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Credit, House Prices, and Risk Taking by Banks in Norway

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Abstract

Motivated by alternative explanations of the financial crisis (e.g., Acharya and Richardson, 2010; Taylor, 2007),[3] I study, first, repercussions between house price growth and household credit growth in Norway, and second, I analyse the impact of expansionary monetary policy on measures of bank portfolio risk (the risk-taking channel). Using aggregate quarterly data from 1979Q1 to 2010Q3, I find evidence of two-way causality between house price growth and household credit growth, but I find no evidence for the bank risk-taking channel: low key policy rates do not seem to have induced a higher share of troubled loans nor increased our measure of banks' riskiness.

***Keywords*: house prices, household credit, risk-taking, money and credit**

***JEL classification*: E44, E50, E51, G01, G21**

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[3] Acharya and Richardson (2009) argue that the main cause of the current financial crisis has been credit booms and house prices, while Taylor shows this was caused mainly by low monetary policy rates.

1. Introduction

Many policy makers have argued that as a result of the worldwide growth of monetary and credit aggregates over the last decade, asset markets have abundant liquidity, and that this situation has been responsible for low capital market yields and inflated asset prices, at least until mid 2007 (Goodhart and Hofmann, 2008). In particular, recent years have seen strong rates of money and credit growth accompanied by strong increases in house prices in many industrialised countries. A natural question arises: does the observed coincidence between house prices and monetary variables, such as credit growth, simply reflect the effects of a common driving force (such as monetary policy or the economic cycle), or does it reflect a direct link between the two variables? If the latter is true, which way does it go?

Motivated by similar observations, many researchers have suggested that monetary policy (in particular, easing of monetary policy) was a key contributing factor to the recent financial crisis (Acharya and Richardson, 2010). Indeed, through the risk-taking channel of monetary transmission, a monetary policy of low interest rates makes, first of all, riskless assets less attractive and may lead to a search-for-yield by financial intermediaries (Rajan, 2005), and, secondly, may induce banks to soften their lending standards by improving banks' liquidity and net worth, collateral values, in particular housing collateral (Allen and Gale, 2007; Diamond and Rajan, 2009a; Acharya and Naqvi, 2010). This is the second question I am addressing in this paper: do lower key interest rates induce risk-taking by banks in Norway?

In the context of the current crisis, Acharya and Richardson (2010) argue that the fundamental causes of the crisis were the credit boom and the housing bubble. For Taylor (2007), these were largely spurred by too low monetary policy rates. Both sides of the debate are related to risk-taking by banks: this may be caused directly, by low interest rates and search for yield, but also by higher valuation of assets and housing as collateral, caused in turn by lower interest rates. In this work I try to address the two sides of the discussion for the Norwegian market, using macro level data. As I will detail below, while certain results are strong, some others will need further analysis at a more micro level.

In sum, the purpose of this study is twofold: First, to identify causal links between house prices and monetary variables, and the direction of such causality in Norway using macro level data. Second, to test whether expansionary monetary policy, in the form of low key interest rates, has indeed spurred risk-taking by banks in the same market.

In an attempt to identify the determinants of the co-movement of house prices and credit growth (in particular household credit), I try to see whether this reflects merely the effects of a common driving force, such as monetary policy, or if there is a direct link between the two variables. If there is a direct link, I identify the direction of the causality. In my modeling, I follow Goodhart and Hofmann (2008), who also look at the relationship between house prices, credit and the macro-economy in a set of OECD countries. As is their approach, I employ a VAR model where all variables are endogenous. In line with their results, I find that house prices cause credit growth. However, the causality from credit growth to house prices is not as robust.[4] My approach is different from that of Amundsen and Jansen (2011) (who find a two-way relationship between house prices and credit in Norway), where real house prices and household debt are endogenous, but where in contrast to my approach, the after-tax interest rate is not included in the model of house prices. Their argument is that an interest rate change will merely feed into disposable income. Interest rate changes as well as levels, however, can be effective through two more channels: risk-taking (boosting demand for housing through expansive lending to lower-income groups of the population), and asset prices (via discounting and higher valuation). Using Norwegian data several other papers look at household debt (Jacobsen and Naug, 2004), and house prices (Hammersland and Bolstad Træe, 2010; Jacobsen and Naug, 2005), separately. In the latter, household borrowing is not among the explanatory variables for house prices. I model the whole credit block, including house prices and household credit, in a VAR model, taking into account the monetary policy stance via policy rates.

The impact of short-term interest rates on credit variables has been widely analysed in policy as well as academic circles. Studies have looked at changes in the aggregate *volume of credit* in the economy (Bernanke and Blinder, 1992, Kashyap and Stein, 2000). The changes in the *composition of credit* in response to changes in the quality of the pool of borrowers have been documented in Gertler and Gilchrist (1994), Bernanke, Gertler and Gilchrist (1996). Altunbas et

[4] My analysis complements theirs by taking into account banks' risk-taking and their portfolio quality. I also analyse key policy variables in Norway in more detail.

al (2009) looked at bank risk taking by identifying the determinants of expected default frequency in a number of European countries and the US (the sample does not include Norway).

This paper looks at the impact of short-term interest rates on the banks' risk-taking in Norway by analysing closely the monetary policy stance (key policy rates and central bank liquidity auctioning). It also looks at bank risk-taking in conjunction with the house price and credit boom. Low interest rates may entail more risk-taking in lending by banks directly and via weakening banking monitoring standards or high securitisation.[5] Because of severe agency problems in banking, due to bail-outs and liquidity assistance, low interest rates may induce banks to soften their lending standards by improving banks' liquidity, as in Allen and Gale (2007).

