}_{t-1} + \gamma_t \mathrm{f}_t + \varepsilon_t^{\hat{y}}, \text{where } \varepsilon_t^{\hat{y}} \sim N(0, \sigma^2_{\varepsilon^{\hat{y}}}) \tag{4}$$

with

$$\gamma_t = \gamma_{t-1} + \varepsilon_t^{\gamma}, \text{where } \varepsilon_t^{\gamma} \sim N(0, \sigma^2_{\varepsilon^{\gamma}}) \tag{5}$$

Estimation procedure

- Both models are cast in the state-space form allowing us to estimate the unobserved factor via the Kalman filter (Harvey and Todd (1983), Harvey (1985))
- Specify the prior of the parameters following the literature
- Estimate the mode of the posterior distribution by maximizing the log posterior function, which combines the prior information on the parameters with the likelihood of the data evaluated by Kalman filter.
- Sample from the posterior with a Markov Chain Monte Carlo to obtain the posterior distribution.

BDJ Estimation over 1870-2013

One of the potential problems when using real credit growth as a proxy for the financial cycle is that the trend in f_t may pass onto output gap estimates. To avoid this issue, we demean f_t before the estimation using a 10 year moving average.

		Prior distribution			**Posterior Distribution**		
	Domain.	Distr.	Mean	St. Dev.	Mean	$[5\%, 95\%]$	PSRF
ρ	(0,1)	Beta	0.80	0.10	0.85	[0.76, 0.94]	1.00
$\sigma^2_{\varepsilon_{\bar{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	1.00	1.00	0.58	[0.25, 1.17]	1.00
$\sigma^2_{\varepsilon_{\hat{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	20.0	20.0	23.9	[18.9, 30.0]	1.00
γ	$\mathbb{R}$				0.24	[0.12, 0.37]	1.00

Notes: We do not restrict any prior belief on the parameter γ. The posterior distribution is obtained by the Metropolis-Hastings algorithm. PSRF- Potential Scale Reduction Factor. Real credit is obtained by deflating the total loans to non-financial private sector by CPI.

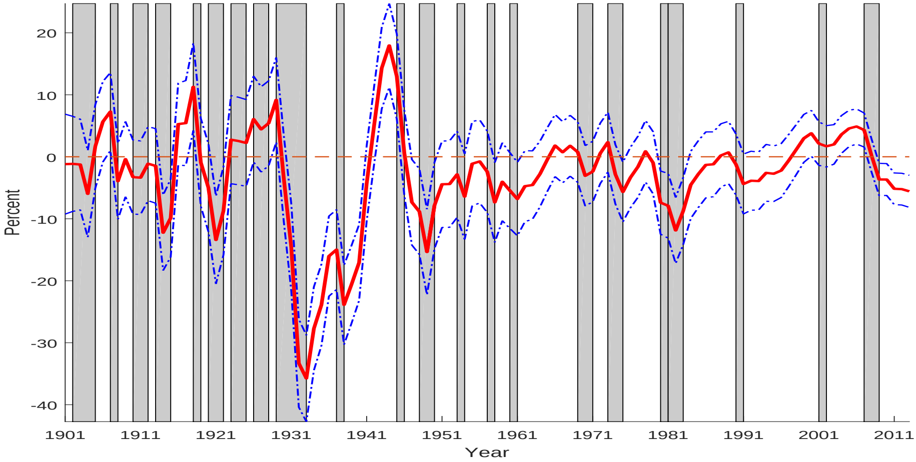
TVP-OG Estimation over 1870-2013

The TVP-BDJ model allows the information content that financial factors have for output gap to change over time by modelling the financial parameter γ_t as a driftless random walk process.

		Prior distribution			**Posterior Distribution**		
	Domain.	Distr.	Mean	St. Dev.	Mean	[5%, 95%]	PSRF
ρ	(0,1)	Beta	0.80	0.10	0.85	[0.76, 0.93]	1.00
$\sigma^2_{\varepsilon_{\bar{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	1.00	1.00	0.56	[0.25, 1.09]	1.00
$\sigma^2_{\varepsilon_{\hat{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	20.0	20.0	15.8	[11.9, 20.4]	1.00
$\sigma^2_{\varepsilon_{\gamma}}$	$\mathbb{R}^+$	Inv.Gam.2	0.10	1.00	0.05	[0.02, 0.10]	1.00

Output Gap Estimates

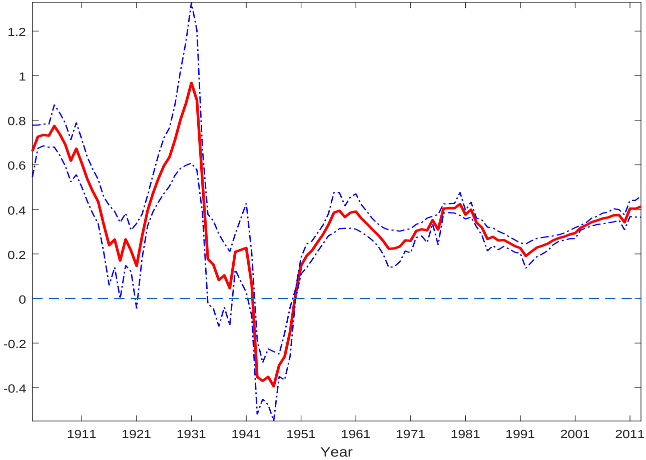
Figure: Output Gap Estimates (+/2 SE)



