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Learning about banks' net worth and the slow recovery after the financial crisis

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Non-technical summary

Research Question

Despite uncertainty about the future stance of the real economy in conjunction with an imperfect assessment of banks' soundness, most of the explanations for the slow recovery discard information processing of economic agents. During normal times it is known that information processing is not free of frictions. Given that the onset of the recession was at least partly due to heightened uncertainty about financial sector developments, we ask in this paper to which extent the imperfect assessment of banks' soundness was responsible for the slow recovery.

Contribution

We are the first to examine what kind of information rigidity prevails in financial markets over time and to incorporate this type of information rigidities into a macroeconomic general equilibrium model. We focus on the two well-established forms of information rigidities that have been found to characterize expectations about inflation and test for them in the financial market. 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 given by survey data.

Results

We find that expectations about banks' profitability are severely and significantly biased, particularly during the financial crisis. Before and after the financial crisis, profits are structurally underestimated, whereas the opposite is true for the financial crisis. The forecast error of professional analysts cannot be attributed to sticky information but rather to noisy information. The updating of new information is characterized by learning about past data, while during the onset of the crisis between 2007 and 2008 the speed of updating drops significantly. Comparing then the evolution of key macro variables under full information and incomplete information in relation to the true data, we clearly see that the latter is much better able to replicate the slow recovery.

Nichttechnische Zusammenfassung

Fragestellung

Trotz hoher Unsicherheit über die zukünftige Entwicklung der Ökonomie zusammen mit einer unvollkommenen Einschätzung über den Zustand der Banken, vernachlässigen die meisten Erklärungen für die langsame Erholung der Volkswirtschaft nach der Krise die Informationsverarbeitung von Wirtschaftssubjekten. Es ist bekannt, dass auch während normalen Zeiten die Informationsverarbeitung nicht ohne Friktionen abläuft. Da zumindest der Beginn der Rezession teilweise durch eine erhöhte Unsicherheit über Entwicklungen auf dem Finanzmarkt ausgelöst wurde, fragen wir in diesem Papier, bis zu welchem Grad eine unvollkommene Einschätzung der Kreditwürdigkeit der Banken für die langsame Erholung verantwortlich war.

Beitrag

Wir untersuchen, welche Art von Informationsrigidität auf dem Finanzmarkt über die Zeit dominiert hat und bauen diese Informationsfriktion in ein makroökonomisches Gleichgewichtsmodel ein. Wir beschränken uns dabei auf die zwei gängigen Formen von Informationsfriktionen, welche Inflationserwartungen charakterisieren und testen darauf im Finanzmarkt. Im Speziellen überprüfen wir, wie Informationen in Bezug auf Eigenkapital im Bankensektor verarbeitet werden und entsprechend Erwartungen gebildet werden. Wir messen die Erwartungen über Bankkapital durch Erwartungen über zukünftige Gewinne anhand von Umfragedaten.

Ergebnisse

Ein zentrales Ergebnis ist, dass die Erwartungen über die Profite im Bankensektor besonders während der Finanzkrise ernsthaft und signifikant verzerrt waren. Bevor und nach der Krise wurden Profite auf dem Finanzmarkt strukturell unterschätzt, wohingegen während der Krise das Gegenteil der Fall war. Der Vorhersagefehler von professionellen Analysten kann nicht auf starre, sondern auf gestörte Informationsverarbeitung zurückgeführt werden. Die tatsächlich genutzte Informationsmenge wird über ein Lernverhalten stetig angepasst. Die Geschwindigkeit dieser Überarbeitung fällt beim Beginn der Krise zwischen 2007 und 2008 signifikant ab. Wenn die Entwicklung von wichtigen makroökonomischen Zeitreihen unter voller und unvollständiger Informationsverabeitung mit den tatsächlichen Daten verglichen wird, beobachtet man bei letzterer eine deutlich bessere Nachbildung der langsamen Wirtschaftserholung.

Bundesbank Discussion Paper No 39/2016

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

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Abstract

In this paper, we examine the influence of information rigidities concerning the net worth of banks on the real economy over time. In a first part, we show empirically that expectations about the net earnings of banks (as growth of net worth) are truly biased, particularly during the financial crisis. The forecast error of professional investors cannot be attributed to sticky information but rather to noisy information. Investors display a learning behavior with regard to 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, by quantitatively incorporating this type of information updating and expectations formation about the net worth of banks, noisy information can produce a slow recovery compared to a full information rational expectation case.

Keywords: DSGE Model, Survey Data, Imperfect Information, Learning, Slow Recovery

JEL classification: E3, E44

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1 Introduction

As a consequence of the 2007-08 financial crisis, the US economy entered one of the deepest recessions for decades. The downturn was a result of a profound cut in the credit supply as the balance sheets of financial intermediaries were under pressure. Financial intermediaries faced severe liquidity problems as uncertainty about further losses from asset holdings stopped the provision of funds. The correct evaluation of current and future banks' soundness was one of the main reasons behind this development. An ensuing reduction in the credit supply eventually caused investment in capital to decline.

Besides the depth of the recession, which became known as the Great Recession, it also took much longer for the US economy to recover than after previous recessions. Empirically, this development can be attributed to further financial shocks or the persistency of the crisis shocks (Christiano, Motto, and Rostagno, 2014; Christiano, Eichenbaum, and Trabandt, 2015; Galí, Smets, and Wouters, 2012). More generally, heightened uncertainty about future economic growth and the financial health is often used to explain both the Great Recession and the slow recovery (see Bloom (2014) and the references therein). However, the definition of uncertainty is rather broad and imprecise. "Uncertainty" ultimately means that agents are unable to assess future developments with absolute precision. This can happen because future developments are not known, as they will result from future shocks or there is so much information and agents need to extract the relevant information from their information set. Given that there was uncertainty about the future stance of the real economy in conjunction with an imperfect assessment of banks' soundness, where both might be interrelated, most of the explanations for the slow recovery discard information processing. During normal times it is known that information processing is not free of frictions. Given that the onset of the recession was at least partly due to heightened uncertainty about financial sector developments, it seems an obvious matter to scrutinize the extent to which the imperfect assessment of banks' soundness was responsible for the slow recovery.

If information processing and expectation formation are impaired, consequences for real economic activity might automatically arise. As the banking sector stood at the center of the recession, the investigation of expectation formation should start from there. If agents need longer to correctly assess the situation in the banking sector, the credit supply needs longer to recover as banks are still receiving fewer funds. This might happen even though creditworthiness could actually have improved. Hence, the speed of the recovery is a consequence of the preceding crisis. In this paper, we analyse, in a first step, information processing by financial market participants with regard to the profit situation of banks in the United States over time in a first step and, in a second step, deduct the effects this had on the macroeconomy.

Given that economic agents have limitations in terms of how perfectly any available information can be processed, we generally make a distinction between different forms of updating information. In the macro literature some studies have incorporated incomplete information, so far only about inflation. One kind is information rigidities where only one part of agents can update information at any given point in time (see, for example, Mankiw and Reis, 2002) and the other is noisy information where all agents update constantly, but only estimate the underlying true values. The latter occurs because the agents are either bounded rational or rationally inattentive (Mackowiak and Wiederholt, 2009). The investigation of information processing in financial markets has a long history (see Fama (1970) or Shiller (2003), for instance), but, to our knowledge, we are the first to examine what kind of information rigidity prevails in financial markets over time and to incorporate this type of information rigidities into a macroeconomic framework. Although more forms of information processing certainly exist in the literature, we focus on the two well-established forms that have been found to characterize expectations about inflation and test for them in the financial market. 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, using survey data on expected earnings per share of the banking sector for the US, we show empirically that expectation formation seems to be unbiased for the banking sector over the entire time horizon starting in the mid-1990s and ending in 2015. This outcome might seem surprising against the backdrop of all the ups and downs in the financial sector. Therefore, we decompose the whole sample and allow for structural breaks. It follows that expectation formation is severely and significantly biased, particularly during the financial crisis. Before and after the financial crisis, profits are structurally underestimated, whereas the opposite is true for the financial crisis.

Since this result could be simply related to the size of the financial shock, we investigate information processing more carefully and are interested in figuring out the type of information rigidity that is responsible for this result. Thus, we regress the expectations error onto orthogonal shocks (coming from a VAR) that explain a large part of economic activity. The underlying idea goes back to Coibion and Gorodnichenko (2012) who test the type of information processing with respect to expected inflation. If, upon a shock, the resulting impulse responses are significant beyond the forecast horizon, we conclude that the information set of agents used to form expectations regarding the net worth of banks is incomplete. In a follow-up step, we apply a simple test in order to distinguish between noisy and sticky information. As the forecast dispersion is not systematically related to the shocks from the fundamentals, we can conclude that agents operate with the same information set. Therefore, we show by using the expectational error that information processing cannot be attributed to sticky information but rather to noisy information.

Starting from this result, it is possible to test whether agents learn about bank equity by deriving a time-varying Kalman gain for the agents' updating of the banks' net worth. At the beginning of the sample, it is not significantly different from one, which means that agents show nearly no learning behavior up to the crisis. This changes with the onset of the crisis between 2007 and 2008, where the Kalman gain drops to very low values before recovering nearly two years later. Up until the end, it is possible to reject the notion of full information rational expectations. By investigating information processing, we can show that agents adjust the mean expectations about bank profits during the crisis by looking at their expectation error, which is consistent with the notion of learning.

The second step takes the results from the first step and introduces a parsimonious structural model which includes some of the features that we found in the data and allows for macro-financial linkages. The working hypothesis is that the distribution of shocks is known to the agents and that all information is used to make optimal choices in the economy, but net worth can be observed only uncompletely. Agents filter the state of the one economic fundamental, net worth. This is how we include noisy information, as opposed to incomplete information where only a subset of agents are able to update their information set from time to time. Agents form expectations and learn about the true value of net worth over time. We calibrate stress in our model's banking sector roughly to the one in the data.

The advantage of knowing the time profile of agents' information processing from our first econometric steps allows us to simulate the economy with an empirical Kalman gain for each period over the past decade. Calibrating the signal-to-noise ratio in learning models is critical. One major contribution of this paper is to implement a new way of incorporating a time-varying Kalman gain as the underlying signal-to-noise ratio for the time profile of learning. Comparing then the evolution of key macro variables under full information and incomplete information in relation to the true data, we clearly see that the latter is much better able to replicate the slow recovery.

After the financial crisis had peaked, banks' net worth started to improve again. As agents update slowly and learn about the (in)efficiency only gradually, they use an outdated value for the efficiency of net worth and base their consumption and investment decision wrongly on the old value. Due to a higher perceived leverage ratio, deposits recover more slowly, which fuels this process. It takes some time for households to realize that they were off and to converge to the new true level of net worth, whereas a persistently higher credit spread in the meantime lowers investment and therefore output relative to the full information framework.

The paper is structured as follows: We start out to investigate the true nature of information processing and expectations formation in Section 2. Next, in Section 3, we discuss the non-standard part of our model, the way we introduce the empirical results in the model and how we simulate the crisis. We present all baseline results in Section 4. Section 5 concludes.

2 Information processing about the banking sector

2.1 (Un)biasedness of expectations

Our interest in this paper is in a first step in shedding light on how professional analysts form expectations about banks' profit situation which is linked to the build-up of bank equity or bank net worth. Bank equity is crucial for the determination of the leverage ratio and is therefore a central variable for the soundness of the financial system. 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 implications 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 as to how information is processed.

To investigate expectations formation and information processing in an empirical application for financial markets, one can rely on survey data collecting forecasts about future earnings reported by professional analysts. 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 weekly frequency for banks listed in the S&P 500 stock market index starting in January 1995. Within these surveys, analysts are asked to report their judgment about future earnings per individual bank. These earnings can be related to shares outstanding in order to allow easier comparisons across banks or firms. Concretely, we draw on the earnings per share, or short EPS, for which one year, two and three years ahead forecasts together with realizations are available. Although individual forecasts for specific banks are available, we are basically interested in the sector forecast which arises from aggregation. In order to account for the dispersion in expectations across analysts, we also look at the cross-sectional standard deviation. Since we will also link earnings per share to macroeconomic variables, we convert the data to a monthly frequency by using the latest value available in the respective month.

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 formed 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 n-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 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.[1] Since realized 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

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

Our sample period runs from January 1996 to December 2015 due to the conversion in growth rates.[2] The results of running regression (2) may be found in Table (1).

As can be seen, the joint hypothesis of unbiasedness in forming expectation cannot be rejected, as the corresponding p-value is 0.366. This is also reflected by the fact that the individual restrictions hold. The β coefficient with a value of 0.773 is not statistically different from one and the α coefficient is not statistically different from zero. Considering seasonal calendar effects, i.e. including dummies for each month except December, does not change this result, as seasonal effects are insignificant (Table 8 in the Appendix). These results are surprising for two reasons: the results are basically at odds with earlier results found in the literature (Keane and Runkle, 1990, 1998) and the financial crisis is included in our sample. However, drawing on two years and three years growth rates and their expectations seems to produce other results, which is also true when using 12 months ahead forecasts in levels (see again Table 8 in the Appendix). The result of

[1] We are only interested in unbiasedness of expectations and not in the efficiency of the forecast. In order to test for 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)).

[2] 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.

Table 1: Tests on unbiased expectations (from 1996:01 to 2015:12)

	$\frac{x_t - x_{t-12}}{x_{t-12}}$
α	0.200
	[1.374]
β	0.773***
	[3.058]
$H0: (\alpha = 0)$	1.887
	(0.170)
$H0: (\beta = 1)$	0.810
	(0.368)
$H0: \begin{pmatrix} \alpha = 0 \\ \beta = 1 \end{pmatrix}$	2.012
	(0.366)
Observations	240
$\bar{R}^2$	0.726

Notes: 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 $x_t = EPS_t^{12M}$ are the earnings per share. $H0$ denotes the null hypothesis for Wald tests with restrictions given in parentheses. $\bar{R}^2$ is the adjusted coefficient of determination. 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% (***) level.