For the monetary policy stance, I look at several short-term policy rates. Even though banks may rely on long-term funding, low short-term rates may also spur risk-taking, because most interest rates may be floating in step with interbank rate fluctuations (e.g., NIBOR plus a constant rate). For robustness checks I use several key rates present in the Norwegian market, including the marginal liquidity rate, which represents possible effects (Eitrheim and Klovland 2008).

I use VAR analysis and Granger causality tests to identify the direction of causality between house prices, aggregate credit and loans. To take account of possible crisis episodes, I use several non-linear models (Akram and Eitrheim 2008). To identify whether causalities between house price booms and credit booms are stronger at times when house prices are growing too fast, I follow Goodhart and Hofmann (2008) and use a persistent deviation of real house prices from a smooth trend to identify boom periods.

[5] See for example Allen, Carletti and Marquez (2009).

2. House Prices, Credit, and the Macroeconomy

A link between credit and house prices may arise via two channels: first, via housing wealth and collateral effects on credit demand as well as collateral effects on credit supply (as banks become willing to supply credit against higher value collateral). Second, credit supply fluctuations may have further repercussions on house prices.

The life-cycle model of household consumption postulates that a permanent increase in housing wealth leads to an increase in household spending and borrowing when homeowners try to smooth consumption over the life cycle. On the supply side, the collateral effect of house prices works through valuation of houses that are pledged as collateral for loans and mortgage loans: this is the strongest collateral channel, as houses are immobile and can, therefore, not easily be put out of a creditor's reach. As a consequence, higher house prices not only induce homeowners to spend and borrow more, but also enable them to do so by enhancing their borrowing capacity, increasing banks' willingness to provide more credit.

While an increase in the physical stock of houses represents an augmentation of the nation's wealth, the effects of a change in housing wealth induced by a change in house prices is less clear, rendering the analysis important for income distribution and financial stability. The reason is that a permanent increase in house prices will not only have a positive wealth and collateral effect, but it will also have a negative income effect on tenants who now have to pay higher rents, as well as on prospective buyers (particularly first time buyers). Thus, only those who have already satisfied their housing requirements will gain. Moreover, a large proportion of the 'losers' from a relative house price increase are the unborn and below working age population. Thus, there is also an asymmetry between gainers and losers, which works in favor of a positive wealth or collateral effect of house prices on consumption. On the other hand, higher house prices may lead to higher credit supply and over-borrowing by households above capacity and may eventually lead to large-scale defaults.

3. Empirical Analysis

I begin this section by analysing the link between house price growth and household credit growth in Norway using a VAR model. The data used is aggregate quarterly data from 1979 to 2010. I also analyse the relationship separately for normal times vs. house price boom times. In the last part of the section, I look at the impact of monetary policy on banks' portfolio risk.

3.1 Data

Identifying the effective key rate in Norway is not quite straightforward. Academicians and policymakers, too, have taken different approaches to proxying the monetary policy stance. Bernanke and Blinder (1992), among others, use the overnight interest rate as the indicator of the U.S. monetary policy stance. In the euro area, the Governing Council of the ECB determines the corridor within which the overnight money market rate (EONIA) can fluctuate. Therefore, the overnight rate is also a sensible measure of the monetary policy stance in the Euro area. My first approach, however, is to use NIBOR following Altunbas et al (2008, 2009), who use three month money market rate (Euribor). They claim that this measure, unlike the interest rate on main refinancing operations, is capable of capturing the effect of the recent credit crisis on the actual cost of bank refinancing. Furthermore, I compute Taylor-rule residuals for Norway (Maddaloni 2010). Finally, following Altunbas et al (2010), I calculate the difference between the short term nominal rate and the one implied by a Taylor rule estimated by equal weights for the inflation and output gaps and without interest rate smoothing (Altunbas et al 2010).

As a second approach, I borrow a constructed monetary policy measure from Eitrheim and Klovland (2008) to take account of Norges Bank liquidity injections via auctions.

3.2 Econometric analysis

My empirical analysis is based on quarterly data in Norway spanning from 1979Q1 to 2010Q3 for most of the sample. However, some of the equations are analysed over a shorter time period owing to lack of data. The data series include nominal GDP, the consumer price index (CPI), several interest rate variables showing the short-term monetary policy stance (see details below), nominal house prices, total bank and credit to households. The analysis is based on a VAR model given by:

$$Y_t=\alpha+A(L)Y_t+\varepsilon_t$$

where Y_t is a vector of endogenous variables, ε_t is a vector of errors, A(L) is a matrix polynomial in the lag operator whose order will be determined by the Akaike information criterion considering orders up to four. The vector of endogenous variables comprises the log difference of nominal GDP (Δy), the log difference of the consumer price index (Δcpi), the level of the short-term nominal interest rate (R), the log difference of nominal residential house prices (Δph), and the log difference of nominal total credit or credit to households, Δc. The vector Y is therefore given by

$$Y= (\Delta y, \Delta cpi, R, \Delta ph, \Delta c) \qquad (1)$$

Goodhart and Hofmann perform a similar study on a sample of 17 OECD countries. They use a panel of 17 countries from 1973 to 2006. A drawback of the panel approach is that it imposes pooling restrictions across countries and thereby disregards cross-country differences in the estimated dynamic relationships.[6] A country level analysis by the example of Norway is complementary to this work and provides additional insight that is lost in the panel analysis. First, notably, Norway has had the most frequent periods of house price booms among all OECD countries. Second, I complement the study by taking into account liquidity injections by the monetary authority both as an input in the monetary stance, and through their impact on policy

[6] Goodhart and Hoffman (2008) actually check the validity of the pooling restrictions implied by the panel set-up, and they find that they were consistently rejected.

rates. Finally, I move on to analyse risk-taking by looking at monetary policy's impact on bank's portfolio quality (share of troubled loans).

