Learning about Banks' Net Worth and the Slow Recovery after the Financial Crisis *

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Abstract

In this paper, we discuss imperfect information about the net worth of banks and its consequences for the real economy. In a first part, we show empirically that expectations about the net earnings of banks (as growth of net worth) are truly biased during and in the aftermath of the financial crisis. This forecast error of professional investors cannot be attributed to information rigidities but to noisy information. This leads investors to follow a learning behavior about past forecast errors in forming their expectations about future earnings during the crisis. In a second part, by drawing on a New Keynesian general equilibrium model with a banking sector we demonstrate that incorporating this type of information updating and expectations formation about the net worth of banks can produce a slow recovery compared to a full information rational expectation case. We therefore argue that the slow recovery after the financial crisis in the US can be partly traced back to imperfect information about the net worth of banks.

Keywords: DSGE Model, Bank Capital, Imperfect Information, Learning, Slow Recovery

JEL classification: E3, E44, G3

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1 Introduction

Economic agents rely on information regarding economic decisions all the time and the more precise the information the better they generally fare. This is due to the fact that with more or better information households or financial market participants are able to form expectations that are less biased and less often subject to revisions. In this paper we analyse the expectations of financial market participants about the profit situation of banks in the United States. We show that expectation formation regarding the profit situation of bank is not processed in a stable way over time and displays a high degree of biasedness during the financial crisis. This is an indication that banks' net worth is also incorrectly assessed. Given that economic agents have cognitive limitations as to how perfectly all available information can possibly be processed we generally distinguish different forms of information processing. One kind is simply information rigidities where agents update information irregularly over time and the other is noisy information where agents update constantly but never get to know the true value. The latter happens because the agent is either bounded rational or rationally inattentive. With respect to the profit siuation of the banking sector financial market participants seemed to display noisy information during the last couple of years. Given this behavior in financial markets we are interested in how this type of information processing spills over to the real economy and try to see if there are economic anecdotes that we are able to explain by this behavior. Given a lagged picture for the evolution of net worth under a learning setup we deduct a much slower recovery compared to the full information rational expectations framework.

Historical evidence shows that economic recoveries after financial crises are slower and former trend output is only reached many quarters later compared to usual business cycle recessions. This fact is most prominently exemplified in Reinhart and Rogoff (2014) for a sizeable number of countries and decades. The recent financial crisis is no exception to this rule and lately researchers have been trying to find out the various reasons for this phenomenon. A widespread explanation comprises the notion of general uncertainty surrounding the whole economy which tends to be higher during and after those episodes as is pointed out by Bloom (2014) which leads firms and households to delay investment (Gilchrist, Sim, and Zakrajsek (2014)). Additionally, uncertainty about fiscal and monetary policy in their struggle to counteract the crisis may send mixed signals and leave economic agents with a lack of policy guidance for the future (see Hollmayr and Matthes (2013) and Baker, Bloom, Canes-Wrone, Davis, and Rodden (2014)). This tends to depress investment even further.

With this paper we remain in the realm of economic uncertainty but shift the focus of uncertainty onto the banking sector and the consequences hereof back to the real economy. Expectations regarding banks' profits seems to be unbiased before the onset of the crisis and again once the old output trend has been reached. We identify various stages of different degrees of biasedness of expectations and deduct how information is processed and expectations are formed during those times. This is of paramount importance to the speed of the recovery. Unlike Galí, Smets, and Wouters (2012) we do not focus on the notion of the jobless recovery and leave the labor market and its high and persistent level of unemployment out of the picture. Weak demand following from an elevated number of people looking for a job and a possible simultaneous weak external demand from the trading partners may also be seen as important factors for the delayed recovery but are not dealt with in this paper.

Various recent macro-finance models show that bank equity is important for financial intermediation (Gerali, Neri, Sessa, and Signoretti, 2010; Gertler and Karadi, 2011; Gertler, Kiyotaki, and Queralto, 2012; Zeng, 2013). These models belong to the class of rational expectations models in which agents behave not only rationally but they also have perfect information at every point in time. In reality, the actual value of equity is not observable at every point in time, i.e. agents are faced with imperfect information. Against this backdrop, agents need to extract information from all observable fundamentals in order to deduce their beliefs for the level of bank equity. During the financial crisis imperfect information about the assets held by banks was one of the main reasons why the interbank market froze (Taylor and Williams, 2009).[1] Since banks feared that their counterparties cannot repay their borrowings, they stopped lending. The rise in credit spreads during the financial crisis can be largely attributed to the uncertainty related to imperfect information. Imperfect information about the quality of assets held by banks is translated to uncertainty about the development of bank equity which is tied to the evolution of net earnings. Since the erosion of bank equity is important for the severity of financial frictions that impede financial intermediation, it is of importance to investigate whether professional investors are able to form expectations about the evolution of bank equity correctly. For this reason, we scrutinize how information is processed and expectations are formed with respect to bank equity. We measure expectations about the evolution of bank equity with the expectations about future earnings.

In a first step we show empirically that expectation formation is biased for the banking sector while it is unbiased for the industrial sector. In the case of the banking sector, however, the driving force for biased information can be inferred once we split the sample and allow for breaks. It follows that during the crisis and a few periods afterwards, but not beforehand and most recently, expectation formation is severely biased. Digging deeper we show that the resulting expectational error cannot be attributed to sticky information but to noisy information. Given the nature of the information error and its time profile for it we conduct a simple test to show how professional investors form their expectations. As agents suspect that their prediction might underly some noise the updating during the crisis happend according to some sort of a learning framework.

The second step introduces a structural model that includes some of the features that we found in the data. The working hypothesis for this is that shocks are observable and all information is used but net worth cannot be completely observed. This is the difference to information rigidities where subsets of agents are only able update their information set from time to time. Taking the data seriously our approach is therefore closer to noisy information models in which agents filter the state of economic fundamentals. This is how they learn about the true value of net worth. Given the model with all basic ingredients we can replicate the slow recovery. Our results show that imperfect information about bankers' net worth slows down the recovery because agents need to learn that the efficiency of the banking sector is recovering. While Gertler et al. (2012) explicitly take uncertainty under perfect information into account, by focussing on the stochastic steady state, we start from the deterministic steady state but introduce imperfect information about the

[1] Taylor and Williams (2009) argue that counterparty risk evolves because lenders change the risk perception of counterparties. This can be understood as a reflection of imperfect information.

current stance of bank net worth.[2]

The paper is structured as follows: We start out to investigate the true nature of information processing and expectations formation in Section 2. This empirical result is incorporated in the structural model which we present in Section 3. In Section 5 we discuss the modeling of the expectation formation of agents and how they process and update information. Our experiment which tries to mimic the financial crisis is explained in Section 6. We present all baseline results and a policy conclusion in Section 7. Section 8 concludes.

2 Information processing about the banking sector

2.1 (Un)biasedness of expectations

Our interest in this paper is to shed light on how professional investors build expectations about the profit situation of banks which is linked to the build-up of bank equity or bank net worth. Bank equity is the central variable which shows the health of the financial system because it controls financial frictions. In a first step, we investigate whether expectation formation with respect to future bank earnings is unbiased. Such a test is the prerequisite for thinking about the consequences of expectation formation in a macroeconomic context. If agents' expectations are always unbiased, there is no systematic misperception of the profit situation of banks. However, if information is biased, the question arises how information is processed.

To test for expectations in an empirical work one way is to rely on survey data which collects forecasts about future earnings reported by professional investors. In this analysis we make use of analysts' forecasts from the Institutional Brokers Estimate System (I/B/E/S), as done by Lim (2001) or Keane and Runkle (1998), for instance. The data are available on a quarterly frequency for banks listed in the S&P 500 stock market index for the period January 1995 to November 2014. Within theses surveys analysts are ask to report their judgment about future earnings per individual bank or firm. These earnings can be related to shares outstanding to allow for easier comparision across banks or firms. Concretely, we draw on the earnings per share or short EPS regarding the expectations about future profits. Although individual forecasts for specific firms or banks are available, we are basically interested in the mean forecast which can be seen as the aggregate. In order to account for the dispersion in expectations across analysts we also look at the cross-sectional standard deviation.

We start with the investigation of the unbiasedness of expectations of professional forecasters. We denote realized earnings per share at time t over a horizon of h months with EPS_t^h, whereas the expectations built at time t for the horizon h in n periods are denoted by $E_t\left(EPS_{t+n}^h\right)$. In our cases h and n coincide since we look at h-months' earnings per share in n-months. Expectations are unbiased if there is a systematic one-to-one relationship between the expected value in n-periods and the realizations of the n-th period (see Keane and Runkle (1998), for instance). This hypothesis can be tested

[2] In the stochastic steady state, or risky steady state, no shocks occur but agents know the distribution of shocks and take into account that shocks can hit. See Coeurdacier, Rey, and Winant (2011), for instance.

Table 1: Tests on unbiased expectations (from 1996:01 to 2014:11)

	Banks	Industrials	Aggregate
α	0.26*	-0.019**	-0.058***
	[1.634]	[-2.184]	[-3.947]
β	0.595***	1.018***	1.213***
	[3.81]	[19.099]	[15.343]
$H0:\ (\alpha = 0)$	2.669	4.769**	15.581***
	(0.102)	(0.029)	(0.000)
$H0:\ (\beta = 1)$	6.745***	0.118	7.286***
	(0.009)	(0.731)	(0.007)
$H0:\ \begin{pmatrix} \alpha = 0 \\ \beta = 1 \end{pmatrix}$	7.992**	5.549*	16.049***
	(0.018)	(0.062)	(0.000)

Note: The table shows the results of the unbiasedness regression $\frac{x_t - x_{t-12}}{x_{t-12}} = \alpha + \beta \frac{E_{t-12}(x_t) - x_{t-12}}{x_{t-12}} + e_t$, whereas $x_t = EPS_t^{12M,i}$ are the earnings per share of sector i. $H0$ denotes the null hypothesis for Wald tests with restrictions given in parentheses. Numbers in brackets give t-statistics and in parentheses p-values. T-statistics base on Newey-West standard errors. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

by regressing the realized earnings per share on their expectations

$$EPS_t^h = \alpha + \beta\, E_{t-n}\left(EPS_t^h\right) + \epsilon_t, \tag{1}$$

where α is a constant, β a coefficient, and ϵ_t i.i.d. innovations. Unbiasedness requires the restriction $\alpha = 0$ and $\beta = 1$ to hold.[3] Since earnings per share do not clearly show a variance-stationary behavior by applying conventional unit root tests to the time series, we transform them into annual growth rates and Eq. (1) becomes

$$\frac{EPS_t^h - EPS_{t-n}^h}{EPS_{t-n}^h} = \alpha + \beta \frac{E_{t-n}\left(EPS_t^h\right) - EPS_{t-n}^h}{EPS_{t-n}^h} + \bar{\epsilon}_t. \tag{2}$$

We are predominantly interested in expectations regarding the banking sector. However, we also present results for the industrial sector and the aggregate to allow for comparisons. Including the industrial sector in this analysis may help us to make the point that expectations are differently biased across sectors. Our sample period runs from January 1996 to November 2014 due to the conversion in growth rates.[4] The results of running regression (2) can be found in Table (1).

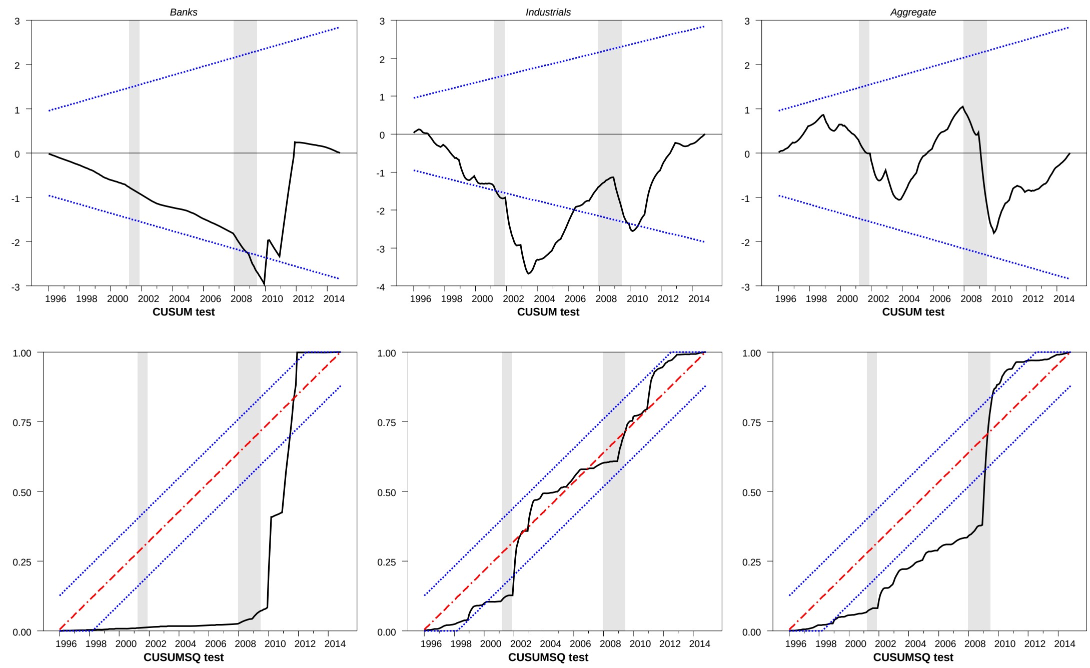
As can be seen, for the banking sector, the industrial sector, and the aggregate, the joint hypothesis of unbiasedness in forming expectation can be broadly rejected. However the significance levels differ slightly. While the unbiasedness hypothesis can be rejected with at the 5% with a p-value of 0.018 in the banking sector, the corresponding hypothesis can only be rejected at the 10% level with a p-value of 0.062 for the industrial sector. While in the banking sector the β coefficient is statistically different from zero, this is not the case in the industrial sector. Here, the constant term is statistically different from zero for industrials which means that there is evidence for a constant forecast bias in the

[3]We are only interested in unbiasedness of expectations and not in the efficiency of the forecast. In order to test for the efficiency, additional explanatory variables can be included in Equation (1) which regression coefficients must be zero for efficiency to hold (see Nordhaus (1987) or Keane and Runkle (1990)).