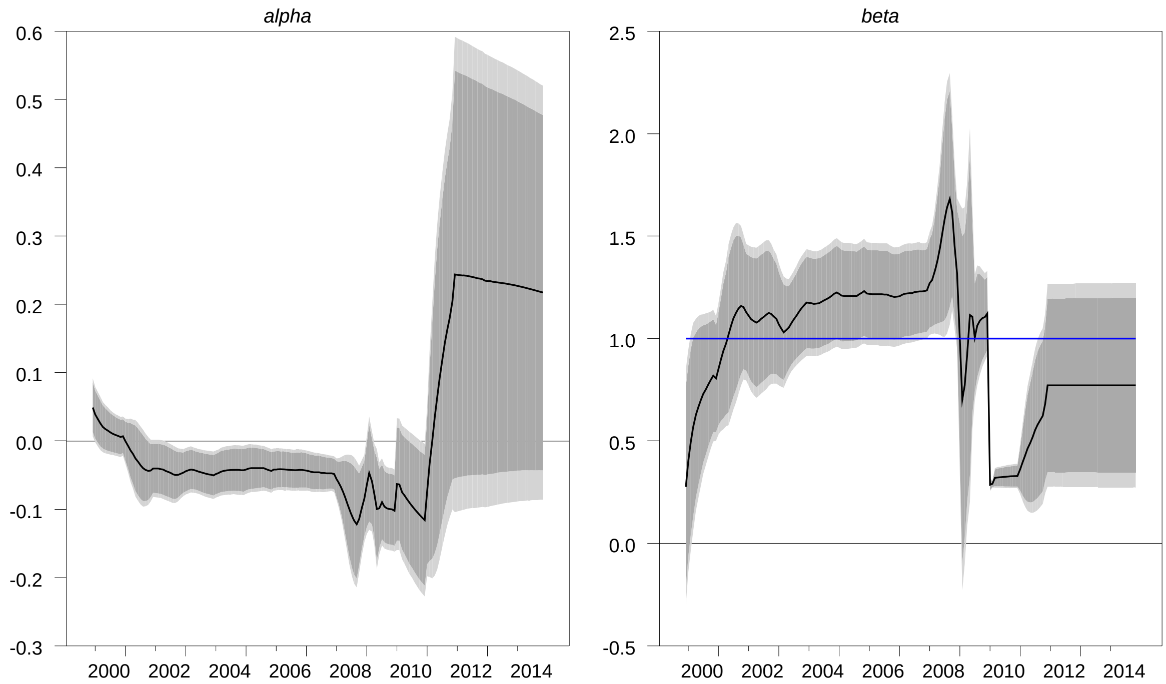
unbiasedness does not seem to be very robust. In order to investigate the stability of the found relationship, we estimate Equation (2) recursively. As an initial period we estimate the model for the period running from 1996:01 to 1999:12, and thenadd one additional observation, and re-estimate the model. This is done until the end of the sample is reached. The time profile for the coefficients may be found in Figure (1). The last estimates correspond to the values reported in Table (1). Obviously, the financial crisis has a strong impact on the estimation results. In the period stopping before the outbreak of the financial crisis, the constant term in the unbiasedness regression turns out to be negative, while the slope coefficient tends to be larger than one. However, the value of one lies within the confidence bands most of the time. The financial crisis drove the slope dramatically below one. This is an indication that impediments to the expectation-forming and/or the information process were at work.

Since the recursive estimation provides indications of structural changes, we are interested in identifying potential regimes by allowing for structural breaks in the regression coefficients. Regarding potential structural breaks and different regimes, 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 $i = T_{j-1}+1, ..., T_j$ with $j = 1, ..., m+1$ and m as 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, 2003a). The number of breaks is mainly determined with the help of the sequential sup $F_T(m+1|m)$ test of $m+1$ versus m structural changes after having verified, using the sup $F(m)$ test of m versus no structural changes, that structural breaks

Figure 1: (Un)biased expectations over time



Notes: The chart shows the results for the estimated α (LHS) and β (RHS) from a recursive OLS estimation. The regression from Table 1 is estimated for an initial period and after adding one further obervation the estimation is repeated. This is done until the end of the sample is reached. The dark (bright) grey shaded area is the 95% (90%) confidence band based on Newey-West standard errors.

occur, as proposed by the authors, but we also look at information criteria. An essential parameter in the estimation procedure is the trimming factor, which is the fraction of the minimal period without breaks relative to the sample size. This means that, by setting the trimming parameter, the minimal period without breaks is determined. Bai and Perron (2003a,b) argue that a relative high trimming factor should be chosen for highly autocorrelated and heterogenous data. For this reason, we follow their suggestion and take a trimming factor of 0.2, which implies a minimal period without breaks of 48 months. The application of the sequential test together with the information criteria suggest two breaks occuring at 2006:12, and 2010:12 (Table 2). As a consequence, three regimes with fixed coefficients arise. Hence, the first regime lasts nearly ten years and stops before the subprime mortgage crisis emerged, which was the origin of the following financial crisis. The second regime almost completely covers the financial crisis and the trough of the Great Recession. The last regime then comprises the recovery.

The results for the estimated coefficients and the unbiasedness tests are presented in Table 3. As opposed to the fixed-coefficients approach, the tests on unbiasedness are now widely rejected in every regime, i.e. even in the periods not covering the financial crisis. By inspecting the results from the different regimes, it becomes clear that the two regimes not covering the financial crisis are basically very close to each other in terms of estimated coefficients. In the first regime the constant is -0.043 while it is -0.065 in the third regime. The slope coefficients are even closer to each other with 1.205 in the first regime and 1.243

Table 2: Test on number of breaks in unbiasedness regression for the banking sector

Panel (a): Information Criteria				
	0	1	2	3
BIC	0.59	-1.38	-1.58	-1.54
LWZ	0.64	-1.27	-1.42*	-1.33

Panel (b): Sequential test			
	0 vs. 1	1 vs. 2	2 vs. 3
$\sup F_T\,(m+1\|m)$	783.3*	32.5*	1.1
$\sup F_T - 95\%$CV	10.8	12.8	13.7

Panel (c): Estimated break points			
		Lower 95%	Upper 95%
1	2006:12	2006:11	2006:12
2	2010:12	2010:10	2011:01

Notes: The Table shows in Panel (a) and (b) model selection results for the number of breaks. The corresponding break dates are given in Panel (c). The techniques are described in Bai and Perron (2003a) and critical values are based on the response surface regressions as given by Bai and Perron (2003b). The term $\sup F_T\,(m+1|m)$refer to the sequential break test which tests between m and $m+1$ breaks with m as the number of breaks. BIC and LWZ refer to information criteria. The trimming factor is set to 0.2. The number of observations is 240.

in the last regime. Regarding a test on the equality of the coefficients, the corresponding null hypothesis cannot be rejected. Nevertheless, the reason for the rejection of unbiased expectations seems to be different. While the constant term in the first period is not significantly different from zero, it is in the third regime, although the p-value of the corresponding test is close to 0.1. Thus, in the last regime, realizations and expectations co-move but agents constantly underestimate the realizations. With respect to the slope coefficients, the opposite it true. While the hypothesis of the slope being equal to one can be broadly rejected, the p-value of the corresponding hypothesis in the first regime is only slightly above 0.1. From this point of view, there was a perfect comovement between the realized growth of banks' earnings per share and the expectations, albeit but with a constant wedge. This result can be a reflection of strategic misreporting of expectations.

While the β coefficient was close to or slightly greater than one in the first and last regime, respectively, it is drastically reduced during the financial 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 crisis is still negative with a relatively high absolute value, while the β coefficient with a value of 0.288 is very low. Realized earnings per shares are drastically below their expectations in this period because agents systematically overestimated the profit situation in the banking sector. The large negative value of the constant term shows that agents were obviously unable to gauge banks' profit situation correctly in this regime. The end of this crisis regime roughly coincides with the start of the recovery. The switch from very biased expectations back to more mildly biased expectations could be an indication that agents learned from the experiences during the financial crisis.

The findings regarding the structural breaks and the estimated coefficients in the regimes are quite robust. We reduce the trimming factor to 0.15, which means a reduction

Table 3: Tests on unbiased expectations for banking sector with multiple breaks regression (from 1996:01 to 2014:11)

Regimes	1996:01-2006:12	2007:01-2010:12	2010:12-2015:12
α	-0.043***	-0.626***	-0.065
	[-2.722]	[-4.417]	[-1.549]
β	1.205***	0.288***	1.243***
	[9.426]	[12.214]	[25.248]
$H0: (\alpha = 0)$	7.411***	19.511***	2.398
	(0.006)	(0.000)	(0.121)
$H0: (\ \beta = 1\ )$	2.567	907.982***	24.404***
	(0.109)	(0.000)	(0.000)
$H0: \begin{pmatrix} \alpha = 0 \\ \beta = 1 \end{pmatrix}$	7.677**	984.798***	24.518***
	(0.022)	(0.000)	(0.000)

Notes: 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 $x_t = EPS_t^{12M}$ are the earnings per share and i denotes the subsequent regimes. The model is estimated with the techniques developed by Bai and Perron (2003a). The number of breaks and their dates are given in Table 2. $H0$ 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.

in the minimal period without breaks to 36 months. The breaks are rather similar, although the crisis regime starts five months later (Table 9 in the appendix). However, this does not affect the evaluation of the regimes (Table 10 in the appendix). Also, the use of two and three years earning growths provides similar results. Again, the breaks and the interpretation of the results are largely robust (see Tables 11 and 12 in the appendix). It is only for the three years horizon that a third break occurs. Nevertheless, the interpretation of the last three regimes is identical.

2.2 Sticky or noisy information?

Since there is evidence of biased expectations regarding earnings per share of banks, especially during the financial, it is of interest to shed light on the specific form of information processing. As Coibion 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 form 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 such models, agents 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 Coibion and

Gorodnichenko (2012). The authors argue that sticky and noisy information models can be tested by investigating whether the forecast error systematically responds to economic shocks in addition to that which can be interpreted as news. The idea behind this is that shocks already known to the agents at the time when expectations are formed must drive realizations and expectations in the same way such that the forecast error does not react. We generate our structural shocks from a Vector autoregressive model. The VAR is estimated using monthly data and comprises the variables annual growth of industrial production, inflation rate as the annual growth in consumer price index, policy rate, unemployment rate, annual return on the bank share price index, annual returns on 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 sequence corresponds to the previous listing of the variables before. Our regression model is

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

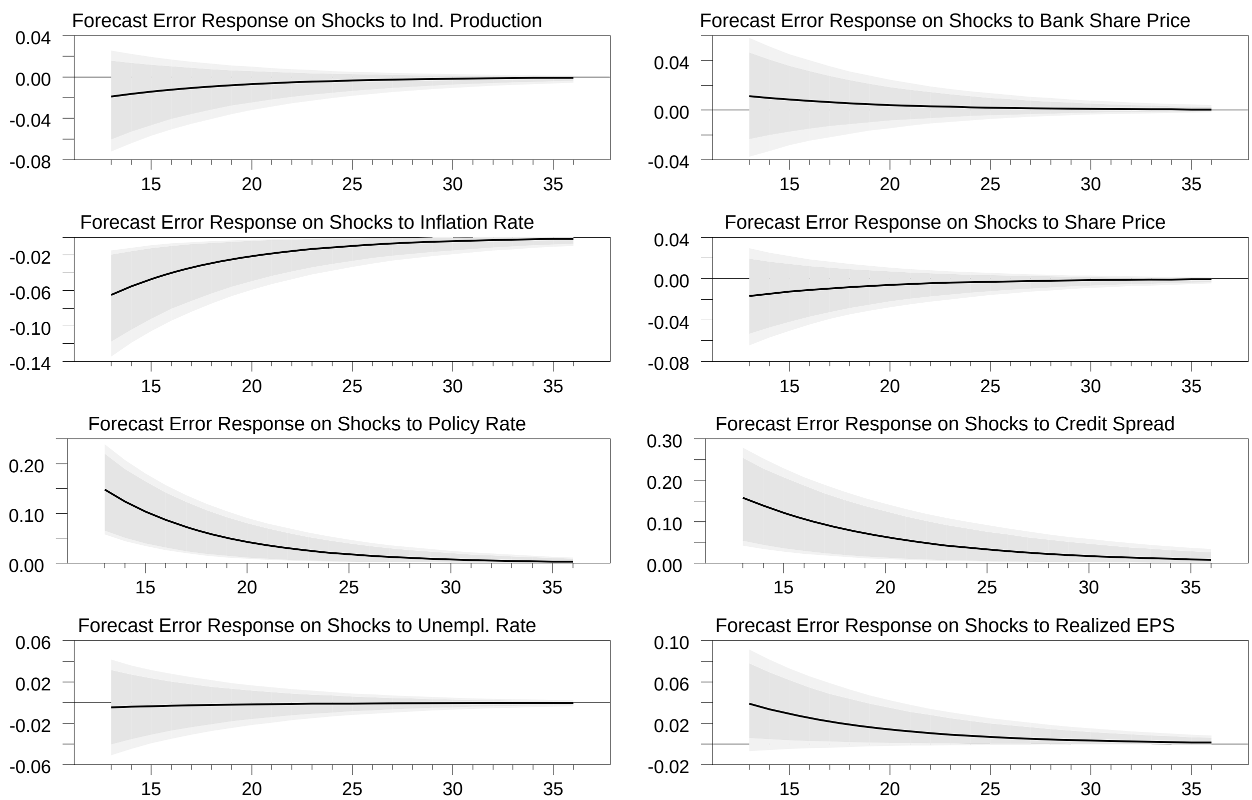
where c is a constant, δ and ς are regression coefficients and e_t are i.i.d. innovations. The expectational error is denoted by $exp.err$ $\left(exp.err_t = EPS^{12M}_t - E_{t-12}\left(EPS^{12M}_t\right)\right)$. The test on sticky/noisy information is whether $\delta_i = 0$ for $i > 13$. To test this 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. 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 labeling of the shocks is related to the position in the sequence, because we cannot attribute a precise economic identification to the shocks. This is not necessary because we just need orthogonal shocks.[3] The dark (bright) shaded area is the 90% (95%) confidence band around the implied responses. The idea behind this is to determine 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 clearly exhibits significant responses. The shock on realized EPS is a boundary case as the zero line only lies within the 95% range. All other confidence bands comprise the zero effect line. From this it follows that there is evidence in favor of sticky or noisy information.

