

Capital regulation and macroeconomic activity: Implications for macroprudential policy

Roland Meeks*
Bank of England and
Centre for Applied Macroeconomic Analysis

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Abstract

This paper studies the macroeconomic effect of changes in the capital requirements set by microprudential bank regulators. The central result is that unanticipated increases in capital requirements lower lending to firms and households, reduce aggregate expenditure and raise credit spreads. A financial accelerator effect is found to amplify the macroeconomic responses to shifts in bank credit supply. Results from a counterfactual experiment that links capital requirements to house prices and mortgage spreads indicate that a counter cyclical capital buffer could be an effective macroprudential tool. The reported simulations show that tighter macroprudential policy would have lowered house prices and mortgage lending in the early 2000s, with easier monetary policy acting to offset the contractionary effects on output.

Keywords: bank lending and the macroeconomy; bank capital regulation; housing market; macroprudential policy; Basel III

JEL codes: E51, E58, G21, G38

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1 Introduction

Compared to non-financial firms, banks fund a relatively small proportion of their assets using capital. As a result, capital takes on special importance for banks, and is the focus of attention for prudential regulators, who have a long history of setting down minimum capital standards.¹ Since the turmoil in advanced economy banking systems that began in 2007, reforms to the Basel Accords (Basel Committee on Banking Supervision, 2010a) have granted regulators new macroprudential powers that allow them to vary capital requirements in response to aggregate credit conditions. The central empirical question confronting the operation of counter cyclical macroprudential policy is whether aggregate variables respond to changes in bank capital, and if so by how much.²

Answering this question is far from straightforward. The first difficulty is that most variation in bank capital is likely to be the result of disturbances to macroeconomic variables, such as output or interest rates. These variables affect capital directly by causing variation in retained earnings and the prices of assets held in bank trading books (the ‘bank capital channel’, Gambacorta and Mistrulli, 2004). The same disturbances also affect credit demand, creating an identification problem. While specific one-off events have provided some convincing evidence for a channel from changes in bank capital to economic activity, via lending, progress has otherwise been limited by a lack of suitable instruments.³

The second difficulty is that it is necessary to isolate changes in capital caused by regulation. In most jurisdictions, such changes have been infrequent. Where systematic reviews of individual banks’ capital requirements did take place, the effects of regulation on bank-level loan supply can be estimated, but a useful model must provide estimates of the ‘total’ effect of a shift in bank capital on loan supply, taking into account feedbacks between the banking system and the macroeconomy. This is not possible with a purely bank-level analysis (Hancock, Laing, and Wilcox, 1995).

In this paper we claim to go some way towards resolving these problems. We make use of data on the actual capital requirements set by regulators for individual banks operating in

¹Since the introduction of the Basel Accords in 1988, capital requirements on banks in jurisdictions that adopted the international rules have been formulated in terms of the ratio of capital to assets, or risk-weighted assets. Although capital requirements date back to the mid-19th Century, historically countries have set a wide variety of restrictions including fixed minimum levels of capital, minimums that depended on the population in a bank’s operational locale, and from the early 20th Century minimum proportions of liabilities (Grossman, 2010, Ch. 6).

²Theoretical arguments rest on there being an economically large deviation from the Modigliani-Miller irrelevance proposition, leading higher capital requirements to raise bank funding costs (Miller, 1995). If such costs are passed through to borrowers, a reduction in credit, and by extension aggregate expenditure, may result.

³See for example Peek and Rosengren (2000), Ashcraft (2005) and Ziebarth (2013). These event-type studies provide a high level of econometric credibility, but by their nature have a scope that is limited in time and place. An influential earlier literature examined the introduction of leverage restrictions and risk-based capital requirements in the US as part of the first Basel Accords; see Berger and Udell (1994), Hancock and Wilcox (1997, 1998).

the UK. Over the 1989-2008 period covered in this study, regulators required banks to hold surplus capital (a capital ‘buffer’) above the time-invariant minimum levels set down in the Basel Accords. They operated a system in which there was variation in capital requirements both over time and across banks. This variation, coupled with institutional knowledge, make it possible to identify regulation-induced shocks to banking system capital and to assess the dynamic interactions between the banking system and the macroeconomy in a standard monetary vector autoregression (VAR).⁴ Ours is the first paper to study the pass-through of changes in microprudential regulation to macroeconomic aggregates.