Note: Estimates of output gap, which is 100 times natural log deviation of output from its potential level using the *TVP-OG* model. Shaded areas: recessions (NBER)

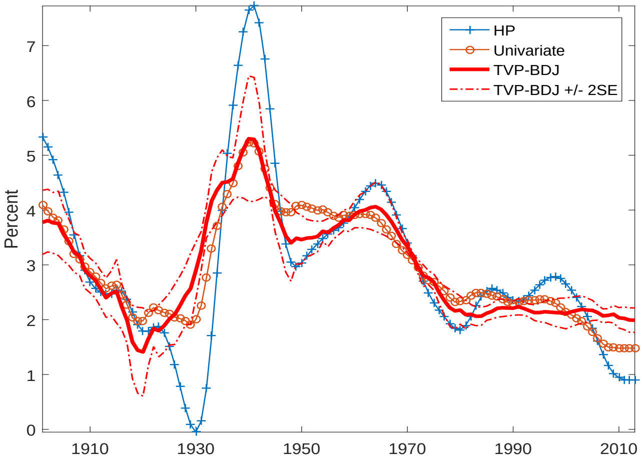
Sensitivity of the output gap to the credit gap

Figure: Real Credit Growth Time-Varying Parameter (+/- 2 SE)



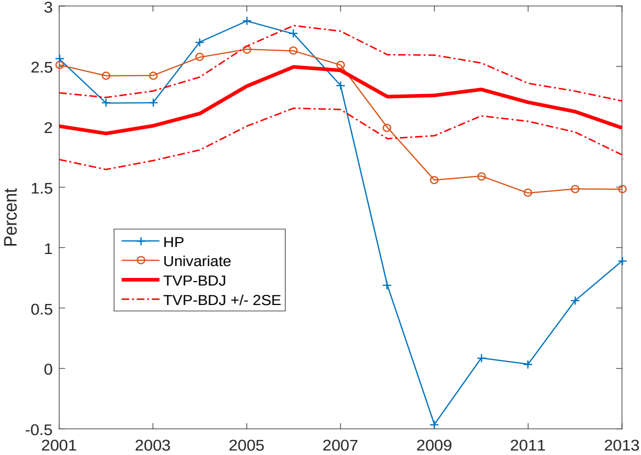
Note: This figure presents the time-varying influence of real credit growth on output gap γ_t.

A comparison of methodologies



Notes: The figure shows the smoothed estimates of the potential growth of output ($\Delta\overline{y}_t$) from three different models: the HP filter, the univariate model, and the TVP-OG model.

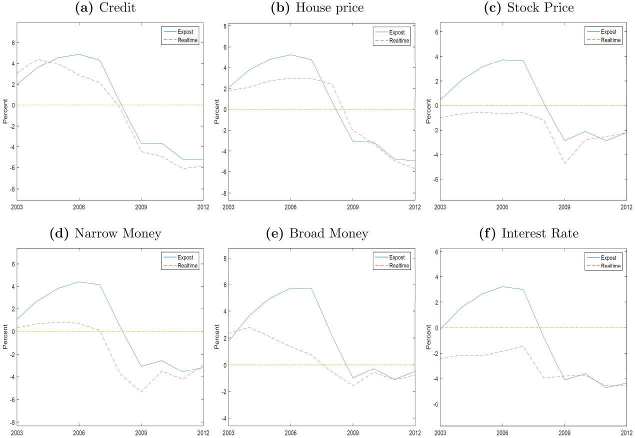
Potential Growth - Zooming In



Notes: The figure shows the filtered estimates of the potential growth of output ($\Delta\overline{y}_t$) from three different models: the HP, the univariate model, and the TVP-BDJ model. The filtered estimates are those estimated using the sample of data available up to the point of estimation. For the HP, it is the one-sided HP estimate with the smoothing parameter being equal to 100.

1929

Note: The figure shows the real-time (dashed) and ex-post (solid) output gap estimates for the 1925-1934 period using the TVP-BDJ framework with different proxies for financial information.



Note: The figure shows the real-time (dashed) and ex-post (solid) output gap estimates for the 2003-2012 period using the TVP-BDJ framework with different proxies for financial information.

Building More Economic Structure

With more frequent and richer output and financial data, investigate the relative weight finance vs. labor plays in determining the state of the economic cycle.

