

**Global Banks, Financial Shocks and International Business Cycles:  
Evidence from Estimated Models**

Robert Kollmann (\*)  
ECARES, Université Libre de Bruxelles and CEPR

Matthias Paustian  
Bank of England

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The global financial crisis that erupted in 2007 has stimulated much research that incorporates financial intermediaries into dynamic open economy models. So far, this research has focused on stylized, calibrated models. This paper puts that class of models to the US and Euro Area (EA) data, using Bayesian econometric methods. The estimation results suggest that global financial intermediaries strengthen the positive international transmission of real economic disturbances. Shocks that originate in the banking sector account for roughly 20% of the forecast error variance of investment, and about 5% of the forecast variance of US and EA GDP. Bank shocks explain between 5% and 10% of the fall in US and EA real activity, during the Great Recession.

Key words: financial crisis, financial intermediaries, real activity, investment, Bayesian econometrics.

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(\*) Corresponding author.

Addresses: R. Kollmann, ECARES, CP 114, Université Libre de Bruxelles; 50 Av. Franklin Roosevelt; B-1050 Brussels, Belgium; robert\_kollmann@yahoo.com.

Matthias Paustian, Monetary Assessment and Strategy Division, Bank of England, Threadneedle Street, London EC2R 8AH, United Kingdom; matthias.paustian@bankofengland.co.uk

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## 1. Introduction

In the years before the recent (2007-09) financial crisis, the leverage of many major financial institutions increased steadily, and reached unprecedented levels. The crisis revealed the fragility of the financial sector, and of many highly indebted non-financial firms and households, and it has triggered the sharpest global recession since the 1930s. Before the crisis, structural macro models largely abstracted from financial intermediaries. Recently, much effort has therefore been developed to the development of macro models that include financial intermediaries; see, e.g., Davis (2011), Gamber and Thoenissen (2011), Devereux and Sutherland (2011), In't Veld et al. (2011), Kollmann et al. (2011), Nguyen (2011), Paustian and Sondergaard (2010), Perri and Quadrini (2011), Perri and Kalemli-Ozcan (2011), Ueda (2011) and van Wincoop (2011) who present open economy models with banks.<sup>1</sup> In these models, the net worth of banks is a key state variable for real activity. This literature has highlighted several important mechanisms through which the presence of banks affects the transmission of macroeconomic and financial shocks. For example, a negative shocks to bank capital will tend to raise the spread between banks' lending and deposit rates, and thus lower lending and real activity; thus, shocks in one country that lower global banks' capital can trigger a worldwide recession. So far, however, this research has focused on relatively stylized, calibrated models.

A key contribution of this paper is to take this new class of models to the data. Specifically, we estimate a two-country DSGE model with a financial intermediary, using US and EA data, by Bayesian econometric methods.<sup>2</sup> In accordance with the intuition discussed above, the estimation results suggest that global financial intermediaries strengthen the positive international transmission of real economic disturbances. Shocks directly linked to the banking sector account for roughly 20% of the forecast error variance of investment, but a much smaller share of the forecast variance of US and EA

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<sup>1</sup> Closed economy macro models with banks were, i.a., presented by Aikman and Paustian (2006), Van den Heuvel (2008), Gertler and Kiyotaki (2009), Dib (2009), Adrian and Shin (2010), de Walque et al. (2010), and Challe et al. (2011).

<sup>2</sup> There exists a small literature that estimates open economy DSGE, but that literature has abstracted from banks; also, that literature has mainly focused on small open economies (e.g. Justiniano and Preston (2010)). Two-country models were estimated by de Walque et al. (2005) and Peersman and Jacob (2011).

GDP. Bank shocks explain about 5% of the fall in real activity, during the Great Recession.

Section 2 presents the model that we estimate. Section 3 discusses the econometric approach. Section 4 describes key data features. Section 5 reports the estimation results. Section 6 concludes.

## 2. A two-country world with a global financial intermediary

We consider a two-country model that builds on Kollmann et al. (2011).<sup>3</sup> There is a representative global bank. In each of the two countries, ‘Home’ and ‘Foreign’, there is a representative worker, an entrepreneur and a government. All agents are infinitely lived. The bank collects deposits from Home and Foreign workers, and makes loans to Home and Foreign entrepreneurs. The bank faces a collateral constraint, that ties the maximum amount of debt that the bank can issue to the bank’s net worth.<sup>4</sup> There is a final good that is produced by Home and Foreign entrepreneurs using local labor and capital. The good can freely be traded. It is used for consumption, and for capital accumulation (by entrepreneurs). All markets are competitive. Preferences and technologies have the same structure in both countries. The following exposition thus focuses on the Home country. Foreign variables are denoted by an asterisk.

### The Home worker

The Home worker consumes the final good, provides labor to the Home entrepreneur and invests her savings in one-period bank deposits. Her date  $t$  budget constraint is:

$$C_t + D_{t+1} + T_t^W = W_t N_t + D_t R_t^D, \quad (1)$$

where  $C_t$  and  $W_t$  are her consumption and the wage rate, respectively (the final good is used as numéraire).  $T_t^W$  is a lump sum tax.  $N_t$  are hours worked.  $D_{t+1}$  is the bank deposit held by the Home worker at the end of period  $t$ .  $R_t^D$  is the gross interest rate on deposits, between  $t-1$  and  $t$  ( $R_t^D$  is set at  $t-1$ ). The worker’s expected life-time utility at date  $t$  is:

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<sup>3</sup> The model here is different in that, i.a., a government, and a larger number of exogenous shocks are assumed.

<sup>4</sup> To focus on the role of banking frictions, we assume that other agents (workers, entrepreneurs) do not face collateral constraints.

$$E_t \sum_{s=0}^{\infty} \beta^s [u(C_{t+s}) + \Psi^D \cdot u(D_{t+1+s}) - \Psi_t^N \cdot \chi(N_{t+s})], \quad (2)$$

where  $u(x) = (x^{1-\sigma} - 1)/(1-\sigma)$  and  $\chi(N) = (N^{1+1/\eta})/(1+1/\eta)$ ,  $\sigma > 0$ ,  $\eta > 0$ .  $\Psi^D > 0$  is a constant.  $\Psi_t^N$  is an exogenous stochastic taste shock that affects the worker's labor supply.  $0 < \beta < 1$  is the subjective discount factor. Workers, entrepreneurs and the banker have the same subjective discount factor. We assume that deposits provide utility to the worker (liquidity services). This allows us to calibrate the model in such a way that, in steady state, the deposit rate is smaller than the lending rate, and that workers hold deposits while entrepreneurs borrow.

The Home worker maximizes (2) subject to the period-by-budget constraint (1). That decision problem has these first-order conditions:

$$R_{t+1}^D E_t \beta u'(C_{t+1})/u'(C_t) + \Psi^D u'(D_{t+1})/u'(C_t) = 1, \quad u'(C_t) W_t = \Psi_t^N \chi'(N_t).$$

### The Home entrepreneur

The Home entrepreneur accumulates physical capital and uses capital and local labor to produce the final good. Home final good output, denoted  $Z_t$ , is produced using the Cobb-Douglas technology  $Z_t = \theta_t (K_t)^\alpha (N_t)^{1-\alpha}$ , with  $0 < \alpha < 1$ .  $K_t$  is the capital stock used at  $t$ . Home TFP  $\theta_t$  is an exogenous random variable that follows an AR(1) process (see below). The law of motion of the Home capital stock is  $K_{t+1} = (1-\delta)K_t + \Xi_t I_t$ , where  $0 \leq \delta \leq 1$  is a depreciation rate and  $I_t$  is gross investment.  $\Xi_t > 0$  is an exogenous shock to investment efficiency (see Fischer, 2002, 2006; Greenwood et al., 1997; Justiniano et al., 2007). Gross investment is generated using the final good. Let  $\xi(I_t)$  be the amount of the final good needed to generate  $I_t$ , with  $\xi(I_t) \geq I_t$ ,  $\xi'(I_t) > 0$ ,  $\xi''(I_t) \geq 0$ . The Home entrepreneur's period  $t$  budget constraint is:

$$L_t R_t^L - \Delta_t + T_t^E + \xi(K_{t+1} - (1-\delta)K_t) + W_t N_t + d_t^E = L_{t+1} + \theta_t (K_t)^\alpha (N_t)^{1-\alpha}, \quad (3)$$

where  $L_t$  is a one-period bank loan received by the Home entrepreneur in period  $t-1$ .  $R_t^L$  is the gross rate on that loan, set at  $t-1$ . We assume that in period  $t$ , the bank defaults on an exogenous amount  $\Delta_t$  on the contracted amount  $L_t R_t^L$  that she owes the bank.  $T_t^E$  is a

lump sum tax paid by the entrepreneur.  $d_t^E$  is the entrepreneur's dividend income at  $t$ . The entrepreneur consumes her dividend income. Her expected lifetime utility at  $t$  is  $E_t \sum_{s=0}^{\infty} \beta^s u(d_{t+s}^E)$ , Maximization of that life-time utility subject to (3) yields these first-order conditions:

$$\begin{aligned} W_t &= (1 - \alpha)\theta_t K_t^\alpha N_t^{1-\alpha}, \\ R_{t+1}^L E_t \beta u'(d_{t+1}^E) / u'(d_t^E) &= 1, \\ E_t \beta (u'(d_{t+1}^E) / u'(d_t^E)) \{ \theta_{t+1} \alpha K_{t+1}^{\alpha-1} N_{t+1}^{1-\alpha} + q_{t+1} (1-\delta) \} / q_t &= 1, \end{aligned} \quad (4)$$

where  $q_t \equiv \xi'(K_{t+1} - (1-\delta)K_t)$  is the marginal cost of gross investment at date  $t$ .