The model by Hammersland and Træe (2005) estimates house prices and household credit separately. Nominal house price growth (Δph) is in the short run explained by growth in nominal income (Δinc), as well as changes in the policy interest rate (ΔR)[7] and deviations from steady state. In the short run, growth in real household debt (Δc) reacts positively to growth in real income and real house prices and decreases with higher interest rates on loans. I estimate the VAR model (1) by OLS and first perform standard Granger causality tests. In my analysis, a variable x is said to Granger-cause another variable y if the hypothesis that the coefficients on the lags of variable x in the equation of variable y are all equal to zero (i.e. that the lags of variable x can be excluded from the equation of variable y in the VAR model) is rejected by a Wald test.

To justify the variables included in the reduced VAR model (1), I do block-exogeneity (block-Granger-causality) tests which look at whether the lagged values of any variables Granger-cause any other variable in the system. At least in house price boom times (defined later) all the variables are endogenous in the model. The ordering of the variables does not matter for the Granger causality tests.

I first estimate the model using the longest sample period 1979Q1-2010Q3, with a lag order of four. The lag order of four is justified by the Akaike information criterion.[8] Table 1 displays an overview of results from Granger causality tests. The table provides evidence for causality between house prices, credit, GDP, the CPI and interest rates. In particular, GDP growth seems to Granger-cause both house price growth and nominal interest rate increases. More importantly, we see that house price growth causes growth in total credit, but total credit growth does not Granger-cause house price growth. Moreover, interest rates do not seem to be important for determining the growth of credit.

[7] Both the change and the level of interest rates are significant.

[8] This is also confirmed in Hannan-Quinn information criterion as well as sequential modified LR test statistic at 5% level.

Table 1. Granger causality: The table shows only the variables Granger-caused by another variable in VAR model (1): by GDP growth (first row), inflation (second row) and house price growth (third row). The arrows show the direction of causality while the signs in brackets show whether the impact is positive or negative. Sample period 1979Q1-2010Q3; number of observations 109.

$\Delta y \rightarrow \Delta R$ (+) 0.08		$\Delta y \rightarrow \Delta ph$ (+) 0.00	
	$\Delta cpi \rightarrow \Delta y$ (+) 0.05		
			$\Delta ph \rightarrow \Delta c$ (+) 0.02

3.3 Household credit and house price growth in boom and normal times

Evidence suggests that the link between the credit level and asset prices is particularly strong in times of asset price booms. Figures 2 and 3 show growth in real house prices and household credit in Norway. As can be seen from the figures, real house prices have grown almost every quarter after the end of the Norwegian banking crisis in 1993. The growing house prices were accompanied by a growing household debt.

Following the approach Goodhart and Hofmann (2008) in defining aggregate asset price booms, the definition of a house price boom is based on a persistent deviation of real house prices from a smooth trend, calculated by using a one-sided HP filter with a smoothing parameter of 100,000. A boom is defined as a positive deviation of house prices from this smooth trend of more than 5% lasting for at least 12 quarters. According to this definition, the periods with booms in Norway are 1985Q1-1988Q3, 1995Q4-2002Q4 and 2004Q1-2006Q4. This is by far the highest frequency of house price booms in OECD countries.

Table 2 below shows that house prices affect total credit to households at 1% significance level, but only at boom times.[9] This result is also robust when we investigate total lending by banks instead of household credit. As discussed in the introduction, recent theories of monetary transmission imply such a result due to the collateral effect and the life cycle consumption hypothesis. The result is therefore in line with the prediction: by increasing collateral values for mortgage loans, house price increases improve the creditworthiness and debt capacity of the borrowers. Furthermore, the wealth increase may stimulate borrowing and current consumption in light of consumption smoothing. Such effects are exacerbated by the fact that house price boom periods present in Norway were longest and most frequent among all OECD countries during the period 1978-2009.

Moreover, interest rates do not seem to Granger-cause credit to households at normal times, even though they do so at boom times (statistically significant at the 5% level). At first sight, this may seem counterintuitive, since one may think of interest rates as being less effective at times when rapid house price growth is believed to drive household credit growth on its own. However, this may be due to risk-taking by banks caused by low key interest rates. Indeed, as seen from the interest rate and house price growth plots, decreasing rates coincide with house price increases, especially during 1992-2006, a period that covers two of the boom periods identified above.[10]

[9] In tables 2 to 7, the sign on variable R is negative, while the rest are positive, as expected.
[10] We later use a boom definition based on two-sided HP-filter, and we see that the interest rate ceases to be significant.

Table 2. Granger causality tests: household credit growth. The table shows the result of the block Granger causality test from VAR model (1) with the same ordering. Household credit growth is the dependent variable. Sample period 1979Q1-2010Q3; number of observations 109.

House price boom times

variable	Prob.
R	0.0311
Δy	0.1872
Δph	0.0023
Δcpi	0.2176
All	0.0021

Normal times

variable	Prob.
R	0.7095
Δy	0.6722
Δph	0.1605
Δcpi	0.9181
All	0.7804

On the other hand bank risk-taking may have contributed to household credit growth. Below is an output of the following VAR model

$$Y= (\Delta y, \Delta cpi, R, \Delta ph, \Delta c, \Delta \text{troubled loan}) \qquad (2)$$

which adds the share of troubled loans to VAR model (1).[11] However, the share of troubled loans is not significantly related to household credit growth. The collateral channel of risk-taking is also corroborated in Table 3, which again uses VAR model (2) (house price growth explains household credit).