Unemployment or Credit: Which One Holds the Potential? Results for a Small-Open Economy with a Low Degree of Financialization, Economic Systems (2018)

Introduction: What we do

Based on the MUC model, this paper

1. Investigates the real-time performance of output gap estimation: According to Orphanides and van Norden (2002), real-time estimates are challenged by:
    - Data in subsequent quarters become available, hindsight may help to clarify our position in the business cycle (update/revision of the model given the the arrival of new data)
    - Output data is often subject to revisions

Introduction: What we do

Based on the MUC model, this paper

1. Investigates the real-time performance of output gap estimation: According to Orphanides and van Norden (2002), real-time estimates are challenged by:
   - Data in subsequent quarters become available, hindsight may help to clarify our position in the business cycle (update/revision of the model given the the arrival of new data)
   - Output data is often subject to revisions
2. Studies the role of information from financial sector in measuring output gap
   - Borio et al. (2016, 2014) and Melolinna and Toth (2016) have argued that the inclusion of financial variables improve the real-time performance of measuring output gap.
     - Credit-to-GDP ratios in UK, US, and Spain (those considered in their studies) over the 1999-2016 period are 150 percent, 163 percent, and 173 percent respectively.
   - We explore the role of financial factors for the estimation of output gap in Lithuania, a small open economy with a low level of financialization, with a credit-to-GDP ratio of 45 percent.

Introduction: What we find

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.

Introduction: What we find

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.
- Once information about unemployment is accounted for, adding information about credit does not substantially alter either the estimates of output gap or its performance in real time.

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.
- Once information about unemployment is accounted for, adding information about credit does not substantially alter either the estimates of output gap or its performance in real time.
- We uncover a strong negative correlation between the model-implied unemployment gap (without credit) and real credit growth. This explains the relatively muted impact of the financial variable on the level and dynamics of the output gap.

Introduction: What we find

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.
- Once information about unemployment is accounted for, adding information about credit does not substantially alter either the estimates of output gap or its performance in real time.
- We uncover a strong negative correlation between the model-implied unemployment gap (without credit) and real credit growth. This explains the relatively muted impact of the financial variable on the level and dynamics of the output gap.
- Data revisions appear not to be the primary source of revisions on output gaps estimates.

Baseline Model

Let $\bar{y}_t$ denote the unobserved trend component of log real GDP and $\hat{y}_t$ its cycle (or output gap). Following Harvey and Todd (1983), Harvey (1985) and Harvey et al. (2007), the decomposition of y_t is written as follows:

$$y_t = \bar{y}_t + \hat{y}_t \tag{6}$$

The model structure for GDP comprises three equations and is subject to three shocks as follows:

$$\bar{y}_t = \bar{y}_{t-1} + g_{t-1} + \varepsilon_t^{\bar{y}} \tag{7}$$

$$g_t = g_{t-1} + \varepsilon_t^{g} \tag{8}$$

$$\hat{y}_t = \rho_1 \hat{y}_{t-1} + \varepsilon_t^{\hat{y}} \tag{9}$$

Unemployment rate is modelled as a sum of trend (or natural rate of unemployment) and cyclical component:

$$u_t = \bar{u}_t + \hat{u}_t, \tag{10}$$

where the trend and cyclical component is given by,

$$\bar{u}_t = \bar{u}_{t-1} + \varepsilon_t^{\bar{u}}, \tag{11}$$

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} - \gamma_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{u}}. \tag{12}$$

Baseline Model

A system of motion equations describing the evolution of inflation is also incorporated in the model, in line with Kuttner (1994), Melolinna and Toth (2016), and Stock and Watson (2016):

$$\pi_t = \bar{\pi}_t + \hat{\pi}_t, \tag{13}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \varepsilon_t^{\bar{\pi}}, \tag{14}$$

$$\hat{\pi}_t = \alpha_1 \hat{\pi}_{t-1} + \alpha_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{\pi}}. \tag{15}$$

Model with Credit

To incorporate the financial factor, we follow a relatively parsimonious approach suggested by Melolinna and Toth (2016) by adjusting the dynamics of output gap as follows:

$$\hat{y}_t = \rho_1 \hat{y}_{t-1} + \delta \bar{f}_{t-1} + \varepsilon_t^{\hat{y}}. \tag{16}$$

This variable follows an AR(1) process and is observed with errors:

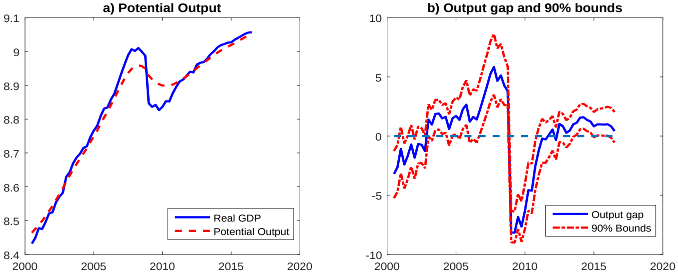
$$\bar{f}_t = \beta \bar{f}_{t-1} + \varepsilon_t^{\bar{f}}, \tag{17}$$

$$f_t = \bar{f}_t + \varepsilon_t^{f}. \tag{18}$$

Estimation procedure

- Present the model in the state-space form
- Specify the prior of the parameters
- Estimate the mode of the posterior distribution by maximizing the log posterior function, which combines the prior information on the parameters with the likelihood of the data evaluated by Kalman filter.
- Sample from the posterior with a Markov Chain Monte Carlo to obtain the posterior distribution.