Taking into account that there are breaks in the expectations formation as we showed in the previous section, we perform the exercise again with data up until the start of the crisis (2006:12). The results are exemplified in Figure 11. It turns out that, until the start of the crisis, information seems not to be rigid at all. This can be seen as, from period 12 onwards, all impulse responses are insignificant. As we do not have enough data points for the crisis to perform the exercise for this time period, we cannot clearly show that

[3] Giving the shocks a structural interpretation is not straightforward. However, it is not necessary at this point do to so. For ease of exposition, we label the shocks following the related left-hand side variable in the VAR. Since industrial production appears first, we speak about a shock to industrial production regarding the first shock in the system.

Figure 2: Responses of Forecast Error on various Shocks

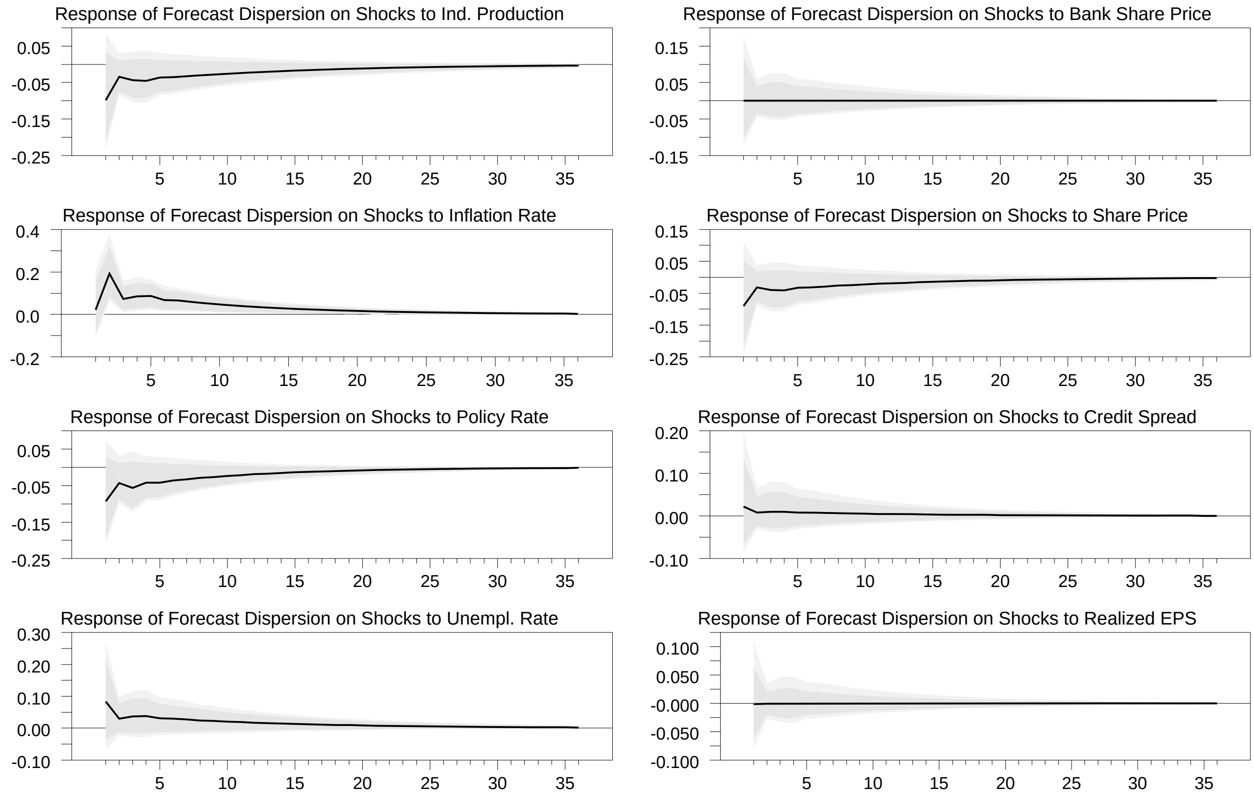


Notes: The chart shows the responses of the forecast error, as the difference between the realized value and the previous expected value for the corresponding period, on various shocks. The shocks are structural shocks resulting from a SVAR with Choleski decomposition and the sequence given in the graph (from first left to last right position). The darker shaded areas denote the confidence interval based on the 90% level and the brighter shaded areas denote that based on the 95% level. Confidence intervals are generated with the help of bootstrapping.

there are information rigidities lately. But both charts combined give us a clear indication that the rigidities have evolved during and after the crisis. Taken together, there is slight evidence in favor of sticky or completely noisy information. 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 bank variables is affected. In noisy information models, responses can be different across different shocks as imperfect information is asymmetric.

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

Figure 3: Tests for Sticky Information



Notes: The chart shows the responses of the forecast dispersion among professional analysts measured as the cross-sectional standard deviation on various shocks (in absolute terms). The shocks stem from a Vector autoregressive model with the variables given in the left-hand column. Shocks are identified by applying the Choleski decomposition with the sequence corresponding to the order in the table. The darker shaded areas are the confidence interval based on the 90% level and the brighter shaded areas on the 95% level. Confidence intervals are generated with the help of bootstrapping.

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 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. The results are presented in Figure 3. As can be seen, significant responses can be broadly rejected, which means that no coefficient is statistically significant with one exception. In the case for a shock on the inflation equation, the responses are slightly different from zero. In general, the dispersion in forecasts is not systematically related to fundamental shocks, either to their contemporaneous effect or to their history.

Based on 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. Our results for information processing in the financial sector are in line with findings for expectations about inflation as shown by Coibion and Gorodnichenko (2012).

2.3 Do professional analysts learn about profits?

The previous sections have shown that information rigidities are at work regarding the expectations about banks' profit situation, which can be related to noisy information models. In this section, we present evidence in favor of a time-varying nature of learning, which can be attributed to the financial crisis. As a side-effect, the results in this section are able to serve as a robustness check for the results obtained so far. Based on our conclusions that a noisy information setting is to apply and learning can be represented by Kalman filtering, we start from

$$E_t EPS_t = E_{t-1} EPS_t + K_t (EPS_t - E_{t-1} EPS_t), \tag{4}$$

where K_t is the Kalman gain.[4] In line with Coibion and Gorodnichenko (2015), Equation (4) states that the current periods' expectations depend on past periods' expectations and the expectation error weighted by the Kalman gain. An alternative interpretation is that the current period's expectations are a weighted average between the realizations and past expectations, whereas the weight is the Kalman gain, which becomes clear after rearranging Equation (4). Furthermore, the equation can be expressed as

$$(EPS_{t+h} - E_t EPS_{t+h}) = \frac{1 - K_t}{K_t} (E_t EPS_{t+h} - E_{t-1} EPS_{t+h}) + error_{t+h,t} \tag{5}$$

with the help of several manipulations. The expectation error appears again on the left-hand side of Equation (5) while the expectation revision enters the right-hand side. This relationship states that the forecast error is related to the forecast revision if agents learn, whereas the Kalman gain again controls the slope. If agents learn immediately, the signal is perfectly revealing and the Kalman gain becomes one. In this case, the expectation error solely depends on the innovation to the economy captured by $error_{t+h,t}$. Equation (5) can be interpreted as a regression equation which makes it possible to estimate the Kalman gain directly. Thus, we estimate

$$(EPS_{t+h} - E_t EPS_{t+h}) = \beta_t (E_t EPS_{t+h} - E_{t-1} EPS_{t+h}) + error_{t+h,t}, \tag{6}$$

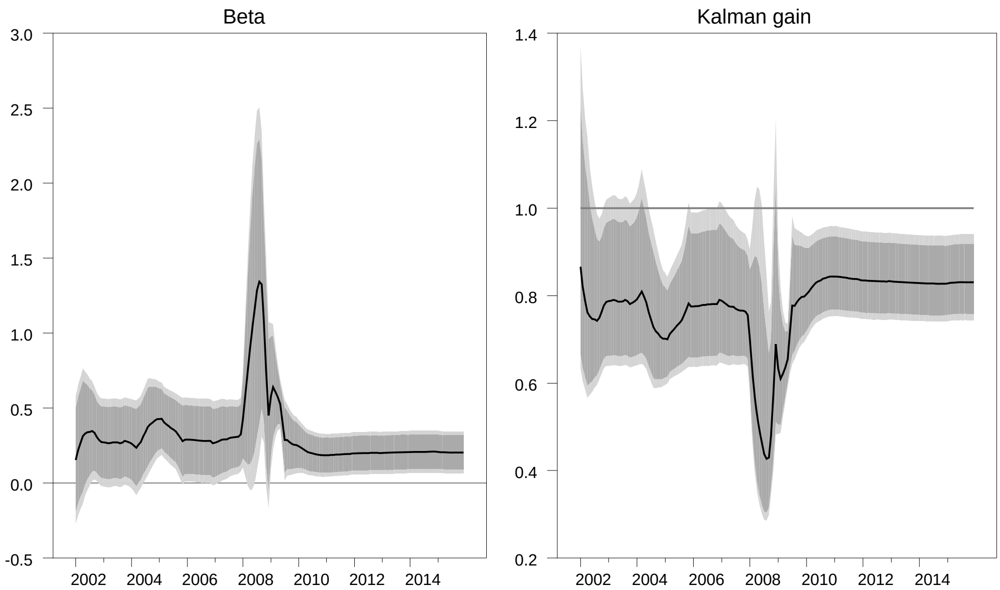
whereas the Kalman gain is

$$K_t = 1/(1 + \beta_t).$$

Since we know that the financial crisis has an impact on the information processing of agents, we estimate Equation (6) recursively with the OLS approch. In Figure 4, we present the results for the time-variation in β on the left-hand side, and the transformation

[4] Equation 4 can be derived from a noisy information mode, where the variable being tracked follows a Gaussian AR(1) process and agents receive a noisy signal of the form "true state plus i.i.d. noise". The noise is independent across agents, so it washes out in the aggregate.

Figure 4: Learning about bank profits



Notes: The Figure shows the results from the estimation of Equation (6) for β (LHS) and the transformation into the Kalman gain (RHS). The latter is reported as the averages across the last three months. Shaded areas refer to the 95% confidence bands.

into the Kalman gain on the right-hand side. Shaded areas refer to the 90% (bright gray) and 95% (dark gray) confidence bands. For most of the time β fluctuates around the zero line but increases dramatically during the financial crisis. It turns out that agents learn at a particularly slow speed during the financial crisis, which places another layer on the results presented in the previous sections. The recursive estimation provides evidence that agents also learn in the aftermath of the financial crisis, but at a faster speed than before, i.e. the signal is more revealing.[5] We conclude that the signal is noisier during the financial crisis, which is in line with Coibion and Gorodnichenko (2015). Learning per se is not only related to the banking sector. Agents also learn about profits in the industrial sector (seen in Figure 13) during the financial crisis. However, the noise in the banking sector is much more elaborated, which allows us to conclude that agents particularly need to discover developments occuring in the banking sector. In the next section we take a closer look at the expectation formation process and its role in learning.

2.4 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 profits for the next 12 months on a constant, realized and expected macroeconomic variables summarized in Z_t. The expected macroeconomic variables comprise the expected growth of gross domes-

[5]Figure 12 compares the estimation of β following recursive OLS with that obtained by applying a state-space model estimated with the Kalman filter. As can be seen, the behavior of β over time is very similar. We choose to work with recursive OLS as it takes all information into account without weighting.

tic product over the next 12 months, the expected rate of inflation in 12 months, and the expected short-term interest rate in 12 months, which enter with their contemporaneous values. All three variables stem from professional forecasters and are the mean forecasts as reported by Consensus Forecasters. The realized macroeconomic variables are annual growth of aggregate share price index, annual growth of a share price index for banks, realized annual inflation, the unemployment rate, the annual growth of industrial production, and the credit spread as the difference between yields on corporate bonds with an investment grade rating and government bonds. The regression model becomes

$$E_t\left(EPS_{t+12}^{12M}\right) = \mu + \Gamma Z_t + \eta_t, \tag{7}$$

where μ is a constant, Γ is a vector of parameters γ_i and η_t are i.i.d. innovations. Results are given in Table 4. Indeed, macroeconomic factors are relevant in forming expectations for future earnings in the banking sector. The expected GDP growth is highly significant and enters with a positive sign, which is consistent with the notion that professional analysts expect an increase of earnings if they expect an economic expansion in general. The expected short-term interest rate enters with a negative sign, which is also true of the expected rate of inflation, while the latter is only statistically significant at the 10% level. Higher expected inflation is, in turn, related to higher policy rates. One interpretation for both could be that higher short-term rates are expected to lower profits by raising funding costs. While the realized growth in industrial production is not statistically significant, the realized rate of inflation shows a positive sign and the unemployment rate a negative sign. Both can be interpreted as indicators of the current stance of the economy. The credit spread is also highly significant for explaining the expected profits in the banking sector, whereas the negative sign might be related to the feedback effects of expected defaults on banks' profits. Besides the explanatory variables, the constant term, which has a positive sign, is also highly significant. The variables explain roughly 80 per cent of expected earnings.