### The Home government

At date  $t$ , the Home government makes exogenous final good purchases  $G_t$ . These purchases are financed using the lump sum taxes levied on the Home household, the Home entrepreneur, and by a lump sum tax levied on the global banker (see below):  $G_t = T_t^W + T_t^E + T_t^B$ , where  $T_t^B$  is the Home tax paid by the bank. The total tax burden is divided between these agents, according to their shares in steady state consumption, i.e.  $T_t^i = \lambda^i G_t^i$  for  $i=W,E,B$  where  $\lambda^i$  is a time-invariant factor that equals agent  $i$ 's consumption share in total country H consumption.<sup>5</sup>

### The global bank

In period  $t$ , the global bank receives deposits  $D_{t+1}$  and  $D_{t+1}^*$  from the Home and Foreign workers, respectively, and makes loans  $L_{t+1}$  and  $L_{t+1}^*$  to the Home and Foreign entrepreneurs. Let  $D_{t+1}^W \equiv D_{t+1} + D_{t+1}^*$  and  $L_{t+1}^W \equiv L_{t+1} + L_{t+1}^*$  be worldwide stocks of deposits and loans at the end of period  $t$ . The bank faces a capital requirement: her date  $t$  capital  $L_{t+1}^W - D_{t+1}^W$  should not be smaller than a fraction  $\gamma_t$  of the bank's assets  $L_{t+1}^W$ . One may view this as an implicit requirement reflecting market pressures, or as a legal requirement.  $\gamma_t$  is an exogenous random variable. Bank can hold less capital than the

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<sup>5</sup> E.g.  $\lambda^H = C / (C + d^E + d^B / 2)$ , where  $d^S$  is the banker's steady state consumption (of which 50% is assumed to occur in country H).

required level, but this is costly. Let  $x_t \equiv (L_{t+1}^W - D_{t+1}^W) - \gamma_t L_{t+1}^W = (1 - \gamma_t)L_{t+1}^W - D_{t+1}^W$  denote the bank's 'excess' capital at the end of period  $t$ . The bank bears a cost  $L^W \phi(x_t/L^W)$  as a function of  $x_t$ , where  $L^W$  is the steady state stock of loans.  $\phi$  is a convex function ( $\phi'' \geq 0$ ) for which we assume:  $\phi(x_t) > 0$  for  $x_t < 0$ ;  $\phi(0) = 0$ . Thus, for  $x_t < 0$  the bank incurs a positive cost. The cost is zero when the bank meets its capital requirement. At  $t$ , the bank also bears an operating cost  $\Gamma \cdot (D_{t+1}^W + L_{t+1}^W)$ , where  $\Gamma > 0$  is the real marginal cost of taking deposits and making loans. The bank's period  $t$  budget constraint is:

$$L_{t+1}^W + D_t^W R_t^D + \Gamma \cdot (D_{t+1}^W + L_{t+1}^W) + L^W \phi(\{L_{t+1}^W(1 - \gamma_t) - D_{t+1}^W\}/L^W) + T_t^B + T_t^{B*} + d_t^B = L_t^W R_t^L + D_{t+1}^W, \quad (5)$$

where  $d_t^B$  is the profit (dividend) generated by the bank at  $t$ .  $T_t^B + T_t^{B*}$  is the total tax paid by the bank. Loan rates and deposit rates are equated across countries (due to competition). The banker does not have access to other assets, and thus she consumes her dividends. Her expected life-time utility at  $t$  is:  $E_t \sum_{s=0}^{\infty} \beta^s u(d_{t+s}^B)$ . The banker maximizes life-time utility subject to (5). Ruling out Ponzi schemes, that problem has these first-order conditions:

$$R_{t+1}^D E_t \beta u'(d_{t+1}^B) / u'(d_t^B) = 1 - \Gamma + \phi', \quad R_{t+1}^L E_t \beta u'(d_{t+1}^B) / u'(d_t^B) = 1 + \Gamma + (1 - \gamma) \phi',$$

with  $\phi' \equiv \phi'(\{(1 - \gamma_t)L_{t+1}^W - D_{t+1}^W\}/L^W)$ .

### Market clearing

Market clearing for the final good requires:

$$Z_t + Z_t^* = C_t + C_t^* + d_t^E + d_t^{E*} + d_t^B + \xi(I_t) + \xi(I_t^*) + G_t + G_t^* + L^W \phi(\{L_{t+1}^W(1 - \gamma_t) - D_{t+1}^W\}/L^W).$$

### Loan rate spreads and bank capital

The bank's Euler equations imply  $R_{t+1}^L / R_{t+1}^D = (1 + \Gamma + (1 - \gamma_t) \phi') / \{1 - \Gamma + \phi'\}$ ; hence,

$$R_{t+1}^L - R_{t+1}^D \cong 2\Gamma - \gamma_t \phi'(x_t/L^W) \cong 2\Gamma - \gamma_t \phi'(0) - \gamma \phi''(0) \cdot (x_t/L^W).$$

Note that  $x_t/L^W \cong cr_t - cr$ , where  $cr_t \equiv (L_{t+1}^W - D_{t+1}^W)/L_{t+1}^W$  is the bank's capital ratio at  $t$ .

Hence, the curvature of the bank's penalty function  $\phi''(0)$  governs the sensitivity of the

loan spread to change in the bank's capital ratio. A 1 percentage point increase in the capital ratio lowers the loan spread by  $4\gamma\phi''(0)$  percentage points per annum.

As deposits provide liquidity services to workers, and as financial intermediation is costly, the steady state deposit rate is lower than the steady state loan rate. This implies that  $\phi'(0) < 0$  has to hold, for a steady state to exist. A rise in excess bank capital  $x_t \equiv L_{t+1}^W(1-\gamma_t) - D_{t+1}^W$  lowers the loan rate spread  $R_{t+1}^L - R_{t+1}^D$  when the cost of excess capital is strictly convex,  $\phi'' > 0$ . Holding constant total loans and deposits  $L_{t+1}^W, D_{t+1}^W$ , a rise in the 'benchmark' bank capital ratio likewise raises the loan spread.

### Forcing variables

There are 11 exogenous forcing variables: Home and Foreign TFP  $(\theta_t, \theta_t^*)$ , investment efficiency  $(\Xi_t, \Xi_t^*)$ , government purchases  $(G_t, G_t^*)$ , labor supply shocks  $(\Psi_t^N, \Psi_t^{N*})$ , loan defaults  $(\Delta_t, \Delta_t^*)$  and the benchmark bank capital ratio  $(\gamma_t)$ . We allow for a large number of non-bank related shocks, to give the model the chance to explain the data, in the absence of banking shocks. The recent empirical estimates of DSGE models suggest that many shocks are needed to enable these models to adequately capture the data (Smets and Wouters (2007)). There is also a technical reason for assuming many shocks—without measurement error, the number of fundamental shocks has to at least as large as the number of empirical variables used in estimation (otherwise the model is stochastically singular).

As is standard in the empirical DSGE literature, we assume that the forcing variables follow univariate AR(1) processes:  $\ln(x_t/x) = \rho^x \ln(x_{t-1}/x) + \varepsilon_t^x$  for exogenous variable  $x_t$  ( $x$  is the value of the variable in a deterministic steady state).<sup>6</sup>  $\varepsilon_t^x$  is i.i.d. and normally distributed with mean zero. We allow for cross-country correlation of the same type of forcing variable, but different types of shocks are uncorrelated.<sup>7</sup>

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<sup>6</sup> The current version of our simulation code assume that loan default has mean zero; the default of the Home entrepreneur follows  $\Delta_t/Y = \rho^\Delta \Delta_{t-1}/Y + \varepsilon_t^\Delta$ , where  $Y$  is steady state Home GDP.