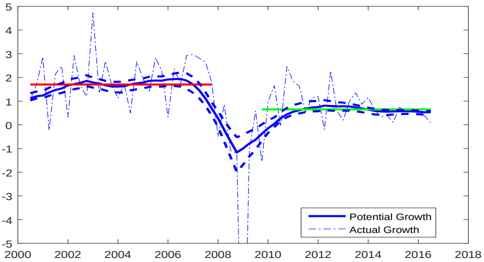
Figure: Potential Output and Output Gap



Notes: The graph shows the smoothed sequences of (log of) potential output in the left panel and its associated output gap with 90% bounds in the right panel.

Analysis 2: Potential Growth

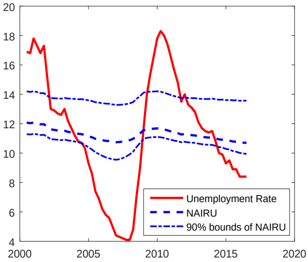
Figure: Potential Growth



Notes: The graph shows the potential growth (%) and its 90 percent bounds together with the actual output growth (%). The red and green lines illustrate the average of potential growth in the pre- and post-crisis, respectively.

Analysis 3: Unemployment gap

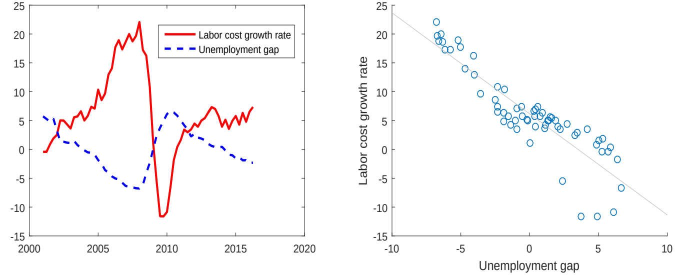
Figure: Unemployment Gap



Notes: The graph shows the smoothed sequences of natural rate of unemployment (%) in the left panel and the deviation of unemployment gap from its natural rate (%) in the right panel.

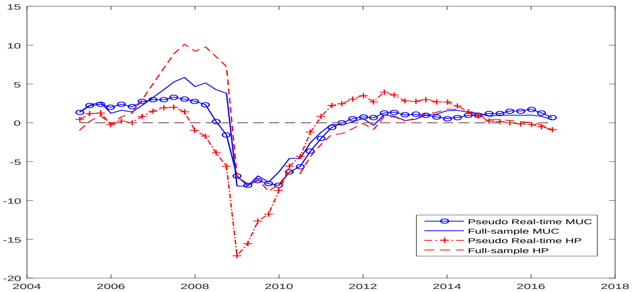
Analysis 3: Unemployment gap and labor cost growth rate

Figure: Labor cost



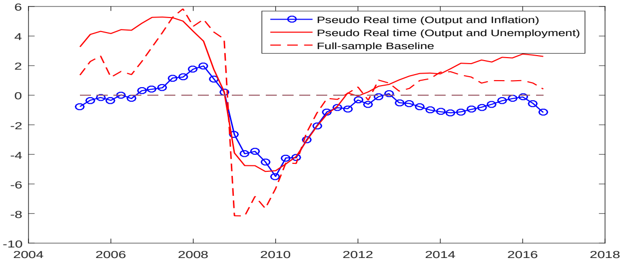
Notes: The graph shows the smoothed sequences of unemployment gap (%) and the labor cost growth rate (%).

Figure: Output gap in Real time



Notes: The pseudo real-time output gap is obtained by recursively estimating the models, MUC *versus* HP, using 1998:Q1-2005:Q1 as the initial sample and adding one by one observation from 2005:Q2-2016:Q3.

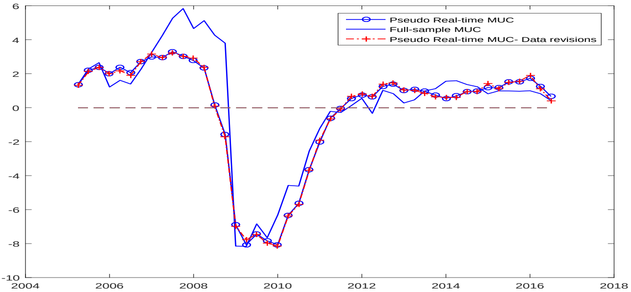
Figure: Output gap in Real time: Two Alternative Models



Notes: Two alternative models are: the MUC model with output and inflation and the MUC with output and unemployment rate. The pseudo real-time output gap is obtained by recursively estimating the models using 1998:Q1-2005:Q1 as the initial sample and adding one quarter by one from 2005:Q2-2016:Q3.

Analysis 5: Output gap in Real time with Data revisions

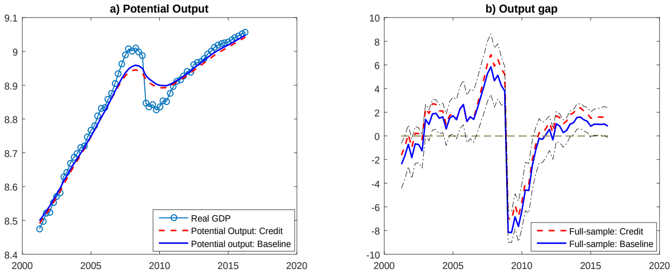
Figure: Output gap in Real time: Data with Measurement Errors



Notes: The pseudo real-time output gap is obtained by recursively estimating the models, with actual data and data with errors, using 1998:Q1-2005:Q1 as the initial sample and adding one quarter by one from 2005:Q2-2016:Q3.