Our most important finding is that unanticipated changes in the level of capital requirements affect not only bank lending, but also the wider economy. A tightening of capital requirements reduces credit growth to households and non-financial firms, and raises spreads on home mortgages and on corporate bonds. Housing market activity is also damped down, with both lower average house prices and a higher proportion of mortgages in arrears. A systematic easing of monetary policy acts to cushion the effect on output, which for a 50 basis point shock is on average roughly 0.2% lower than trend, two-to-three years after the shock. The finding that a financial shock—one that alters the mix of liabilities at financial intermediaries—has distinct real effects adds to the growing literature on the importance of credit markets as a source of aggregate fluctuations, as in Gilchrist and Zakrajšek (2012), Meeks (2012) and Walentin (2014).

We argue that our findings can inform the use of time-varying capital requirements as a macroprudential tool (the so-called counter cyclical buffer found in Basel III). We report that a counterfactual macroprudential policy rule, linking capital requirements to house prices and mortgage spreads, would have led to a substantially higher aggregate capital ratio, and would have had a moderating influence on credit growth and house prices, prior to 2007. A rule that responds to the credit-to-GDP gap, suggested as an indicator for setting the counter cyclical buffer, performs noticeably less well.

The VAR model that we use is similar to those adopted by Berrospide and Edge (2010), Iacoviello and Minetti (2008), and Walentin (2014), but includes a somewhat richer set of variables to account simultaneously for bank balance sheet dynamics, credit conditions, and housing market and other macroeconomic responses. We share with Bassett, Chosak, Driscoll, and Zakrajšek (2014) the goal of identifying shifts in the supply of bank lending. But whereas the survey responses used in that paper are not specific about the source of the supply shift, in this paper we isolate the effect of capital requirements. Shocks to capital requirements affect

⁴Francis and Osborne (2009b) provide a description of the institutional environment, and summarise trends in UK banking capitalisation. The Bank of England was responsible for banking regulation prior to 1997, with the Financial Services Authority (FSA) in charge thereafter. The Prudential Regulatory Authority, a subsidiary of the Bank, took over from the FSA in April, 2013. However, the earlier date of December 2008 marks a distinct change in FSA policy to an ‘Enhanced Prudential Regime’, and so we end our analysis in 2008:Q3 (see Bailey, 2012). I am grateful to Michael Straughan for clarifying these points.

bank capital ratios, like the shocks identified by Berrospide and Edge (2010), but in our set-up they have a plausibly exogenous source in regulatory actions.

The econometric estimates we present exploit bank-level variation in required capital ratios, as in Aiyar, Calomiris, and Wieladek (2012), Francis and Osborne (2009a) and Labonne and Lamé (2014), to sharpen our estimates of the relationship between changes in regulation and changes in bank lending. Formally, estimates from bank-level panel data inform the prior parameter distribution of a standard Bayesian VAR. The idea of combining micro and macro information via a Bayesian prior was employed in the context of a dynamic stochastic general equilibrium (DSGE) model by Chang, Gomes, and Schorfheide (2002).⁵ The estimation approach includes as a special case the ‘plug in’ method adopted by De Graeve, Kick, and Koetter (2008), but rather than treating micro estimates as fixed parameters, allows the additional information present in aggregate data to affect aggregate dynamics, and an appropriate assessment of parameter uncertainty.

A related idea is to identify shocks at the micro level, and then to aggregate them in order to assess their macroeconomic effects, which requires adequate controls for bank-level credit demand to be found. Examples of this approach can be found in Amiti and Weinstein (2013), Mésonnier and Stevanovic (2012) and Bassett, Chosak, Driscoll, and Zakrajšek (2014). Another approach to incorporating micro information is to augment a VAR with statistical factors extracted from disaggregate data on bank balance sheets. In such a factor-augmented VAR (FAVAR), the dynamic properties of the common components of important banking variables, extracted from institution-level data, are modeled alongside an array of macroeconomic data, see Jimborean and Mésonnier (2010) and Buch, Eickmeier, and Prieto (2010).⁶ None of the cited studies were able to examine directly the effects of regulatory capital requirements, the subject of the present paper.

The rest of this paper is organized as follows. Section 2 reviews the necessary background material that underlies our empirical approach, and gives details of the data that is used in the empirical work. Our main results can be found in section 3, while section 4 reports on the results of a counterfactual experiment in which capital requirements are set according to a macroprudential rule. Section 5 presents robustness checks on the estimation method and identification, and our conclusions can be found in section 6.