<sup>7</sup> E.g. Home and Foreign TFP innovations may be correlated, but Home and Foreign TFP innovations are uncorrelated with, say, Home and Foreign government purchases (by contrast, the empirical DSGE

## 2.2 Model solution

We take a linear approximation of the model equations around a deterministic steady state. The solution of the linearized model is given by  $s_t = \Lambda_1 s_{t-1} + \Lambda_2 \varepsilon_t$ , where  $s_t$  is a vector consisting of states, controls and forcing variables chosen (or realized) in period  $t$ , expressed as in deviation from the deterministic steady state.  $\varepsilon_t$  is the vector of date  $t$  innovations to the forcing variables.  $\Lambda_1$  and  $\Lambda_2$  are matrices whose elements are functions of the structural parameters.<sup>8</sup>

## 3. Econometric approach

The estimation uses empirical information on a subset of the variables included in the vector  $s_t$ . Let  $\tilde{z}_t$  be the vector of variables used for the estimation:  $\tilde{z}_t = \Lambda_3 s_t$ , where  $\Lambda_3$  is a ‘selection matrix’. The econometrician is assumed to observe the vector  $z_t$  given by  $z_t = \tilde{z}_t + \omega_t$ , where  $\omega_t$  is a vector of Gaussian i.i.d. measurement errors that has mean zero (measurement error is independent across variables).

Given the assumption that structural innovations and measurement errors are Gaussian, the likelihood function of the data  $Z_T \equiv \{z_t\}_{t=1, \dots, T}$  can easily be derived. See, e.g., Hamilton (1994, ch.13) and Schmitt-Grohé and Uribe (2011). Let  $L(Z_T | \Theta)$  denote the likelihood function, where  $\Theta$  is the vector of model parameters.

The model is estimated using quarterly data for the US and the EA, for the period 1990q1-2010q3. The following 12 empirical series are used for estimation: US and EA GDP, private consumption, investment, employment, the stock of US and EA commercial bank loans (deflated using the GDP deflator), the loan spread of US commercial banks, and the capital ratio of US commercial banks (based on Flow of Funds data). EA loan spreads are only available for the period since 2003q1; as predicted by the model, the EA loan spread closely tracks the US loan spread (see below). We thus use the US loan spread as a measure of the global loan spread. We also take the US bank

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literature generally assumes that shocks are independent). An important avenue for future research is to allow for richer dynamics of the forcing variables, and a richer patterns or shock correlations. A promising avenue would be to assume a factor structure.

<sup>8</sup> We use Chris Sims’ MATLAB proc gensys.m to solve the linearized model (see Sims (2000)).



capital ratio as a proxy for the capital ratio of the global bank. For estimation, the capital ratio is linearly detrended, the loan spread is demeaned. The other variables are linearly detrended in log-form. (EA data are taken from the ECB's Euro-Area-Wide-Model data base, and from the ECB Monthly Statistical Bulletin. See the Data Appendix for a more detailed description of the data.)

We calibrate parameters whose values are uncontroversial and/or pinned down by (banking) regulations and/or average long run features of bank balance sheets. Following much of the recent literature on the estimation of DSGE models, we follow a Bayesian approach to estimate the remaining parameters (e.g., Otrok (2000), Smets and Wouters (2007)). Let  $p(\Theta)$  be a prior density of  $\Theta$ . According to Bayes' law, the posterior density of  $\Theta$  is  $p(\Theta|Z_T)=L(Z_T|\Theta)p(\Theta)/L(Z_T)$ , where  $L(Z_T) \equiv \int L(Z_T|\Theta)p(\Theta)d\Theta$  is the marginal data likelihood of the model. For each model variant discussed below, we report the mode and standard deviation of the posterior parameter density, and the marginal likelihood (a measure of model fit).

### *Calibrated parameters*

The elasticity of final good output with respect to capital is set at  $\alpha=0.3$ , while the (quarterly) depreciation rate of physical capital is set at  $\delta=0.025$ . We consider a baseline specification in which all agents have log utility,  $\sigma=1$ , and labor supply is infinitely elastic,  $\eta=\infty$ ; these values of  $\sigma, \eta$  have widely been used in macro model (Hansen and Rogerson (1995)), and they are especially useful in the model here as they imply that  $\Psi_t^N=W_t/C_t$  (from the worker's first order condition), which allows direct estimation of the labor supply shock  $\Psi_t^N$ .

The mean value of the required bank capital ratio is set at  $\gamma=0.05$ . Empirically, the capital ratios of the major EA banks and of major US investment banks (i.e., ratios of bank equity to total (non risk-weighted) assets) have typically ranged between 3% and 5% in the period 1995-2010, while the capital ratios of US *commercial* banks have generally been in the range of 7%-8%.

The steady state deposit rate and the loan rate are set at 1% and 2.5% per annum. We thus set the (quarterly) subjective discount factor at  $\beta=0.9938$  (as  $\beta R^L=1$ , from the

entrepreneur's Euler equation). The bank's Euler equations imply  $R^D\beta=1-\Gamma+\phi'$  and  $R^L\beta=1+\Gamma+(1-\gamma)\phi'$ . This pins down the steady state penalty function slope  $\phi'$ .

We assume that excess bank capital is zero in steady state,  $L^W(1-\gamma)=D^W$ , and set the loans to physical capital ratio at 1/3:  $L/K=L^*/K^*=1/3$ . This calibration pins down the workers' preference parameter  $\Psi^D$ , and the steady state value of the labor supply parameter  $\Psi^N$ . It also entails that the ratio of loans to annual GDP is 81% in steady state. Empirically, the mean ratio of bank loans to non-financial businesses divided by annual GDP was about 45% in the US, and 90% in the EA, during the past decade. The steady state ratio in the model lies between these empirical ratios.<sup>9</sup>

In the first estimation exercise discussed below, we directly estimate (by OLS) the parameters of the AR(1) time series processes of TFP, investment efficiency, the labor supply shock, and government purchases, using empirical measures of these quantities; we use the estimated autocorrelations, cross-country correlations and standard deviations of these forcing variables in the model calibration. The motivation for this approach is that it is easy to measure these 8 forcing variables. Instead of drawing inference about the law of motion of these forcing variables through the lens of the model, it seem interesting to start by using direct information about the forcing variables. The estimated time series parameters are reported in Table 2 below (where a description of the empirical measures used in estimation can also be found). TFP, investment efficiency (measured as the ratio of the CPI to the investment price index), the labor supply shock (measured as the ratio of wage earnings to consumption) and 'exogenous demand' (the sum of government spending and a country's net exports vis-à-vis third countries) are all highly persistent (AR coefficients in the range 0.8-0.98). US innovations to investment efficiency, the labor supply shock and exogenous demand are more volatile than the corresponding EA innovations. 'Exogenous demand' is negatively correlated across the US and EA (-0.13), the other forcing variables are positively correlated across the US and EA.

In the first set of estimates discussed below, we thus only estimate the time series processes of defaults, and of the benchmark (required) bank capital ratio, as well as

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<sup>9</sup> In steady state, the ratio of the capital stock to annual GDP is 2.41, while the consumptions of the worker, the banker and the entrepreneur represent 71.56%, 0.11% and 4.01% of GDP, respectively.

selected behavioral parameters (see below), using the full DSGE model. In a second estimation exercise below, the parameters of all exogenous processes are estimated through the lens of the model.

### **Estimated behavioral parameters**

We assume that the cost of investment is given by  $\xi(I_t) = I_t + 0.5 \cdot \Xi \cdot (I_t/I - 1)^2$ , where  $I$  is steady state Home investment. The curvature parameter  $\Xi$  controls the volatility of investment. When  $\Xi=0$ , then investment is excessively volatile. We estimate  $\Xi$  using the Bayesian method. We likewise estimate the curvature of the bank's penalty function,  $\phi''$ , using the Bayesian approach.

As our model features 11 shocks, we need to assume that *at least* one of the 12 empirical series used for estimation is measured with error (in order to ensure that the model is non-singular). One set of results reported below assumes that the four empirical banking variables (US and EA loans, the loan spread and the bank capital ratio) are measured with error. Another set of results assumes measurement error in all empirical series. Assuming measurement error seems justified, as (especially the) banking data are probably only rough proxies of the theoretical variables. For example, the empirical measure of bank capital is based on accounting data on bank assets and bank equity—those accounting data may differ from market values.