The highly significant constant term gives an indication that profits in the banking sector are expected to be positive on average. Regarding learning, various settings would be possible. Agents could learn about the entire economy or only about the persistence of specific shocks. We take a closer approach and try to ask whether agents revise the mean profit expectations in relation to the forecast error. 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 θ also affects net worth. This (in)efficiency can easily be related to the past period's equity position. 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 rewritten with the help of the balance sheet constraint $A_t^B = N_t + L_t$ to obtain

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

Table 4: Expectation formation for expected earnings per share one year ahead and determinants

	Coefficient	T-statistic
Constant	46.108***	[9.767]
Annual growth of share price index$_{t-1}$	-4.427	[-1.349]
Annual growth share price index $_{t-1}$ - banking sector	-1.254	[-0.450]
Expected GDP growth in 12 months$_t$	1.970***	[2.880]
Expected rate of inflation in 12 months$_t$	-3.343*	[-1.925]
Exp. short-term int. rate in 12 months$_t$	-0.930**	[-2.332]
Realized annual inflation$_{t-1}$	1.161***	[3.094]
Unemployment rate$_{t-1}$	-2.781***	[-7.363]
Annual growth of ind. production$_{t-1}$	-14.682	[-1.172]
Credit Spread$_{t-1}$	-5.550***	[-4.916]
No. of observations	240	
$\bar{R}^2$	0.805	

Notes: The Table shows the estimation results for Equation (7). T-statistics base on Newey-West standard errors. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level. $\bar{R}^2$ is the adjusted coefficient of determination.

This expression can easily be transformed into growth rates

$$\frac{N_t}{N_{t-1}} = \left(R_t^A - R_t^L\right) lev_{t-1} + R_t^L - \theta, \tag{8}$$

where lev_t is the leverage ratio. In expectations, we get

$$E_t\left(\frac{N_{t+1}}{N_t}\right) = E_t\left[\left(R_{t+1}^A - R_{t+1}^L\right) lev_t + R_{t+1}^L - \theta\right], \tag{9}$$

As can be seen in the last equation, the (in)efficiency 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. The growth of bank equity is determined by earnings, i.e. it is proxied by earnings per share. This means that growth in bank equity can be proxied by earnings per share without a loss of generality. We posit a learning problem in which agents learn about (a part of) the constant in Equation (7) which is equivalent to learning about θ in Equation (9). Assuming that $E_t\left[\left(R_{t+1}^A - R_{t+1}^L\right) lev_t + R_{t+1}^L\right]$ is a function of fundamentals $f(Z_t)$, we can rewrite the regression model in a time-varying coefficient framework

$$E_t\left(EPS_{t+12}^{12M}\right) = \mu_t + \Gamma_t Z_t + \eta_t \tag{10}$$

where the coefficients are supposed to evolve as AR-processes

$$\begin{aligned} \mu_t &= \mu_{t-1} + b \cdot (exp.err_t) + \nu_{\mu,t} \\ \gamma_{it} &= \gamma_{i,t-1} + \nu_{i,\gamma,t}. \end{aligned} \tag{11}$$

The model is written in state space form and is estimated with the Kalman filter. The

Table 5: Response of constant term on forecast error by taking structural breaks into account

Panel (a): Regression results				
	Model 1: no breaks		Model 2: breaks	
	Coefficient	T-statistic	Coefficient	T-statistic
b	0.060***	[4.548]		
b_1			-0.033	[-0.892]
b_2			0.070***	[5.329]
b_3			0.071	[0.711]
Log-lik.	-338.6		-335.6	
Log-lik. in model w/o bs	-347.4			

Panel (b): Model tests				
$LR\,(Model1\vert Model2)$	6.115**	(0.047)		
$LR\,(Model0\vert Model1)$	17.523***	(0.000)		
$LR\,(Model0\vert Model2)$	23.638***	(0.000)		

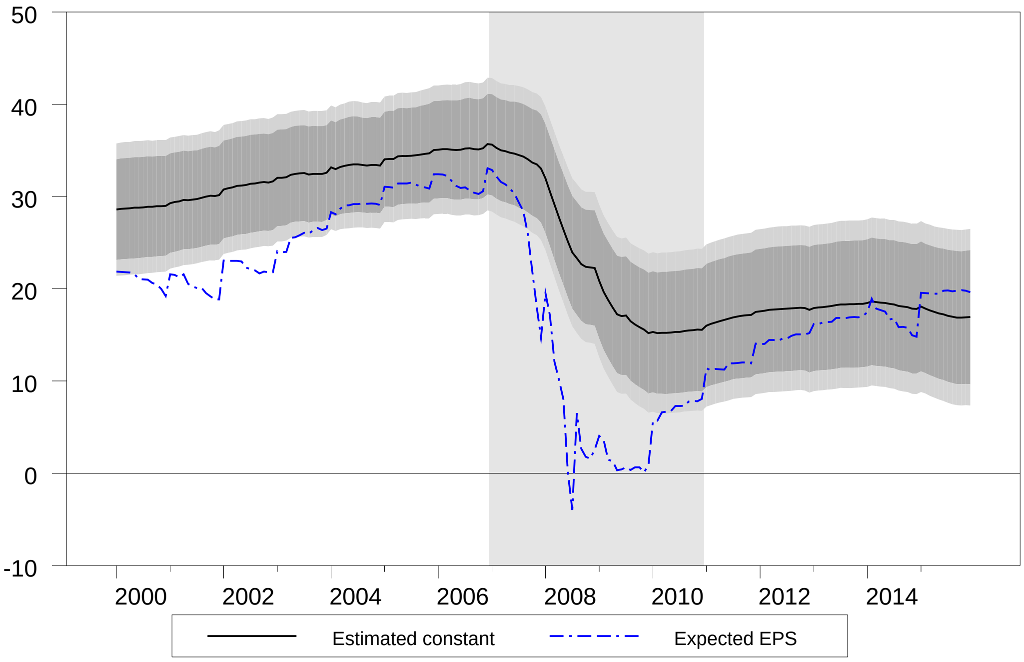
Notes: The Table shows in Panel (a) the estimated coefficients on the forecast error in the state equation for the mean profit expectations. Panel (b) shows test for discriminating different models. In Model 0 the state equation for the constant is a random walk, in Model 1 it is modified by the expectation error, and in Model 2 the expectation errors are allowed to have a different impact in different regimes. The regimes are $I_1(1995:01 \leq t << 2006:12)$, $I_2(2006:12 < t << 2010:12)$, and $I_3(2010:12 < t << 2015:12)$. The term LR refers to likelihood ratio tests. Numbers in brackets give t-statistics and in parentheses p-values. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level. level.

state equation for the constant term can be used to test for learning about the mean profit expectations in the banking sector. If μ_t systematically responds to the forecast error of earnings per share, i.e. the regression coefficient b is statistically different from zero, agents revise their mean profits expectations by taking the difference between current realized profits and their prior expectations into account. Of course, all $\gamma_{i,t}$ can also be related to a learning scheme. However, we want to focus on the mean expectations for a simple test on learning about banks' profits.

We run three different models. The results are presented in Panel (a) of Table 5. 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. The null hypothesis of b to be zero can clearly be rejected. 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. To form regimes, we take the breaks reported in Table 2. This is model 2. Using these breaks seems to be rather arbitrary. We could simply use the model from Equation (7) and re-run several structural break point tests in the tradition of Bai and Perron (2003a). However, by allowing every coefficient to change, the resulting break dates would also be related to breaks in the relationship to the fundamentals and could produce different break points. Our approach has the advantage that the breaks are independent of the estimation model. Nevertheless, they are well-founded. Consequently Equation (11) becomes

$$\mu_t = \mu_{t-1} + b_1 \cdot (exp.err_t)\, I_1 + b_2 \cdot (exp.err_t)\, I_2 + b_3 \cdot (exp.err_t)\, I_3 + \nu_{\mu,t}$$

Figure 5: Expectation formation and the relation to the forecast error



Notes: The chart shows the time-varying mean from Equation (10) surrounded by the 95% (dark gray shaded) and the 90% (bright gray shaded) confidence bands. The blue dotted line shows the expected earning per share in the banking sector 12 months ahead. The period 2006:12 to 2010:12 is highlighted.

By taking these regimes into account we can clearly obtain evidence in favor of learning agents only during the crisis, as b_2 is the sole coefficient which is statistically different from zero. Thus, the overall result from model 1 is driven by this period. The constant term in the expectation formation equation systematically responds to expectation errors during the financial crisis, which means that agents adjust their mean expectations regarding bank profits based on realized forecast errors. Likelihood ratio tests can be used to show that this configuration is preferable to the others. Model 1 and 2 are also superior to model 0 which sets all bs to zero.

In Figure 5 we plot μ_t together with the expected earnings per share 12 months ahead. The dark (bright) gray shaded area refers to the 90% (95%) confidence band, and the crisis regime, reflecting the period 2006:12 to 2010:12, is also highlighted. The non-systematic part in the expectation formation regarding bank profits, is rather stable before and after the crisis regime, while it is lower during it. During the financial crisis there is a smooth adjustment from the higher to the lower level. Our results show that a part of this adjustment can be traced back to learning from forecast errors.

We see this test as sufficient for testing whether agents learn about the past in forming expectations about future profits in the banking sector. Taken our results together, they imply that agents' forecasts of bank profits are biased, particularly during the financial crisis. Sticky information processing does not seem to be responsible for this finding. Since agents take forecast errors during the financial crisis into account in forming expectations about future banks' earnings, agents seem to learn about banks' profit situation, which means that they indirectly learn about banks' net worth. Based on these findings, there arises the question about the consequences for the real economy following from imperfect information about banks' net worth. 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 use 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. This is akin to the approach developed by Gertler and Karadi (2011) and Gertler and Kiyotaki (2010). Since the banking sector is of central importance for our purposes, this sector and the assumptions we apply are explained in detail in this section. The rest of the otherwise completely standard model ingredients are relegated to the appendix including all first-order conditions. A banking sector has an important role because it is assumed that the goods producing sector cannot obtain funds directly from the households. As a consequence, a financial intermediary which we call "banking sector", is necessary to indermediate the funds from households to capital producers. With regard to this linkage, we assume that an agency problem exists between households and bankers. From this agency problem it 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 use physical capital together with labor to produce intermediate goods which are differentiated by retailers. By applying a bundling technology, the differentiated goods are transformed into 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. Furthermore, this section explains the solution algorithm, ie. how learning is integrated into the whole setup as well as our simulation exercise.

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 will 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 is 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 that $Q_t S_{jt} = Q_t K_{j,t+1}$. The balance sheet constraint of the banks becomes

$$Q_t S_{jt} = N_{jt} + D_{jt}, \tag{12}$$

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. The law of motion for net worth becomes

$$N_{jt+1} = R_{kt+1} Q_t S_{jt} + R_{t+1} D_{jt} - \tilde{\theta}_{t+1}^N. \tag{13}$$

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. Incorporating a time-varying constant is in line with the test we developed earlier (see equation (8)) to examine whether agents are learning at all. In searching for a more microfounded explanation of this time-varying parameter, it can be argued that it is similar, though not identical, to the modelingdevice of Gertler and Kiyotaki (2015) who incorporate bank runs into their model. 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 equation (13) can be rewritten with the help of the balance sheet constraint to obtain

$$N_{jt+1} = \left(R_{kt+1} - R_{t+1}\right) Q_t S_{jt} + \left(R_{t+1} - \theta_{t+1}^N\right) N_{jt}. \tag{14}$$

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.[6] 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' lives. Consequently, transfers of funds from bankers to workers only take place at the end of bankers' lives. Thus, the objective of bank managers is to maximize the franchise value of the bank V_{jt} by deciding on the volume of assets and the required external funds by taking the expected return on capital and the risk-free rate as given

$$V_{jt} = \max E_t \sum_{i=0}^{\infty} \left(1-p\right) p^i \beta^{i+1} \Lambda_{t,t+1+i} \left[\left(R_{kt+1+i} - R_{t+1+i}\right) Q_{t+i} S_{jt+i} + \left(R_{t+1+i} - \theta_{t+1+i}^N\right) N_{jt+i} \right], \tag{15}$$

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 constrains 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

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

the case of diversion, they transfer the resources back to their households immediately 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

$$V_{jt} \geq \lambda Q_t S_{jt} \tag{16}$$

holds.