⁵There have been a few attempts to estimate fully structural DSGE models that incorporate banks, as in Gerali, Neri, Sessa, and Signoretti (2010) for the euro area; Hirakata, Sudo, and Ueda (2011) for the U.S.; and Villa and Yang (2011) for the UK. However, each of these studies introduces banking in a different way, making it hard to draw general conclusions.

⁶Something of a drawback of the FAVAR approach is that first stage extraction of principal components does not deal well with the type of rotating panel data typically encountered in practice. This has lead Jimborean and Mésonnier and others to filter out banks which enter or exit over their sample period, including due to mergers, which raises concerns of sample selection bias.

2 Data sources and empirical methodology

2.1 Data sources

Three categories of information are used in the analysis: aggregate macroeconomic data, aggregate banking data, and micro banking data. Details of the data and its sources can be found in table A.1. The macroeconomic data includes a set of standard core variables (in levels): log real gross domestic product, the log consumer price index and the Bank of England base rate. In common with Walentin (2014) and Iacoviello and Minetti (2008), who also build models on UK data, we include average house prices and mortgage spreads. In addition, we include the proportion of households 6 months or more in arrears.⁷ As a rough proxy for the marginal cost of external finance for corporations, we use the spread between average investment grade corporate bond yields and 10 year gilts.

Turning to the banking data, we have an institution-level panel on a number of balance sheet items recorded over some 19 years. The panel is unbalanced and rotating, principally due to multiple merger and takeover events.⁸ The key variable in the micro data set is the confidential information on how much capital regulators required banks to fund themselves with, over and above the Basel minimum. Breaches of this additional requirement, referred to as ‘individual capital guidance’ (ICG), would trigger regulatory action, so the ratio of regulatory capital (including the ICG) to risk weighted assets will be referred to as the ‘trigger ratio’.⁹ In the data, banks are seen to maintain surplus capital to avoid accidentally triggering intervention from regulators, and to preserve future lending capacity (Repullo and Suarez, 2013). Changes to the capital buffer, rather than capital ratios themselves, are then associated with changes in lending.¹⁰ After filtering, the dataset contains 644 observations on 21 UK banks, treating pre- and post-merger banks as separate entities.

In addition to the required capital ratio, we have information on banks’ published capital ratio, constructed as the ratio of tier 1 or ‘core’ capital to risk-weighted assets. We also make use of two measures of bank lending: to private non-financial corporates (PNFCs), and secured mortgage lending to households. Both credit variables are measured in terms of the flow of

⁷The principal reason for including arrears is to explain the data in the early 1990s, when a significant housing bust and high interest rates led a large number of UK households to fall behind on repayments, and to nearly 350,000 homes being repossessed. These factors continued to depress mortgage lending long after a general economic recovery was underway.

⁸Davies, Richardson, Katinaite, and Manning (2010) detail some history of UK banking sector consolidation.

⁹Throughout, the Basel minimum requirement was a risk-asset ratio of 8%, of which at least 4% had to be tier 1 capital. The ICG framework was initially implemented under the Basel I regime, but was extended under Pillar 2 of Basel II (introduced in 2004).

¹⁰For a *given* required capital ratio, bank capital buffers have been found to vary substantially over the business cycle. A number of studies have concluded that there has been a systematic tendency for banks to run down their capital buffers during expansions, and rebuild them during contractions: amongst others, Ayuso, Pérez, and Saurina (2004) for Spain, and Stolz and Wedow (2011) for Germany. The results here indicate that, at the aggregate level, an additional source of counter-cyclical variation in capital buffers is variation in overall capital requirements.