### **4. Data plots and business cycle statistics.**

Figure 1-3 plot key macro/financial series. Given the key role of the bank capital ratio, in the model, Figure 1 compares different measures of leverage.<sup>10</sup> Figure 1 shows quarterly time series for leverage, based on Flow of Funds data, for three broad US financial sectors: insurance companies, INS; securities brokers-dealers, SBD; commercial banks, CB (also shown: leverage for households, HH, and for non-financial corporate businesses, BUS). Asset and liabilities reported in the FoF are partly measured at book

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<sup>10</sup> Leverage is defined as the total assets/(total assets – financial liabilities), i.e. leverage is the inverse of the capital ratio.

values, and may thus differ from market values.<sup>11</sup> We thus complement the FoF leverage measures using the ratios of (book-value) assets to the *market value* of equity, for US financial companies included in three Dow Jones stock price indices (as reported by Datastream): ‘US-Banks’, ‘US-Insurance’ and ‘US-Financial Services’; <sup>12</sup> we refer to these sectors as BNK-MV, INS-MV and FIN-MV, respectively (where ‘MV’ stands for market value). The sample averages of FoF-based leverage ratios of households (1.2) and of non-financial corporations (2.0) are much lower than those of the financial sectors (CB: 8.9; INS: 7.7; SBD: 27.3). The sample averages of the financial sector leverage measures based on the market value of equity are lower than the FoF-based finance sector leverages (BNK-MV: 5.9; INS-MV: 4.0; FIN-MV: 2.6).<sup>13</sup>

Note also that these three leverage measures, and securities brokers-dealers (SBD) leverage (from FoF), undergo much bigger fluctuations than the other leverage series. SBD leverage grew very strongly until the crisis, reaching a peak of 55 in 2008q3, and then (after the Lehman bankruptcy) collapsed to about 20. BNK-MV, INS-MV and FIN-MV leverage likewise grew strongly, and peaked in 2009q2 (i.e. at the point in time when bank equity prices reached their lowest values, during the recent crisis), before falling noticeably.<sup>14</sup> By contrast, FoF-based commercial-bank leverage has had a flat trend since about 2005, and held up well during the crisis. It has been argued that this may partly reflect accounting discretion, which has allowed banks to overstate the value of their assets in the crisis (e.g., Huizinga and Laeven, 2009).

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<sup>11</sup> Deviations from market values are likely to be smallest when the balance sheets in a given sector are marked to market and when assets and liabilities are short term.

<sup>12</sup> Datastream provides the aggregate market valuation of the firms included in each of these indices, as well as the corresponding (book-value) assets. The ‘US-Banks’ index includes commercial banks; ‘US-Financial Services’ includes investment banks, credit card issuers, and institutions specializing in consumer loans, and thus overlaps only partially with the FoF ‘securities brokers-dealers’ (SBD) category. These indices only include the major financial institutions, while Flow of Funds data cover all firms in a given sector.

<sup>13</sup> This partly reflects the fact that the *market* value of equity is generally greater than its *book* value. Leverage measures based on *book-value* equity (also available from Datastream) are much closer to FoF-based leverage measures: 13.8, 7.5 and 14.0, respectively, for ‘US-Banks’, ‘US-Insurance’ and ‘US-Financial Services’ (1993q3-2010q3).

<sup>14</sup> These movements of the BNK-MV, INS-MV, FIN-MV and SBD leverage measures are largely driven by the sizable fluctuations in these sectors’ equity. BNK-MV, INS-MV, FIN-MV leverage are also highly negatively correlated with the overall stock market (the correlation of year-on-year growth of these three leverage measures and the annual Fama-French stock market returns is about -0.7).

Kollmann and Zeugner (2011) conduct a detailed statistical analysis of the link between these US leverage variables, and real activity; they find that the joint information in sectoral leverage series is more relevant for predicting future real activity than the information contained in any individual leverage series—the market-value based leverage measures do not dominate the Flow of Funds series. The current version of the present paper uses US Commercial Bank leverage, based on Flow of Funds data, as a measure of the global bank's leverage. (Future versions of the paper will consider alternative empirical leverage measures.)

Figure 2 plots linearly detrended logged bank loans, loan spreads (% p.a. not demeaned or detrended) and loan loss rates (write-downs, as an annualized % fraction of the stock of loans), for US commercial banks and EA Monetary and Financial Institutions (MFIs). (EA loan losses and loan spreads are only available for 2003q1-2010q3). Loans and loan spreads are highly positively correlated across the US and EA. Loans rose strongly (relative to trend), during the five years preceding the crisis, and then fell sharply. Loan loss rates in the US have likewise increased strongly since 2007, especially in the US (the EA loan loss rate series exhibits sizable short-term movements). Loan spreads have risen sharply since the start of the crisis, both in the US and EA; the correlation between US and EA loan spreads (undetrended) is 0.90.

Figure 3 plots linearly detrended (log) GDP, private consumption, investment and employment. In the second half of 2008, these variables contracted sharply, in the US and EA. US and EA output fell roughly by the same amount (-6%) between 2007q4 and 2009q4. Consumption and investment fell much more sharply in the US than in the EA (e.g. US investment was 34% below trend in 2009q2, while EA investment was 8% below trend in the same quarter).

Table 1 reports moments of HP filtered key macro and banking variables, for the US and the EA (1990q1-2010q3). Output volatility is very similar in the US (1.12%) and the EA (1.14%). Consumption is less volatile than GDP, while investment is markedly more volatile. US investment is almost twice as volatile as EA investment. In both countries, loans are more volatile than output, while the loan spread is countercyclical. The variables considered in the Table are positively correlated across the US and EA.

## 5. Model estimates

### 5.1. Baseline specification

Table 3 reports the priors and the posterior estimates, for the baseline set-up.

#### *Prior distributions*

The priors on the parameters (that are not calibrated) are shown in column (1). We set the mean of the prior distribution of  $\phi$  (slope coefficient of the bank's penalty function) at 0.6, which implies that a 1 percentage point increase in the bank capital ratio lowers the loan spread by 12 basis points p.a., a value in the range of prior empirical estimates of the sensitivity of the loan spread (e.g., Hubbard et al. (2002), Santos and Winton (2009)). The mean of the prior distribution of  $\Xi$  is set at 1. The standard deviations of these prior distributions are set at half of the mean of the distribution, which (for the gamma prior distribution assumed here) implies that a wide range of parameter values around the mean has non-negligible mass.

The prior distributions of the standard deviations of innovations to loan default (normalized by steady state GDP) and to the benchmark (required) bank capital ratio are all set at 0.5%, which is in the range of the standard deviations of the innovations to the other forcing variables. The standard deviation of the prior is set at 0.1%.<sup>15</sup> The priors of the AR(1) correlation coefficients and cross-country correlations are beta distributions with mean 0.5 and standard deviation 0.1. As mentioned above, the baseline estimation set-up allows for i.i.d. measurement error in four of the empirical data series (US and EA loans, loan spread and bank capital ratio). The prior distribution of the standard deviation of measurement error is inverted gamma, with a mean equal to 1/4 of the standard deviation of the corresponding empirical series, and a standard deviation that is set at 1/5 of the mean.

#### *Posterior estimates*

Columns (2) and (3) of Table 3 report the mode of the posterior parameter distribution, and the standard deviation of the posterior.<sup>16</sup> The data are informative about the estimated

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<sup>15</sup> The prior distribution of the standard deviations of shock innovations is inverted gamma (IG). The IG has fatter tails than the normal distribution. Hence, a 0.1% standard deviation of the prior is not very restrictive. A sensitivity analysis shows that the empirical results do not depend very much on that 0.1% prior std.

<sup>16</sup> The mode of the posterior distribution is the parameter vector  $\Theta$  that maximizes the posterior distribution; the standard deviations of the posterior reported here are based on a Normal approximation of the posterior distribution; see, e.g., Canova (2007), p.340.

parameters: in most cases, the posteriors have lower standard deviations than the priors, and the posterior estimates (modes) differ noticeably from the priors. The posterior mean and standard deviation of the curvature  $\phi''$  are 0.63 and 0.016, respectively. This is consistent with a small but significant effect of changes in the bank capital ratio on the loan spread. Interestingly, the model suggests that US defaults are less volatile than EA defaults (posterior std. 0.56% and 1.13%, respectively). The required bank capital ratio undergoes sizable fluctuations (posterior std.: 0.8%).

### ***Business cycle moments implied by posterior estimates***

Table 4 implies business cycle statistics (of HP filtered theoretical variables) implied by the posterior parameter mode. The reported moments pertain to country 1, which we take as the theoretical counterpart of the US (the predicted moments for the EA are similar). Column (1) allows for all 11 structural shocks. In Columns (2)-(7), only one type of shocks is considered (the model is not re-estimated). Column (8) reports empirical moments (from Table 1). The model with all shocks generates moments that are broadly in the range of the empirical moments. The predicted standard deviation of GDP, 1.55% is larger than the empirical standard deviation, 1.12% (when the parameters of all forcing variables are estimated through the lens of the model, then the model matches more closely the standard deviation of GDP, as might be expected—see below).