Next, we conjecture that the franchise value of the bank, as given in Eq. (15), can be rewritten in a linear fashion

$$V_{jt} = \nu_t Q_t S_{jt} + \eta_t N_{jt} \tag{17}$$

where

$$\nu_t = E_t \left[(1-\theta) \beta \Lambda_{t,t+1} \left(R_{kt+1} - R_{t+1} \right) + \beta \Lambda_{t,t+1} \theta x_{t,t+1} \nu_{t+1} \right] \tag{18}$$

$$\eta_t = E_t \left[(1-\theta) + \beta \Lambda_{t,t+1} \theta z_{t,t+1} \eta_{t+1} \right]. \tag{19}$$

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 $t+i$

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

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

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.

$$\phi_{jt} = \frac{\eta_t}{\lambda - \nu_t} \tag{20}$$

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.

$$N_{ot} = p \left[\left(R_{kt} - R_t \right) \phi_t + R_t - \theta_t^N \right] N_{t-1}, \tag{21}$$

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

$$\log\left(\theta_t^N\right) = \left(1 - \rho^\theta\right) \log\left(\bar{\theta}_t^N\right) + \rho^\theta \log\left(\theta_{t-1}^N\right) + \epsilon_t^\theta, \tag{22}$$

where the persistency is controlled by ρ^θ and is driven by i.i.d. innovations ϵ_t^θ. In Equation (22), $\bar{\theta}_t^N$ 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

$$N_{nt} = \omega Q_t S_{t-1}. \tag{23}$$

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

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

3.2 The learning mechanism

We know from the econometric tests above how agents update expectations about financial institutions' net worth over time. The challenging part is to introduce this pattern as well as possible into the model. We therefore rely on the approach by Cogley, Matthes, and Sbordone (2015) and Hollmayr and Kühl (2016), which is rather intuitive and fits the description of the behavior of agents pretty well. The upside to this implementation is that learning stays very close to full information rational expectations. In particular. it allows us to single out the one feature that we want to analyze in detail, incomplete information about net worth in the banking sector, without increasing agents' uncertainty in other model parts. The whole model is completely known to the agents, ie. they know both the structure of the economy and all parameter values. Hence, they are able to observe 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 the autoregressive parameter ρ^θ while the only thing in the process which is uncertain to the agents is the potentially time-varying value of this steady state of θ.[7] Another result derived from the econometric test we performed in Section 2 is that agents have noisy information and, hence, a homogeneous set of new information. This is an important assumption with respect to aggregation and it allows us to assume that all private agents share the same beliefs about the inefficieny parameter and henceforth update their identical information. The updating step in every period is carried out via the Kalman filter. We can write the ensuing state space system in the following form where the observation equation is given by

$$\mathbf{log}\left(\theta_{\mathbf{t}}^{\mathbf{N}}\right) = \hat{\theta}_t^N + \rho^\theta \mathbf{log}\left(\theta_{\mathbf{t-1}}^{\mathbf{N}}\right) + \epsilon_{\mathbf{t}}^\theta \tag{24}$$

and the state equation by

$$\hat{\theta}_t^N = \hat{\theta}_{t-1}^N + \nu_t \tag{25}$$

and $\hat{\theta}_t^N = \left(1 - \rho^\theta\right) log\left(\bar{\theta}_t^N\right)$. 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.[8]

[7] 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.

[8] Agents have knowledge about 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.

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 0.0025 that is also known by the agents. For the state equation we assume a random walk for $\hat{\theta}_t^N$. A detailed description of how $\hat{\theta}_t^N$ evolves over time is given in the next section, where we specify a process so that we can match the evolution of the recession in the data.

Besides the specification of the variance in the AR-process, which is also referred to as the noise in the signal extraction literature, another key assumption is to set the variance of the state equation which is the signal. The signal-to-noise ratio determines how rapidly agents are updating. Other studies such as Hollmayr and Matthes (2015) calibrated this variance proportionally to the size of the change of the state. One contribution of this paper is to implement a new way of calibrating this key parameter. Once again, we rely on the results from the econometric analysis in the last section. We deduced that there are differences in updating over time and found that the Kalman Gain was time-varying with particularly low values during the crisis. As we simulate the economy for the past decade, we rely in every quarter on the respective value of the Kalman gain that was shown in Figure(4). That is, in the early periods of the crisis, when the updating speed of agents actually dropped, we include this in the simulation as well. Given the variance of the observation equation that is constant over time in this analysis, the time variation of the Kalman gain can be traced back to a time-varying signal that the agents receive. This means we let the agents receive signals every period and update their beliefs accordingly. In the beginning of the simulation periods, updating is hence very fast, as agents are close to full information rational expectations; updating drops heavily during the crisis, however. This feature enhances the modeling setup by bringing the expectations formation closer to the data.

The timing convention in each iteration is key in this model. First of all, economic agents enter any given period t with the belief of a certain steady state of net worth inefficiency which stems from the last period's updating step. Then, given this perceived state which determines all the other steady states in the economy as well, households and firms carry out all optimization steps based on their perceived steady state values as if those values hold forever. This assumption is known as anticipated utility and was originally developed by Kreps (1998). Though it is a simplifying assumption, it 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 $\bar{\theta}_t^N$ is set for this period t. Either bankers become more or less inefficient in a given 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 inefficiency value θ_t^N all agents try to deduce whether the change was due to the innovations or a new value in the steady state. They are faced with a signal-extration problem. In particular they solve equation (26) where K_t denotes the given Kalman gain in period t.

$$log(\hat{\theta}_{t+1}^N) = log(\hat{\theta}_t^N) + K_t \cdot [(log(\theta_t^N) - \rho^{\theta} \cdot log(\theta_{t-1}^N)) - (log(\hat{\theta}_t^N)] \tag{26}$$

With the updating step in the Kalman filter they enter period $t+1$ with a new belief of what the steady state inefficiency is supposed to 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 parameter changes and the alterations of the steady state are sufficiently small, instationarity never occurs. Therefore, we can avoid using 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-linearize the model around the perceived inefficiency steady state and write it in the system-based form in the following way:

$$\mathbf{A}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\mathbb{X}_{\mathbf{t}} = \mathbf{B}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\mathbf{E}^*_{\mathbf{t}}\mathbb{X}_{\mathbf{t+1}} + \mathbf{C}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\mathbb{X}_{\mathbf{t-1}} + \mathbf{D}\varepsilon^*_{\mathbf{t}} \tag{27}$$

with $\varepsilon^*_{\mathbf{t}}$ as the perceived shock. Those are the innovations the agents observe and the shock on the inefficiency of net worth thereby contains 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.

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

The closer the perceived steady state is to the true steady state ie. the fewer information rigidities agents have in a particular period, the closer the actual shock is to 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 parameter and is therefore termed the perceived law of motion and can be expressed as

$$\mathbb{X}_{\mathbf{t}} = \mathbf{S}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\mathbb{X}_{\mathbf{t-1}} + \mathbf{G}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\varepsilon^*_{\mathbf{t}} \tag{28}$$

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

$$\mathbf{S}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}}) = (\mathbf{A}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}}) - \mathbf{B}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\mathbf{S}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}}))^{-\mathbf{1}}\mathbf{C}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}}) \tag{29}$$

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

$$\mathbf{G}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}}) = (\mathbf{A}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}}))^{-\mathbf{1}}\mathbf{D}. \tag{30}$$

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.

$$\overline{\mathbf{A}}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\overline{\mathbf{Y}}_{\mathbf{t}} = \overline{\mathbf{B}}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\mathbf{E}^*_{\mathbf{t}}\overline{\mathbf{Y}}_{\mathbf{t+1}} + \overline{\mathbf{C}}^{\mathbf{actual}}(\hat{\theta}^{\mathbf{N}}_{\mathbf{t-1}})\overline{\mathbf{Y}}_{\mathbf{t-1}} + \overline{\mathbf{D}}\varepsilon_{\mathbf{t}}. \tag{31}$$

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

$$\overline{\mathbf{Y}}_{\mathbf{t}} = H(\hat{\theta}^N_{t-1})\overline{\mathbf{Y}}_{\mathbf{t-1}} + G(\hat{\theta}^N_{t-1})\varepsilon_t. \tag{32}$$

Obviously, matrix $H(\hat{\theta}^N_{t-1})$ that determines the actual outcomes is identical to $S(\hat{\theta}^N_{t-1})$

if information rigidities are zero, ie. $C^{true}(\hat{\theta}^N_{t-1}) - C(\hat{\theta}^N_{t-1})$ vanishes. The bigger the information friction is and the more slowly agents update new information, the bigger the difference between the perceived law of motion and the actual law of motion.

$$H(\hat{\theta}^N_{t-1}) = S(\hat{\theta}^N_{t-1}) + \left(A(\hat{\theta}^N_{t-1}) - B(\hat{\theta}^N_{t-1})S(\hat{\theta}^N_{t-1})\right)^{-1}\left(C^{true}(\hat{\theta}^N_{t-1}) - C(\hat{\theta}^N_{t-1})\right) \tag{33}$$

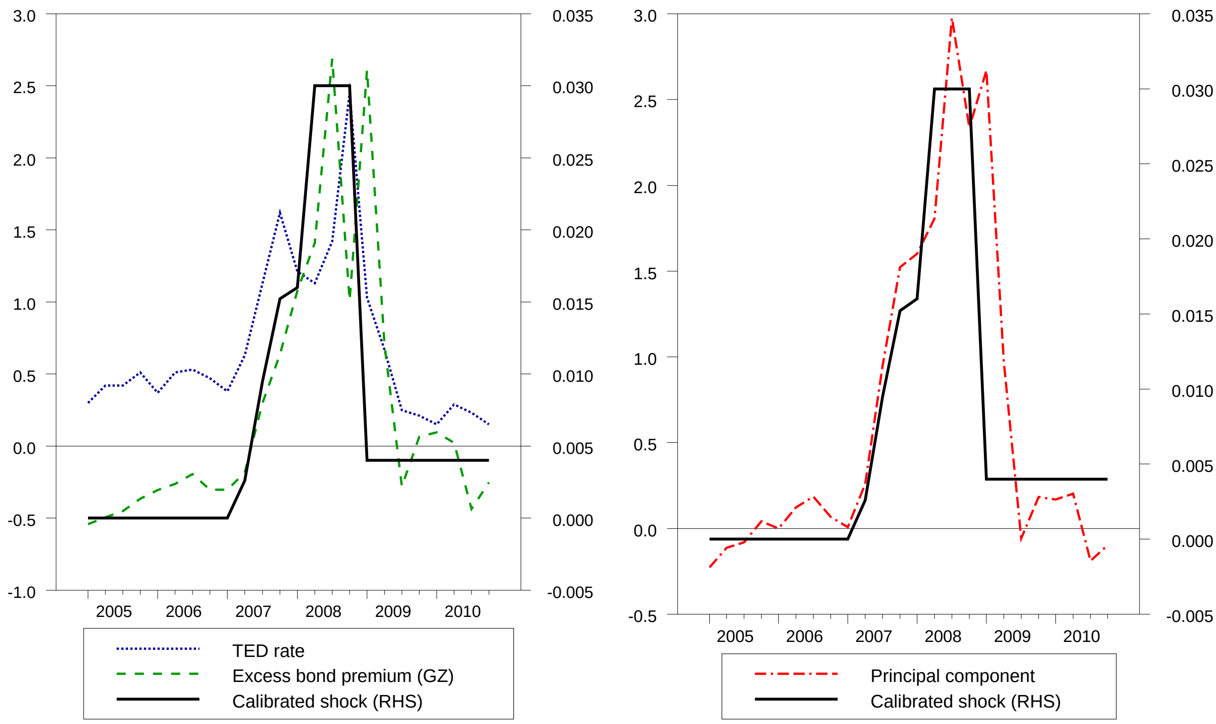
3.3 Simulation Setup

Given the model and the way agents update their beliefs based on the arrival of new information about banks' net worth, the next step isdescribing the simulation exercise to generate the economic downturn. As θ^N is the variable of interest that determines the (in)efficiency of net worth, we generate a certain path for the steady state of this variable over time. In the beginning of the simulation the steady state of inefficiency is zero. In addition to the steady state the variable is determined by its innovation that is normally distributed. Thus, the variable fluctuates mildly around the steady state in every period.[9] In order to generate the recession, we calibrate the evolution of the steady state of net worth inefficiency over time to match the spread in the data. The spread in the model captures the difference between the risk-free short rate and the return on capital. In the data there are several close matches for this variables. In Figure 6 we plot the TED rate over the past ten years as well as the excess bond premium. Both display a similar pattern with the TED rate exhibiting a first spike relatively early and the excess bond premium increasing sharply and resulting in two spikes in the year 2008. Coming from two different plateaus before the crisis and developing not entirely in sync during the crisis, we perform a principal component analysis to obtain the common driver from both underlying time series (see right-hand chart in Figure 6). Along with that artifical time series, we calibrate the steady state of our variable to match it as closely as possible. As a result, the two spikes become a prolonged plateau and the initial rapid run-up in the excess bond premium is somehow relaxed. In this way we try to mimic the structural development of the inefficiency of the banking system during the past decade. As the frequency of the model is quarterly, the evolution of the credit spread during the crisis also follows a quarterly frequency. The starting period of the calibrated steady state corresponds with the first quarter that agents update with the Kalman filter from our earlier empirical results.

We start by simulating the model under full information rational expectations 500 times. In this case updating of agents is immediate and there is no incomplete information about the steady state value in every quarter. Then, 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 we report the median for all variables. As can be seen in the next section, the perceived steady state value for the spread closely follows the full information rational expectations evolution. The results are therefore not driven primarily by a possible major disconnect of this variable and this is not responsible for any deviations between macrovariables under learning versus rational expectations. The effects of the difference between both types of expectation formation are displayed and explained in the next section.

[9] Note that in the end we report the median of all simulations. This means that, given a high enough number of simulations, single positive and negative shocks should cancel out.

Figure 6: Spreads in the data and a resulting inefficiency of net worth



Notes: The chart shows two different measures of spreads in the data, the excess bond premium and the TED rate. Obtaining its common driver, the time-varying steady state of net worth inefficiency is calibrated to follow this process and generate the crisis in the outcomes in the model. The axis on the left-hand side corresponds to real data, whereas the right-hand axis corresponds to the theoretical data.