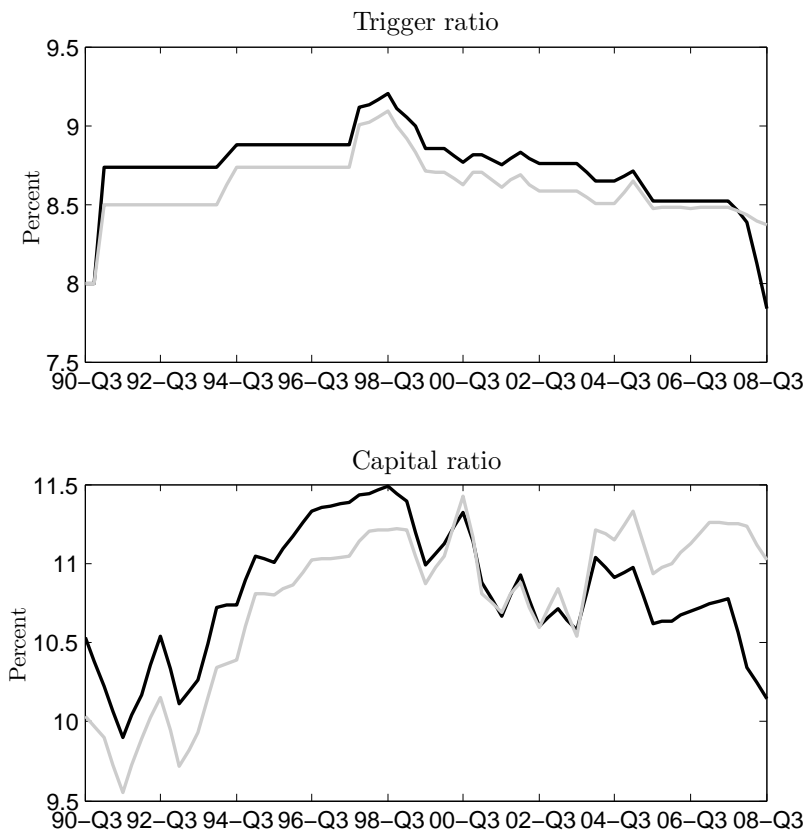


Figure 1. Required and actual banking system capital ratios. *Note:* black line – weighted by share of lending; gray line – unweighted (simple average).

new lending in the current quarter (which differs from the change in the stock of lending due to write-offs and other items) scaled by the stock of loans outstanding in the previous quarter.¹¹

We construct aggregate counterparts of the bank-level capital and trigger ratios by taking the weighted average across banks each period (with weights determined by banks' lending share).¹² The aggregate data, plotted in figure 1, naturally inherit the relatively short history of the underlying micro data. The central point of note is that variation in trigger ratios is not averaged away by aggregation, as Aiyar, Calomiris, and Wieladek (2012) also remark, which is a crucial pre-requisite for identification. Moves in the trigger ratio are relatively infrequent over the first part of the sample, but tend to be large; ignoring zero and very small changes, the

¹¹Aggregate counterparts of the lending series are obtained from Bankstats, and are based on a moderately larger sample of lenders than those in the micro data. From the late 1990s onwards, the Bank of England has collected securitization adjusted data on lending stocks, and we use these throughout. Securitization made a negligible contribution to UK lending prior to that time. We refer the reader to Bridges, Gregory, Nielsen, Pezzini, Radia, and Spaltro (2014) for additional description of the micro dataset, and details of its underlying sources.

¹²The results below are near identical when using the unweighted series, so we report only on the weighted series.

average change in system-wide capital requirements was 15 basis points over the full sample. The aggregate capital ratio is substantially more variable than capital requirements, as expected. Interestingly, the size-weighted series lies substantially below the unweighted series from the mid-2000s to 2008, as the largest banks ran down their capital ratios over this period.

2.2 Model and identification

The tool we adopt to investigate the macroeconomic impact of prudential policy is a structural VAR. The advantage of the VAR approach is that captures complex dynamic interactions between banking and macro variables, while imposing few restrictions. Letting \mathbf{y}_t be a vector containing the $m = 11$ aggregate variables listed in table A.1, and $\mathbf{x}_t = (\mathbf{y}_{t-1}^\top, \dots, \mathbf{y}_{t-p}^\top, 1)^\top$ be a vector of lag terms, the structural VAR(p) is given by:

$$\mathbf{y}_t^\top \mathbf{A} = \mathbf{x}_t^\top \mathbf{F} + \boldsymbol{\nu}_t^\top, \quad \boldsymbol{\nu}_t \sim N(0, \mathbf{I}) \quad (1)$$

where \mathbf{A} summarises the contemporaneous relationships between the elements of \mathbf{y}_t , $\boldsymbol{\nu}_t$ is a vector of independent stochastic disturbances, and $\mathbf{F} = (\mathbf{F}_1^\top, \dots, \mathbf{F}_p^\top, \mathbf{c})^\top$ collects together both the intercept vector \mathbf{c} and the lagged autoregressive matrices. Individual structural equations are read down columns of $[\mathbf{A}^\top; \mathbf{F}^\top]^\top$, with variables in rows. The corresponding reduced form VAR is given by:

$$\mathbf{y}_t^\top = \mathbf{x}_t^\top \mathbf{B} + \mathbf{u}_t^\top, \quad \mathbf{u}_t \sim N(0, \boldsymbol{\Sigma}_u) \quad (2)$$

where $\mathbf{B} = \mathbf{F}\mathbf{A}^{-1}$, $\mathbf{u}_t^\top = \boldsymbol{\nu}_t^\top \mathbf{A}^{-1}$ and $\boldsymbol{\Sigma} = \mathbb{E}[\mathbf{u}\mathbf{u}^\top]$. We discuss estimation of (1) in section 2.3.3 below.