11 low rates reduce the yields on riskless assets, while inducing institutional investors seeking benchmark yields, to embark on riskier, higher-yield asset acquisition:

Table 4 looks at variables explaining troubled loans. I find that the interest rate is not significant for bank risk-taking at boom times (Table 4: p-value is 0.177). Nevertheless, the troubled loan share seems to mostly be accounted for by the higher house price inflation (p-value 0.0430), which means that the collateral effect of the risk-taking channel is present: house price increase may allow borrowers to take on more debt (e.g., mortgages), as higher collateral value is a guarantee for the increased loan amount, in line with the discussion above.

Table 3. Granger causality test: household credit growth. The table shows the result of the block Granger causality test from VAR model (2) with household credit growth as the dependent variable. Sample period 1979Q1-2010Q3; number of observations 109.

House price boom times

variable	Prob.
R	0.1023
Δy	0.5071
Δph	0.0434
Δcpi	0.4149
Δtroubled loan	0.9251
All	0.2007

Normal times

variable	Prob.
R	0.8828
Δy	0.0333
Δph	0.6158
Δcpi	0.6650
Δtroubled loan	0.2181
All	0.1176

While house price growth in boom periods is significant for the share of troubled loans, the interest rate is not: there is no evidence for the search-for-yield channel (lower interest rate does not (significantly) cause higher share of troubled loans).

Table 4. Share of troubled loans. The table shows the result of the block Granger causality test from VAR model (2) with share of troubled loans as the dependent variable. Sample period 1979-2010; number of observations 109.

House price boom times

variable	Prob.
R	0.1774
Δy	0.0637
Δph	0.0430
Δcpi	0.4058
Δc	0.5256
All	0.0003

Normal times

variable:	Prob.
R	0.3885
Δy	0.7191
Δph	0.2437
Δcpi	0.0066
Δc	0.5639
All	0.0666

To see whether our results are sensitive to the definition of boom times, we move on to define the housing boom based on a two-sided HP filter. The two-sided filter uses more information, both past and future, whereas a one-sided filter uses only past information, and it can therefore be argued that boom periods based on the two-sided filter is a more accurate approach.[12]

12 It is important to mention that the two-sided filter puts a higher weight to the end of sample observations, which are likely to be significantly revised, and hence it is not very appropriate for determining whether or not you are currently experiencing a boom.

With a smoothing parameter 100,000 as before, boom times defined this way extend until the second quarter of 2008. There are two significant changes compared to the analysis based on the one-sided filter. First, in this case the causality goes in both directions: housing credit does indeed cause house prices to rise in boom times (Table 5, leftmost). Second, in contrast to Table 3, interest rates are significant for household credit growth at the 10% level in normal times and in the total sample (Table 6).

Table 5. House price growth: two-sided HP filter. The table shows the result of the block Granger causality test from VAR model (1) where house price growth is the dependent variable. Sample period 1979-2010; number of observations 109.

House price boom times

variable	Prob.
R	0.0436
Δy	0.4391
Δc	0.0155
Δcpi	0.0384
All	0.0172

Total sample

variable	Prob.
R	0.3470
Δy	0.0598
Δc	0.8594
Δcpi	0.5239
All	0.0579

Normal times

variable	Prob.
R	0.1887
Δy	0.0437
Δc	0.8543
Δcpi	0.3435
All	0.0147

Table 6. Household credit growth: two-sided HP filter. The table shows the result of the block Granger causality test from VAR model (1) where household credit growth is the dependent variable. Sample period 1979-2010; number of observations 109.

House price boom times		Total sample		Normal times	
variable	Prob.	variable	Prob.	variable	Prob.
R	0.1812	R	0.0517	R	0.0595
Δy	0.2968	Δy	0.1875	Δy	0.8520
Δph	0.0508	Δph	0.2471	Δph	0.4780
Δcpi	0.3422	Δcpi	0.6229	Δcpi	0.5341
All	0.0029	All	0.0212	All	0.1112

In fact, the plots of interest rate, house price growth and household credit reveal an interesting relationship: During 2007 and the beginning of 2008, interest rate hikes are accompanied by high growth rates in credit and prices. While a negative relationship was established between interest rates and household credit in boom periods before 2007 (when the one-sided HP filter included years up to 2006Q4), the relationship is not any more significant when the last quarters (years 2007Q1-2008Q2) are included in the boom. This suggests that housing credit, when already expansive enough at the peak of a boom, may become the leading driver of further increases in house prices, while hardly leaving room for interest rates to have an effect.

Figure 1. The figure plots quarterly house prices (in thousands of NOK per square metre) from 1979Q1 – 2010Q3. *Source:* Association of Norwegian Real Estate agents, Finn.no.