[4]Since the reporting date of I/B/E/S data have a lag, i.e. the statistical date lags behind, we adjust for the statistical date.

industrial sector. This is different for the banking sector where the null hypothesies of α to be zero is not rejected. The results for the entire sample indicate that expectations of professional investors seem to be basically biased (by looking at the individual tests) for the entire sample but slightly less biased in the industrial sector. These results are basically in line with results found in the literature although we support earlier findings (Keane and Runkle, 1990, 1998).

Figure 1: Cumulated and cumulated squared residuals from the unbiasedness regression for banks, industrials, and the aggregate



Note: The graph shows the cumulated residuals (first line) and cumulated squared residuals (second line) from the regression model for banks, industrials, and the aggregate in Table 1. The series are standardized by the sample variances for each residual series. The blue dotted lines represent upper and lower asymptotic boundaries for the 5% significance level. The red dashed lines with dots give the path for the cumulated squared residuals assuming constancy in parameters. The shaded areas depict NBER recessions for the USA.

However, the financial crisis is embedded in the period of observation which has particularly influenced the banking sector. Therefore it can be expected that this period might affect the estimations for the entire sample. To get an impression about the stability of the fixed coefficient regression from Equ. (2), we compute the cumulated and the cumulated squared residuals for the three regressions following the ideas of the CUSUM and the CUSUM of squares test (CUSUMSQ), respectively (see Brown, Durbin, and Evans, 1975). The results are presented in Figure 1. It turns out that the cumulated residuals for the aggregate are mostly within the 5% significance bands for detecting structural changes over the entire period while the cumulated squared residuals give evidence for instabilities. The CUSUMSQ test is more suited to detect unsystematic changes in the coefficients. For the industrial sector, the cumulated residuals cross the lower band during the 2000s for about three years but return then back to the stability regime. A look at the cumulated squared residuals support the finding that the relationship is rather stable.

Table 2: Tests on unbiased expectations for banking sector with multiple breaks regression (from 1996:01 to 2014:11)

1996:01	2008:07 {2008:06 2008:09}	2010:03 {2009:08 2010:03}	2011:03 {2010:12 2011:11}	2014:11
α	-0.109***	-0.825***	0.510	0.034
	[-2.420]	[-6.767]	[0.637]	[0.970]
β	1.567***	0.235***	0.683***	1.117***
	[5.579]	[34.456]	[7.884]	[27.596]
$H0:(\alpha=0)$	5.857 **	45.793***	0.405	0.94
	(0.016)	(0.000)	(0.524)	(0.332)
$H0:(\ \beta=1\ )$	4.071**	12551.734***	13.342***	8.296***
	(0.044)	(0.000)	(0.000)	(0.004)
$H0:\begin{pmatrix}\alpha=0\\ \beta=1\end{pmatrix}$	6.327**	89020.416***	17.047***	0.000***
	(0.042)	(0.000)	(0.000)	(0.000)

Note: The table shows the results of the unbiasedness regression $\frac{x_t-x_{t-12}}{x_{t-12}}=\sum_{i=1}^{m}\left[\alpha_i+\beta_i\frac{E_{t-12}(x_t)-x_{t-12}}{x_{t-12}}\right]I_i+e_t$, whereas $x_t=EPS_t^{12M,i}$ are the earnings per share of sector i. The model is estimated with the techniques developed by Bai and Perron (2003). The number of breaks is chosen based upon the BIC and LWZ criteria. $H0$ denotes the null hypothesis for Wald tests with restrictions given in parentheses. Numbers in brackets give t-statistics and in parentheses p-values. T-statistics base on Newey-West standard errors. Braces give the confidence interval for the break points. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

More evidence in favor of stronger structural changes can be found for the banking sector. Although the cumulated residuals only leave the band following the financial crisis for a year, the cumulated squared residuals give evidence in favor of instabilities in the parameters of the unbiasedness regression. Following the financial crisis the cumulated squared residuals change dramatically their path which implies further structural changes.

Since the CUSUM and CUSUMSQ tests provides indications for structural changes particulary for the banking sector, we take a closer look at these effects by allowing for structural breaks in the regression coefficients. Having seen that the industrial sector and the aggregate exhibits less instability we focus our analysis henceforth on the banking sector. As our interest lies in expectations of future bank profits and the financial crisis has heavily affected the banking sector, we solely focus on breaks in the unbiasedness regression in the earnings per share of the banking sector. Regarding the structural breaks we run the regression

$$\frac{EPS_t^h-EPS_{t-n}^h}{EPS_{t-n}^h}=\sum_{i=1}^{m}\left[\alpha_i+\beta_i\frac{E_{t-n}\left(EPS_t^h\right)-EPS_{t-n}^h}{EPS_{t-n}^h}\right]I_i+\epsilon_t^*, \tag{3}$$

with I_i as an indicator function which takes the values one in the period $T_i\leq t\leq T_{i+1}$, with $i=1,...,m$ and m as the the number of breaks, and zero otherwise. We allow for multiple structural breaks which are endogenously estimated by applying the approach of Bai and Perron (1998, 2003). The minimal period without breaks is set to a year and the number of breaks is determined with the help of the sequential $\sup F(l+1|l)$ test of $l+1$ versus l structural changes after having verified with the help of the $\sup F\,(l)$ of l versus no structural changes that structural breaks occur, as proposed by the authors. The application of the sequential test suggests three breaks occuring at 2008:07, 2010:03, and 2011:03. As a consequence four regimes with fixed coefficients arise. The results are presented in Table 2.

There are two longer periods without a break. The period starting at the beginning of the sample lasts about twelve years and is followed by period covering the the subprime crisis. The second longer period is the period which prevails until the end of the sample period and lasts nearly three years. All other regimes last between one and one and a half years. In the aftermath of the financial crisis, two different regime changes can be observed which indicate that agents' expectations building process might have changed during the financial crisis. Nevertheless, the common restriction tests for unbiased expectations can be broadly rejected for every regime whereas the p-value of 0.042 is the greatest in the period before the emergence of the financial crisis. This is mainly related to the estimated β coefficient. Although the β coefficient in the last regime is visually very closer to one, which would indicate that expectations are less biased from 2011:03 onwards, this is not true on statistical ground because the standard error is very small. In the period before the crisis, the constant term α is even negative which means that earnings per shares in the banking sector are constantly lower than expected. This is not true in the last regime in which this parameter is statistically not different from zero.

While the β coefficient has been greater than one in the first and last regime it is drastically reduced during and in the aftermath the crisis. The estimated coefficients and tests suggest that agents might have changed their information processing and expectation formation as a result of the severity of the crisis. The α coefficient in the regime covering the peak of the crisis is still negative with a relatively high value while the β coefficient is with a value of 0.235 very low. This underpins that the crisis has not been fully anticipated. Realized earnings per shares are drastically below their expectations in this period. The end of this regime roughly coincides with the start of the recovery. In the following regime agents also predicted the right sign of earnings per share growth but still drastically overestimated the earnings per share grwoth as the β coefficient is below one. Nevertheless, the β coefficient recoveres compared to the regime before. Compared to the previous regime the constant term is not statistically significant. This shows that agents could obviously not gauge the profit situation of banks correctly in these regimes, i.e. in the periods which directly follow the financial crisis. In the last regime, the β coefficient exceed one, which shows that the expectations become more pessimistic with increasing distance from the financial crisis. The change from more biased expectations to more unbiased expectations could be a hint that agents learned from the experiences during the financial crisis.

2.2 Sticky or noisy information?

Since there is evidence of biased expectations regarding earnings per share of banks at least during some points in time, it is of interest to shed lights on the specific form of information processing. As Coibin and Gorodnichenko (2012) show, various forms of information processing can be distinguished. In models with sticky information, agents cannot acquire the full set of information every period they optimize. Basically, they behave fully rationally given their information set. However, agents can only partially adjust their information set. It follows that all agents with the same information set build the same expectations about the future. Dispersion in beliefs and forecasts results from the fact that the entire continuum of agents does not operate with the same information set. This is different from noisy information models. In these models the information set is the same across all agents, however, they need to extract the current state of the economy from a series of noisy signals. In this respect one can distingish between different sub-models. Models in which agents focus on specific information (rational inattention) or in which agents have only limited information about specific variables or parameters.

In order to test for these type of models, we follow the tests proposed by Coibin and Gorodnichenko (2012). The authors argue that sticky and noisy information models can be tested by investigating whether the forecast errors systematically responds to economic shocks in addition to that what can be interpreted as news. The idea is that shocks must drive realizations and expectations in the same way such that the forecast error does not react. As opposed to Coibin and Gorodnichenko (2012) we generate our structural shocks from a Vector autoregressive model. The VAR is estimated with monthly data and comprises the variables industrial production, inflation rate, policy rate, unemployment rate, the bank share price index, the aggregate share price index, the credit spread, and realized earnings per share growth. The number of lags is chosen with the help of the BIC. The reduced form residuals are converted to structural shocks by applying the Choleski decomposition. Thus, we are not able to give a clear economic identification to these shocks. The ordering corresponds to the listing of the variables before. The regression model following Coibin and Gorodnichenko (2012) becomes

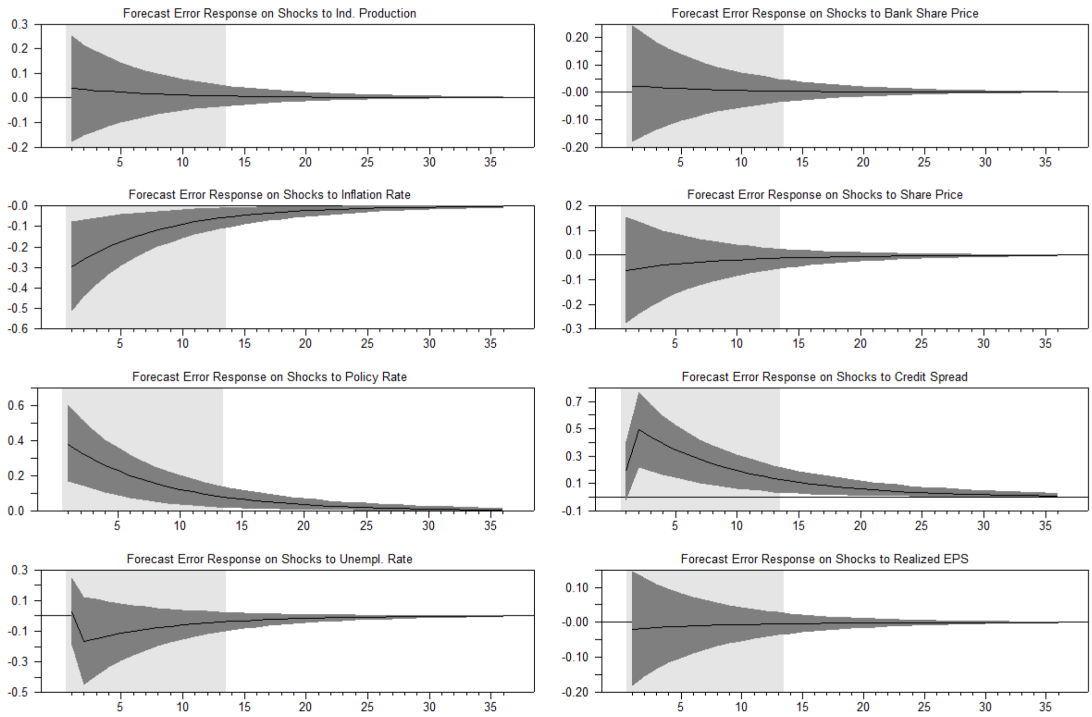
$$exp.err_t = c + \sum_{i=0}^{p} \delta_i shock_{t-i}^k + \sum_{j=1}^{q} \varsigma_j exp.err_{t-j} + e_t$$

in our case, where c is a constant, δ and ς are regression coefficients and e_t are i.i.d. innovations. The expectational error is denoted by $exp.err$. The test on sticky/noisy information is whether $\delta_i = 0$ for $i > 13$. To test this hypothesis for every k-th shock, we run individual regressions and evaluate the implied impulse-resonses. The number of lags p and q are selected with the help of the BIC.

In a first step, we regress the difference between the realization and its previously expected value on structural shocks $\left(exp.err_t = EPS_t^{12M} - E_{t-12}\left(EPS_t^{12M}\right)\right)$. In Figure 2, we present the responses of the forecast error on structural shocks obtained by the structural VAR which we identify with the Choleski decomposition. The labelling of the shocks is related to the position in the ordering because we cannot attribute a precise economic identification to the shocks. This is not necessary because we just need orthogonal shocks. The dark shaded area is the 90% confidence band around the implied responses, whereas the brighter shaded area is the first year after the shock which has the interpretation of news to the system. While Coibin and Gorodnichenko (2012) exclude this period because this information is not available for the forecast, we show this period to demonstrate how new information affect the variables. The idea is whether the responses are different from zero following the 13th period. As can be seen, the shocks on the inflation rate and the policy rate show slight significance while the shock on the credit spread shows cleary significant responses. All other confidence bands comprise the zero effect line. From this follows, that there is evidence in favor of sticky or noisy information.

Taken together, there is only slight evidence in favor of sticky or completely noisy information, except where shocks hit bank specific variables. The impact of shocks on the credit spread equation could be related to the fact that bank-specific developments and the credit spread of corporates are related (see Gilchrist, Yankov, and Zakrajsek, 2009, for instance). Our results may indicate that information processing with respect to

Figure 2: Responses of Forecast Error on various Shocks



Note: The graph shows the reponses of the pure forecast error, as the difference between the realized value and the previous expected value for the corresponding period, on various shocks. The shocks are structural shocks resulting from a SVAR with Choleski decomposition and the ordering given in the graph (from first left to last right position). The darker shaded areas are the confidence interval based upon the 90% level. The brighter shaded areas comprises the first year after the shock which means that these responses can be interpreted as new information on fundamentals.

bank variables is affected. In noisy information models responses can be different across different shocks as imperfect information are asymmetric (Coibin and Gorodnichenko, 2012, p. 125).