As it stands, the model in (1) embodies no restrictions, aside from the requirement that \mathbf{A} be full rank, and so is not identified. The remainder of this section details the assumptions made in order to identify the effects of changes in regulatory capital. They are based on two features of the institutional practice followed by regulators in the UK between 1989 and 2008.

First, bank trigger ratios were not public information, but were rather communicated privately between the regulator and an individual regulated institution. The fact that the changes in the trigger ratio were not directly observed by the public makes it plausible to believe that no macroeconomic variable responded directly to shocks to the trigger ratio, either within the quarter or with a delay. Accordingly, the trigger ratio is excluded from the macroeconomic block of the VAR. By contrast, banking variables are permitted to respond. We allow actual capital ratios—and so capital buffers—to respond immediately to changes in the trigger ratio (for example through changes to capital or risk-weighted assets outside the banking book), but restrict the response of loan quantities and our proxies for the cost of credit not to change. This assumption is consistent with there being some delays in arranging new loans, and some stickiness in loan prices, and is in line with the balance sheet dynamics reported for US banks

by Hancock, Laing, and Wilcox (1995). In their analysis of bank leverage shocks, Berrospide and Edge (2010) make a similar assumption, but the results we present below are in any case insensitive to placing capital variables ahead of other bank-related variables in the causal chain.

Coupled with the restriction that actual capital ratios did not directly impact macroeconomic variables, the assumption underlying the analysis is that the transmission mechanism linking bank capital ratios to the wider economy is via bank lending alone. Perhaps the most substantive aspect of this restriction is the assumption that monetary policy did not respond directly to changes in microprudential regulation, over the period studied here. As a check, we examined the official record of Monetary Policy Committee meetings. There is no mention of capital requirements or of banking system capital until September 2007; references remain infrequent thereafter, and do not appear to have had a direct bearing on the monetary policy decision.¹³ This is understandable given that the only instance of modest banking instability that the UK experienced in this period was amongst small- and medium-size banks during 1991-1994 (see Logan, 2001), and given the removal of direct supervisory powers from the central bank after independence in 1997. Although not conclusive, the official record does not provide evidence that contradicts our assumption.

The second institutional factor informing our identification concerns the behavior of prudential policy itself. The scope for supervisors to set individual capital requirements by reference to the state of the macroeconomy was in practice limited: supervisory reviews were conducted at set two-year intervals, rather than in response to economic conditions; and under Basel rules business cycle effects were just one of a panoply of risks not captured by minimum (Pillar 1) standards for supervisors to consider.¹⁴ Nevertheless, others have argued that the result, if not the intention, of supervisory actions was to produce counter-cyclical movements in aggregate capital requirements.¹⁵ The baseline assumption adopted below allows systematic changes

¹³Official minutes of the Monetary Policy Committee meetings are available from June 1997; prior to that, minutes of the monthly meetings between the Chancellor of the Exchequer and the Governor of the Bank of England are available from April 1994. The sole mention of prudential regulation during the sample period we consider is contained in the minute of the January, 2008 meeting (para. 4): '[B]anks were becoming more cautious about expanding their balance sheets ... [and] the introduction of the new Basel II regulatory regime for all banks at the beginning of 2008 ... might have a knock-on effect on their willingness to lend'.

¹⁴The risks to be covered by supervisory review under Basel II Pillar 2 included: concentrations of credit risk; interest rate risk in the banking book; and operational, reputational and strategic risk. The Basel documents speak of being 'mindful' of the state of the business cycle, but also that Pillar 1 requirements already account for 'uncertainties ... that affect the banking population as a whole' (Basel Committee on Banking Supervision, 2006, paras. 726 and 757), so giving little concrete guidance on where and how to account for the business cycle.