The model (with all shocks) captures the fact that investment and US employment are more volatile than GDP. The model also captures the cross-correlations of the variables with domestic GDP—it correctly predicts that the loan spread is countercyclical. Finally, the model correctly predicts that the variables considered in the Table are *positively* correlated across the US and the EA--although it underpredicts the cross-country correlation of GDP, and generates a predicted cross-country consumption correlation (0.72) that is higher than the empirical correlation (0.39).

The model variants with just one type of shock show that TFP shocks and Labour supply shocks are the main drivers of GDP fluctuations (predicted std. of GDP with just these shocks: 0.99% and 1.07%, respectively), followed by default shocks (0.40%). Investment efficiency shocks and government purchases shocks induce much smaller fluctuations in GDP (predicted std: 0.16% and 0.25%, respectively).

All types of shocks generate positive cross-country correlations of output. But it should be noted that the predicted cross-country correlations of GDP induced by just TFP shocks, just investment efficiency shocks, and just labor supply shocks are smaller than the assumed cross-country correlations of these shocks (see Table 2). Hence, these shocks do not *endogenously* generate a positive comovement of real GDP (see discussion of the impulse responses below). Interestingly, loan default shocks do induce strong positive endogenous cross-country comovements: with just default shocks, GDP, investment and employment that are (almost) *perfectly* correlated across the two countries. This is due to the fact that a default by Home entrepreneurs (say) lowers the bank's capital, which triggers a rise in the world-wide loan spread--loans, investment and GDP fall in both countries.

#### ***Forecast variance decomposition***

Table x [to be added] decomposes the forecast error variance of GDP, consumption, investment, employment, loans, and spreads. 'Banking shocks' (i.e. the default shocks and the shocks to the required bank capital ratio) account for about 5% of the forecast error variance of country 1 and country 2 GDP, and for about 20% of the forecast error variance of investment, at horizons ranging between 1 and 100 quarters. Slightly less than half of each country's GDP forecast variance is accounted for by foreign default shocks. The 'banking shocks' account for 99% of the forecast error variance of the loan spread and of country 2 loans, and for 65% of the forecast error variance of country 1 loans (at all horizons).

#### ***Decomposing historical time series***

A decomposing the historical time series into contributions of the different shocks yields a picture that is consistent with the forecast error variance decompositions. Banking shocks account for a small component of the historical time series on GDP and investment. Figures 4 and 5 show the contribution of GDP and investment series that can be accounted for by banking shocks. The banking shocks account for about 10%-15% of the fall in the variables during the financial crisis. The contribution of banking shocks to the decline in EA investment is more sizable—close to 50%.



### ***Does global banking matter for the (international) transmission of shocks?***

While bank-specific *shocks* only play a relatively modest role for fluctuations in GDP, the existence of (global) banks matters for the transmission of shocks to GDP. Hence, banks do not matter primarily as a source of disturbance, but because they affect the transmission mechanism. When we (essentially) eliminate the bank, by eliminating the bank-specific shocks, setting the steady state loan spread at a very small number, and setting the curvature of the bank's penalty  $\phi$  very close to zero, so that the loan spread is (essentially) constant (and close to zero), then the model here behaves like a standard international RBC model with a 'bonds-only-structure' (Kollmann (1996)). The cross-country correlation of GDP and investment drop to -0.08 and -0.17 (compared to 0.32 and 0.59 in the baseline model with banks). These predicted correlations are obtained by 'switching off' the bank, in the baseline mode, without re-estimating the non-banking parameters. Re-estimating a model variant in which the bank is a 'veil' yields much lower predicted cross-country output correlations (-0.40). The marginal likelihood of the baseline model (with banking friction) is 2122.42, while the marginal likelihood of the model without a bank is -92488.<sup>17</sup> Thus, the model with a global bank is overwhelmingly preferred to the model without bank.

To be added:

Results are robust to estimating the time series parameters of all forcing variables and also other behavioral parameters (risk aversion, labor supply elasticity etc.).

Other extensions: allow for richer correlations between shocks (e.g. it might be important to allow for correlation between TFP and default shocks).

### **5.2. Model with an international investment bank**

The model above assumes make loans whose returns are non-state contingent (except for default). Yet, banks do hold vast amounts of state-contingent assets. We thus also consider a model variant with an 'investment bank' that purchases physical which she rents to the entrepreneur. Hence, the return on the bank's assets now is directly tied to TFP and the other macro shocks. Thus, bank capital plays a much more important role in

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<sup>17</sup> We compute the marginal likelihood using a Laplace approximation.

the transmission of these shocks. There is a form of default too in this world, as sometimes the entrepreneur steals some of the physical capital that he rented from the bank. [To be completed]

## **6. Conclusion**

Shocks originating in the banking system were not a major source of fluctuations in US and EA GDP (but these shocks matter more for investment). However banking has a noticeable effect on the transmission of other macro shocks. Global banking leads to more synchronized national business cycles.

## **DATA APPENDIX**

To be added

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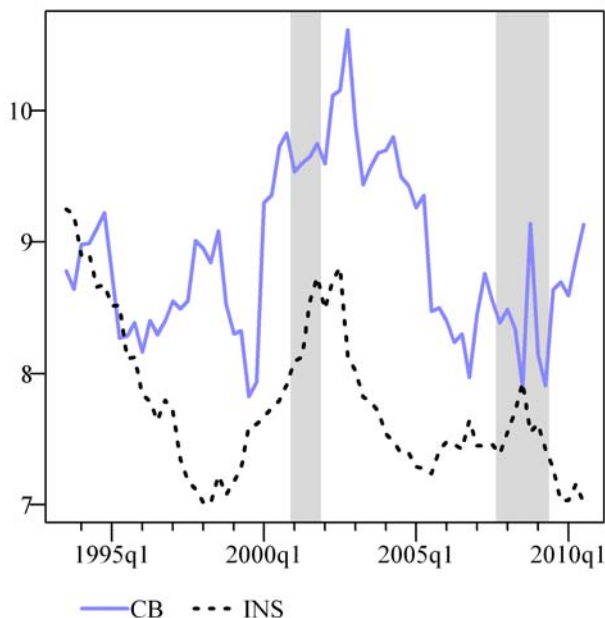
Santos, J. A. and A. Winton (2008). "Bank loans, bonds, and information monopolies across the business cycle". *Journal of Finance* 63 (3), 1315-1359.

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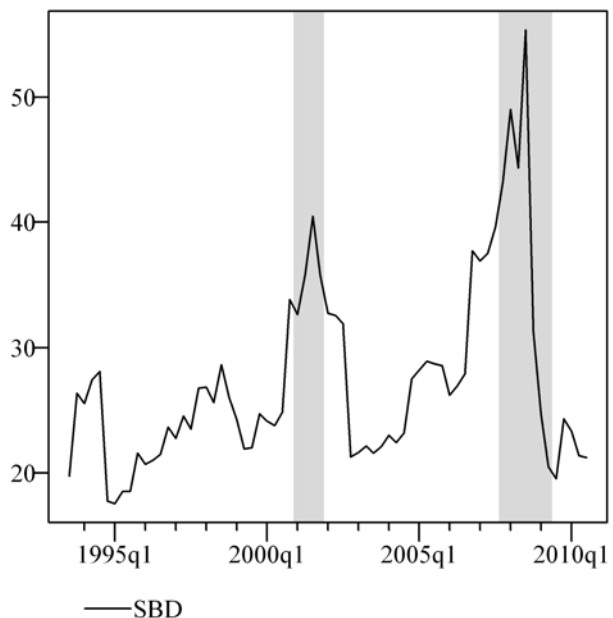
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**Figure 1. Leverage ratios (Assets/Net worth)**

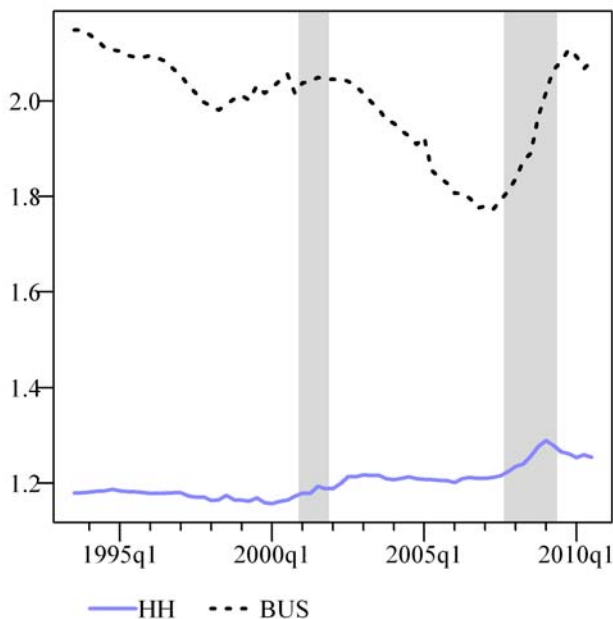
**(a) Insurance, commercial banks (FoF)**