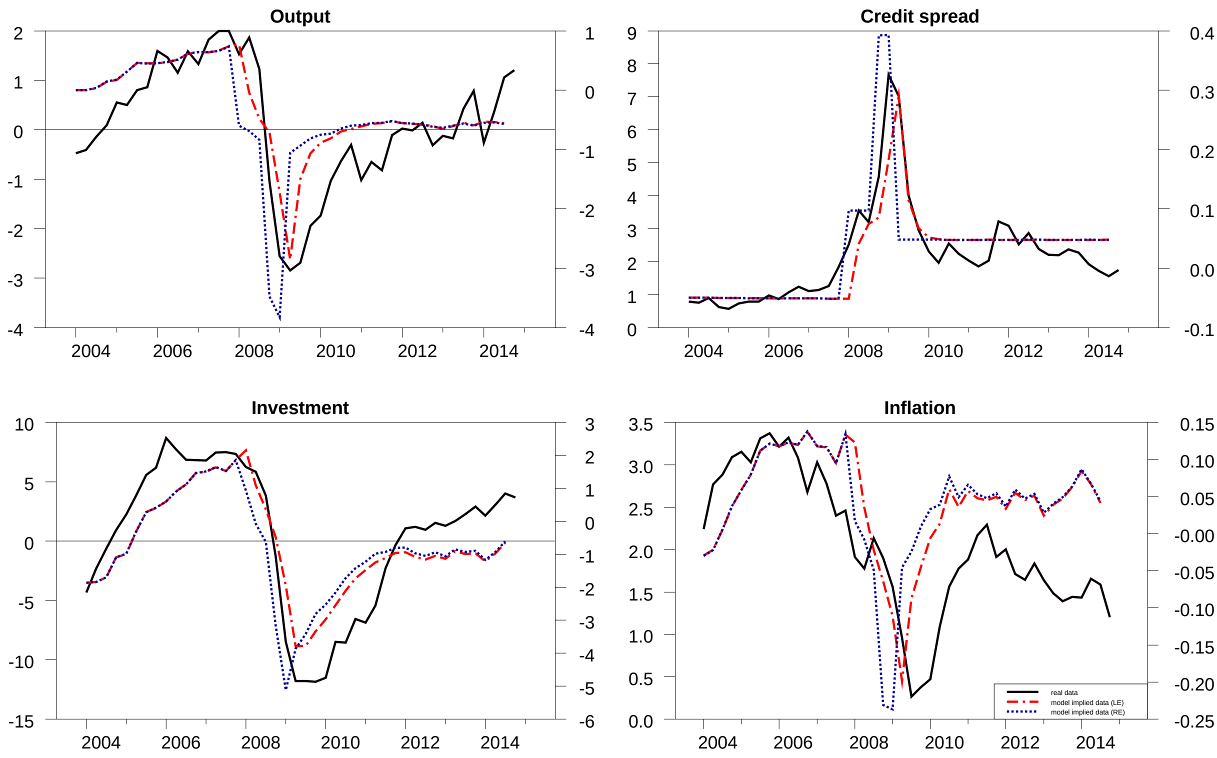
4 Results of simulation

4.1 Main results

Both under rational expectations and under learning the run up to the crisis in 2007 is almost identical, as the difference between the Kalman gain and full information rational expectations is minor. Only from 2007 onwards do we detect slight changes between both approaches. The economic intuition of this period is given by an initial rise in stress in the banking sector which depresses banks' net worth and which in an increase in the leverage ratio. Banks cut their credit supply for initializing a deleveraging process. As a consequence, the interest rate spread widens and makes investment in 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 qualitative effects are the same under both expectations formations. After the trough, a countermovement is initialized when the stress in the banking sector vanishes, i.e. after reaching the peak of the crisis.

As described above, the crisis takes around two years to form and another two years to unwind. In this time the Kalman gain is no longer equal to one and updating of new information is slower than under full information rational expectations. As can be seen

Figure 7: Outcomes of macroeconomic variables for learning (LE), and rational expectations (RE) contrasted with real data

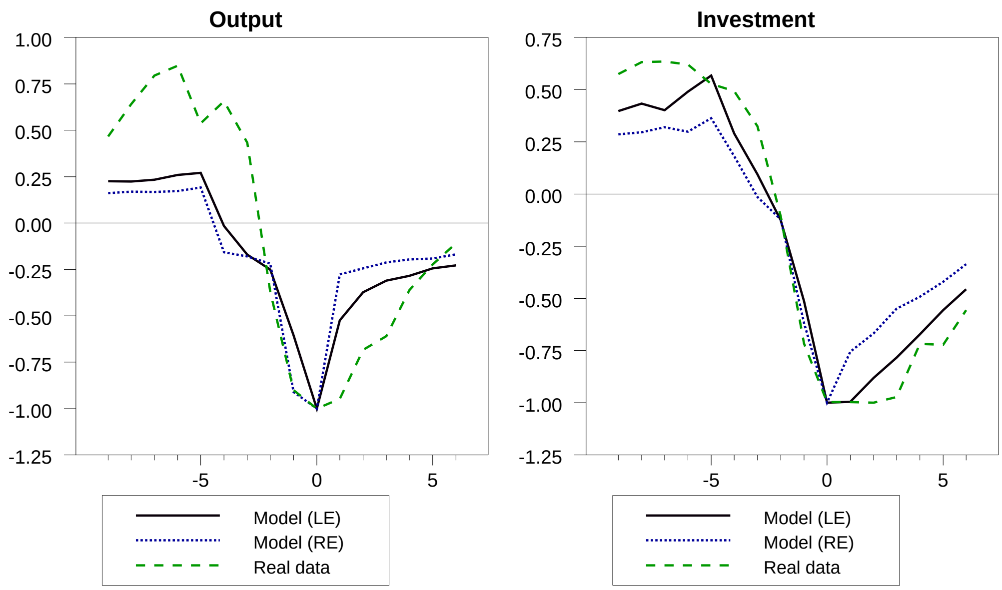


Notes: This chart shows the difference between outcomes under learning and rational expectations and contrasts them with real data. The axis on the left-hand side corresponds to real data, whereas the right-hand axis corresponds to the theoretical data. All are expressed as percentages of the respective trend.

in Figure 7 this is also the period when the macroeconomic development between the two approaches diverges. The reason for this is that agents cannot observe the correct inefficiency and, hence, banks' net worth at each point in time. At the time when inefficiency increases, agents realize this with a lag, which follows in a slightly delayed economic contraction compared to full information rational expectations. Once the peak of inefficiency is reached, however, households are still behind the curve and still think that net worth is too low compared to rational expectations. Consequently, they provide fewer funds to the banking sector, even though the banking sector is already in better shape again. The learning behavior about stress in the banking sector matches the data pretty well. The data for all maroeconomic variables in Figure 7 is detrended by an HP filter. Due to this behavior of slower updating on behalf of households, both output and investment in our setup recover much more slowly and are moreconsistent with real data. Furthermore, there is a small time lag between stress indicators in the banking sector and the rise in the credit spread. In the model with rational expectations this slight disconnect cannot be captured easily. In the case of introducing learning into an otherwise standard banking model we are able to produce this slight disconnect.

In Figure 7 it seems that under full information rational expectations the downturn

Figure 8: Output and investment under learning (LE) and rational expectations (RE) contrasted with real data relative to their respective troughs



Notes: This chart shows the five periods before and after the respective trough in the data, under learning and under rational expectations. Relative to each other it can be observed that the quarters before the negative peak are similar, whereas the recovery is slower under learning in the quarters thereafter. Learning is depicted by the black lines, rational expectations by the blue lines and real data by the green lines.

would have been more severe but shorter, while under learning the trough was smaller but the recovery lasted longer. In order to make the two approaches more comparable and see the feature of a slow recovery more clearly, we divide the simulated series for output and investment by the respective trough and look at the development five periods before and after the trough. Once again, we compare this to real data (see Figure 8). In the baseline the run-up is very similar; the recovery, especially for investement, varies a lot for both forms of expectations formation. At the peak of the crisis, households still think that the relevant level of net worth inefficiency and, hence, net worth is the previous one. Therefore, their optimized consumption and savings decision is different thanthe case where inefficiency is already starting to decrease. In contrast to the full information setup, households decrease their deposits, which is consistent with the perceived lower leverage ratio. Fewer deposits lead to less financing of entrepreneurial investment, which reduces output as well. Realizing over time that the inefficiency is falling, households catch up and start behaving in a prescribed way by increasing their deposits. As they do not actually perceive the true inefficiency level for a considerable time and always overestimate new worth inefficiency, and hence underestimate true net worth, investment and output are considerably lower and therefore closer to the actual data. In Figure14 in the Appendix we reperform the simulation and include different time-varying Kalman gains. The respective upper and lower bounds are taken as the 5% and 95% significance levels of the true learning of financial markets experts from Figure(4).We can therefore interpret these as an upper and lower bound to the learning outcome both for investment and output. The lower bound of the Kalman gain yields an even slower recovery and already matches the data pretty well.

Hence, we can derive two different results from our simulation in which agents learn about the stress level in the banking sector. Firstly, learning led to a later downturn and a later recovery, as implied by the underlying driving process. Secondly, not only did the recovery occur later under learning, the economy recovered was also slower than under full information rational expectations. This is the key result from our simulation: imperfect information about the stress level in the banking sector, which we called "inefficiency", does indeed result in a prolonged recession. Hence, we can provide an additional explanation for the slow recovery in the US following the Great Recession, particularly in light of the fact that the implemented learning speed is based on an estimation and the calibration for the underlying inefficiency process reflects the actual stress seen in the banking sector. In the following section, we provide evidence that the slow recovery is a feature of introducing learning.

4.2 Sensitivity

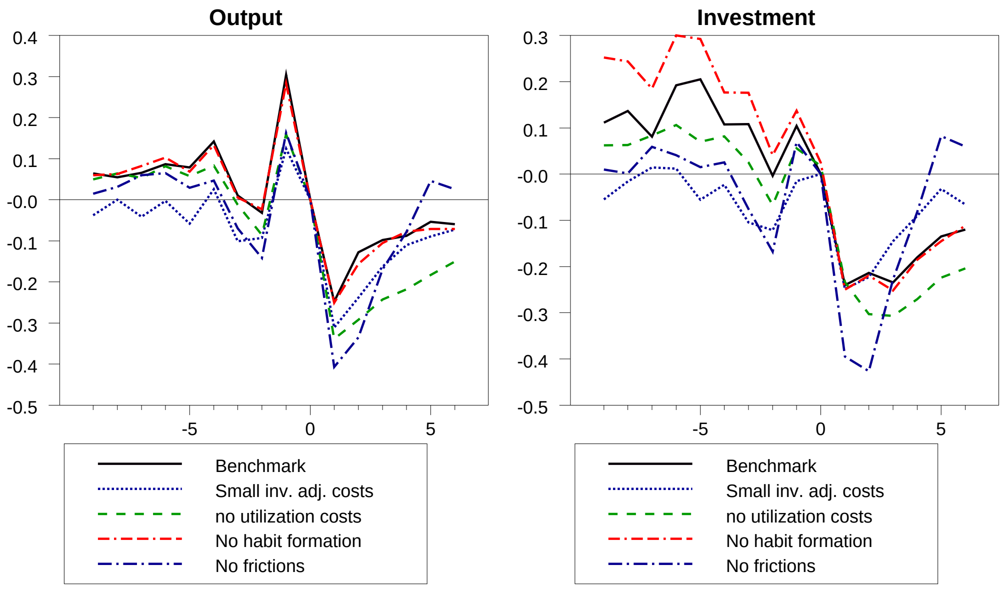
We relate imperfect information about bank equity in the US to the slower recovery. Although we abstract from sticky wages, the model we are using exhibits - in the form of sticky prices, habit formation in consumption, investment adjustment costs, and utilization costs of capital - several real frictions which have the potential to impact on our results. In order to show that the result regarding the slow recovery can be related solely to the learning mechanism, we shut down some frictions and repeat the simulation for these cases. We draw on four different cases presented together with the benchmark (solid black lines) in Figure 9. The bright blue dotted lines represent the case in which we reduce the parameter which markedly drives down investment adjustment costs down (from 1.728 to 0.1).[10] Furthermore, we set the utilization costs of capital to zero (dashed green lines) and remove habit formation in consumption (double-dashed red lines with dots). All cases combined are reflected by the dark blue dashed lines with dots. Since changes in the parameters also affect the full information rational expectations outcomes, Figure 9 plots the differences between the learning case and rational expectations, whereas both ingredients are expressed relative to their respective trough as is done in Figure 8.

Positive (negative) values consequently indicate that output or investment under learning are above (below) their respective levels under full information rational expectations. The troughs occur at period 0. It turns out that the outcomes under learning are persistently below their rational expecations counterparts in the periods following the trough. This is also true of the case where most of the real frictions are turned off. While real frictions are needed to replicate real data for the US as given in Figure 7 based on the calibration outlined in Figure 6, the slow recovery itself is predominantly driven by learning.

To show the impact of learning, we run a counterfactual experiment where we leave everything in our benchmark simulation unchanged except the Kalman gain. Regarding the Kalman gain, we start from the estimation as presented in Figure 4 but prolong the minimum to last two years before returning to the estimated level. In Figure 10 we depict the learning benchmark case and the new case (denoted by case 2) together with real data,

[10] We do not set the parameter to zero because in this case the price for capital would disappear and capital would only remain in the balance sheet of banks.