¹⁵Aiyar, Calomiris, and Wieladek (2012) argue that regulators operated a *de facto* macro-prudential regime (between 1998 and 2007), pointing to evidence that 'average capital requirements across the banking system were ... strikingly counter-cyclical' (p. 10). They report a correlation between the average trigger ratio and annual GDP growth of between 0.44 and 0.64, depending on the weighting scheme used in aggregation. On our 1989-2008 sample and weighting capital ratios by UK lending share, the correlation is 0.40 (s.d. 0.10), which although still large is significantly below the Aiyar, Calomiris, and Wieladek figure.

Table 1. Exclusion restrictions

Impact matrix \mathbf{A}					Lag matrix \mathbf{F}_ℓ				
<i>Variables</i>	M	B	K	P	<i>Variables</i>	M	B	K	P
M	×	×	×		M	×	×	×	
B		×	×		B	×	×	×	×
K			×		K		×	×	×
P			×	×	P		×	×	×

Note: An \times indicates position of non-zero coefficient blocks in the \mathbf{A} and $\mathbf{F}_\ell, \ell = 1, \dots, p$ matrices in equation (1). M – macroeconomic variables; B – bank lending variables; K – system-wide capital ratio; P – prudential policy variable (trigger ratio).

in system-wide requirements to be related to aggregate lending and capital, but not to other macroeconomic variables. However, robustness checks reported below indicate that neither relaxing this assumption to allow for systematic feedbacks to prudential policy, nor strengthening it to make the trigger exogenous, has much impact on the results.

Table 1 summarizes how the identifying restrictions map into the VAR, partitioning \mathbf{y}_t into four distinct blocks of variables: those categorized above as macroeconomic ('M'); bank lending ('B'); the aggregate bank capital ratio ('K'); and a policy equation determining how the trigger ratio is set ('P'). It is straightforward to check that, under these restrictions, the model is globally identified (Rubio-Ramírez, Waggoner, and Zha, 2010, Theorem 2).

2.3 Prior settings

The mid-size VAR that we work with, containing 11 variables, two lags and an intercept requires us to estimate a large number of parameters. Dense parameterization can in practice lead inference to be unstable. Under the Bayesian approach to estimation, a prior distribution for the parameters that contains substantive information along some, but not necessarily all, dimensions is used to help overcome this difficulty. The following sections detail how the task of setting the prior is approached in this study. The robustness checks detailed in section 5 show how prior information affects the main results.

Following Sims and Zha (1998), we take equations to be *a priori* independent. Then denoting columns of the \mathbf{A} and \mathbf{F} matrices by lower case letters, for each equation i the prior parameter distributions can be written:

$$\mathbf{a}_i \sim \mathbf{N}(\mathbf{0}, \underline{\mathbf{S}}_i) \quad \mathbf{f}_i | \mathbf{a}_i \sim \mathbf{N}(\underline{\mathbf{P}}\mathbf{a}_i, \underline{\mathbf{H}}_i) \quad (3)$$

where $\underline{\mathbf{S}}_i$ and $\underline{\mathbf{H}}_i$ are symmetric, positive definite matrices defined in Appendix B, and $\underline{\mathbf{P}}$ is defined below. We always apply the same prior to equations in the $i = M$ and $i = B, K, P$ blocks respectively.

2.3.1 Priors from micro data

The relationship between bank lending and capital requirements underpins the effect of prudential policy on aggregate activity. In the micro data, several hundred changes to individual bank trigger ratios are recorded (see Bridges, Gregory, Nielsen, Pezzini, Radia, and Spaltro, 2014, Table B), providing variation that we can use to estimate reduced form relationships between capital requirements and lending at the micro level. It is intuitively appealing to combine micro and macro information, in the hope of improving inference on the aggregate parameters of ultimate interest. The Bayesian approach to combining data taken here follows the same rationale as Chang, Gomes, and Schorfheide (2002).¹⁶

The approach we take is to estimate an auxiliary model on bank-level data, with a specification typical of those commonly adopted to model balance sheet dynamics in the banking literature (see Hancock, Laing, and Wilcox, 1995, for example).¹⁷ Letting \mathbf{y}_{it} be a vector of micro-level bank lending and capital variables, we formulate a dynamic two-way error component model as:

$$\mathbf{y}_{it} = \sum_{\ell=1}^p \mathbf{\Phi}_{\ell} \mathbf{y}_{i,t-\ell} + \mathbf{\Phi}_z \mathbf{z}_{i,t-1} + \varphi_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where: φ_i represents an unobserved individual fixed effect; λ_t is a time fixed effect that captures the common impact of the macroeconomic environment and seasonal factors; ε_{it} is an i.i.d. bank-specific error term, assumed independent of the other error components; and \mathbf{z}_{it} is a vector of bank-specific controls.¹⁸ The parameters in $\mathbf{\Phi}_{\ell}$ capture the reduced form dynamics of capital and lending variables, which are the micro analogues of the reduced form parameters in the bank lending and capital blocks of (2). The blocks of \mathbf{P} that determine interactions between bank lending and bank capital—in terms of table 1, (K,B) and (P,B) in the bank lending equations, and (B,K) in the capital ratio equation—and the dynamic interaction between actual and required capital, are then set equal to corresponding estimates $\hat{\mathbf{\Phi}}_{\ell}$.

¹⁶The key assumption in Chang, Gomes, and Schorfheide (2002, p. 1502) is that micro and macro data are conditionally independent, given the parameters that are not common to the micro and macro models—the equivalents to (4) and (2). This considerably simplifies the analysis, at the cost of making what may be a somewhat crude approximation. However, common practice amongst macro modelers is implicitly to make a stronger independence assumption, which disregards micro data entirely. We check the robustness of our results to relaxing the micro prior in section 5 below.

¹⁷Our modeling work stops short of the detailed treatment of balance sheet components in Hancock, Laing, and Wilcox, in part due to lack of data and also to keep the number of endogenous variables in the aggregate analysis manageable. Those authors examine the dynamic effect of a shock to bank capital on several categories of loans, on securities, and on equity capital and other liabilities in a panel VAR, but the study does not make the link from bank credit to real activity.

¹⁸The common set of control variables are: size (total assets); the loan-to-deposit ratio; the provision ratio; the Basel risk-asset ratio; and capital quality (the ratio of tier 1 to total regulatory capital); see table 2.

2.3.2 Priors from pre-sample data

The period covered by the bank-level data at our disposal encompasses a single business cycle recovery, and a single downturn. Although longer historical aggregate series are available for both macroeconomic and bank lending data, unfortunately there is no consistent capital data to draw on.¹⁹ The short sample makes statistical detection of the financial cycle; which Drehmann, Borio, and Tsatsaronis (2012) characterize as a ‘medium-term’ cycle, lasting on average around 16 years; problematic. In the UK context, failing to capture this medium-term relationship between output and credit tends to over-weight an episode of macroeconomic and financial volatility in the early 1990s. This unusual period combined a strong economic recovery with weak bank mortgage lending associated with a major housing bust (on which, see Muellbauer and Murphy, 1997).

To counteract the potential bias arising from the short history at our disposal, we estimate an auxiliary VAR in the macroeconomic and bank lending variables on pre-sample data running from 1975:Q1-1989:Q4 under an uninformative prior. Consistent with the assumptions made on the macro and lending blocks of the VAR in table 1, the VAR is unrestricted.²⁰ The block of the \underline{P} matrix corresponding to these variables—blocks (M,M), (M,B), (B,M) and (B,B)—is set equal to the resulting estimate of the posterior mean $\hat{\mathbf{B}}$ from (2). The effect is to center the prior for dynamic interactions between macroeconomic and bank lending variables on pre-1990 patterns, while allowing posterior estimates to be based on the complete 1975:Q1-2008:Q3 data set.

The prior for the remaining parameters is centered on zero feedback from the macroeconomy to banking system capital, so that posterior estimates reflect the influence of macro factors on capital during the sample period alone. Finally, the intercept vector has a diffuse prior.

2.3.3 Estimation

The VAR is estimated in two steps. In the first step, we estimate the auxiliary models detailed in sections 2.3.1 and 2.3.2. To estimate equation (4) we apply a fixed effects estimator equation-by-equation. Posterior estimates of the parameters of the full VAR are obtained using

¹⁹The ground work for the Basel Accords were laid in the mid-1980s, and included the Basel Committee’s framework for capital measurement which cemented the role of risk weighting assets in capital adequacy assessments, and a bilateral US-UK capital adequacy agreement concluded in 1987 (see Tarullo, 2008). The Bank of England detailed its proposed rules for implementation of Basel I in October, 1988. The Accord was fully introduced to UK law in 1990. Prior to 1990, the regulatory treatment of capital, and reported capital ratios, were not on the same basis as afterward.