Sticky and noisy information models share principally the same dynamics regarding the responses of the forecast error on lagged shocks. As Coibin and Gorodnichenko (2012) argue, the forecast disagreement, i.e. the dispersion of forecasters, in noisy information models does not react to fundamental shocks. To test whether we are faced with a sticky or a noisy information problem we follow their approach and regress the forecast dispersion as the cross-sectional forecast standard deviation regarding the EPS forecasts in twelve months $\sigma_t^{E_t\left(EPS_{t+12}^{12M}\right)}$ on the absolute value of contemporaneous or lagged shocks. Thus, we run the regression

$$\sigma_t^{E_t\left(EPS_{t+12}^{12M}\right)} = c^\sigma + \sum_{i=0}^{p} \delta_i^\sigma \left|shock_{t-i}^k\right| + \sum_{i=j}^{q} \varsigma_i^\sigma \sigma_{t-j}^{E_t\left(EPS_{t+12}^{12M}\right)} + e_t^\sigma$$

for every k-th shock with c^σ, δ^σ and ς^σ as parameters and e_t^σ as i.i.d. innovations. A hypothesis in favor of noisy information models is the fact that every δ_i^σ is zero. In order

Table 3: Tests for Sticky Information

Shock on	contemporaneous		0 to 6 lags		0 to 12 lags	
	Test Statisitic	p-value	Test Statisitic	p-value	Test Statisitic	p-value
Industrial production	1.084	(0.298)	7.919	(0.34)	11.707	(0.552)
Inflation rate	0.041	(0.839)	8.799	(0.267)	14.48	(0.341)
Federal funds rate	2.553	(0.11)	6.589	(0.473)	17.744	(0.168)
Unemployment rate	0.172	(0.679)	5.059	(0.653)	14.287	(0.354)
Bank share prices	0.297	(0.586)	8.979	(0.254)	9.777	(0.712)
Aggr. share prices	0.893	(0.345)	8.538	(0.288)	12.065	(0.522)
Credit spread	0.389	(0.533)	6.766	(0.454)	18.578	(0.137)
Earnings per share growth	0.185	(0.667)	9.582	(0.214)	22.468**	(0.049)

Note: The Table shows Wald tests on excluding the absolute shocks over all lags in the regression $\sigma_t^{E_t(EPS_{t+12}^{12M})} = c^\sigma + \sum_{i=0}^{p} \delta_i^\sigma \left|shock_{t-i}^k\right| + \sum_{i=j}^{q} \varsigma_i^\sigma \sigma_{t-j}^{E_t(EPS_{t+12}^{12M})} + e_t^\sigma$, where σ_t is the cross-sectional standard deviation across all forecasters. k denotes the specific shock. The shocks stem from a Vector autoregressive model with the variables given in the left column. Shocks are identified by applying the Choleski decomposition with the ordering corresponding to the order in the table. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

to select the number of lags for the autoregressive part and the responses on lagged shocks we consult the usual information criteria AIC and BIC. Except AIC for the shock on the federal funds rate with a number of 15, in all other cases the information criteria suggest zero lags for the shocks. This result is a first indication that the economic shocks we identified do not help to explain the forecast dispersion. To verify this conjecture, we apply Wald tests on the contemporaneous effect and F-tests on the contemporaneous and the lagged effects up to 6 lags (half a year) and 12 lags (one year) which tests the joint hypothesis that the related coefficients are zero. The results are presented in Table 3. As can be seen all null hypotheses can be rejected which means that no coefficient is statistically significant with one exception. In the case for up to 12 lags the joint restriction is only rejected for the shock on earnings per share growth with a p-value close to 0.05. Thus, the dispersion in forecasts is not systematically related to fundamental shocks, neither to its contemporaneous effect nor to their history.

Based upon the results, we see evidence that a sticky information model can be rejected for the case of earnings per share. Combining the results for the responses of the forecast error on fundamental shocks and for the dispersion of forecasts, our results give evidence that there is a noisy information problem regarding bank specific shocks. This means that agents probably update information in a way that is consistent with a learning approach in the banking sector.

2.3 Formation of expectations and learning about forecast errors

To shed light on the expectation formation for EPS we investigate the determinants which help to explain the forecast. For this reason, we regress the expected growth for the next twelve month on a constant, its one-period lagged values, the last realized one-month growth in earnings per share and further realized and expected macroeconomic variables summarized in Z_t. The expected macroeconomic variables comprises the expected growth of the gross domestic product over the next 12 months, the expected rate of inflation in 12 months, and the expected short-term interest rate in 12 months. All three variables stem from professional forecasters and are the mean forecasts as reported by Consensus Forecasters. The realized macroeconomic variables are realized annual inflation, the unemployment rate and the annual growth of industrial production. The regression model becomes

$$\begin{aligned}\frac{E_t\left(EPS_{t+12}^{12M}\right)-EPS_t^{12M}}{EPS_t^{12M}} &= \mu+\beta_1\frac{E_{t-1}\left(EPS_{t+11}^{12M}\right)-EPS_{t-1}^{12M}}{EPS_{t-1}^{12M}} \\ &\quad +\beta_2\frac{EPS_t^{12M}-EPS_{t-1}^{12M}}{EPS_{t-1}^{12M}} \\ &\quad +\Gamma Z_t+\eta_t,\end{aligned} \tag{4}$$

where μ and β_i are parameters, Γ is a vector of parameters and η_t are i.i.d. innovations. The results show that agents place no weight on past EPS expectations (Table 4). The converse is true for realized EPS developments in the recent past. The agents adjust their EPS expectations conversely to last realized EPS growth. This can be a reflection of the fact that professional forecasters are aware of an upward bias. Macroeconomic factors are relevant in building expectations for future returns, particularly, when expectations about the expected earnings growth do not matter.

Analogously to Table 2, we also test the expectation formation process, as presented in Equation (4), for breaks. As opposed to this regression the application of the BIC induced four breaks instead of five.[5] The breaks occur at 2008:02, 2009:03, 2010:05, and 2011:06. By taking the confidence bands into account, these breaks largely correspond to the last four breaks as presented in Table 2. Obviously, the structural changes in the unbiasedness regression coincide with changes in the expectation formation process. The regimes are presented in Table 4 but we do not discuss every estimated parameter. The most relevant variables are the constant term, the coefficients β_1 and β_2. As can be seen, the constant term is statistically significant in every regime except the period running from 2011:06 to the end of the sample. Furthermore, it has a negative sign before the financial crisis but a positive during and in the aftermath of the financial crisis. This means that EPS growth expectations are always reduced by a specific amount before the financial crisis and are always set higher when it becomes positive. Regarding the past expectations about earnings growth they show a positive sign before the financial crisis and in the period following 2011:06. During the financial crisis the professional forecasters reacted inversly to their past expectations. Obviously, forecasters extrapolate their forecasters in calm times but react conversely in times of financial stress. As discussed for the fixed coefficients regression, the forecasts are negatively related to past realized EPS growth. For the regime-dependent coefficients regression this result only changes for the period of the financial crisis, i.e. between 2008:02 and 2009:03. Here, the positive sign indicates that forecasters related their expectations about future earnings positively to past realizations, i.e. they extrapolate the most recent development. This is an indication that forecasters did not completely rely on fundamentals to built expectations during the financial crisis.

This time-varying coefficient approach gives evidence that the expectation forming process of agents changed during the financial crisis. However, it is not able to show whether theses changes can be related to the past behavior of forecasters. In noisy information models, agents try to extract relevant information from noisy signals. This means, *inter alia*, that they react systematically to their own forecast errors, i.e they learn from the

[5]The minimal period without breaks is set to 12 months. This choice takes the number of variables in the regression into account.

Table 4: Regressions for the expected annual earnings per share growth

	Fixed coefficients	Regime-dependend coefficients				
	1996:01-2014:11	1996:01-2008:01	2008:02-2009:02	2009:03-2010:04	2010:05-2011:05	2011:06-2014:11
Constant	-4.181**	-0.190**	54.432***	142.990***	62.524***	-0.177
	[-2.450]	[-2.236]	[17.181]	[5.855]	[5.743]	[-0.506]
$\frac{E_{t-1}(EPS_{t+11}^{12M})-EPS_{t-1}^{12M}}{EPS_{t-1}^{12M}}$	0.148	0.472**	-2.417***	-0.437***	-2.931***	0.614***
	[0.780]	[2.394]	[-22.212]	[-22.636]	[-5.911]	[2.732]
$\frac{EPS_{t-1}^{12M}-EPS_{t-13}^{12M}}{EPS_{t-13}^{12M}}$	-0.173**	-0.260*	83.068***	-0.439***	-5.613***	-0.007
	[-2.274]	[-1.775]	[14.040]	[-9.241]	[-5.887]	[-1.047]
Residual bank share price	-0.040	0.003	11.002**	-2.546**	9.213	0.036
	[-0.041]	[0.106]	[2.128]	[-2.051]	[1.130]	[0.420]
Expected GDP growth in 12 months	0.249	0.035**	-12.663***	-20.621***	-4.431***	-0.072**
	[1.627]	[2.515]	[-3.269]	[-12.408]	[-4.057]	[-2.592]
Expected rate of inflation in 12 months	-1.848***	-0.015	29.538***	-15.113**	29.873***	-0.061
	[-2.878]	[-0.341]	[3.906]	[-2.611]	[4.551]	[-0.541]
Exp. short-term int. rate in 12 months	0.531***	0.014	-4.256**	-5.031***	1.619	0.058
	[2.990]	[1.148]	[-1.874]	[-5.068]	[1.137]	[1.619]
Realized annual inflation	0.373**	-0.015**	-9.332***	0.856***	-2.765***	0.034
	[2.491]	[-2.026]	[-4.435]	[4.231]	[-4.611]	[1.474]
Unemployment rate	0.767***	0.031*	0.441	-3.925	-5.340***	0.054**
	[3.223]	[1.676]	[0.587]	[-1.027]	[-5.357]	[2.249]
Annual growth of ind. production	25.588***	0.424	388.796***	151.272***	-321.012***	0.464
	[2.756]	[1.106]	[7.100]	[10.676]	[-3.463]	[0.324]

Note: The table reports estimated coefficients for explaining the expected annual growth of earnings per share. The LHS regression model can be found in Eq. (4) in the main text. The RHS regression is estimated with the techniques developed by Bai and Perron (2003). The number of breaks is chosen based upon the $\sup F_T\left(l+1|l\right)$ test which tests $l+1$ breaks versus l breaks and is determined at the 5% significance level. EPS_t^{12M} is the earning-per-shares over twelve months. $E_t\left(\bullet\right)$ is the expectational operator. GDP is the gross domestic product. The "Residual bank share price" is the residual from the regression of the share price index for banks on all explanatory macro variables. Numbers in brackets give t-statistics which base on Newey-West standard errors. Asterisks denote statistical significance at the 1% (***).

realizations relative to their previous expectations. To get an idea whether professional forecasters indeed react to their forecasting errors and learn for building expectations, we need to develop a test in this respect. Our approach is motivated by simple arithmetics regarding the evolution of bank equity (excluding equity injections). Equity (N_t) arises as the difference between returns (R_t^A) on total assets of the bank (A_t^B) and the costs (R_t^L) for liabilities (L_t). In addition, we assume that an efficiency parameter $\tilde{\theta}$ also affects net worth. This (in)efficiency can easily be expressed as a proportion of equity $\tilde{\theta} = \theta N_{t-1}$. For the law of motion of bank equity we get

$$N_t = R_t^A A_{t-1}^B - R_t^L L_{t-1} - \theta N_{t-1},$$

which can be re-written with the help of the balance sheet constraint $A_t^B = N_t + L_t$ to obtain

$$N_t = \left(R_t^A - R_t^L\right) A_{t-1}^B + \left(R_t^L - \theta\right) N_{t-1}.$$

This expression can easily be transformed into growth rates

$$\frac{N_t}{N_{t-1}} = \left(R_t^A - R_t^L\right) lev_{t-1} + R_t^L - \theta, \tag{5}$$

where lev_t is the leverage ratio. As can be seen in the last equation, the inefficiency parameter is a constant in an equation with equity growth. By assuming that bank efficiency changes over time, a time index can be attributed to θ_t which might now obey a process we define later. The growth of bank equity is determined by earnings, i.e. it is proxied by earnings per share. Furthermore, this Equation (5) can be linked to the growth in earnings per share without a loss of generality. Learning about the inefficiency parameter means that agents learn about (a part of) the constant in Equation (4). Assuming that $\left(R_t^A - R_t^L\right) lev_{t-1} + R_t^L$ is a function of fundamentals $f\left(Z_t\right)$, we can re-write the model in a time-varying coefficient framework

$$\begin{aligned} \frac{E_t\left(EPS_{t+12}^{12M}\right) - EPS_t^{12M}}{EPS_t^{12M}} &= \mu_t + \gamma_{1,t}\frac{E_{t-1}\left(EPS_{t+11}^{12M}\right) - EPS_{t-1}^{12M}}{EPS_{t-1}^{12M}} \\ &\quad + \gamma_{2,t}\frac{EPS_t^{12M} - EPS_{t-1}^{12M}}{EPS_{t-1}^{12M}} + \Gamma_t Z_t + \eta_t \end{aligned}$$

where the coefficients are supposed to evolve as AR-processes

$$\begin{aligned} \mu_t &= \mu_{t-1} + b_0 \cdot \left(exp.err_{t-1}\right) + \nu_t \\ \gamma_{it} &= \gamma_{i,t-1} + \nu_t^{\gamma_i}. \end{aligned}$$

The model is written in state space form and is estimated with the Kalman filter. The state equation for the constant term can be used to test for learning about the "efficiency" in the banking sector. If μ_t systematically responds to the forecast error of earnings per share, i.e. the regression coefficient b_0 is statistically different from zero, we argue that agents learn about the "efficiency" of the banking sector by observing growth in banks' net worth relative to the expectations they had before. Of course, μ_t might also be related to other macro variables as well as all $\gamma_{i,t}$ can also be related to a learning scheme. However, we see this test as sufficient to test whether agents learn about the past in building expectations about future growth of banks' net worth.