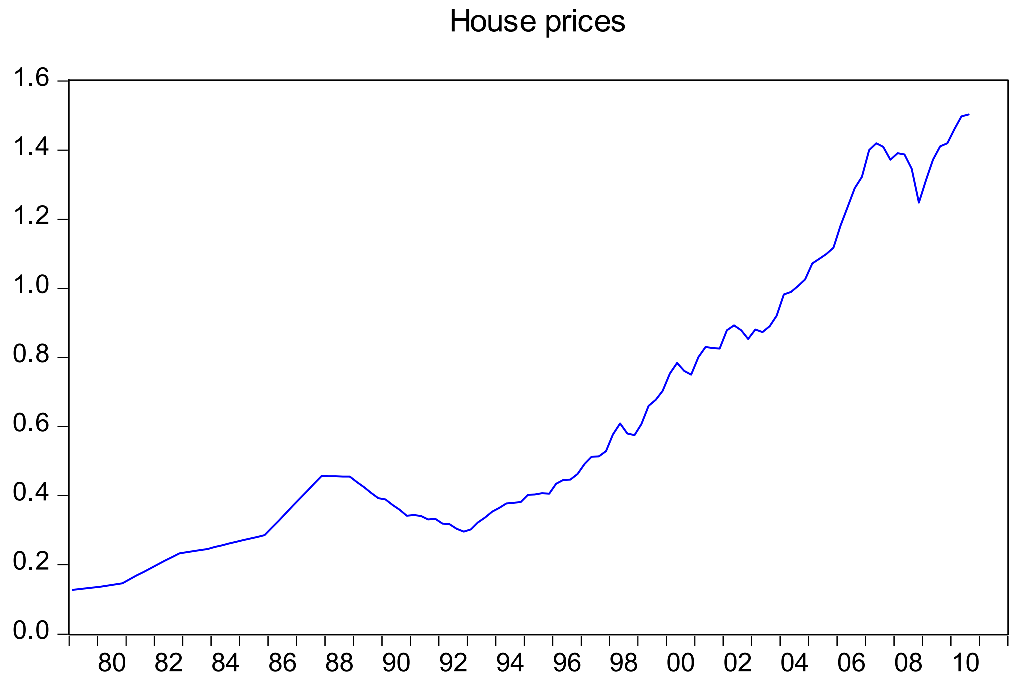


Figure 2. The figure graphs log of quarterly real house prices from year 1979Q1 – 2010Q3. *Source:* Statistics Norway Annual Report.

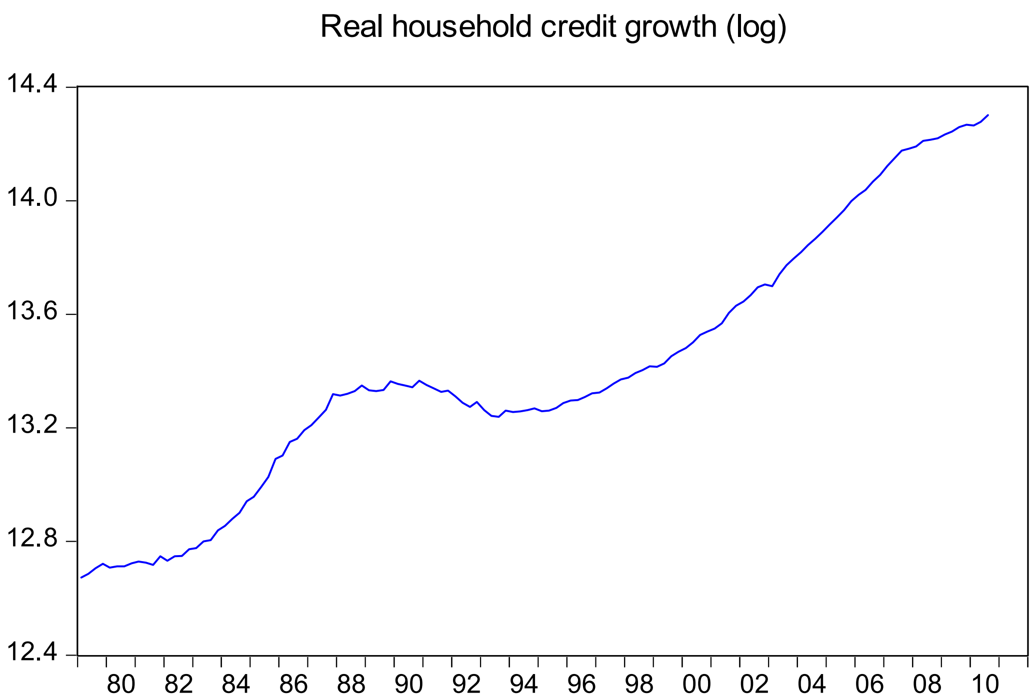
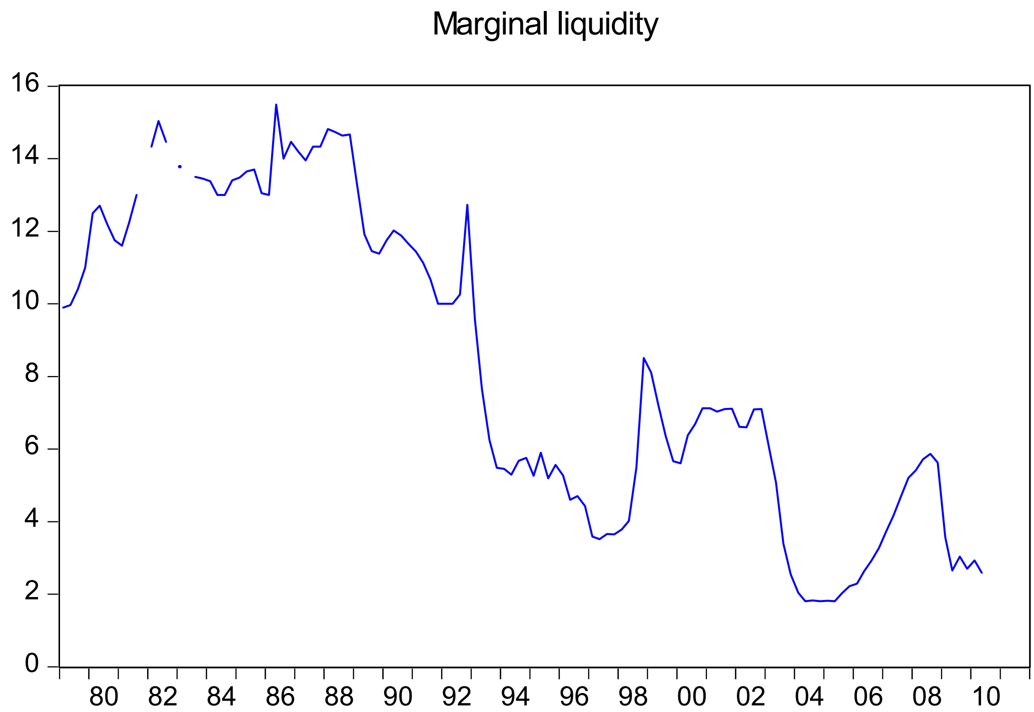