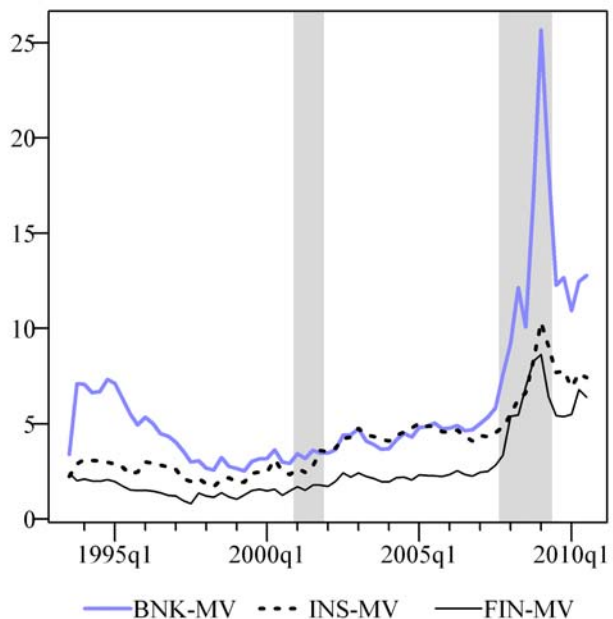
**(b) Securities brokers-dealers (FoF)**



**(c) Households, non-financial business (FoF)**



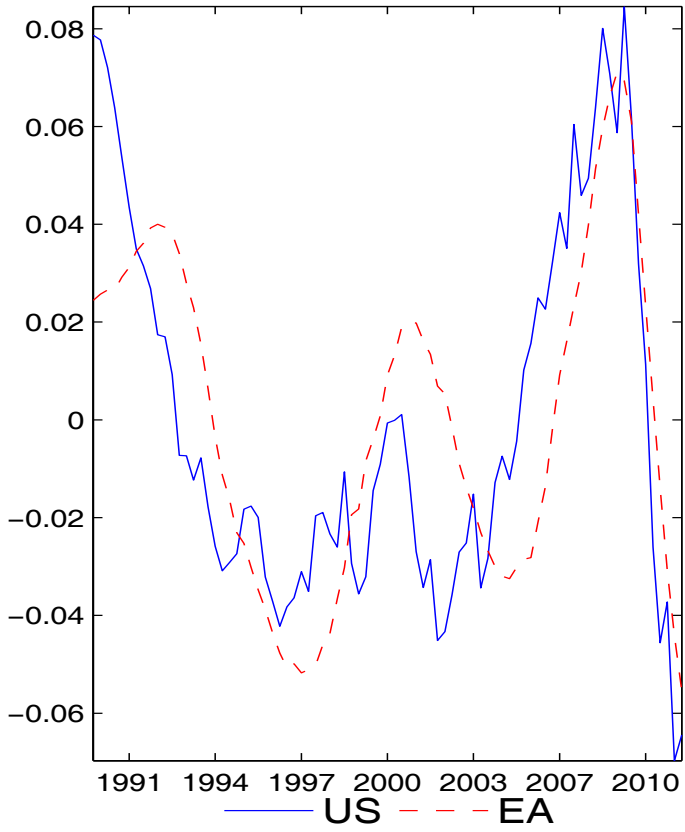
**(d) Banks, insurance, fin. services (equity mkt val.)**



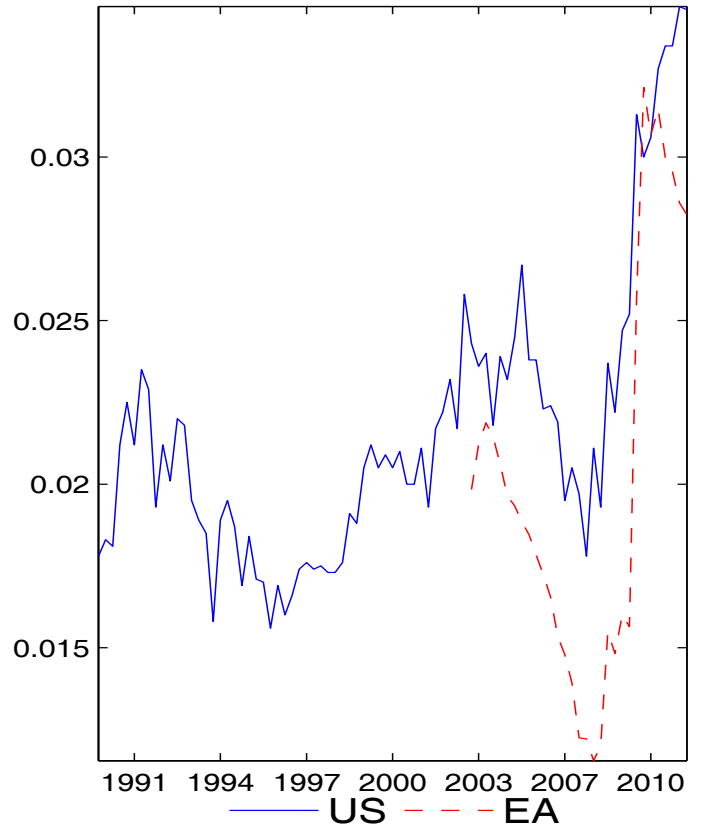
The Figure plots the time series of leverage ratios for the following sectors— CB: commercial banks (from Flow of Funds, FoF); INS: insurance (FoF); SBD: securities brokers and dealers (FoF); HH: households (FoF); BUS: non-financial corporate businesses (FoF); BNK-MV, INS-MV, FIN-MV: Banks, insurance and financial services, respectively, based on equity market values. Sample period: 1993q3-2010q3. Shaded areas indicate NBER recessions.