Figure 9: Learning and the impact of real frictions



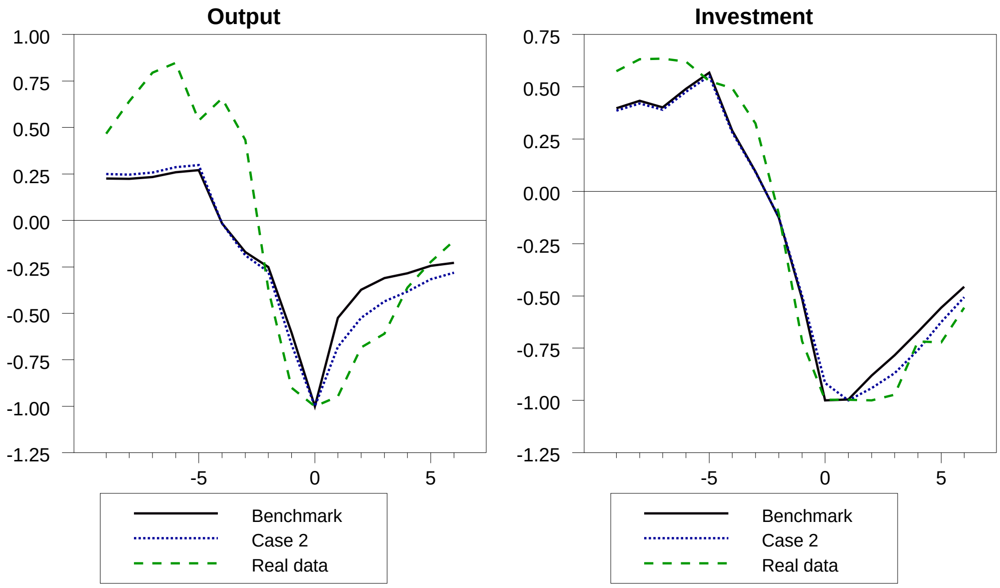
Notes: This chart shows the differences between learning and rational expectations for models with different degrees of real frictions, whereas, in each model, the outcomes are expressed relative to their respective trough.

again expressed relative to the troughs. A noisier signal leads to an even more pronounced slower recovery, as the outcomes from the counterfactual experiment are closer to the real data. This result underpins our finding that learning about bank equity is an important element in explaining the slow recovery, although it is not the only ingredient of the story.

5 Conclusion

In this paper, we offer an additional reason why the recovery in the US was slow after the financial crisis. First of all, we show empirically that there is an expectations bias about banks' net worth during and in the aftermath of the financial crisis and that financial market participants' information on this is incomplete. Agents update this information by a learning setup. On the basis of 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 a learning behavior about banks' net worth that is consistent with the empirical results. Using 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 and investment are significantly lower and protracted after the crisis has peaked compared to the full information rational expectations benchmark. The key mechanism in our model is related to our empirical results. Agents cannot observe the true net worth of banks. We do not want to argue that imperfect information is the key factor for the slow recovery. Nevertheless, our results add another layer to an understanding of the slow recovery. A point worth exploring would be to go beyond the aggregate banking sector and look more into individual banks. This avenue is left for

Figure 10: Output and investment under learning (LE) and rational expectations (RE) contrasted with real data relative to their respective troughs (Robustness)



Notes: This chart shows the five periods before and after the respective trough in the data, under learning and under rational expectations if investment adjustment costs are interacting with learning. Learning is depicted by the black lines, rational expectations by the blue lines and real data by the green lines.

future research.

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Appendix

1. Model Description

1.1 Households

A continuum of identical households with a mass of unity populates the household sector. Every household can be split into two groups. Household members who consume, save, and supply labor to the intermediate goods sector belong to the first group. Their share f does 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 maximize their lifetime utility where future periods' utilities are discounted by the rate of time preference β .

$$\max E_t \sum_{i=0}^{\infty} \beta^i \left[\ln \left(C_{h,t+i} - h^C C_{h,t+i-1} \right) - \frac{\chi}{1+\varphi} L_{h,t+i}^{1+\varphi} \right] \tag{34}$$

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 denominated in real terms consists of deposits $D_{h,t}$ and government bonds $B_{h,t}$. The gross period return of both assets, which each have a maturity of one period, is denoted by R_t. Government bonds are assumed to be 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 receive net transfers $\Pi_{h,t}$ from banks and the real sector (retailers and capital producers). As a consequence, the budget constraint arises as

$$C_{h,t} + B_{h,t} + D_{h,t} = W_t L_{h,t} + R_t \left(B_{h,t-1} + D_{h,t-1} \right) - T_{h,t} + \Pi_{h,t}. \tag{35}$$

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

$$\varrho_t = \left(C_t - h^C C_{t-1} \right)^{-1} - \beta h^C E_t \left(C_{t+1} - h^C C_t \right)^{-1} \tag{36}$$

the first-order condition for labor becomes

$$\varrho_t W_t = \chi L_t^{\varphi} \tag{37}$$

and the Euler equation is

$$E_t \beta \Lambda_{t,t+1} R_{t+1} = 1 \tag{38}$$

with

$$\Lambda_{t,t+1} \equiv \frac{\varrho_{t+1}}{\varrho_t}. \tag{39}$$

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

1.2 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

$$Y_t = A_t \left(U_t \xi_t K_t\right)^{\alpha} L_t^{1-\alpha}, \tag{40}$$

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 is a shock on the total factor productivity A_t which obeys an autoregressive process with i.i.d. normally distributed innovations ϵ_t^A

$$\log\left(A_t\right) = \rho^A \log\left(A_{t-1}\right) + \epsilon_t^A. \tag{41}$$

The second is a shock on the quality of capital ξ_t with i.i.d. innovations ϵ_t^{ξ}that are normally distributed. This shock also follows an autoregressive process

$$\log\left(\xi_t\right) = \rho^{\xi} \log\left(\xi_{t-1}\right) + \epsilon_t^{\xi}. \tag{42}$$

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 there follows the demand for physical capital as

$$P_{mt} \alpha \frac{Y_t}{U_t} = \delta' \left(U_t\right) \xi_t K_t \tag{43}$$

and the demand for labor as

$$P_{mt} \left(1-\alpha\right) \frac{Y_t}{L_t} = W_t. \tag{44}$$

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

$$R_{kt+1} = \frac{\left[P_{mt+1} \alpha \frac{Y_{t+1}}{\xi_{t+1} K_{t+1}} + Q_{t+1} - \delta\left(U_{t+1}\right)\right] \xi_{t+1}}{Q_t}. \tag{45}$$

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

1.3 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 $\left(I_{nt}\right)$, whereas the conditions $f(1) = f'(1) = 0$ and $f''(1) > 0$ for investment function are satisfied. Net investment is defined as investment $\left(I_t\right)$ not used to replace depreciated capital $\delta\left(U_t\right) \xi_t K_t$. In a market of perfect competition, capital producers maximize profits

$$\max\ E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} \Lambda_{t,\tau} \left\{ \left(Q_\tau - 1\right) I_{n\tau} - f\left(\frac{I_{n\tau} + I_{ss}}{I_{n\tau-1} + I_{ss}}\right) \left(I_{n\tau} + I_{ss}\right) \right\}, \tag{46}$$

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

$$Q_t = 1 + f\left(\frac{I_t}{I_{t-1}}\right) + \frac{I_t}{I_{t-1}} f'\left(\frac{I_t}{I_{t-1}}\right) - E_t \beta \Lambda_{t,t+1} \left(\frac{I_{t+1}}{I_t}\right)^2 f'\left(\frac{I_{t+1}}{I_t}\right). \tag{47}$$

The aggregate law of motion for capital becomes

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

1.4 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 $1-\gamma$.If a firm cannot set the price freely, it follows an indexation rule into which the lagged rate of inflation π_t enters. The optimal price P_t^* is set by the retailers as a consequence of profit maximization by taking the demand for its good and the corresponding price as given

$$\max\ E_t \sum_{i=0}^{\infty} \gamma^i \beta^i \Lambda_{t,t+1} \left[\frac{P_t^*}{P_{t+i}} \prod_{k=1}^{i} \left(1+\pi_{t+k-1}\right)^{\gamma_p} - P_{mt+i}\right] Y_{ft+1}, \tag{48}$$

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

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

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

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

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 simply have the function of introducing nominal price rigidities into the model.

1.5 Public sector

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

$$i_t = \rho i_{t-1} + (1-\rho)\left[i + \kappa_\pi \pi_t + \kappa_y \left(\log Y_t - \log Y_t^*\right)\right] + \epsilon_t^i, \tag{49}$$

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

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

1.6 Market clearing

Consumption, investment, public expenditures G_t, and investment adjustment costs determine the aggregate demand which is equivalentto 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 means that government budget is balanced every period.

2 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. 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.

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 smoothing. 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

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).[11]

Table 7: Calibrated Parameters of the model

Description	Symbol	Value
Autoregressive parameter. capital quality shock	ρ_ξ	0.66
Autoregressive parameter. incentive shock	ρ_λ	0.85
Autoregressive parameter. total factor productivity	ρ_A	0.7
Standard deviation. monetary policy shock	σ_i	0.0008
Standard deviation. capital quality shock	σ_ξ	0.002
Standard deviation. incentive shock	σ_λ	0.0025
Standard deviation. total factor productivity	σ_A	0.005

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

3. Additional Results (Robustness)

Table 8: Tests on unbiased expectations (from 1996:01 to 2015:12) - further results

	x_t	$\frac{x_t - x_{t-12}}{x_{t-12}}$	$\frac{x_t - x_{t-24}}{x_{t-24}}$	$\frac{x_t - x_{t-36}}{x_{t-36}}$
	(1)	(2)	(3)	(4)
α	0.702	0.619	-0.177**	0.008
	[0.538]	[1.381]	[-2.207]	[0.041]
β	0.884***	0.78***	0.937***	0.737***
	[10.898]	[3.157]	[23.27]	[16.774]
$H0: (\alpha = 0)$	0.289	1.907	4.87**	0.002
	(0.591)	(0.167)	(0.027)	(0.967)
$H0: (\beta = 1)$	2.030	0.794	2.462	35.732***
	(0.154)	(0.373)	(0.117)	(0.000)
$H0: \begin{pmatrix} \alpha = 0 \\ \beta = 1 \end{pmatrix}$	7.561**	1.97	9.454***	38.821***
	(0.023)	(0.373)	(0.009)	(0.000)
$H0: no\, seasonal\, effects$		4.853		
		(0.847)		
Observations	241	240	228	216
$\bar{R}^2$	0.777	0.712	0.981	0.975

Notes: 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 $x_t = EPS_t^{12M}$ are the earnings per share $H0$ denotes the null hypothesis for Wald tests with restrictions given in parentheses. Seasonal effects are tested with the help of dummies for each month except for December. The respective test for seasonal effects is an exclusion test on the dummies. $\bar{R}^2$ is the adjusted coefficient of determination. 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% (***) level.

Table 9: Test on number of breaks in unbiasedness regression for the banking sector - with BP trimming factor 0.15

Panel (a): Information Criteria				
	0	1	2	3
BIC	0.59	-1.36	-1.62*	-1.59
LWZ	0.64	-1.25	-1.46*	-1.38

Panel (b): Sequential test			
	0 vs. 1	1 vs. 2	2 vs. 3
$\sup F_T\,(m+1\|m)$	767.2	41.8*	1.8
$\sup F_T - 95\%\text{CV}$	11.3	13.4	14.3

Panel (c): Estimated break points			
		Lower 95%	Upper 95%
1	2007:05	2007:04	2007:05
2	2010:12	2010:10	2011:01

Notes: The Table shows in Panel (a) and (b) model selection results for the number of breaks. The corresponding break dates are given in Panel (c). The techniques are described in Bai and Perron (2003a) and critical values are based on the response surface regressions as given by Bai and Perron (2003b). The term $\sup F_T\,(m+1|m)$refer to the sequential break test which tests between m and $m+1$ breaks with m as the number of breaks. *BIC* and *LWZ* refer to information criteria. The trimming factor is set to 0.15. The number of observations is 240.

Table 10: Tests on unbiased expectations for the banking sector with multiple breaks regression (from 1996:01 to 2015:12) - with BP trimming factor 0.15

Regimes	1996:01-2007:05	2007:06-2010:12	2011:01-2015:12
α	-0.043***	-0.626***	-0.065
	[-2.722]	[-4.417]	[-1.549]
β	1.205***	0.288***	1.243***
	[9.426]	[12.214]	[25.248]
$H0:\ (\alpha=0)$	9.225 ***	26.352***	2.398
	(0.002)	(0.000)	(0.121)
$H0:\ (\ \beta=1\ )$	3.003*	1022.750***	24.404***
	(0.083)	(0.000)	(0.000)
$H0:\ \begin{pmatrix}\alpha=0\\ \beta=1\end{pmatrix}$	9.646***	1093.997***	24.518***
	(0.008)	(0.000)	(0.000)

Notes: 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 $x_t=EPS_t^{12M}$ are the earnings per share and i denotes the subsequent regimes. The model is estimated with the techniques developed by Bai and Perron (2003a). The number of breaks and their dates are given in Table 9. $H0$ 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.