Figure 3. The figure graphs quarterly marginal liquidity rate from 1972Q1 -2010Q2. This takes account of Norges Bank liquidity injections via auctions. The series is a combination of data from discount rate, CB-loan average, CB-loan marginal rate and market paper. The CB-loan average data, extracted from Norges Bank publications, are missing for 5 quarters in the early 1980's. Source: Eitrheim and Klovland (2008).



Based on the one-sided HP filter definition of a house price boom, average quarterly house price growth is 2.5%, while it is 1.8%, when the two-sided HP filter is considered. Even with the latter average growth rate (with the boom period lasting for six more quarters), it is one of the highest among all OECD countries. Interestingly, however, the causality from household credit to house prices is only significant when the latest stages of the boom (years 2007Q1-2008Q2) are included, pointing to a possible delayed feedback from household credit to house prices.

Finally, the results are similar when I restrict the sample to after 1988, when full deregulation of credit markets was in place (Table 7). As part of this deregulation, most of the interest rate norms were removed and interest rates were allowed to float freely, bond issuing was fully liberalised and additional reserve requirements were removed.[13]

[13] For details, see Jensen and Krogh (2011), Appendix A, Table 1.

Table 7. Household credit growth: The table shows the result of the block Granger causality test from VAR model (1) for household credit growth. Sample period 1988Q1-2010Q3; number of observations 90.

House price boom times

variable	*Prob.*
R	0.3949
Δy	0.5336
Δph	0.0700
Δcpi	0.2240
All	0.0021

Normal times

variable	Prob.
R	0.0416
Δy	0.0554
Δph	0.0058
Δcpi	0.2227
All	0.0000

3.4 Non-linear Models

In this section I try to complement my analysis of relationship between house price growth and household credit growth by estimating non-linear models. To test whether monetary policy is less effective when house price growth is high, I interact key policy rate with house prices growth. Table 8 shows a positive coefficient estimate representing the interaction of house price growth and the key policy rate, but it is not statistically significant. This means that even when house price growth is very high the key policy rate does not change its impact. In particular, a positive coefficient estimate representing the interaction term implies lower growth in total housing credit when the key rate decreases (due to the negative significant coefficient estimate of the key rate). This result is also unchanged when I use the overnight rate or the three month NIBOR. The interest rate effect on household credit growth in boom time is, however, significant in Table 2. I exclude the third lag on household credit growth as it is insignificant.[14] The table also shows the residual properties; the null of no heteroskedasticity and autocorrelation cannot be rejected:

Table 8. Household credit growth: The table shows the result of OLS estimation for household credit growth. Sample period 1979Q1 – 2010Q3.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\Delta c(-1)$	0.193745	0.076330	2.538271	0.0126
$\Delta c(-2)$	0.173683	0.081007	2.144054	0.0343
$\Delta c(-4)$	0.441280	0.073726	5.985423	0.0000
$\Delta R(-2)$	-0.387807	0.132831	-2.919559	0.0043
ΔInc	0.302601	0.062680	4.827726	0.0000
CS1	-0.009311	0.003093	-3.010485	0.0033
CS2	-0.015628	0.003801	-4.111619	0.0001
CS3	-0.010638	0.003156	-3.370139	0.0010
$\Delta R(-2)\Delta ph(-2)$	0.051458	0.053498	-0.961881	0.3383
$\Delta ph(-2)$	-0.027623	0.047614	-0.580138	0.5630
R-squared				0.6733
Heteroskedasticity		Breusch-Pagan-Godfrey		0.9054
Autocorrelation		Breusch-Godfrey		0.7025
Normality		Jarque-Bera		0.11
Number of observations				117

[14] However, including all lags up to four does not alter the results.

Furthermore, I also use a logistic function to check whether non-linearities in the effect of key rates are present. The logistic term on the key policy rate has a p-value of only 0.20, thus rejecting the null hypothesis that at very high (and very low) house prices, policy rates are less effective in regulating the level of credit (Table 9).[15]

Table 9. Household credit growth: The table shows the result of logistic estimation for household credit growth. Sample period 1979Q1 – 2010Q3.

variable	Coefficient	Std. Error	t-Statistic	Prob.
Δc(-1)	0.217213	0.078137	2.779901	0.0095
Δc(-2)	0.199070	0.083952	2.371226	0.0197
Δc(-4)	0.467981	0.076988	6.078594	0.0000
R	-0.480989	0.124387	-3.866887	0.0002
ΔInc	0.299803	0.065990	4.543180	0.0001
CS1	-0.008300	0.003099	-2.678429	0.0168
CS2	-0.014010	0.003913	-3.580041	0.0010
CS3	-0.009125	0.003180	-2.869306	0.0075
R_logistic	-0.003720	0.002904	-1.280846	0.2837
Δph(-2)	-0.018034	0.046565	-0.387281	0.6876
R-squared				0.6839
Heteroskedasticity		Breusch-Pagan-Godfrey		0.6980
Autocorrelation		Breusch-Godfrey		0.7386
Normality		Jarque-Bera		0.13
Number of observations				111

[15] The logistic regression looks similar also with average bank lending rate as the p-value on the non-linear coefficient b1 and b2 are significant at 0 level, however the significance is lost when the exponential term includes also a constant

As a final test of the monetary policy's differential impact at boom vs. normal times, I use a deterministic regime switching model, by defining regimes according to whether house price increases have been below or above the mean of house price growth over the sample (the boom times defined in this way extend until the end of the second quarter of 2007). Below is an estimated equation (Table 10), where a boom dummy enters with an interaction with key rates. It is not significantly different from zero, whereas the key rate alone does have a negative impact on credit growth.