The results are presented in Table 5.[6] We present three different models in which we test for a feedback effect on the constant term running from the expectation error. In model 1, we test the general case for learning, i.e. whether the constant term reacts systematically on the expectation error over the entire sample. This can be clearly rejected because the coefficient b_0 is not statistically different from zero. However, we know that the financial crisis seems to have changed the expectation formation of agents. As a consequence, we allow for structural breaks in the parameter. As regimes, we take the breaks reported in Table 4. This is model 2. By taking breaks into account we can cleary obtain evidence in favor of learning agents. The constant term in the expectation formation equation systematically responds to expectation errors during and in the aftermath of the financial crisis but not before the financial crisis or after 2011. In model 3 we omit this last period and Likelihood ratio tests show that this configuration is preferrable to the others. Model 3 shows that agents reducing the weight of the constant term in building expectations with increasing expectation errors. In the second period, in which the sign is statistically significant, the magnitude of the coefficient is much larger than in the period in which the financial crisis occurred. This can be an indication that agents learn stronger during this period.

[6] Results for the estimated coefficients are presented in the appendix in Tables 7 and 8. We do not discuss the results because they largely coincide with the results from the regime-dependent regression model.

Table 5: Explanatory variables in state equations for expectations in the last period and last period's realized annual growth of earnings per share

	Model 1	Model 2	Model 3
b_0	0.001	0.009	0.009
	[0.214]	[1.612]	[1.604]
b_{01}		-0.035***	-0.034***
		[-3.434]	[-3.322]
b_{02}		-0.847***	-0.858***
		[-3.03]	[-3.748]
b_{03}		-0.011	
		[-0.156]	
LR(Model 1 | Model 2)	7.569*		
	(0.056)		
LR(Model 1 | Model 3)	7.563***		
	(0.006)		
LR(Model 2 | Model 3)	0.006		
	(0.940)		

Note: The table reports the estimated state equation for α. The models are:
$Model\,1:\ \alpha_t = \alpha_{t-1} + b_0 \cdot \left(exp.error^k_{t-1}\right) + \nu^\alpha_t$,
$Model\,2:\ \alpha_t = \alpha_{t-1} + b_0 \cdot \left(exp.error^k_{t-1}\right) + \sum_{i=1}^{4} b_{0i} \cdot \left(exp.error^k_{t-1}\right) \cdot I_i + \nu^\alpha_t$,
and $Model\,3:\ \alpha_t = \alpha_{t-1} + b_0 \cdot \left(exp.error^k_{t-1}\right) + \sum_{i=1}^{3} b_{0i} \cdot \left(exp.error^k_{t-1}\right) \cdot I_i + \nu^\alpha_t$, with
$I_1\,(2008:07 \leq t \leq 2010:02)$, $I_2\,(2010:03 \leq t \leq 2011:02)$, and $I_3\,(2011:03 \leq t \leq 2014:11)$ as indicator function which take the value of one in the defined period and zero otherwise. The expectation error is
$exp.error^{pure}_t = EPS^{12M}_t - E_{t-12}\left(EPS^{12M}_t\right)$. LR are Likelihood ratios which tests model i against model j. Numbers in brackets give t-statistics and in parentheses p-values. Asterisks denote statistical significance at the 1% (***) level.

This result is consistent with what we expect, raising forecast errors reduce the constant component in EPS growth. Taken our results together, they imply that agents' forecasts of bank profits were biased during the entire sample. Regarding the β coefficient, unbiasedness becomes weaker after the financial crisis. Sticky information processing do not seem to be responsible for this finding. Since agents take forecast errors during the financial crisis into account in forming expectations about future earnings of banks, agents seem to learn about the profit situation of banks which means that they indirectly learn about banks' net worth. Based on these findings the question about the consequences on the real economy following from imperfect information about banks' net worth arises. We scrutinize this question in the next section by drawing on a New Keyesian general equilibrium model with a banking sector because a theoretical model is only able to investigate these effects in isolation.

3 Model

In order to investigate the effects of learning about banks' net worth on macroeconomic developments we utilize a New Keynesian dynamic general equilibrium model in the tradition of Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), which additionally exihibits a banking sector. The latter is akin to the approach developed by Gertler and Karadi (2011) and Gertler and Kiyotaki (2010). Since the banking sector is central for our purposes, this sector and the assumptions we apply are thoroughly explained in this section together with the description of the rest of the model. All first order conditions and the whole set of log-linearized equations are delegated to the technical appendix. An important role for a banking sector evolves because it is assumed that the goods producing sector cannot obtain funds directly from the households. As a consequence a financial intermediary, what we call banking sector, is necessary to indermediate the funds from households to capital producers. Regarding this linkage we assume that an agency problem exists between households and bankers. From this agency problem follows that bankers need to combine external funds (deposits) with internal funds (net worth).

The economy consists of households, financial intermediaries (banks), capital producers, intermediate goods producers and retailers. Banks obtain funds from households, combine them with internal funds to create loans given to capital producers. Intermediate goods producers uses physical capital together with labor to produce intermediate goods which are are differentiated by retailers. By applying a bundling technology, the differentiated goods are transformed in the homogenous final good. This intermediate step is required to introduce nominal price rigidities into the model. A central bank obeys a conventional Taylor rule.

3.1 Banking sector

Financial intermediaries intermediate funds between the household sector and the capital producing sector because households are not able to lend directly. Hence, household place deposits D_{jt} at financial intermediaries which shall reflect the banking sector. The banking sector consists of a continuum of banks with a mass of unity in which each bank j is operated by a bank manager. Bank managers stem from the household sector, however, households cannot place deposits at the bank which are operated by their own bank managers. Due to an agency problem which we describe later, external funds can only be attracted by bank managers if there are sufficient internal funds, i.e. net worth N_{jt}. The funds are used to buy claims S_{jt} on capital producing firms at price Q_t. Since capital producing firms solely finance capital production with these funds, the claims can be interpreted as shares on the physical amount of capital K_{jt}., which mean that the entire volume of claims equals the amount of capital $S_{jt} = K_{jt}$. As a result there is no additional price for the shares and it follows $Q_t S_{jt} = Q_t K_{j,t+1}$. The balance sheet constraint of the banks becomes

$$Q_t S_{jt} = N_{jt} + D_{jt}, \tag{6}$$

with D_{jt} as external funds. Since there is no outside equity in the model, net worth results from accumulated net profits of the banks. Net profits arise as the difference between the gross returns on claims R_{kt} and the gross costs for external funds, with R_t as the risk-free interest rate. In addition, we assume that an inefficiency process $\tilde{\theta}_t^N$ also determines banks' net worth, whereas it only takes positive numbers. The law of motion for net worth becomes

$$N_{jt+1} = R_{kt+1} Q_t S_{jt} + R_{t+1} D_{jt} - \tilde{\theta}_{t+1}^N. \tag{7}$$

The idea behind this inefficiency process is to introduce a systematic inefficiency in the banking sector which affects net worth negatively. Our inefficiency process is basically similar to the net worth shock in Gertler and Karadi (2011), however, we restrict the value of $\tilde{\theta}_t^N$ to be positive and allow for a specific law of motion which we will discuss later. The inefficiency parameter can be expressed relative to last period's net worth $\theta_t^N = \tilde{\theta}_t^N / N_{t-1}$

so that Equ. (7) can be re-written with the help of the balance sheet constraint to get

$$N_{jt+1} = (R_{kt+1} - R_{t+1})\, Q_t S_{jt} + \left(R_{t+1} - \theta^N_{t+1}\right) N_{jt}. \tag{8}$$

Banks are effectively owned by households. Bank managers do not operate a bank forever but stay bank managers for more than one period with a specific probability p. Thus, they exit the banking sector with a probability of $1-p$ and return to the household sector in this case.[7] During the time bank managers operate a bank, they try to maximize the resources they can transfer back to their households at the end of their bankers' life. Consequently, transfers of funds from bankers to workers only take place at the end of bankers' life. Thus, the objective of bank managers is to maximize the franchise value of the bank V_{jt} by deciding over the volume of assets and the required external funds by taking the expected return on capital and the risk-free rate as given

$$V_{jt} = \max\, E_t \sum_{i=0}^{\infty} (1-p)\, p^i \beta^{i+1} \Lambda_{t,t+1+i} \left[(R_{kt+1+i} - R_{t+1+i})\, Q_{t+i} S_{jt+i} + \left(R_{t+1+i} - \theta^N_{t+1+i}\right) N_{jt+i} \right], \tag{9}$$

where β is the time-preference rate and Λ_t the growth in households' marginal utility.

Following Gertler and Karadi (2011) and Gertler and Kiyotaki (2010), we introduce an agency problem between households, banks' creditors, and the bank managers which constraints the provision with external funds. Because of limited enforcement bank managers can divert a fraction λ from their total assets at the beginning of every period. In the case of diversion, they transfer the resources immediatly back to their households and bank managers are forced into bankcrupcty. Banks' creditors can only recover the fraction $1-\lambda$ of total assets. Bankers do not divert, i.e. they do not run, if the incentive constraint

$$V_{jt} \geq \lambda Q_t S_{jt} \tag{10}$$

holds.

Next, we conjecture that the franchise value of the bank, as given in Eq. (9), can be re-written in a linear fashion

$$V_{jt} = \nu_t Q_t S_{jt} + \eta_t N_{jt} \tag{11}$$

where

$$\nu_t = E_t \left[(1-\theta)\, \beta \Lambda_{t,t+1} (R_{kt+1} - R_{t+1}) + \beta \Lambda_{t,t+1} \theta x_{t,t+1} \nu_{t+1} \right] \tag{12}$$

$$\eta_t = E_t \left[(1-\theta) + \beta \Lambda_{t,t+1} \theta z_{t,t+1} \eta_{t+1} \right]. \tag{13}$$

with variables $x_{t|t+i}$ and $z_{t|t+i}$ as the gross growth rates for total assets and for net worth, respectively, from period t to period $t+i$

$$z_{j,t|t+1} = \frac{N_{j,t+1}}{N_{jt}} = (R_{kt-1} - R_{t+1})\, \phi_{jt} + \left(R_{t+1} - \theta^N_{t+1}\right)$$

$$x_{j,t|t+1} = \frac{Q_{t+1} S_{j,t+1}}{Q_t S_{jt}} = \frac{\phi_{j,t+1}}{\phi_{jt}} z_{j,t|t+1}.$$

[7]The survival rate of bank managers is $1/(1-p)$, which will be clearly longer than one period.

The term ϕ_{jt} is the leverage ratio which is defined as $Q_t S_{jt}/N_{jt}$. The maximization of banks' franchise value yields a link between the leverage ratio and the expected discounted marginal gain of expanding total assets ν_t, the expected discounted value of extending net worth η_t and the share of diversion λ.

$$\phi_{jt} = \frac{\eta_t}{\lambda - \nu_t} \tag{14}$$

Exiting bankers are replaced by new bankers so that the population of bankers remains constant. The only difference between old and new bankers is the endowment with net worth. Old bankers' net worth N_{ot} results from net profits as described above. i.e.

$$N_{ot} = p\left[\left(R_{kt} - R_t\right)\phi_t + R_t - \theta_t^N\right] N_{t-1}, \tag{15}$$

while new bank managers are endowed with resources by their households. The inefficiency parameter follows an autoregressive process

$$\log\left(\theta_t^N\right) = \left(1 - \rho^\theta\right)\log\left(\bar{\theta}_t^N\right) + \rho^\theta \log\left(\theta_{t-1}^N\right) + \epsilon_t^\theta, \tag{16}$$

which persistency is controlled by ρ^θ and is driven by i.i.d. innovations ϵ_t^θ. In Equation (16), $\bar{\theta}_t^N$ denotes the steady state value of the inefficiency parameter, whereas the time index t indicates that its value can change over time. The net worth of new bankers N_{nt} is assumed to be a fraction ω of claims left over from exiting bankers valued at the period's t price

$$N_{nt} = \omega Q_t S_{t-1}. \tag{17}$$

As a consequence, aggregate net worth is the sum of both components and the aggregate law of motion for banks' net worth becomes

$$\begin{aligned} N_t &= N_{ot} + N_{nt} \\ &= p\left[\left(R_{kt} - R_t\right)\phi_t + R_t - \theta_t^N\right] N_{t-1} + \omega Q_t S_{t-1}. \end{aligned}$$

3.2 Households

A continuum of identical households with a mass of unity populates the household sector. Every household can be split up into two groups. Household members who consume, save, and supply labor to the intermediate goods sector belong to the first group. Their share f do not vary over time. Bank managers, in turn, constitute the second group and their share is consequently $1 - f$. Since bank managers exit the banking sector every period with a specific probability, the share of exiting bankers is $(1 - p) f$.

The workers in each household h have preferences over consumption $C_{h,t}$ and labor $L_{h,t}$ and maximizes their lifetime utility where future periods' utilities are discounted by the rate of time preference β .

$$\max\, E_t \sum_{i=0}^{\infty} \beta^i \left[\ln\left(C_{h,t+i} - h^C C_{h,t+i-1}\right) - \frac{\chi}{1+\varphi} L_{h,t+i}^{1+\varphi}\right] \tag{18}$$

with $\varphi > 0$ as the inverse Frisch elasticity, $\chi > 0$ as a scaling parameter, and h^C shows that household have consumption habits, whereas $0 < h^C < 1$. Financial wealth of households is denominated in real terms consists of deposits $D_{h,t}$ and government bonds $B_{h,t}$. The gross period return of both asset, which both have a maturity of one period, is denoted by R_t. Government bonds are assumed to be in in zero net supply. In addition, household pay lump sum taxes $T_{h,t}$, receive labor income related to the real wage W_t and get net transfers $\Pi_{h,t}$ from banks and the real sector (retailers and capital producers). As a consequence the budget constraint arises as

$$C_{h,t} + B_{h,t} + D_{h,t} = W_t L_{h,t} + R_t \left(B_{h,t-1} + D_{h,t-1}\right) - T_{h,t} + \Pi_{h,t}. \tag{19}$$

The first order condition for consumption with ϱ_t as the marginal utility of consumption results as

$$\varrho_t = \left(C_t - h^C C_{t-1}\right)^{-1} - \beta h^C E_t \left(C_{t+1} - h^C C_t\right)^{-1} \tag{20}$$

the first order condition for labor becomes

$$\varrho_t W_t = \chi L_t^{\varphi} \tag{21}$$

and the Euler equation is

$$E_t \beta \Lambda_{t,t+1} R_{t+1} = 1 \tag{22}$$

with

$$\Lambda_{t,t+1} \equiv \frac{\varrho_{t+1}}{\varrho_t}. \tag{23}$$

Indizes can be dropped because all individuals behave identically as can be seen from the first order conditions.