Analysis 7: Output gap in the Model with Credit

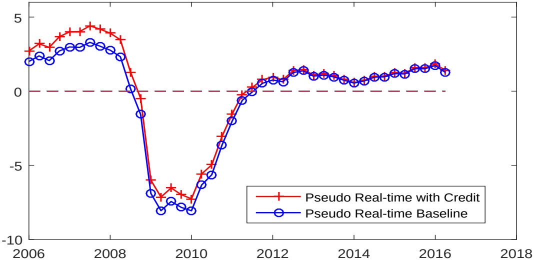
Figure: Output gap in the Model with Credit



Notes: The graph shows in the left panel the smoothed sequences of (log of) potential output in the model with credit and the baseline model and their associated output gaps in the right panel. The dotted lines in the right panel are 90 percent bounds of the baseline estimates.

Analysis 9: Real-time Output gap in the Model with Credit

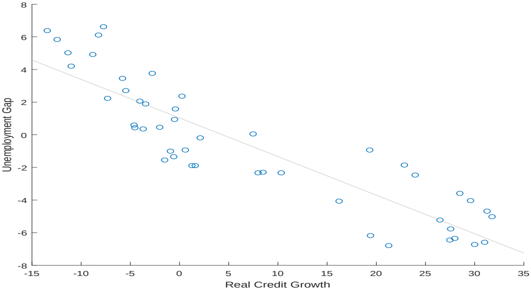
Figure: Output gap in Real time: Model with Credit



Notes: The graph shows the real-time estimates of output gaps in the model with credit and the baseline model. The pseudo real-time output gap series is a collection of the end-point measures obtained by estimating the relevant model recursively by adding one quarter by one till the end of the sample.

Analysis 10: Credit and Unemployment

Figure: Credit and Unemployment: 2004Q4 - 2016Q2



Notes: Real credit growth (%) and unemployment gap estimated from the baseline model (%).

Conclusion

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.

Conclusion

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.
- Once information about unemployment is accounted for, adding information about credit does not substantially alter either the estimates of output gap or its performance in real time.

Conclusion

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.
- Once information about unemployment is accounted for, adding information about credit does not substantially alter either the estimates of output gap or its performance in real time.
- We uncover a strong negative correlation between the model-implied unemployment gap (without credit) and real credit growth. This explains the relatively muted impact of the financial variable on the level and dynamics of the output gap.

Conclusion

- The inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time.
- Once information about unemployment is accounted for, adding information about credit does not substantially alter either the estimates of output gap or its performance in real time.
- We uncover a strong negative correlation between the model-implied unemployment gap (without credit) and real credit growth. This explains the relatively muted impact of the financial variable on the level and dynamics of the output gap.
- Data revisions appear not to be the primary source of revisions on output gaps estimates.

But no country is an economic island

Mind the Global Gap!

In Constantinescu and Lastauskas (2018), we find an important role of cross-sectional averages of GDP, housing and credit as covariates explaining national house price dynamics over more than 120 years of economic history - with different impact over time and in the cross-section.

The Global View

- We provide a century-long view of the contribution of global and national factors to the cyclical component of credit, economic activity, housing and equity markets for all the countries in the JST (2016) and Knoll (2017) dataset.
- We estimate a dynamic multivariate latent factor model similar to Mumtaz (2017) to uncover the increasing importance of global factors at *medium-term* rather than short-term frequencies.
- Given the increasing importance of global factors, our work provides *evidence of the need for global coordination* in both macro-stabilization and macro-prudential policies.
- A high degree of heterogeneity is identified across countries and time in responses to global components.

Brief Literature

- Schularick and Taylor (2012, 2017): *credit is a primary source of macroeconomic shocks not only a channel of shock propagation*.
- The empirical relevance of global factors in the determination of business cycle commonalities across countries has been highlighted in several papers employing dynamic multivariate latent factor models such as Kose, Otrok, and Whiteman (2003) and Del Negro and Otrok (2008).
- More recently, the increasing interdependence of real and financial cycles as well as its heterogeneous nature across both time and countries feature prominently in studies of global economic converge such as Kose, Otrok, and Prasad (2012), Claessens, Kose, and Terrones (2012), Mumtaz (2017).

Our Questions

- Are there common factors potentially at work in both real and financial variables? If yes, policy may benefit from more consideration of joint dynamics of macroeconomic stabilization **and** macro-prudential policies.
- Do effects from common components manifest themselves in the short-term or rather over longer time-frames? Borio (2012) "Characterising the financial cycle: don't lose sight of the medium term!" - if important, effects of QE might surprise us with some unexpected latent effects in the years to come

What We Measure

- Real output to estimate business cycles (BC)
- Real total loans to non-financial private sector for credit cycles (CC)
- Real house prices for house price cycles (HC)
- Stock price for stock price cycles (SC).[3]

The data is annual spanning the period 1870 to 2013 from the Macrohistory database. We consider 16 countries as shown in Table 1.[4] Four cycles are estimated for each country, but Italy and Spain[5]

Table: List of countries

Australia	Belgium	Canada	Denmark
Finland	France	Germany	Italy
Japan	Netherland	Norway	Spain
Sweden	Switzerland	UK	US

[3]The real term is obtain by deflating the nominal term by CPI.