**Figure 2. Bank loans, loan spreads, loan loss rates**

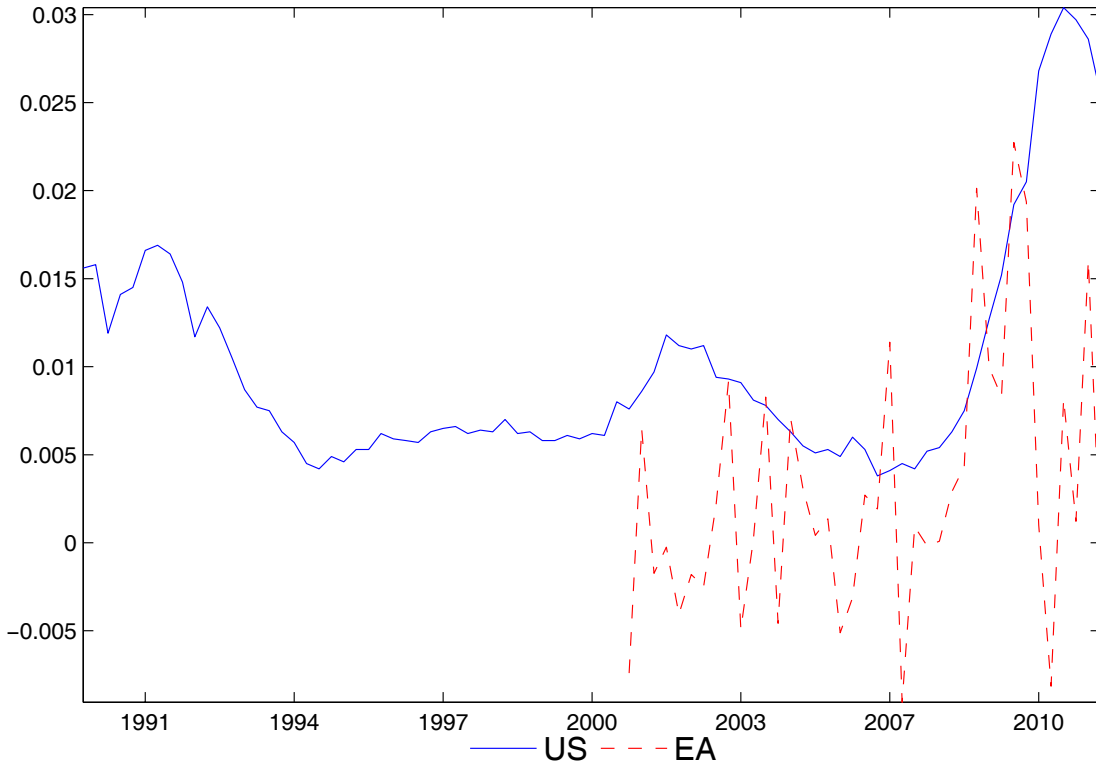
**Bank loans (detrended)**



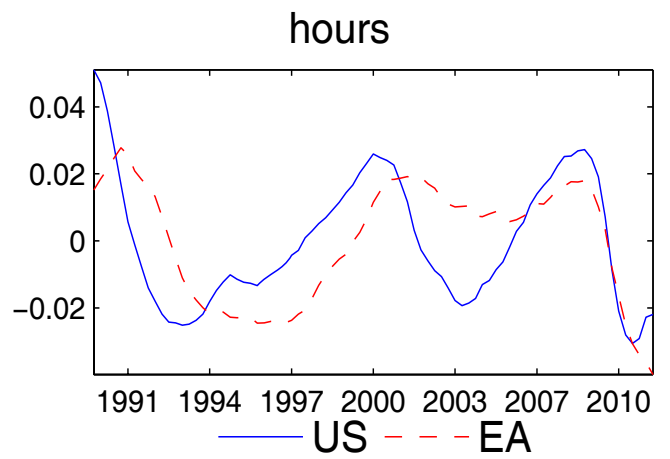
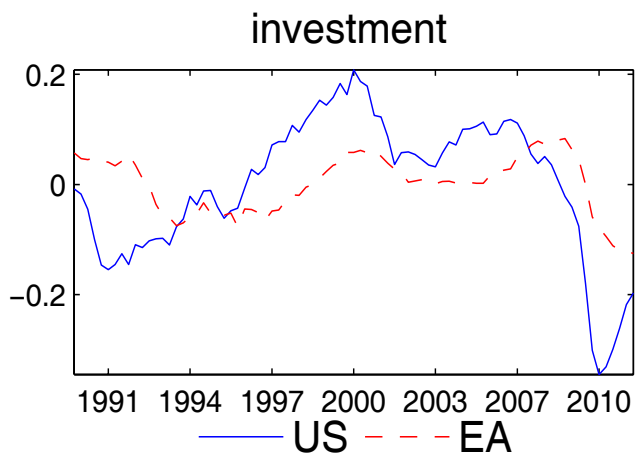
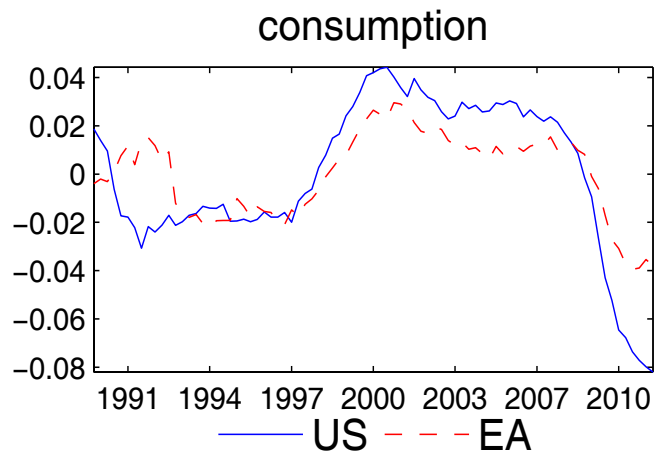
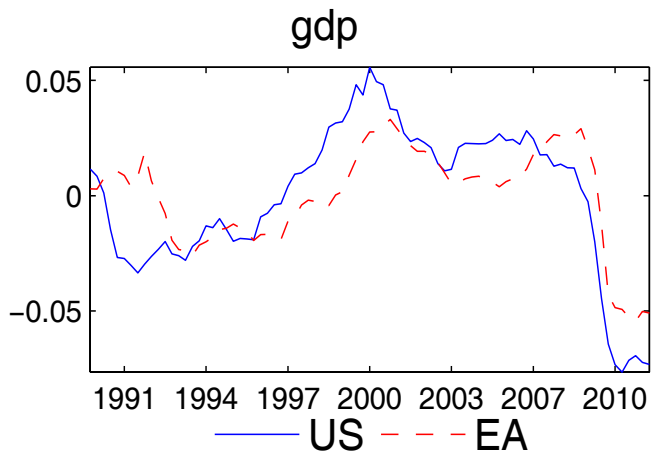
**Loan spreads p.a.**