3.3 Intermediate goods firms

Intermediate goods Y_t are produced in a market of perfect competition firms with physical capital K_{t+1}, bought at the end of the period t, and labor as inputs. The Cobb-Douglas production function is

$$Y_t = A_t \left(U_t \xi_t K_t\right)^{\alpha} L_t^{1-\alpha}, \tag{24}$$

with α as the share of utilized capital in production and U_t the capital utilization rate. The production is exposed to two different shocks. The first one is a shock on the total factor productivity A_t which obeys an autoregressive process with i.i.d. innovations ϵ_t^A

$$\log\left(A_t\right) = \rho^A \log\left(A_{t-1}\right) + \epsilon_t^A. \tag{25}$$

The second one is a shock on the quality of capital ξ_t with i.i.d. innovations ϵ_t^{ξ}. This so-called capital quality shock, as discussed in Gertler and Karadi (2011), also follows an autoregressive process

$$\log\left(\xi_t\right) = \rho^{\xi} \log\left(\xi_{t-1}\right) + \epsilon_t^{\xi}. \tag{26}$$

The parameters ρ^A and ρ^{ξ} control the persistency of the shock. The capital quality shock affects the effective quantity of capital and the return to capital at the same time. By choosing the utilization rate and the labor input intermediate goods producers maximize their profits at time t. The price for intermediate goods P_{mt}, the real wage, and the price for capital are taken as given. From profit maximization follows the demand for physical capital as

$$P_{mt}\alpha\frac{Y_t}{U_t} = \delta'(U_t)\,\xi_t K_t \tag{27}$$

and the demand for labor as

$$P_{mt}(1-\alpha)\frac{Y_t}{L_t} = W_t. \tag{28}$$

Ex post returns are distributed to the households at the end of every period. The return to capital can be defined as

$$R_{kt+1} = \frac{\left[P_{mt+1}\alpha\frac{Y_{t+1}}{\xi_{t+1}K_{t+1}} + Q_{t+1} - \delta(U_{t+1})\right]\xi_{t+1}}{Q_t}. \tag{29}$$

The depreciation rate δ is a function of the capital utilization rate U_t.

3.4 Capital producers

Depreciated physical capital is combined with new investment goods at the end of period t to manufacture the new stock of physical capital. Adjustment costs arise by varying net investment (I_{nt}) , whereas the conditions $f(1) = f'(1) = 0$ and $f''(1) > 0$ for investment function are satisfied. Net investment is defined as investment (I_t) not used to replace depreciated capital $\delta(U_t)\,\xi_t K_t$. In a market of perfect competition capital producers maximize profits

$$\max\ E_t\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Lambda_{t,\tau}\left\{(Q_\tau - 1)\,I_{n\tau} - f\left(\frac{I_{n\tau}+I_{ss}}{I_{n\tau-1}+I_{ss}}\right)(I_{n\tau}+I_{ss})\right\}, \tag{30}$$

with I_{ss} as the steady state level of investment. Profits are redistributed to households. From profit maximization we obtain

$$Q_t = 1 + f\left(\frac{I_t}{I_{t-1}}\right) + \frac{I_t}{I_{t-1}}f'\left(\frac{I_t}{I_{t-1}}\right) - E_t\beta\Lambda_{t,t+1}\left(\frac{I_{t+1}}{I_t}\right)^2 f'\left(\frac{I_{t+1}}{I_t}\right). \tag{31}$$

The aggregate law of motion for capital becomes

$$K_{t+1} = \xi_t K_t + I_t - \delta(U_t)\,\xi_t K_t.$$

3.5 Retail firms

In additon to capital producers and intermediate goods producers, there is a continuum of retail firms with mass of unity. In a market of monopolistic competition they buy the intermediate goods to conduct a product differentiation. These differentiated goods are then used to produce the final good, which results following a CES bundling technology with the output of retailers Y_f as inputs.

$$Y_t = \left[\int_0^1 Y_{ft}^{(\epsilon-1)/\epsilon}df\right]^{\epsilon/(\epsilon-1)}$$

The market power of retailers is related to the degree of substitutability (ϵ) among retailers' output. Following Calvo (1983), each firm can only set the price for its goods optimally with a probability of $1-\gamma$. In the case, a firm cannot set the price freely, it follows an indexation rule in which the lagged rate of inflation π_t enters. The optimal price P_t^* is set by the retailers as a consequence from profit maximization by setting taking the demand for its good and the corresponding price as given

$$\max E_t \sum_{i=0}^{\infty} \gamma^i \beta^i \Lambda_{t,t+1} \left[\frac{P_t^*}{P_{t+i}} \prod_{k=1}^{i} (1+\pi_{t+k-1})^{\gamma_p} - P_{mt+i} \right] Y_{ft+1}, \tag{32}$$

with γ_p as a measure of price indexation. The first order condition becomes

$$E_t \sum_{i=0}^{\infty} \gamma^i \beta^i \Lambda_{t,t+1} \left[\frac{P_t^*}{P_{t+i}} \prod_{k=1}^{i} (1+\pi_{t+k-1})^{\gamma_p} - \mu P_{mt+i} \right] Y_{ft+1} = 0$$

whereas $\mu = \frac{1}{1-1/\epsilon}$ is the price markup. The overall price level results as a weighted average of the optimal price and price indexation

$$P_t = \left[(1-\gamma) \left(P_t^*\right)^{1-\epsilon} + \gamma \left(\Pi_{t-1}^{\gamma_p} P_{t-1} \right)^{1-\epsilon} \right]^{1/(1-\epsilon)}.$$

The demand for each retailers' good arises from costs minimization of producing the final good

$$Y_{ft} = \left(\frac{P_{ft}}{P_t} \right)^{-\epsilon} Y_t$$

with

$$P_t = \left[\int_0^1 P_{ft}^{1-\epsilon} df \right]^{1/(1-\epsilon)}.$$

Retail firms have simply the function to introduce nominal price rigidities in the model.

3.6 Public sector

The central bank obeys a Taylor (1993)-type monetary policy rule with interest-rate smoothing for controlling the policy rate i_t

$$i_t = \rho i_{t-1} + (1-\rho) \left[i + \kappa_\pi \pi_t + \kappa_y \left(\log Y_t - \log Y_t^* \right) \right] + \epsilon_t^i, \tag{33}$$

with Y_t^* as the natural level of output, ρ the smooting parameter with $0 < \rho < 1$, and the parameters κ_π and κ_y for controlling the responsiveness on inflation and the output gap, respectively. The variable ϵ_t^i is an unexpected monetary policy shock. The Fisher equation constitutes the relationship between the nominal and the real interest rates

$$1 + i_t = R_{t+1} \frac{E_t P_{t+1}}{P_t}.$$

3.7 Market clearing

Consumption, investment, public expenditures G_t, and investment adjstment costs determine the aggregate demand which is to the output level. The aggregate resource constraint for the economy becomes

$$Y_t = C_t + I_t + f\left(\frac{I_{nt} + I_{ss}}{I_{nt-1} + I_{ss}}\right) + G_t.$$

Government expenditures are kept constant and equal lump sum taxes which mean that government budget is balanced every period.

4 Calibration strategy and steady state values

Regarding the calibration we take values for the steady state and the deep parameters as in Gertler and Karadi (2011). The values for the deep parameters which we set freely or are pinned down by the steady state can be found in Table 6. In the basic calibration of the model, we set the value for the steady state inefficiency parameter θ_{ss}^N to zero, i.e. the model resembles the model in Gertler and Karadi (2011). As a next step, we treat all parameters as deep parameters, i.e. we keep them constant, and set the value of the steady state inefficiency parameter to 0.001. To obtain the steady state values for all variables we solve all equations by assuming that the steady state values for prices and the policy rate are not affected. Following from the solution, the new steady state values result from agents' optimizing behavior by taking the new inefficiency parameter, which is known to all agents at this step, into account. Furthermore, we increase the value for the steady state inefficiency parameter to 0.065 and we solve again the entire set of equations to obtain another steady state situation which is consistent with how agents react on a geater inefficiency in the banking sector in the absence of shocks.

Table 6: Calibration of parameters

Description	Parameter	Value
Discount rate	β	0.99
Relative utility weight of labor	χ	3.409
Habit parameter	h^C	0.815
Inverse Frisch elasticity of labor supply	ϕ	0.276
Effective capital share	α	0.33
Elasticity of substitution	ε	4.167
Elasticity of marginal depreciation wrt utilization rate	ϑ	7.2
Inverse elasticity of net investment to the price of capital	η_i	1.728
Calvo parameter, probability of keeping goods prices fixed	γ	0.779
Price indexation	γ_p	0.241
Diversion share	λ	0.385
Depreciation rate of capital	δ	0.025
Inflation coefficient. Taylor rule	κ_π	1.98
Output gap coefficient. Taylor rule	κ_y	-0.125
Interest rate smooting. Taylor rule	ρ_i	0.8
Steady state capital utilization rate	U	1
Steady state proportion of government expenditures	G_{SS}/Y_{SS}	0.2

The three different steady state regimes can be found in Table 7. In our benchmark case we set the steady state value of the inefficiency parameter to 0.001. By comparing the new steady state values with those of the original model without the inefficiency parameter, one can see that they are very close to each other. The ratios for net worth, capital, investment and consumption relative to output are not far away from each other. The interest rate spread is only eight basis points greater for the $\theta_{ss}^N = 0.001$ case compared to the case where it is zero. The increase in the steady state inefficiency parameter for net worth is translated into a widening of the spread of more than 600 basis point which is consistent with the developments during the financial crisis. The BBB-spreads rose by more than 600 basis point from the pre-crisis level to the peak. In our model we do not interpret this development as a sequence of shocks but we rather argue that the structural inefficiency of the banking sector during that time was the driving force behind. As can be seen by comparing the ratios under the high financial stress scenario compared to the low stress scenario, one can see that the investment to output ratio shrinks as well as the capital to output ratio. Conversely, the consumption to output ratio rises which is counterintuitive compared to real data. However, our model is very stylized in this respect because the focus is on the relationship between capital and the banking sector. Following the increase in the inefficiency in the banking sector the steady state value of banks' net worth shrinks which is translated into a rise in the leverage ratio of banks. This is at the center of the developments described above. The need for banks to delever cuts credit supply, increases the costs for financial intermediation, and reduces investment and capital.

Table 7: Comparison of different steady state values by varying the steady state inefficiency parameter

Variable	Symbol	$\theta_{ss}^N = 0$	$\theta_{ss}^N = 0.001$	$\theta_{ss}^N = 0.065$
Interest Rate Spread, annualized in basis points	$R^k - R$	100	108	716
Return on Capital, annualized in percentage points	R^k	5.04	5.12	11.20
Leverage Ratio	ϕ	4.000	4.003	4.172
Net worth/Output	N/Y	2.194	2.193	2.104
Labor	L	2.831	2.796	1.499
Capital/Output	K/Y	8.780	8.718	6.227
Investment/Output	I/Y	0.219	0.218	0.156
Consumption/Output	C/Y	0.581	0.586	0.908

In the simulations we conduct in the next sections the low and the high inefficiency regimes become important. For the simulations we activate four different shocks: monetary policy shock, total factor productivity, capital quality shock, and a transitory shock to the inefficiency in the banking sector. The autoregressive parameters and the standard deviation of the shocks are calibrated to roughly match the volatility of output growth in the US during the period 1984-2014 (see Tables 6 and 9 in the appendix).[8]

5 The learning mechanism

There are many ways to implement imperfect information and learning. We rely on the approach by Cogley, Matthes, and Sbordone (2015), which is rather intuitive and fits the description of the data pretty well. We therefore keep the learning very close to full information rational expectations and allow only one slight deviation from that. In particular the model is completely known to the agents and they are able to observe

[8]We start in 1984 because we exclude the period of disinflation at the beginning of the 1980s.

all relevant economic outcomes. Those outcomes are then used to filter out the one unknown value in the model which is the steady state value in the AR process governing the inefficiency of net worth θ. This process is characterized by two parameters and the standard deviation of its innovation. We assume that agents know both the standard deviation and also the autoregressive parameter ρ^{θ} while the only thing in the process and the whole model which is uncertain to the agents is the potentially time varying value of this steady state of θ.[9] As mentioned before, all economic agents know the rest of the economy i.e. both the structure and the rest of all parameters. Another important assumption with respect to aggregation is that all private agents share the same beliefs about the inefficieny parameter and henceforth update their identical information. The updating step is carried out with the Kalman filter. We can write the state space system in the following form where the observation equation is given by

$$\mathbf{log}\left(\theta_{\mathbf{t}}^{\mathbf{N}}\right) = \hat{\theta}_t^N + \rho^{\theta}\mathbf{log}\left(\theta_{\mathbf{t-1}}^{\mathbf{N}}\right) + \epsilon_{\mathbf{t}}^{\theta} \tag{34}$$

and the state equation by

$$\hat{\theta}_t^N = \hat{\theta}_{t-1}^N + 1_t \nu_t \tag{35}$$

with $\hat{\theta}_t^N = \left(1-\rho^{\theta}\right) log\left(\bar{\theta}_t^N\right)$. It is obvious that the observation equation is given by the AR(1) process for net worth inefficiency whereas the state equation determines the dynamics of the constant for the steady state value for $\bar{\theta}_t^N$ over time.[10]

The i.i.d. disturbance of the observation equation is denoted by ϵ^{θ}, which is normally distributed with mean zero and a standard deviation of 0.01 which is also known by the agents. For the state equation we assume a random walk for $\hat{\theta}_t^N$ which is common in the literature and means that the best guess for agents in any period is last period's value. Having specified the variance in the AR-process which is also referred to as the noise in the signal extraction literaure another key assumption is to set the variance of the state equation. We assume that it is positive over the whole simulation horizon which means that agents expect a change in the constant in every period and update it accordingly. This is what we understand as the signal which initiates learning. The variance of $\nu_{\mathbf{t}}$ is calibrated to be a function of the parameter the agents estimate. In particular we set it to be $\nu_t = (0.0025\hat{\theta}_t^N)^2$, but experiment with other values for robustness checks as well. (Motivate better the Calibration!). In addition, to be more in line with the empirical results from above, we let agents learn at the peak of the crisis in 2008Q3. This is done by the indicator function 1_twhich can take two values: 0 and 1. For the periods until the peak of the crisis we set it to zero and induce no signal at all until this point. From then onwards to the end of the sample length the indicator function takes the value 1. This means we let the agents receive signals every period and update their beliefs accordingly.