Table 10. Household credit growth: The table shows the result of OLS estimation for household credit growth. Boom times are those quarters during which house price growth is above the average house price growth over the sample. Sample period 1979Q1 – 2010Q3.

variable	Coefficient	Std. Error	t-Statistic	Prob.
Δc(-1)	0.192583	0.076535	2.516256	0.0133
Δc(-2)	0.180326	0.082089	2.196726	0.0302
Δc(-4)	0.436844	0.074079	5.896986	0.0000
R	-0.491137	0.156666	-3.134925	0.0022
ΔInc	0.296784	0.062933	4.715859	0.0000
CS1	-0.009343	0.003125	-2.990151	0.0035
CS2	-0.015416	0.003804	-4.052065	0.0001
CS3	-0.010420	0.003157	-3.300161	0.0013
ΔR*Boom	0.001329	0.002372	0.560207	0.5765
Δph(-2)	-0.017769	0.046530	-0.381881	0.7033
R-squared				0.7167
Heteroskedasticity		Breusch-Pagan-Godfrey		0.8425
Autocorrelation		Breusch-Godfrey		0.7889
Normality		Jarque-Bera		0.12
Number of observations				117

3.5 Risk-taking by lenders.

Following Altunbas et al. (2010), I use a model where the determinants for a bank risk-taking measure are the monetary policy stance, a measure of economy's risk, RBO (the effective yield of 5-year government bond), asymmetric information (represented by a long-term government bond spread), GDP growth and seasonal dummies. All the variables are taken at current and at one-quarter lags. My measure of bank's risk-taking is the share of troubled loans, and I use a set of determinants similar to Altunbas et al. (2010) in order to test whether monetary policy stance has an effect on troubled loans.

By definition, troubled loans are those where payments due for more than 90 days are not made. To take account of this lag, as well as the fact that loan maturities may be up to several years[16], I take key policy rates at their 6^{th}, 7^{th}, and until 15^{th} quarter lags. Table 11 shows that they do not seem to be significant determinants for the share of troubled loans. This result is in fact robust for any lag larger than three quarters.

Several other tests in the appendix show robustness checks of this result. I follow Maddaloni et al (2010), and proxy monetary conditions by the Taylor-rule residuals obtained by regressing the overnight rates on GDP growth and inflation (Table A2), as well as Altunbas et al (2010) in proxying it by the difference between the nominal short-term interest rate (NIBOR in our case) and that generated by Taylor rule, where the equilibrium rate is calibrated at approximately 3% and the coefficients of the inflation and output gaps are estimated at, respectively, 1.2 and 0.7.

[16]It is generally hard to find significance with such long lags. This is because the relationship becomes much more likely to be affected by variables not included in your specification.

Table 11. Share of troubled loans: The table shows the result of OLS estimation for bank risk-taking via share of troubled loans. Boom times are those quarters during which house price growth is above the average house price growth over the sample. Sample period 1990Q3–2010Q3.[17]

Variable	Coefficient Boom period	Prob.	Coefficient Normal period	Prob.
∆Troubled loan(-1)	-0.096134	0.110575	-0.869404	0.3878
∆Troubled loan(-1)	0.430450	0.111157	3.872448	0.0003
R(-6)	0.012213	0.125055	0.097661	0.9225
R(-7)	0.082822	0.202176	0.409654	0.6834
R(-8)	-0.098040	0.125814	-0.779249	0.4387
∆RBO	-0.109840	0.208641	-0.526453	0.6004
∆RBO(-1)	0.145554	0.207848	0.700291	0.4862
CS1	0.990028	0.419500	2.360020	0.0213
CS2	0.570417	0.496136	1.149718	0.2545
CS3	0.222169	0.385276	0.576649	0.5662
∆Y(-1)	-5.61E-06	1.23E-05	-0.455399	0.6503
∆Y	7.80E-06	1.24E-05	0.631216	0.5301
R-squared				0.3588
Heteroskedasticity		Breusch-Pagan-Godfrey		0.2470
Autocorrelation		Breusch-Godfrey		0.9090
Normality		Jarque-Bera		0.00
Number of observations				77

[17] The share of troubled loans is available from 1990Q3.

As mentioned before, RBO is the effective yield on 5-year government bonds, and measures the economy's risk. Table A2 shows that even for longer lags (13-15), there are no statistically significant signs of bank risk-taking.

As a final robustness check (Tables A3 and A4), I use a bank risk index as a dependent variable. The risk index is calculated from a logit model based on balance sheet data (Andersen 2008). In the regression below, I use the 90th percentile bank risk in the system. The impact of the key rate on banks' risk is yet again not significantly different from zero.

3. Conclusions

In this study I address two main questions. First, whether there are causal links between house prices and credit and what the direction of such causality is, using macro level data for Norway. Second, has expansionary monetary policy, in form of low key interest rates, caused risk-taking by banks?