[4]Portugal is not included because both stock price and house price are not available over a large portion of the estimation sample.

[5]In the latter, house prices are only available from 1970 so the series are excluded from these two countries.

How We Measure It

- Comin and Gertler (2006) document the existence of the medium-term components in GDP which tend to be swept into the trend by conventional filters: rather than working with the filter at frequencies between 2 and 8 years, authors argue in favor of 2 to 20 years.
- Recent emerging studies on the interaction between business cycles and financial cycles document that the financial cycle is much longer than the traditional business cycle and business cycle recessions are much deeper when they coincide with the contraction phase of the financial cycle (Drehmann et al. (2012)).
- To cast light on the importance of the two different frequencies, we estimate the weight of global and national factors (along with idiosyncratic shocks) at both short and medium-frequencies.

Model

We assume that each cycle X_{it} is decomposed according to a dynamic factor model as follows:

$$X_{it} = B_{it}^C F_t^C + B_{it}^W F_t^W + u_{it}. \tag{19}$$

Each factor k of F_t is described by:[6]

$$F_{kt} = \sum_{i=1}^{p} b_{ki} F_{kt-i} + e_{kt}, \quad e_{kt} \sim N(0,1). \tag{20}$$

The idiosyncratic component u_{it} is assumed to follow an $AR(q)$ process:

$$u_{it} = \sum_{j=1}^{q} d_{ij} u_{it-j} + e_{it}, \quad e_{it} \sim N(0,\sigma_i). \tag{21}$$

Factor loadings on the country and world factors, $B_{it} = [B_{it}^C, B_{it}^W]$, are allowed to be time-varying, based on a random walk process:

$$B_{it} = B_{it-1} + \tau_t, \quad \tau_t \sim N(0, Q_i). \tag{22}$$

[6] The standard deviation of e_{kt} is set to one, which is a standard normalization assumption because of the scaling issue.

The variance of $X^i_{c\,t}$ can be decomposed as follows:

$$var(X^i_{c\,t}) = \sum_{k=1}^{K^C}(B^i_{k,c\,t})^2 var(F^i_{k,t}) + \sum_{j=1}^{K^W}(B^{i,W}_{j,c\,t})^2 var(F^W_{j,t}) + var(u^i_{c\,t}). \tag{23}$$

Based on Equation 23, we can evaluate the contribution of each country factor $F^i_{k,t}$ to the variance of $X^i_{c\,t}$ by

$$CV^i_{k,c\ \ t} = \frac{(B^i_{k,c\,t})^2 var(F^i_{k,t})}{\sum_{k=1}^{K^C}(B^i_{k,c\,t})^2 var(F^i_{k,t}) + \sum_{j=1}^{K^W}(B^{i,W}_{j,c\,t})^2 var(F^W_{j,t}) + var(u^i_{c\,t})}, \tag{24}$$

and the total contribution of country factors to the variance of $X^i_{c\,t}$ is:

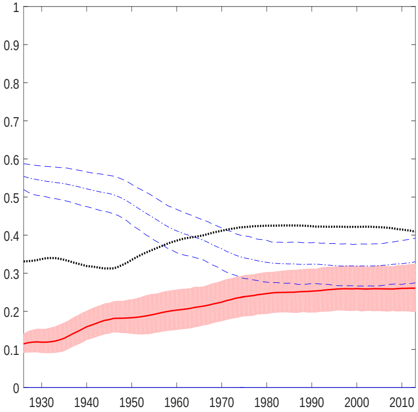
$$CV^i_{c\,t} = \sum_{k=1}^{K^C} CV^i_{k,c\,t}. \tag{25}$$

Similarly, the contribution of each global factor $F^{W}_{j,t}$ to the variance of $X^{i}_{c\,t}$ is calculated by

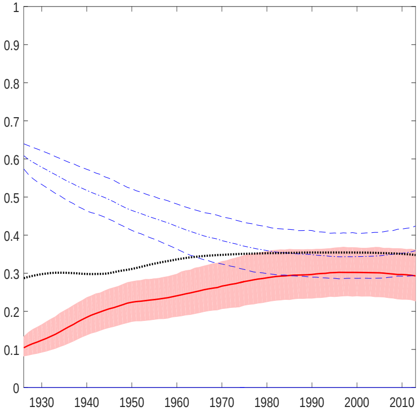
$$GV^{i}_{k,c\ \ t} = \frac{(B^{i,W}_{j,c\,t})^2 var(F^{W}_{j,t})}{\sum_{k=1}^{K^C}(B^{i}_{k,c\,t})^2 var(F^{i}_{k,t}) + \sum_{j=1}^{K^W}(B^{i,W}_{j,c\,t})^2 var(F^{W}_{j,t}) + var(u^{i}_{c\,t})}. \tag{26}$$