The timing convention of each iteration is a key assumption in this setup. First all economic agents enter period t with the belief of a certain steady state of net worth inefficiency which stems from last period's updating step. Then, given this perceived state which determines all the other steady states in the economy as well, households and

[9]It is important to remember that we write the whole model in logs and not in deviations from their respective steady state values. For a complete overview over all equations of the model and their respective constants we refer the reader to the Appendix.

[10]Agents have knowledge over the functional form of the constant and also about the value of the autoregressive parameter. Therefore they can back out the parameter value for the steady state.

firms carry out all optimization steps based on their perceived steady state values as if those values hold forever. This assumption is called anticipated utility and was originally developed by Kreps (1998). This simplifying assumption is standard in many studies in the learning literature (see for example Milani (2007)). With all optimal decisions the true steady state of net worth inefficiency $\bar{\theta}_t^N$ realizes. Either bankers become more or less inefficient in a certain period or stay exactly the same as the period before. In a next step not only the inefficiency shock but also the other three shocks happen randomly. With the banking variables now obvious to the agents and particularly the new inefficieny value θ_t^N all agents try to deduct whether the change was due to the innovations or a new value in the steady state. They are faced with a signal-extration problem. With the updating step in the Kalman Filter they enter period t+1 with a new belief of what the steady state might look like. We start agents out with the true steady state in period one. In subsequent periods we use the posterior mean of the Kalman filter from last period for the belief.

Many studies (see for example Cogley et al., 2015) rely on projection facilities to ensure stationarity in the perceived law of motion. We formally check for stationarity after every iteration and as we change just one parameter and the alterations are small enough we do not have to worry about stationarity issues at all and can avoid using those kind of projection facilities when generating our perceived law of motion (PLM).

In order to obtain first the perceived law of motion and later the actual law of motion we start out by stacking all variables including the constant intercept in a vector $\mathbb{X}_\mathbf{t}$. Then we log-linearized the model around the perceived inefficiency steady state and write it in the system based form in the following way:

$$\mathbf{A}(\hat{\theta}^\mathbf{N}_\mathbf{t-1})\mathbb{X}_\mathbf{t} = \mathbf{B}(\hat{\theta}^\mathbf{N}_\mathbf{t-1})\mathbf{E}^*_\mathbf{t}\mathbb{X}_\mathbf{t+1} + \mathbf{C}(\hat{\theta}^\mathbf{N}_\mathbf{t-1})\mathbb{X}_\mathbf{t-1} + \mathbf{D}\varepsilon^*_\mathbf{t} \tag{36}$$

with $\varepsilon^*_\mathbf{t}$ as the perceived shock. Those are the innovations the agents observe and the shock on the inefficiency of net worth contains thereby the actual shock $\tilde{\varepsilon}_\mathbf{t}$(which is the residual in the AR(1) process). As a result we can express the perceived shock as the actual inefficiency shock and the additional error component which stems from the agents' estimation.

$$\varepsilon^*_\mathbf{t} = \tilde{\varepsilon}_\mathbf{t} + \left(\hat{\theta}_t^N - \hat{\theta}_t^{N,true}\right).$$

The closer the perceived steady state is to the true steady state ie. the better the estimation is carried out by the agents, the closer is the actual shock also approaching the perceived shock. Given that the system exhibits expectations we solve it numerically with the gensys routine developed by Sims (2001). The recursive result hinges on the perceived inefficiency and is therefore termed the perceived law of motion and can be expressed as:

$$\mathbb{X}_\mathbf{t} = \mathbf{S}(\hat{\theta}^\mathbf{N}_\mathbf{t-1})\mathbb{X}_\mathbf{t-1} + \mathbf{G}(\hat{\theta}^\mathbf{N}_\mathbf{t-1})\varepsilon^*_\mathbf{t} \tag{37}$$

where $\mathbf{S}(\hat{\theta}^\mathbf{N}_\mathbf{t-1})$ is the solution to the matrix quadratic equation.

$$\mathbf{S}(\hat{\theta}^\mathbf{N}_\mathbf{t-1}) = (\mathbf{A}(\hat{\theta}^\mathbf{N}_\mathbf{t-1}) - \mathbf{B}(\hat{\theta}^\mathbf{N}_\mathbf{t-1})\mathbf{S}(\hat{\theta}^\mathbf{N}_\mathbf{t-1}))^\mathbf{-1}\mathbf{C}(\hat{\theta}^\mathbf{N}_\mathbf{t-1}) \tag{38}$$

and with $\mathbf{G}(\theta^\mathbf{C}_\mathbf{t-1})$ given by

$$\mathbf{G}(\hat{\theta}^\mathbf{N}_\mathbf{t-1}) = (\mathbf{A}(\hat{\theta}^\mathbf{N}_\mathbf{t-1}))^\mathbf{-1}\mathbf{D}. \tag{39}$$

In a second step we are interested in the actual law of motion. Therefore we substitute the perceived constant of the AR process for the inefficieny of net worth in the matrix $\overline{\mathbf{C}}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})$ by the actual constant. By the same token we also use the actual innovation of the inefficiency AR process.

$$\overline{\mathbf{A}}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\overline{\mathbf{Y}}_{\mathbf{t}} = \overline{\mathbf{B}}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\mathbf{E}^{*}_{\mathbf{t}}\overline{\mathbf{Y}}_{\mathbf{t+1}} + \overline{\mathbf{C}}^{\mathbf{actual}}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\overline{\mathbf{Y}}_{\mathbf{t-1}} + \overline{\mathbf{D}}\varepsilon_{\mathbf{t}}. \tag{40}$$

Given that we previously found the perceived law of motion we can now easily solve for the expectations and obtain:

$$\overline{\mathbf{Y}}_{\mathbf{t}} = H(\hat{\theta}^{N}_{t-1})\overline{\mathbf{Y}}_{\mathbf{t-1}} + G(\hat{\theta}^{N}_{t-1})\varepsilon_{t}. \tag{41}$$

Obviously matrix $H(\hat{\theta}^{N}_{t-1})$ that determines the actual outcomes is now composed both by the deviation of the true from the perceived steady state. As the difference between the two vanishes over time the last term drops out and the actual outcomes are governed by the perceived ones which are close to the true steady state respecively the full information setup.

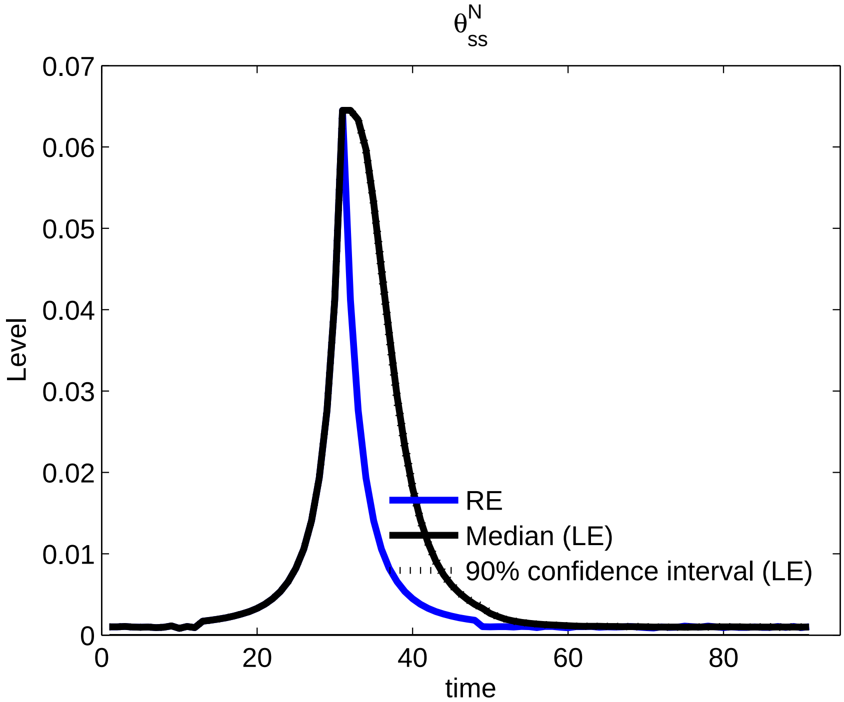
$$H(\hat{\theta}^{N}_{t-1}) = S(\hat{\theta}^{N}_{t-1}) + \left(A(\hat{\theta}^{N}_{t-1}) - B(\hat{\theta}^{N}_{t-1})S(\hat{\theta}^{N}_{t-1})\right)^{-1}(C^{true}(\hat{\theta}^{N}_{t-1}) - C(\hat{\theta}^{N}_{t-1})) \tag{42}$$

6 Experiment

Given the model and the way we set up the updating of expectations based on the arrival of new information about banks' net worth we proceed by describing the simulation exercise that we perform next. As θ^{N} is the variable of interest that determines the (in)efficiency of net worth we generate a certain path for this variable over time. In the beginning of the simulation inefficiency is very low and follows a random walk around its mean but once the crisis breaks out inefficiency increases and reaches a maximum after a couple of periods and falls back to its original level and follows a random walk for the rest of the simulation period. This is the structural development of the inefficiency of the banking system during this time. In addition, we allow for transitory changes which can further worsen or even improve the efficiency of the banking sector. The period we have in mind is the financial crisis, i.e. we try to mimic this episode by as well as possible capturing the spread which is related very closely to the variable with a curve, which is convex to the LHS and concave to the RHS, by the inefficiency variable. The true steady state of the inefficiency corresponds to the rational expectations value and is depicted by the blued curve in Figure 3. The related pattern comes close to the evoluation of the credit spread during the crisis. The frequency is quarterly. The starting period corresponds accordingly with the beginning of the new millenium whereas the end of the simulation does not coincide with most recent data since we are taking more periods following the crisis in our simulation into account.

For the rational expectations case we simulate the model with its steady state 500 times. In the learning case we proceed identically with the only difference that the actual steady state is not known and must be inferred by the agents. Out of 500 simulations the resulting perceived median steady state value for θ^{N} is then given in Figure 3 by the black line. As can be seen the shape of the perceived value of the inefficiency parameter follows

Figure 3: Actual and perceived inefficiency of Net Worth



Note: The graph shows the actual and perceived steady state of theta over time. The hump in the middle tries to mimic the financial crisis with an increase in the inefficiency of net worth. The perceived steady state follows closely but reacts with a certain lag to the true behavior.

closely the true values but with a certain time lag. In the beginning of the simulation period the perceived inefficiency is equivalent to the true one as agents start updating only towards the peak of the crisis. Once inefficiency reaches its maximum agents with the last periods' observation overshoot slightly and perceive a higher inefficiency than the true one. As a result, the peak of the perceived steady state value for θ^N is about half a year after the true peak. Once inefficiency decreases rapidly agents react with a certain lag to the true deviation in net worth inefficiency. Thus, they need time to learn about the true value. This phenomenon leads not only to a lagged profile but also a less steep and lower peak of the inefficiency. The effects of the difference between both types of expectation formations are displayed and explained in the next section.

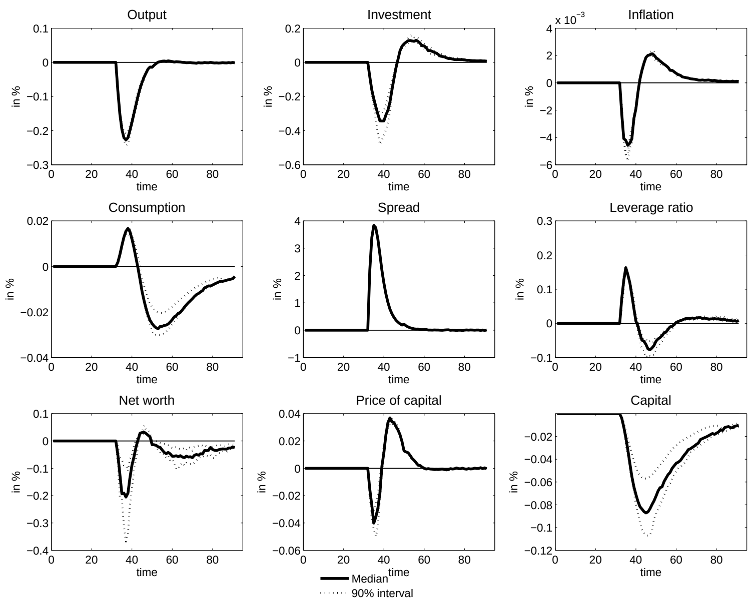
7 Results of simulation

With the paths for the actual and the perceived θ_t^N we have a look at the rest of the simulated variables in our economy.[11] First of all the pattern of both the rational expectations variables and the variables under learning follow the one given by θ_t^N quite closely. Up until the peak of the crisis there is nothing much to detect in the learning framework (as the perceived θ_t^N is following the true one). Therefore in Figure 4 where

[11] For a complete profile of all variables in the system under learning we refer the reader to Figure 9 in the appendix where both the median and the error bands are plotted.

we subtract the median of learning from the median of rational expectations variables there is a no deviation between the two approaches up until period 30. The raise in the inefficiency in the banking sector depresses banks' net worth which results in an increase of the leverage ratio (see Figure 5). In the following banks cut their credit supply for initializing a deleveraging process. As a consequence, the interest rate spread widens and makes investment into capital more costly so that output falls in the end. Output is to a large extent driven by investment the whole time. The reduction in output also puts downward pressure on the rate of inflation. The interesting part is then from period 30 onwards. A countermovement is initialized when the efficiency in the banking sector improves again, i.e. after reaching the peak of the crisis.