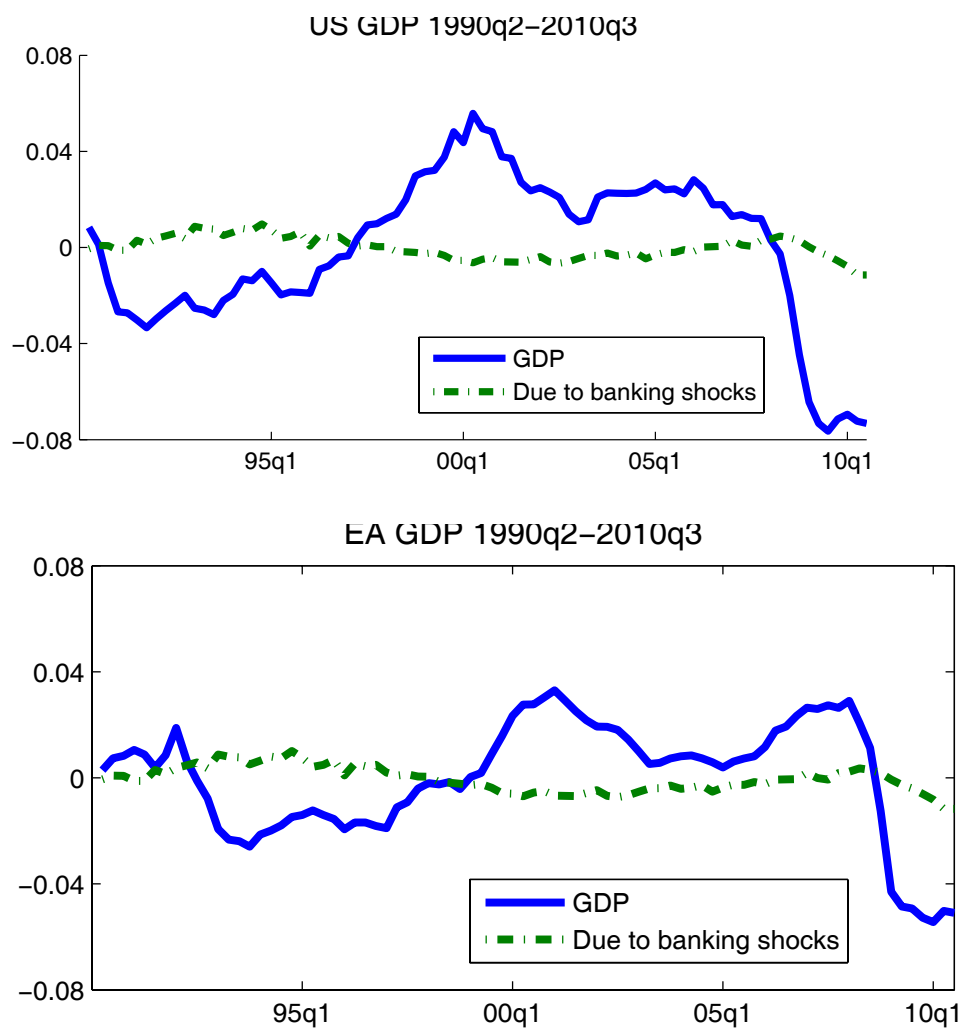
**Loan Loss Rate p.a.**



**Figure 3. Macro data**

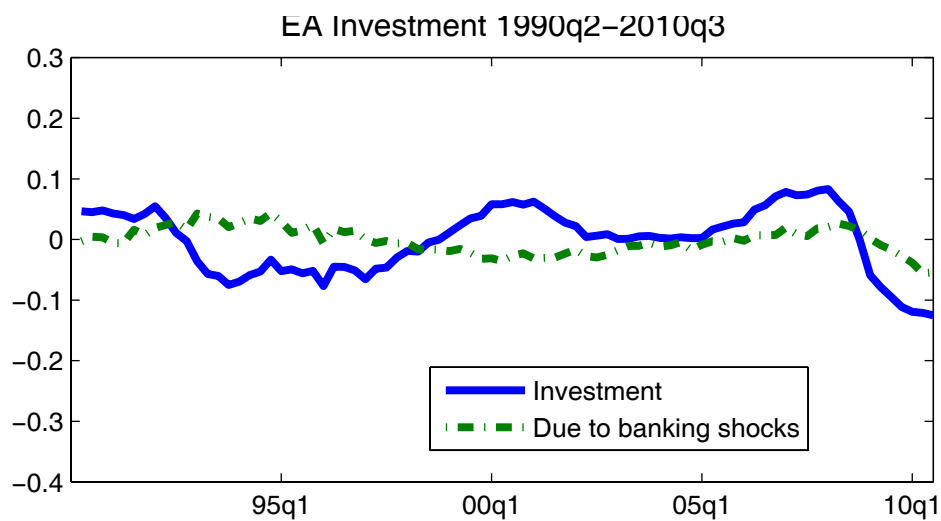
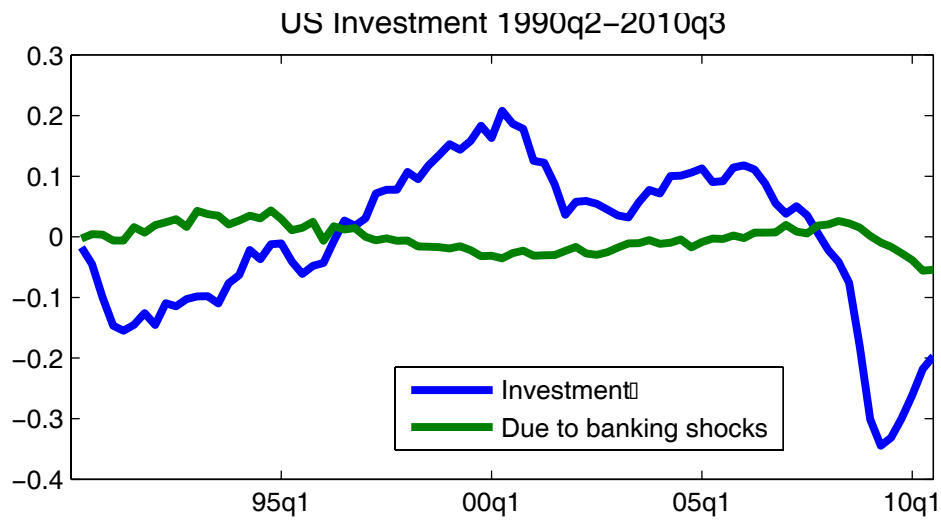


**Figure 4. US and EA GDP and the contribution of banking shocks**





**Figure 5. US and EA investment and the contribution of banking shocks**



**Table 1. Historical business cycle statistics, 1990q1-2010q3**

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	US	EA
<b>Standard deviation (in%)</b>		
GDP (Y)	1.12	1.14
<b>Relative standard deviations (std(x)/std(GDP))</b>		
Consumption	0.82	0.68
Investment	4.54	2.52
Employment	1.03	0.62
Loans	1.68	1.83
Loan spread	0.17	0.33
<b>Correlation with domestic GDP</b>		
Consumption	0.89	0.83
Investment	0.92	0.93
Employment	0.79	0.83
Loans	0.48	0.62
Loan spread	-0.52	-0.91
<b>Cross-country correlations</b>		
GDP	0.56	
Consumption	0.39	
Investment	0.45	
Employment	0.53	
Loans	0.64	
Loan spread	0.79	

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Note: moments of HP filtered series are shown (GDP, consumption, investment, employment and loans were logged before applying the filter). The Loan spread is expressed in decimal fractions). Sample period: 1990q1-2010q3 (except for EA loan spread: 1997q3-2010q3).

**Table 2. Estimated parameters of exogenous processes (1990q1-2010q3)**

	AR coefficients	Standard deviations of innovations	Correlation with foreign counterpart
US TFP	0.97	0.60%	0.65
EA TFP	0.95	0.75%	0.65
US investment efficiency	0.97	0.64%	0.84
EA investment efficiency	0.98	0.31%	0.84
US labor supply shock	0.96	0.80%	0.46
EA labor supply shock	0.93	0.63%	0.46
US exogenous demand	0.91	0.80%	0.46
EA exogenous demand	0.81	0.63%	-0.13

Note: The Table reports the time series parameters if of linearly detrended logged forcing variables. Log TFP is estimated as  $\ln(Y_t) - 0.7\ln(N_t)$  where  $Y_t$  and  $N_t$  are GDP and employment, respectively. Our estimate of investment efficiency is the ratio of the CPI to the investment deflator. Our estimate of the labor supply shock is  $\Psi_t^N = W_t/C_t$ , where  $W_t$  is wage earnings per employee, while  $C_t$  is per capita consumption. Our measure of US ‘exogenous demand’ is the sum of government consumption and of US net exports to countries other than the EA (EA exogenous demand is defined analogously).

**Table 3. Prior and posterior distribution of parameters—baseline specification**

Parameter	Prior Distrib.	Posterior distribution	
		Mode	Std.dev.
	(1)	(2)	(3)
Bank capit. penalty $\phi''$	G(.6,.3)	0.63	0.016
Investment cost curv. $\Xi$	G(1,.5)	0.13	0.01
<b>% Standard deviations of structural shock innovations</b>			
Home default $\Delta_t$	IG(.5,.1)	0.56	0.06
Foreign default $\Delta_t^*$	IG(.5,.1)	1.13	0.12
Required Bk Cap Ratio, $\gamma_t$	IG (.5,.1)	0.54	0.06
<b>AR coefficients</b>			
Home default $\Delta_t$	B(.5,.1)	0.89	0.02
Foreign default $\Delta_t^*$	B(.5,.1)	0.60	0.05
Required Bk Cap Ratio, $\gamma_t$	B(.5,.1)	0.80	0.03
<b>Cross-country correlation</b>			
Default	B(.5,.1)	0.20	0.04
<b>% Standard deviations of measurement errors</b>			
Spread US $R^L - R^D$	IG(.03,.006)	0.02	0.003
Loans US $L$	IG(.95,.19)	1.78	0.15
Loan EA $L^*$	IG(.83,.17)	0.36	0.04
Bank cap. ratio US $cr_t$	IG(.20,.04)	0.43	0.04

Notes: Column (1) shows the prior distribution for the different parameters. G(m,s), B(m,s) and IG(m,s) indicate the gamma, beta and inverted gamma distributions, with mean 'm' and standard deviation 's', respectively. Column (2) reports the mode of the posterior distribution (i.e. the parameter vector  $\Theta$  that maximizes the posterior distribution); Column (3) reports standard deviations of the posterior distribution (based on a Normal approximation of the posterior distribution; see Canova (2007, p.340)).

**Table 4. Country 1 ('US') business cycle statistics implied by posterior mode of model parameters—baseline estimation**

	All shocks	Just shocks to:					Benchmark	
		TFP	Inv Eff	G	LabS	Default	BkCap	DATA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Standard deviation (in%)</b>								
GDP (Y)	1.55	0.99	0.16	0.25	1.07	0.40	0.10	1.12
<b>Relative standard deviations (std(x)/std(GDP))</b>								
Consumption	0.63	0.73	0.62	0.39	0.57	0.41	0.35	0.82
Investment	3.00	2.52	13.14	1.22	2.24	5.17	5.13	4.54
Employment	1.10	0.38	1.11	1.40	1.40	1.41	1.37	1.03
Loans	0.27	0.13	1.11	0.07	0.10	0.86	0.30	1.68
Loan spread	0.15	0.00	0.02	0.00	0.00	0.36	1.91	0.17
<b>Correlation with domestic GDP</b>								
Consumption	0.80	0.94	-0.19	-0.99	0.94	-0.87	-0.90	0.89
Investment	0.82	0.95	0.44	0.46	0.95	0.99	0.99	0.92
Employment	0.85	0.77	0.89	0.99	0.99	0.99	0.99	0.79
Loans	0.27	0.37	0.75	0.11	0.42	0.41	0.75	0.48
Loan spread	-0.16	0.44	0.83	-0.16	0.44	-0.81	-0.90	-0.52
<b>Cross-country correlations</b>								
GDP	0.34	0.42	0.30	0.71	0.15	1.00	1.00	0.56
Consumption	0.72	0.75	0.87	0.78	0.66	0.93	1.00	0.39
Investment	0.59	0.62	0.17	-0.56	0.48	1.00	1.00	0.45
Employment	0.21	-0.28	0.54	0.73	0.16	1.00	1.00	0.53
Loans	0.52	0.65	-0.21	-0.35	0.60	0.60	1.00	0.64

Note: The Table shows moments of HP filtered model variables, for the mode posterior estimate of the model parameters. The moments pertain to country 1, which we take as the theoretical counterpart of the US. Column (1) allows for all 11 structural shocks. In Columns (2)-(7), only one type of shocks is considered (the model is not re-estimated). Column (8) reports empirical moments (from Table 1). Col. (2): just TFP shocks ( $\theta_t, \theta_t^*$ ); Col. (3): just shocks to investment efficiency ( $\Xi_t, \Xi_t^*$ ); Col. (4): just shocks to government purchases ( $G_t, G_t^*$ ); Col.(5): just labor supply shocks ( $\Psi_t^N, \Psi_t^{N*}$ ); Col.(6): just loan default shocks ( $\Delta_t, \Delta_t^*$ ); Col. (7): just shock to benchmark bank capital ratio ( $\gamma_t$ ). Col. (8): historical moments for US.