Table 11: Test on number of breaks in unbiasedness regression for the banking sector- two and three years growth

Panel (a): Information Criteria					
	0	1	2	3	4
Two years growth rates					
BIC	-0.37	-0.89	-1.88	-1.92*	
LWZ	-0.32	-0.78	-1.72*	-1.7	
Three years growth rates					
BIC	0.63	0.23	-2.4	-2.51*	-2.46
LWZ	0.69	0.34	-2.24	-2.30*	-2.19
Panel (b): Sequential test					
$\sup F_T\,(m+1\vert m)$		0 vs. 1	1 vs. 2	2 vs. 3	3 vs. 4
Two years growth rates		134.9	202.9*	9.7	
Three years growth rates		146.1	1435.2	18.3*	-0.85
$\sup F_T - 95\%$CV		10.8	12.8	13.7	14.3
Panel (c): Estimated break points					
		Lower 95%	Upper 95%		
Two years growth rates					
1	2007:04	2007:03	2007:05		
2	2011:02	2010:12	2011:04		
Two years growth rates					
1	2002:12	2002:08	2003:02		
2	2007:12	2007:11	2008:01		
3	2012:05	2012:04	2012:06		

Notes: The Table shows in Panel (a) and (b) model selection results for the number of breaks. The corresponding break dates are given in Panel (c). The techniques are described in Bai and Perron (2003a) and critical values are based on the response surface regressions as given by Bai and Perron (2003b). The term $\sup F_T\,(m+1|m)$refer to the sequential break test which tests between m and $m+1$ breaks with m as the number of breaks.

Panel (a): Two years growth rates

Regimes	1997:01-2007:04	2007:05-2011:02	2011:03-2015:12
α	-0.162**	-0.796***	-0.351***
	[-1.992]	[-5.843]	[-2.726]
β	1.387***	0.827***	1.059***
	[3.893]	[77.025]	[72.577]
$H0: (\alpha = 0)$	3.969 **	34.145***	7.431***
	(0.046)	(0.000)	(0.006)
$H0: (\ \beta = 1\ )$	1.179	258.387***	16.297***
	(0.277)	(0.000)	(0.000)
$H0: \begin{pmatrix} \alpha = 0 \\ \beta = 1 \end{pmatrix}$	14.598***	262.901***	19.205***
	(0.001)	(0.000)	(0.000)

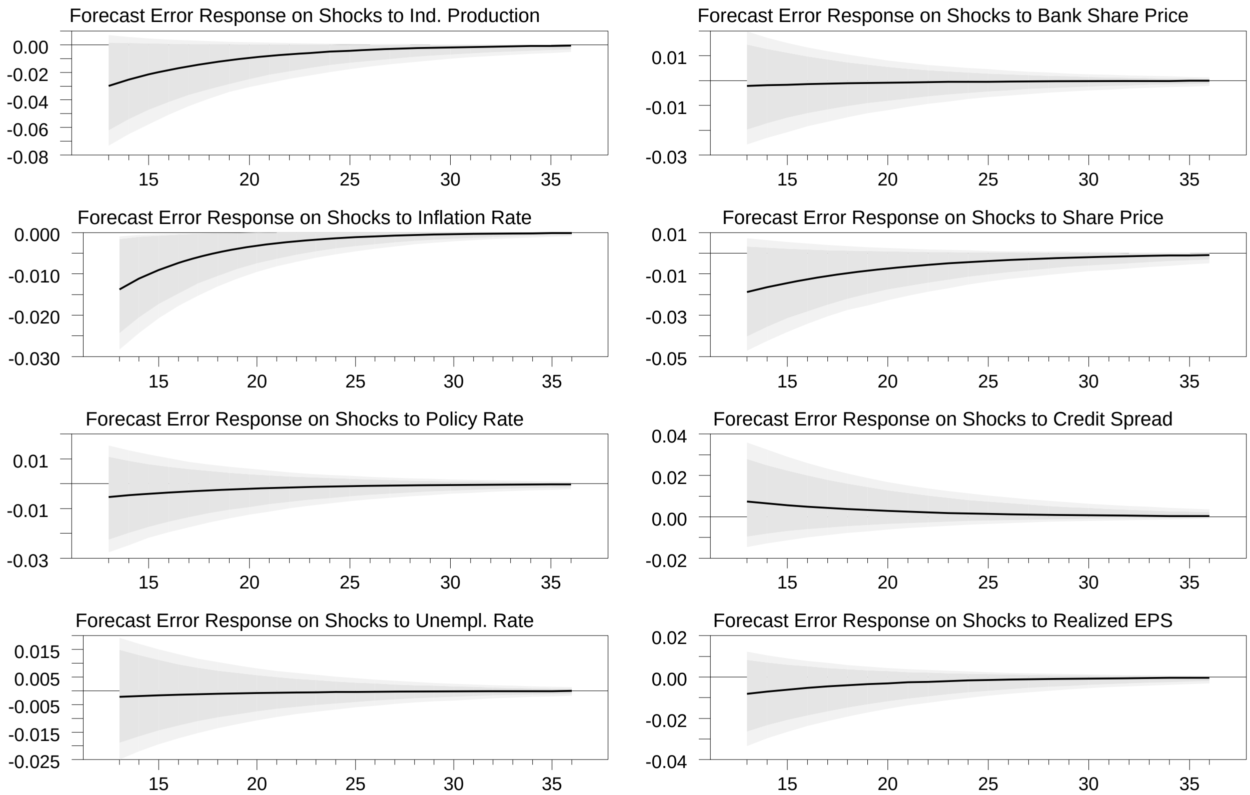
Panel (b): Three years growth rates

Regimes	1998:01-2002:12	2003:01-2007:12	2008:01-2012:05	2012:06-2015:12
α	0.529***	-0.191**	-0.991***	-0.146***
	[8.415]	[-2.411]	[-12.091]	[-3.368]
β	-0.708***	1.415***	0.678***	0.985***
	[-5.020]	[8.392]	[290.108]	[69.464]
$H0: (\alpha = 0)$	70.819 ***	5.812**	146.199***	11.34***
	(0.000)	(0.016)	(0.000)	(0.001)
$H0: (\ \beta = 1\ )$	146.739***	6.054**	18994.669***	1.195
	(0.000)	(0.014)	(0.000)	(0.274)
$H0: \begin{pmatrix} \alpha = 0 \\ \beta = 1 \end{pmatrix}$	238.276***	6.096**	19123.764***	12.675***
	(0.000)	(0.047)	(0.000)	(0.002)

Notes: The table shows the results of the unbiasedness regression $\frac{x_t - x_{t-n}}{x_{t-n}} = \sum_{i=1}^{m} \left[\alpha_i + \beta_i \frac{E_{t-n}(x_t) - x_{t-n}}{x_{t-n}} \right] I_i + e_t$, whereas $x_t = EPS_t^n$ are the earnings per share over n periods and i denotes the subsequent regimes. The model is estimated with the techniques developed by Bai and Perron (2003a). The number of breaks and their dates are given in Table 11. $H0$ 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.

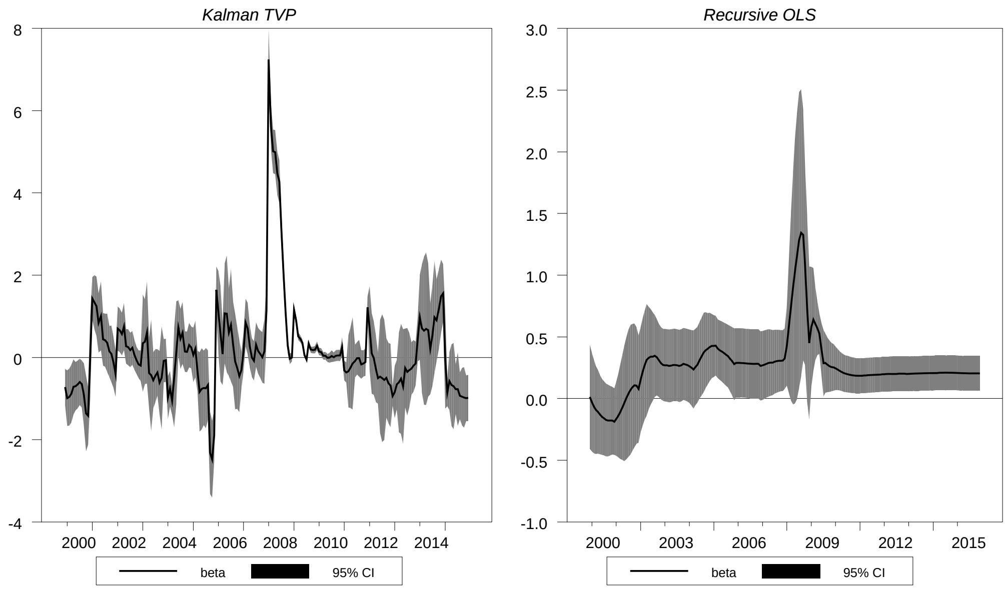
Table 12: Tests on unbiased expectations for the banking sector with multiple breaks regression - two and three years growth rates

Figure 11: Responses of Forecast Error on various Shocks (pre-crisis period)



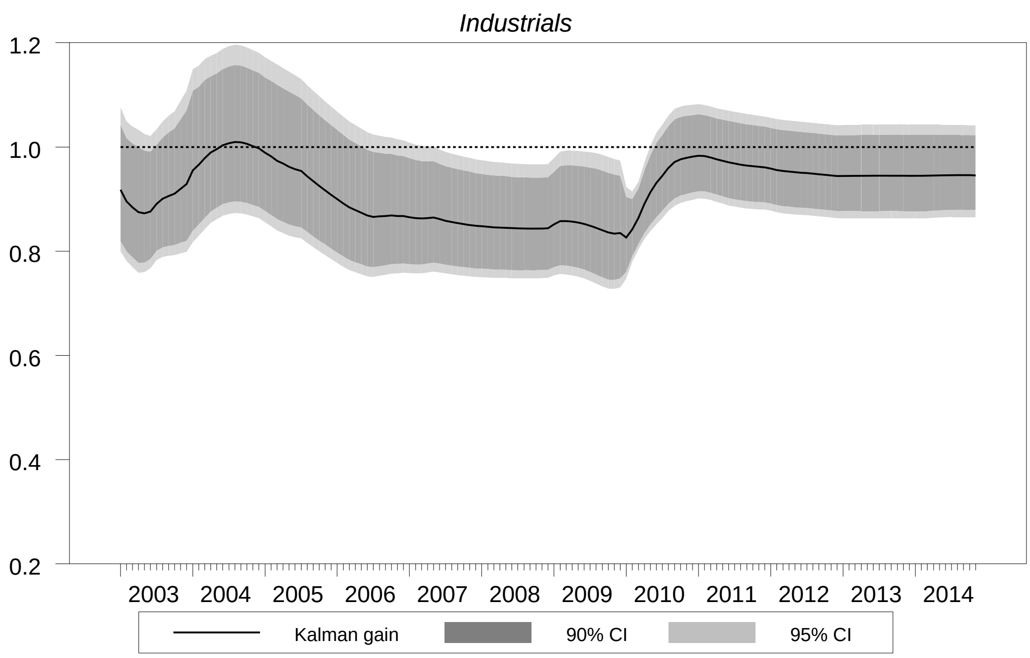
Notes: The chart shows the reponses of the forecast error, as the difference between the realized value and the previous expected value for the corresponding period, on various shocks. The shocks are structural shocks resulting from a SVAR with Choleski decomposition and the ordering given in the graph (from first left to last right position). The darker shaded areas are the confidence interval based on the 90% level and the brighter shaded areas on the 95% level. Confidence intervals are generated with the help of bootstrapping.

Figure 12: Comparison of Kalman TVP estimation with recursive OLS for β



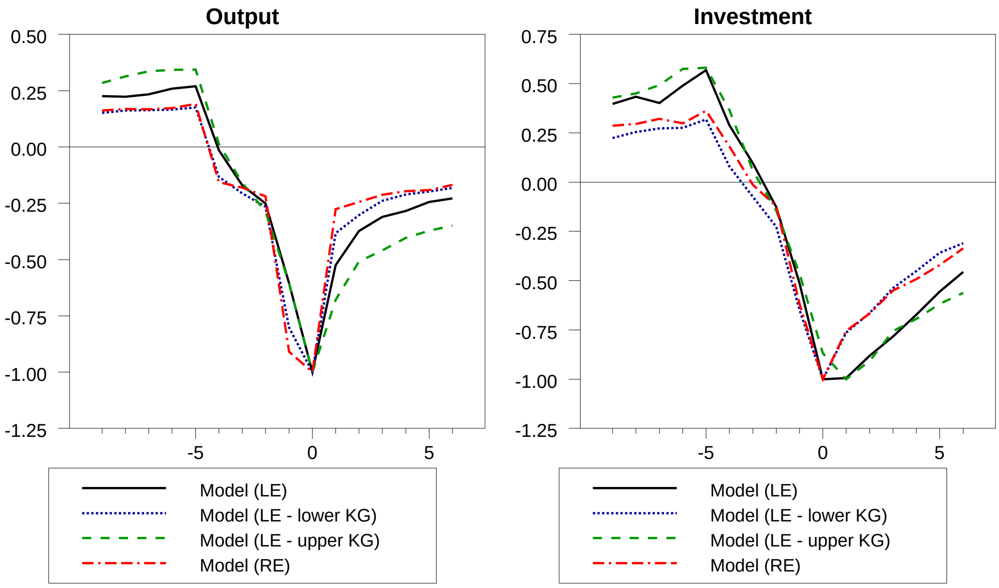
Notes: The chart shows the time-varying β-coefficient from Equation (6) estimated with the Kalman filter (LHS) and recursive OLS (RHS). Gray shaded areas refer to 95% confidence bands.

Figure 13: Kalman gain for industrial sector estimated with recursive OLS



Notes: The chart shows the time-varying Kalman gain based on Equation (6) estimated with recursive OLS for the industrial sector. Dark (bright) gray shaded areas refer to 90% (95%) confidence bands.

Figure 14: Output and investment under learning (LE) with different Kalman gains and rational expectations (RE) (Robustness)



Notes: This chart shows the five periods before and after the respective trough in the data, under learning and under rational expectations if investment adjustment costs are interacting with learning. Learning is depicted by the black lines, rational expectations by the blue lines and real data by the green lines.