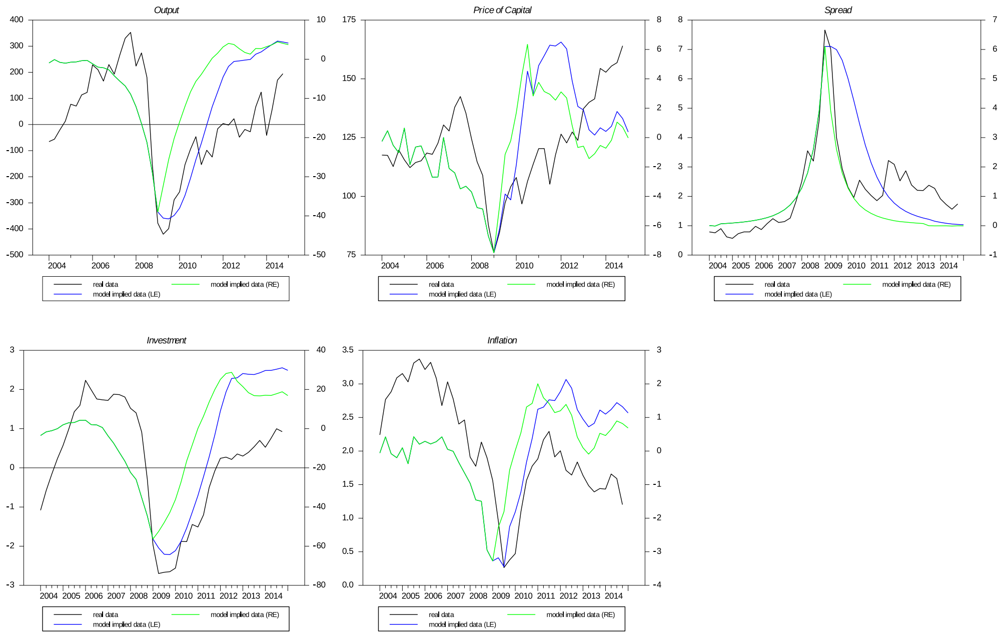
Figure 4: Comparison of outcomes under learning and under rational expectations



Note: This graph shows the difference between the outcomes under learning and rational expectations.

As described above the crisis takes around two years to form and another two years to unwind. After a rougher slump the recovery would be a lot faster and also much smoother. The reason is that agents cannot observe the improvement in net worth exactly at the time when it occurs. Consequently, they provide less funds to the banking sector although the banking sector is already in a better shape. To quantify the results output is around 0.4% lower after the end of the crisis. So the downward spiral which ensues endogenously in our setup is responsible for the prolonged recovery. This is partly due to the heavily diminished investment which is around 1.5% lower than under rational expectations. The same holds true for capital that is also for a prolonged time significantly lower in the aftermath of the crisis. It is important to keep in mind that those results are by no means absolute values but all relative ones where both expectation formations are compared. An essential result is here the asymmetry of many variables both in terms of shape, longevity and also quantitative peaks. The negative peak and duration is much longer under learning than under full information. This speaks for a prolonged adjustment and very slow recovery.

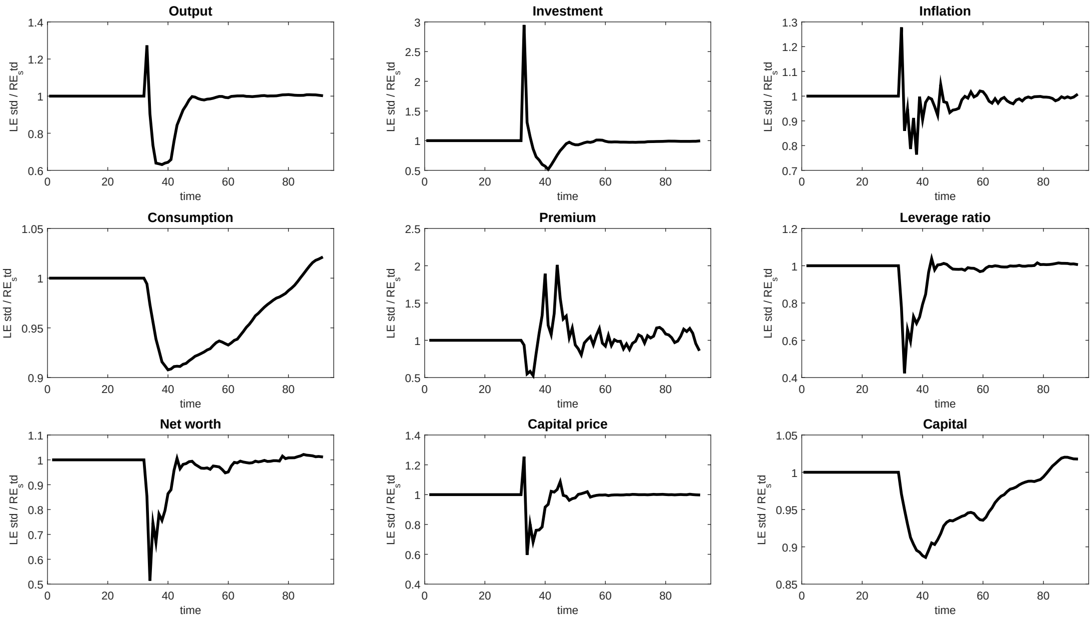
Figure 5: Outcomes of macroeconomic variables for learning (LE), and rational expectations (RE) contrasted with real data



Note: This graph shows the outcomes of the simulations and compares them with real data (solid black lines) for various macroeconomic variables. Learning is reflected by the blue lines and rational expectations by the green lines.

The most slowly moving variable is clearly capital. The first twenty-five periods there is no difference between full information and imperfect information. It diminishes after the end of the crisis and even at the end of the simulation period it has not caught up with the rational expectations value of capital. Due to the strong and prolonged negative reaction in investment this is not surprising. Although most variables are back to their long run mean and more or less equal between both expectations formations capital is at the end of the simulation horizon still below its full information threshold. The slow recovery is therefore also characterized by a slow and inadequate capital formation after the financial crisis. Even varying the starting point at which agents begin updating a few quarters and playing around with the strength of the signal is quite robust. For all those robustness checks the slow recovery, however, is a fact. Hence, we can theoretically show the consequences of the results we derived from our empirical exercise from Section 2adopted in the structural approach. Comparing the outcomes of the rational expectations framework and the learning case we constrast them to real data over the past ten years (see Figure 5). As shown earlier the slow recovery is exclusively seen in the learning case. Unlike the rational expectations we are able to match the data for output, investment and partly also inflation quite well. Also the price of capital is much better captured by the imperfect information case. Due to the fact that agents believe the inefficiency to be more elevated and slower decreasing over time the spread in the economy is much better matched which translates to a closer fit of all the other macroeconomic variables.

Figure 6: Standard Deviation/ respectively uncertainty over time



Note: This graph shows the standard deviation for each variable over time comparing the error bands of the learning approach with those of the rational expectations paradigm. Whenever the value exceeds one learning exhibits more uncertainty, whenever the value is below one rational expectations shows more volatility. At the height of the crisis imperfect information yield higher uncertainty, while in the recovery (although slow, see Figure 4) uncertainty is diminished.

With respect to the uncertainty of imperfect information relative to rational expectations the overall picture in Figure 6 is that imperfect information yields higher uncertainty especially at the very beginning of and during the crisis. Once the actual peak of the inefficiency is reached most variables' volatility is decreasing along with the actual outcomes. As a result we witness a slow recovery with an adjustment to the originial steady state that takes longer than under full information but during this time the uncertainty is also lower than under rational expectations. So despite a prolonged recovery the volatility is reduced. There is one variable, however, that sticks out and is an exception to this overall result. The volatility of the premium exhibits an upward trend from the very beginning and recedes slowly and only slightly during the crisis while afterwards its volatility picks up again to reach a threefold increase in the volatility compared to rational expectations in the end.

8 Conclusion

In this paper we offer an additional reason why the recovery in the US was so slow after the financial crisis. First of all we show empirically that there is an information bias about the net worth of banks during and in the aftermath of the financial crisis and agents update information with learning. Based upon these findings we take a macro-finance model with a prominent role for an active banking sector and relax perfect information in this rational expectation framework in order to introduce imperfect information about banks' net worth. With this model setup we try to replicate the financial crisis with its slow recovery. We find that due to imperfect information about banks' net worth output is higher during the crisis than it would be under rational expectations, i.e. the crisis would have been harder if there was no learning but the recovery would have been much more faster nevertheless. Also uncertainty in the slow recovery is significantly smaller than under rational expectations. The key mechanism in our model is related to our empirical results. Agents cannot observe the true net worth of banks. When the crisis is evolving, the deterioration of net worth is overstimated while it is underestimated during the recovery which is the reason for the slow recovery in our model. We do not want to argue that imperfect information is the key factor for the slow recovery, however, our results put another layer on the understanding of the slow recovery.

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A Log-Linearized Model

$$
\begin{aligned}
UPS_{ss}log(ups_t) &= (1-\theta)\beta(RK_{ss}E_tlog(rk_{t+1}) - R_{ss}log(r_t)) + (1-\theta)\beta(RK_{ss} - R_{ss})E_tlog(uct_{t+1}) \\
&\quad +\beta\theta XT_{ss}UPS_{ss}(E_tlog(uct_{t+1}) + E_tlog(xt_{t+1}) + E_tlog(ups_{t+1})) \\
log(eta_t) &= \beta\theta ZT_{ss}(E_tlog(uct_{t+1} + E_tlog(zt_{t+1} + log(eta_{t+1})) \\
log(xt_t) &= log(\phi_t) - log(\phi_{t-1}) + log(zt_t) \\
log(q_t) &= \eta^i(log(in_t) - log(in_{t-1})/I_{ss} - \beta UCT_{ss}\eta^i(E_tlog(in_{t+1} - log(in))/I_{ss} \\
Y_{ss}log(y_t) &= C_{ss}log(c_t) + I_{ss}log(i_t) \\
log(uct_t) &= log(uc_t) - log(uc_{t-1}) \\
log(\pi_t^*) &= log(f_t) - log(z_t) \\
Z_{ss}log(z_t) &= Y_{ss}log(y_t) + \beta\gamma UCT_{ss}\pi_{ss}^{(}\gamma^p - 1)Z_{ss}(E_tlog(uct_{t+1}) + \gamma^p log(\pi_t) - log(\pi_{t-1}) + E_tlog(z_{t+1})) \\
log(rn_t) &= \rho^i log(rn_{t-1}) + (1-\rho^i)(\kappa_p ilog(\pi_t) + \kappa_x log(x_t) + \epsilon_t^{rn} \\
log(rk_t) &= log(XXI_t) + \frac{1}{RK_{ss}}(\alpha\frac{Y_{ss}}{K_{ss}}(-log(x_t) + log(y_t) - log(k_{t-1}) - log(xxt_t)) + log(q_t) - DEP_{ss}log(dep_t)) \\
&\quad -log(q_{t-1}) \\
ZT_{ss}log(zt_t) &= PHI_{ss}(RK_{ss}log(rk_t) - R_{ss}log(r_{t-1})) + PHI_{ss}(RK_{ss} - R_{ss})log(\phi_{t-1}) + R_{ss}log(r_{t-1}) \\
log(\eta_t) &= \frac{\phi_{\{ss\}}\lambda_{ss}}{ups_{ss}}(log(\phi_t) + log(\lambda_t) + log(ups_t) \\
log(q_t) + log(k_t) &= log(\phi_t) + log(n_t) \\
N_{ss}log(n_t) &= NE_{ss}log(ne_t) + NN_{ss}log(nn_t) \\
log(ne_t) &= log(zt_t) + log(n_{t-1}) \\
log(nn_t) &= log(q_t) + log(xxi_t) + log(k_{t-1}) \\
log(y_t) &= log(a_t) + \alpha log(u_t) + \alpha log(xxi_t) + \alpha log(k_{t-1}) + (1-\alpha)log(l_t) \\
\frac{DEP_{ss}}{(DEP_{ss} - \delta_c)}log(dep_t) &= (1+\vartheta)log(u_t) \\
-log(x_t) + log(y_t) - log(u_t) &= \vartheta log(u_t) + log(xxi_t) + log(k_{t-1}) \\
log(in_t) &= I_{ss}log(i_t) - DEP_{ss}K_{ss}(log(k_{t-1}) + log(xxi_t) + log(dep_t)) \\
K_{ss}log(k_t) &= K_{ss}log(k_{t-1}) + K_{ss}log(xxi_t) + log(in_t) \\
log(uc_t) &= -\frac{1}{((1-\beta h)(1-h))}(log(c_t) - hlog(c_{t-1}) - \beta h(E_tlog(c_{t+1}) - hlog(c_t))) \\
E_t(log(uct_{t+1}) + log(r_t) &= 0 \\
-log(x_t) + log(y_t) - log(l_t) &= -log(uc_t) + \varphi * log(l_t) \\
-log(x_t) &= log(pim_t) - log(\pi) \\
F_{ss}log(f_t) &= Y_{ss}PIM_{ss}(log(y_t) + log(pim_t)) + \beta\gamma UCT_{ss}F_{ss}(E_tlog(uct_{t+1} + log(\pi_t) - log(\pi_{t+1}) + E_tlog(f_{t+1})) \\
log(\pi_t) &= \gamma\gamma^p log(\pi_{t-1}) + (1-\gamma)log(\pi_t^*) \\
log(rn_t) &= log(r_t) + E_tlog(\pi_{t+1}) \\
log(IRS_t) &= E_tlog(rk_{t+1}) - log(r_t) \\
log(a_t) &= \rho_a log(a_{t-1}) - \epsilon_t^A \\
log(\xi_t) &= \rho_\xi log(\xi_{t.-1}) - \epsilon_t^\xi \\
log(\lambda) &= \rho_\lambda log(\lambda_{t-1}) - \epsilon_t^\lambda
\end{aligned}
$$

with the constants given by:

Constant	Expression
$Const_{UPS}$	$-(1-\theta)\beta RK_{ss}log(RK_{ss})+(1-\theta)\beta R_{ss}log(R_{ss})-((1-\theta)\beta(RK_{ss}-R_{ss})$
	$+\beta\theta XT_{ss}UPS_{ss})log(UCT_{ss})-\beta\theta XT_{ss}UPS_{ss}log(XT_{ss})-(\beta\theta XT_{ss}UPS_{ss}-UPS_{ss})log(UPS_{ss})$
$Const_{\eta}$	$(1-\beta\theta ZT_{ss})log(ETA_{ss})-\beta\theta ZT_{ss}(log(UCT_{ss})+log(ZT_{ss}))$
$Const_{XT}$	$log(XT_{ss})-log(ZT_{ss})$
$Const_{IN}$	$-log(Q_{ss})$
$Const_{C}$	$-log(Y_{ss})+\frac{C_{ss}}{Y_{ss}}log(C_{ss})+\frac{I_{ss}}{Y_{ss}}log(I_{ss})$
$Const_{UCT}$	$log(UCT_{ss})$
$Const_{F}$	$log(F_{ss})-log(Z_{ss})-log(\Pi^{*}_{ss})$
$Const_{Z}$	$-Y_{ss}log(Y_{ss})-\beta\gamma UCT_{ss}\Pi_{ss}^{(\gamma_p-1)}Z_{ss}(log(UCT_{ss})+(\gamma_p-1)log(\pi_{ss}))$
	$-(\beta\gamma UCT_{ss}\Pi_{ss}^{(\gamma_p-1)}Z_{ss}-Z_{ss})log(Z_{ss})$
$Const_{\Pi}$	$(1-\rho_i)\kappa_{\pi}log(\Pi_{ss})+(1-\rho_i)\kappa_x log(X_{ss})-(1-\rho_i)log(RN_{ss})$
$Const_{RK}$	$log(RK_{ss})-log(XXI_{ss})-\frac{1}{RK_{ss}}(\alpha\frac{Y_{ss}}{K_{ss}})(-log(X_{ss})+log(Y_{ss})-log(K_{ss})$
	$-log(XXI_{ss}))-\frac{1}{RK_{ss}}log(Q_{ss})+\frac{1}{RK_{ss}}DEP_{ss}log(DEP_{ss})+log(Q_{ss})$
$Const_{\Phi}$	$-log(ETA_{ss})+PHI_{ss}\frac{\lambda_{ss}}{UPS_{ss}}(log(PHI_{ss})+log(\lambda_{ss})-log(UPS_{ss}))$
$Const_{ZT}$	$ZT_{ss}log(ZT_{ss})-PHI_{ss}RK_{ss}log(RK_{ss})+(PHI_{ss}RK_{ss}R_{ss}-R_{ss})log(R_{ss})$
	$-log(PHI_{ss})(PHI_{ss}(RK_{ss}-R_{ss}))$
$Const_{Q}$	$log(Q_{ss})+log(K_{ss})-log(PHI_{ss})-log(N_{ss})$
$Const_{N}$	$N_{ss}log(N_{ss})-NE_{ss}log(NE_{ss})-NN_{ss}log(NN_{ss})$
$Const_{NE}$	$log(NE_{ss})-log(ZT_{ss})-log(N_{ss})$
$Const_{NN}$	$log(NN_{ss})-log(Q_{ss})-log(XXI_{ss})-log(K_{ss})$
$Const_{Y}$	$log(Y_{ss})-log(AA_{ss})-\alpha log(U_{ss})-\alpha log(XXI_{ss})-\alpha log(K_{ss})-(1-\alpha)log(L_{ss})$
$Const_{DEP}$	$\frac{DEP_{ss}}{(DEP_{ss}-\delta)}log(DEP_{ss})-(1+\vartheta)log(U_{ss})$
$Const_{U}$	$(-1-\vartheta)log(U_{ss})+log(Y_{ss})-log(X_{ss})-log(XXI_{ss})-log(K_{ss})$
$Const_{I}$	$I_{ss}log(I_{ss})-DEP_{ss}K_{ss}(log(K_{ss})+log(XXI_{ss})+log(DEP_{ss}))-log(IN_{ss})$
$Const_{K}$	$-log(XXI_{ss})-\frac{IN_{ss}}{K_{ss}}log(IN_{ss})$
$Const_{UC}$	$log(UC_{ss})$
$Const_{R}$	$log(R_{ss})+log(UCT_{ss})$
$Const_{L}$	$(1+\varphi)log(L_{ss})-log(UC_{ss})-log(Y_{ss})+log(X_{ss})$
$Const_{X}$	$-log(X_{ss})-log(PIM_{ss})+log(\Pi_{ss})$
$Const_{PIM}$	$log(F_{ss})(-F_{ss}+\beta\gamma UCT_{ss}F_{ss})+\beta\gamma UCT_{ss}F_{ss}log(UCT_{ss})$
	$+Y_{ss}PIM_{ss}(log(PIM_{ss})+log(Y_{ss}))$
$Const_{\Pi^*}$	$log(\Pi^{*}_{ss})(1-\gamma)-(1-\gamma\gamma_p)log(\Pi_{ss})$
$Const_{RN}$	$log(RN_{ss})-log(R_{ss})-log(\Pi_{ss})$
$Const_{IRS}$	$log(IRS_{ss})-log(RK_{ss})+log(R_{ss})$
$Const_{AA}$	$log(AA_{ss})(1-\rho_a)$
$Const_{XXI}$	$log(XXI_{ss})(1-\rho_i)$
$Const_{\lambda}$	$log(\lambda_{ss})(1-\rho_{\lambda})$

B Calibration

Table 8: Calibrated Parameters of the model

Description	Symbol	Value
Autoregressive parameter. capital quality shock	ρ_ξ	0.66
Autoregressive parameter. incentive shock	ρ_λ	0.98
Autoregressive parameter. total factor productivity	ρ_A	0.7
Standard deviation. monetary policy shock	σ_i	0.002
Standard deviation. capital quality shock	σ_ξ	0.008
Standard deviation. incentive shock	σ_λ	0.01
Standard deviation. total factor productivity	σ_A	0.0138

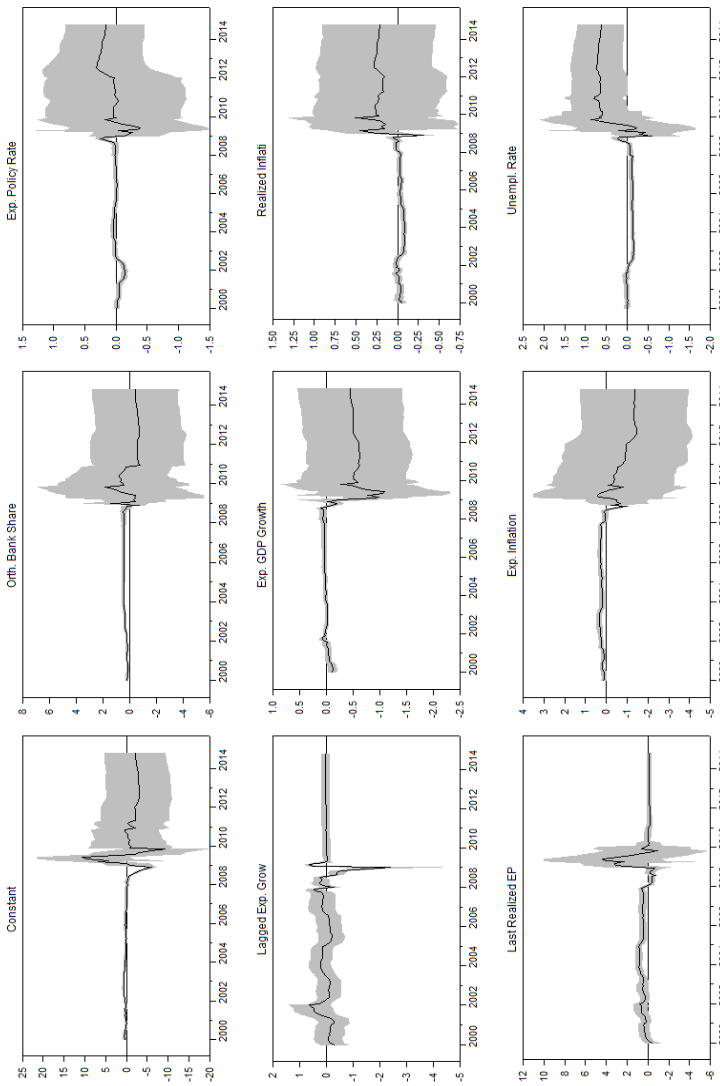
Table 9: Second moments of central variables

		USA (Q1-1984 to Q1-2014)	Model
Output growth. annualized	$SD\,(\Delta Y/Y)$	2.48	2.48
Investment growth. annualized	$SD\,(\Delta I/I)$	7.57	9.99
Rate of inflation. annualized	$SD\,(\pi)$	0.97	0.9
Output growth. investment growth	$corr\,(\Delta Y/Y,\, \Delta I/I)$	0.7	0.97
Output growth. inflation	$corr\,(\Delta Y/Y,\, \pi)$	0.12	0.09

Data: U.S. Bureau of Economic Analysis. Output growth. investment growth. and the rate of inflation are measured quarterly and then annualized. Model moments are simulated over a period of 1000 observations.

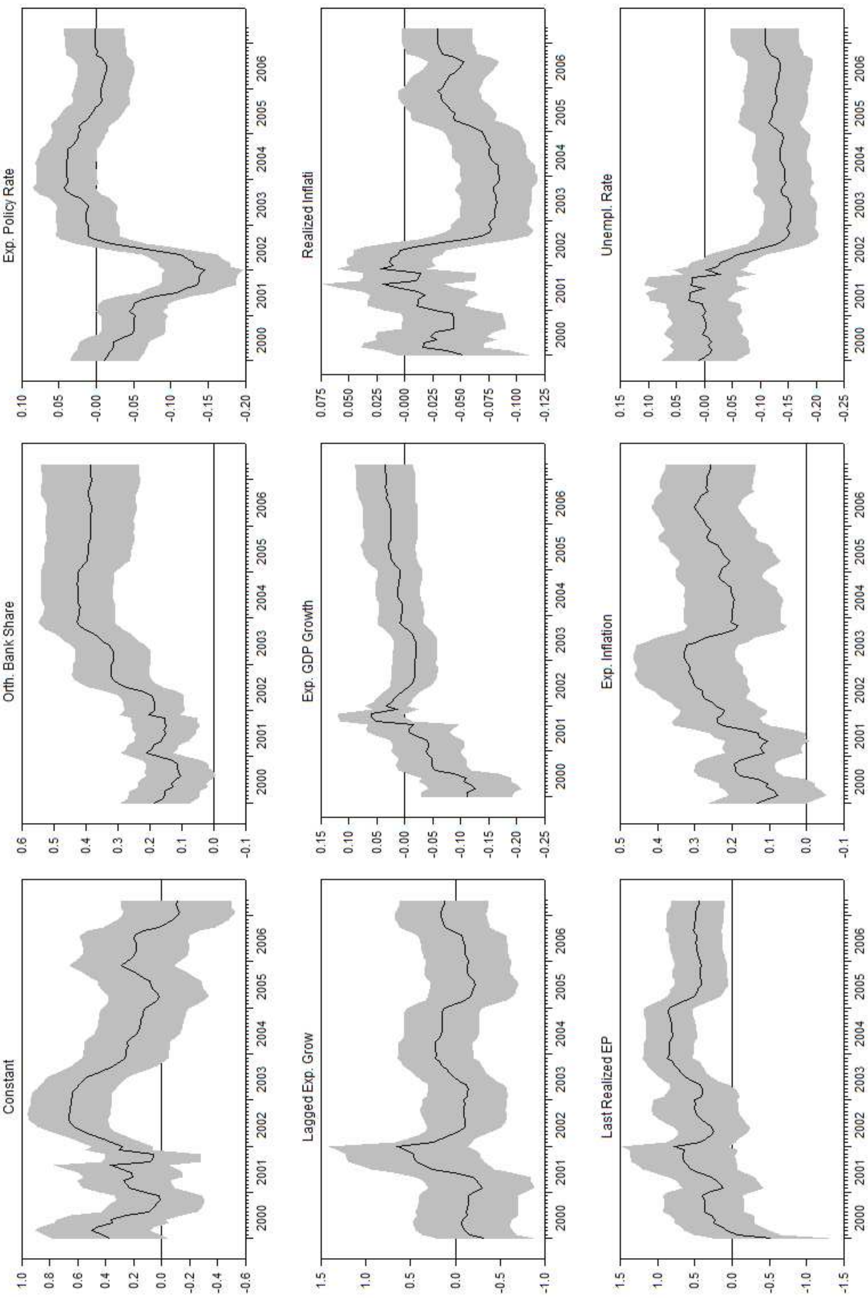
C Additional Figures

Figure 7: Time-varying parameters for the explaining the expected annual earnings per share growth (full sample)



The graph shows the estimated time-varying coefficients for the twelve months ahead growth expectations. The estimates stem from a Kalman filter regression. The shaded areas is the confidence interval based upon the 90% level.

Figure 8: Time-varying parameters for the explaining the expected annual earnings per share growth (pre-financial crisis)



The graph shows the estimated time-varying coefficients for the twelve months ahead growth expectations. The estimates stem from a Kalman filter regression. The shaded areas is the confidence interval based upon the 90% level.

Figure 9: Simulation outcomes under learning