Regarding causality between house prices and credit, evidence presented suggests that house price increase causes credit growth during boom periods of house price growth. The direction in the other way depends on the definition of boom periods. Based on a two-sided HP filter (see text for details), we find evidence of causality from credit to house prices at a 5% level of significance. Importantly, the two-sided HP filter also includes the year 2007 and the beginning of 2008, while the one-sided HP filter includes a boom period up until 2006Q4. Hence the impact of credit growth on house prices may be interpreted as "delayed".

It is important to mention that the two-sided HP filter uses more information, both past and future, whereas one-sided filter uses only past information, and, therefore, based on the two-sided filter a boom period identified in the past may be a more accurate approach. Moreover, interest rates are not significant in boom times for household credit growth but are significant at normal times and for the total sample.

This suggests that housing credit, when already expansive enough at peaks of a credit boom may become the leading driver of further increases in house prices, while hardly leaving room for interest rates.

I extend the analysis to take account of bank risk-taking, and find evidence that this may largely be caused by the collateral channel of risk-taking, whereby increased house prices work as an instrument for creditors to get more credit. In contrast, I do not find robust evidence that low policy rates directly cause household credit growth (absence of search-for-yield)

Regarding, risk-taking by banks, my results do not show statistical evidence of riskier activities following expansionary monetary policy. However, interpretation should be prudent given that the analysis is based on macro-level data: even though banks may have engaged in risk-taking through search for yield as well as collateral effects, this may not be observable: indeed, on the one hand lower rates may generate risky loans, on the other, they increase the repayment capacity of already existing borrowers, thus, possibly making up for risk-taking. More detailed data are necessary to disentangle the two.

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APPENDIX

Table A1. OLS Dependent variable Share of troubled loans. The table shows the result of OLS estimation for bank risk-taking via share of troubled loans. Sample period 1979-2010.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
∆Troubled loan(-1)	0.513026	0.202276	2.536260	0.0196
R(-6)	0.013496	0.030078	0.448680	0.6585
R(-7)	-0.121501	0.057649	-2.107612	0.0479
R(-8)	0.129756	0.047889	2.709534	0.0135
RBO	0.021201	0.073601	0.288057	0.7763
RBO(-1)	-0.039590	0.068411	-0.578713	0.5692
CS1	0.145998	0.095755	1.524707	0.1430
CS2	0.068200	0.083349	0.818243	0.4229
CS3	0.114962	0.096583	1.190288	0.2479
∆ y(-1)	1.38E-06	2.98E-06	0.465072	0.6469
∆ y	8.99E-08	4.44E-07	0.202666	0.8414
TAYLORRESIDS	0.004876	0.026689	0.182690	0.8569
∆ (TAYLORRES(1))	-0.015757	0.035423	-0.444832	0.6612
R-squared	0.576624	Mean depend var.		0.0561

Table A2: Dependent variable Share of troubled loans. The table shows the result of OLS estimation for bank risk-taking via share of troubled loans. c

Variable	Coefficient	Std. Error	t-Statistic	Prob.
∆Troubled loan(-1)	-0.326658	0.196665	-1.660984	0.1087
R(-13)	0.541762	0.773394	0.700499	0.4898
R(-14)	-0.507105	0.663506	-0.764280	0.4516
R(-15)	0.793349	0.507280	1.563927	0.1299
RBO(-13)	-1.369251	0.812421	-1.685395	0.1039
RBO(-14)	1.361618	0.799148	1.703838	0.1003
CS1	1.574906	0.856751	1.838230	0.0775
CS2	0.542565	0.629038	0.862531	0.3963
CS3	0.785224	0.596734	1.315868	0.1997
∆y(-1)	-3.45E-06	2.73E-05	-0.126282	0.9005
∆ y	3.64E-07	1.06E-06	0.342941	0.7344
R-squared	0.341403	Mean dependent var		0.011102

Table A3. Dependent variable, Bank risk measure at 90th percentile. The risk index is calculated from a logit model based on balance sheet data. Sample period 1979-2010. *Source (risk index):* Andersen 2008.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Bankrisk(-1)	-0.252120	0.123498	-2.041493	0.0455
R(-11)	7469.608	9470.437	0.788729	0.4333
R(-10)	352.7057	9856.605	0.035784	0.9716
R(-9)	-1883.798	9476.444	-0.198787	0.8431
RBO	2079.725	14964.88	0.138974	0.8899
RBO(-1)	-10506.56	14650.71	-0.717137	0.4760
CS1	-36914.48	25956.74	-1.422154	0.1601
CS2	-17587.95	23965.12	-0.733898	0.4658
CS3	-3812.852	21601.45	-0.176509	0.8605
Δy(-1)	0.311636	0.803135	0.388025	0.6993
Δy	0.110735	0.050234	2.204395	0.0313
R-squared	0.184819	Mean dependent var		-7390.056

Table A4. Dependent variable, Bank risk measure at 90th percentile. The risk index is calculated from a logit model based on balance sheet data. *Source, Andersen, 2008.* Sample period 1979-2010.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Bankrisk(-1)	-0.476016	0.083926	-5.671873	0.0000
R_average	3.234364	6.163142	0.524791	0.6017
RBO	70.42513	30.50298	2.308795	0.0244
RBO(-1)	-98.08361	30.16621	-3.251439	0.0019
CS1	-7.880902	54.11621	-0.145629	0.8847
CS2	-18.24547	47.13715	-0.387072	0.7001
CS3	32.94581	42.92916	0.767446	0.4458
Δy(-1)	-0.000190	0.001627	-0.116560	0.9076
Δy	0.000308	0.000109	2.838535	0.0062
R-squared	0.438837	Mean dependent var.		-11.67565