and the total contribution of global factors to the variance of $X^{i}_{c\,t}$ is:

$$GV^{i}_{c\,t} = \sum_{j=1}^{K^W} GV^{i}_{j,c\,t}. \tag{27}$$



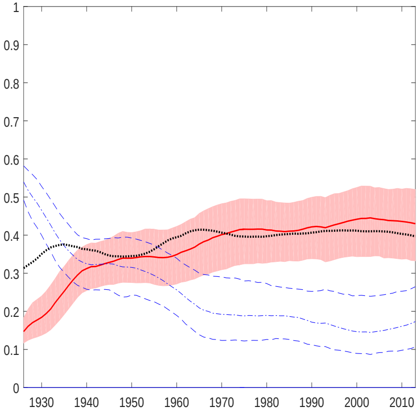
(a) Business



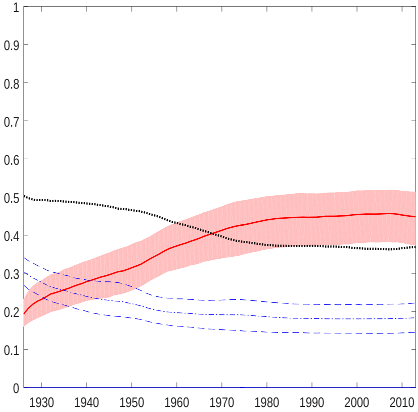
(b) Credit

Note: The contribution to the variance of each series of global factors (red line with 90% error bands - red shaded area), country factors (blue dashdot line with 90% error bands - blue dashed lines) and other factors (black dotted line).

Short-term Average Across Countries: HPC and SPC



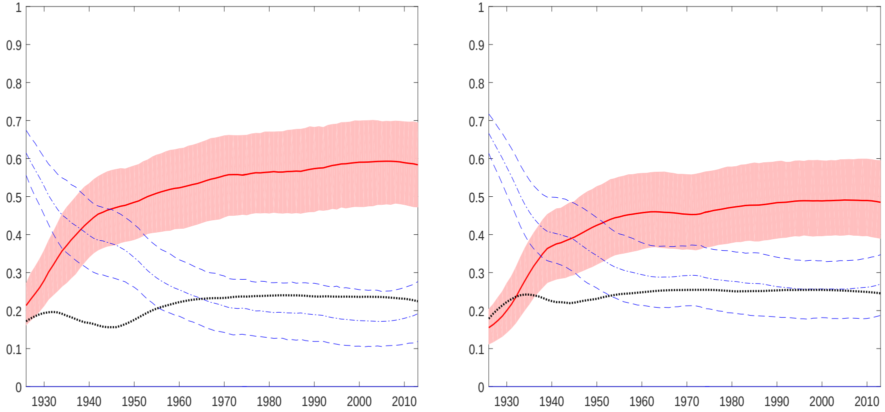
(c) House Price



(d) Stock Price

Note: The contribution to the variance of each series of global factors (red line with 90% error bands - red shaded area), country factors (blue dashdot line with 90% error bands - blue dashed lines) and other factors (black dotted line).

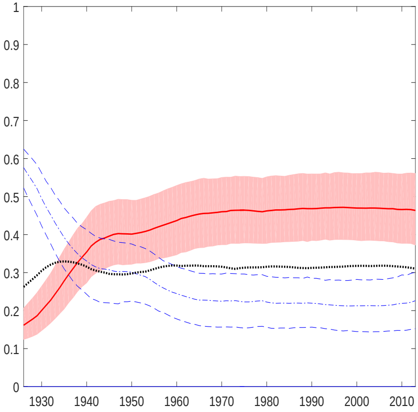
Medium-term Average Across Countries: BC and CC



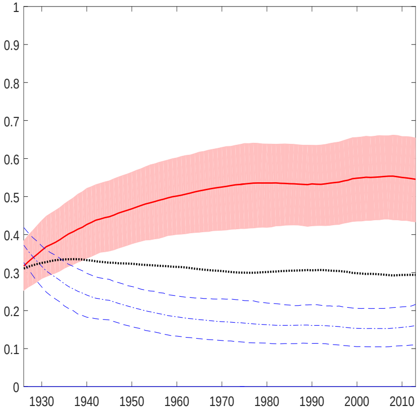
(e) Business (f) Credit

Note: The contribution to the variance of each series of global factors (red line with 90% error bands - red shaded area), country factors (blue dashdot line with 90% error bands - blue dashed lines) and other factors (black dotted line).

Medium-term Average Across Countries: HPC and SPC



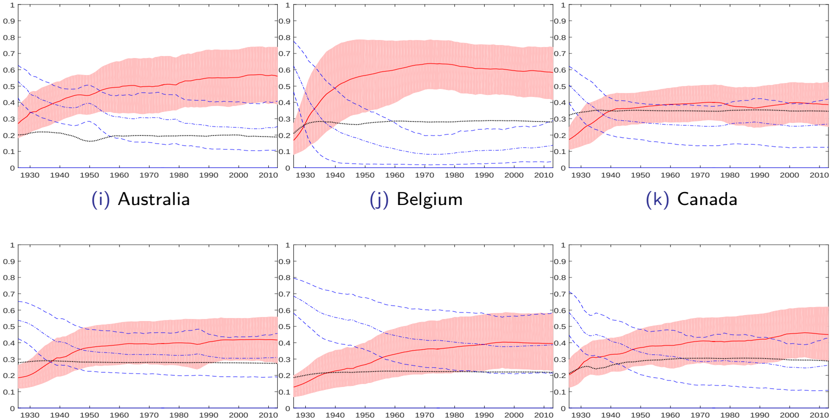
(g) House price



(h) Stock price

Note: The contribution to the variance of each series of global factors (red line with 90% error bands - red shaded area), country factors (blue dashdot line with 90% error bands - blue dashed lines) and other factors (black dotted line).

Country-averages: medium term cycle

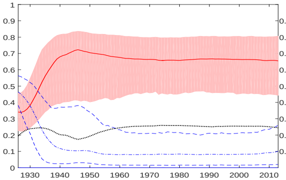


(i) Australia (j) Belgium (k) Canada

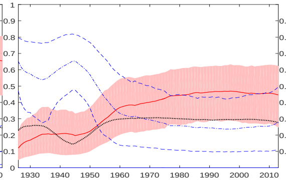
(l) Denmark (m) Finland (n) France

Note: The contribution to the variance of each series of WORLD factors (red line with 90% error bands- red shaded area), COUNTRY factors (blue dashdot line with 90% error bands - blue dashed lines) and IDIOSYNCRATIC factor (black dotted line).

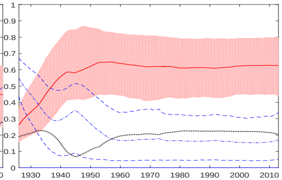
Country-averages: medium term cycle



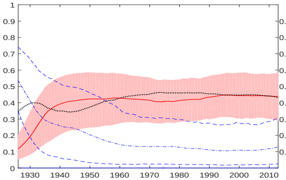
(o) Germany



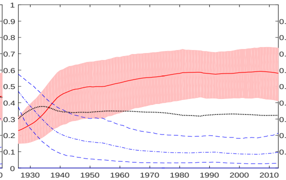
(p) Italy



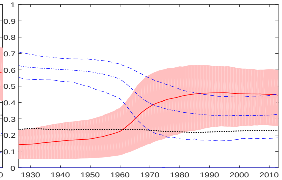
(q) Japan



(r) Netherland



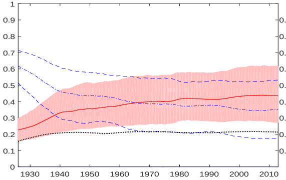
(s) Norway



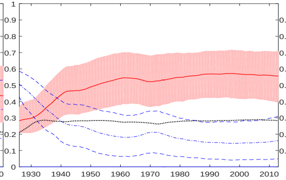
(t) Spain

Note: The contribution to the variance of each series of WORLD factors (red line with 90% error bands- red shaded area), COUNTRY factors (blue dashdot line with 90% error bands - blue dashed lines) and IDIOSYNCRATIC factor (black dotted line).

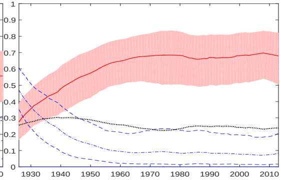
Country-averages: medium term cycle



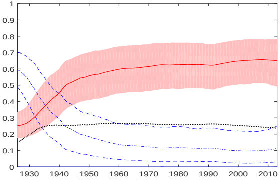
(u) Sweden



(v) Switzerland



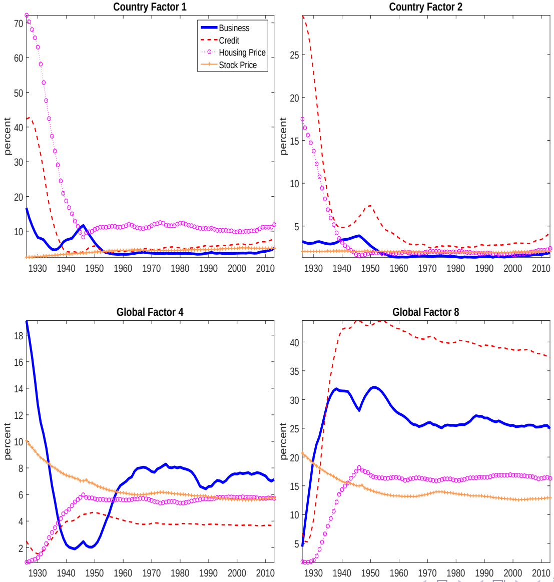
(w) UK



(x) USA

Note: The contribution to the variance of each series of WORLD factors (red line with 90% error bands- red shaded area), COUNTRY factors (blue dashdot line with 90% error bands - blue dashed lines) and IDIOSYNCRATIC factor (black dotted line).

Real-Financial Interaction in Contribution to Variance: Germany



Real-Financial Interaction in Contribution to Variance: US