²⁰The absence of capital variables from the auxiliary model risks inducing omitted variable bias. In this instance, this risk was judged to be preferable to discarding pre-sample information altogether: The particular regime of capital regulation that we study was in place only between 1989 and 2008; setting aside issues of measurement, it is likely that the relationship between bank capital and lending underwent a profound change as a result of banking legislation enacted to incorporate the Basel Accords into UK law, and that bank capital did not act as the same constraint on lending before as after.

the algorithm given in Waggoner and Zha (2003). We set the number of lags $p = 2$ and estimated the model in levels (or log-levels, according to the variable in question).²¹

3 Results

3.1 Microeconomic estimates

Before examining the results for the full macroeconomic model, we briefly review our estimates of the micro-level relationship between capital and lending. As section 2.3.1 explains, these estimates inform our priors for how aggregate lending responds to changes in system-wide capital ratios. Table 2 gives the estimates of panel equation (4).²² The first two columns report on bank lending equations. Mortgage lending growth is moderately persistent, likely due to banks' reluctance to make sudden changes in consumer lending policy. Corporate lending growth shows little persistence, and is sensitive to the proportion of high risk weight assets the bank holds (Basel risk).

The signs on capital variables in the lending equations are as expected, with a higher trigger ratio acting to slow growth both in secured and corporate credit, and a higher capital ratio acting to increase them.²³ The trigger ratio is statistically significant in the corporate lending equation, but not in the secured lending equation. However, the results indicate that there are indirect channels linking the capital requirements to mortgage lending through interactions between components of banks' loan portfolios: in particular, when a bank makes a higher volume of corporate loans, there is a statistically significant reduction in mortgage lending.

The second two columns report on bank capital equations. Both actual and required capital ratios are estimated to be highly persistent, consistent with infrequent adjustment of the latter. The estimates show that a higher trigger ratio tends to substantially raise banks' capital ratios, consistent with banks acting to restore the buffer of capital held above the regulatory minimum (the long-run multiplier is statistically indistinguishable from unity, indicating one-for-one pass through from requirements to actual capital ratios; Francis and Osborne, 2009a). None of the observable controls appear to explain variation in the trigger ratio; the exception is lags of the actual capital ratio, which enter with a very small coefficient.

²¹More or fewer lags were not strongly favoured by the model's marginal likelihood. Increasing lag length beyond four quarters reduced the reliability of panel estimates, and required much higher levels of prior tightness, given the dimension of the VAR.

²²The results are not sensitive to: excluding time fixed effects; including aggregate regressors; or applying the difference-GMM estimator.

²³Similar findings are reported in Aiyar, Calomiris, and Wieladek (2012) and Bridges, Gregory, Nielsen, Pezzini, Radia, and Spaltro (2014); the results presented here differ slightly in sample period and coverage, and/or the treatment of mergers.

Table 2. Effect of regulation on bank-level lending and capital.

Regressor	Dependent variable							
	Secured lending		PNFC lending		Capital ratio		Trigger ratio	
Secured lending	0.534	(8.51)	-0.160	(1.17)	0.025	(2.43)	0.000	(0.15)
PNFC lending	-0.040	(2.81)	0.218	(2.59)	-0.002	(1.41)	0.000	(0.18)
Capital ratio	0.120	(2.74)	0.300	(0.74)	0.794	(17.65)	0.026	(2.99)
Trigger ratio	-0.037	(0.20)	-2.18	(2.23)	0.234	(2.56)	0.897	(34.88)
Basel risk	-0.380	(0.26)	-9.44	(1.33)	-0.571	(1.22)	-0.123	(0.60)
Capital quality	-0.023	(2.45)	0.018	(0.17)	0.001	(0.14)	0.002	(1.22)
Provision ratio	0.711	(1.55)	-0.733	(0.23)	0.185	(1.05)	0.006	(0.14)
Loan-dep. ratio	-0.005	(0.87)	0.046	(3.42)	0.003	(2.36)	0.001	(1.85)
Size	-0.214	(0.34)	-0.935	(0.58)	-0.288	(1.85)	0.001	(0.01)
Time fixed effects	yes		yes		yes		yes	
R ² (within)	0.484		0.282		0.904		0.920	

Note: Table shows estimates of coefficients in (4). Sums of coefficients on lags shown, absolute value of robust t-statistic in parentheses.

3.2 Macroeconomic dynamics following a regulatory shock

The main findings of this paper relate to the macroeconomic effects of changes in microprudential capital requirements. The main experiment we consider is an unanticipated increase in the trigger ratio, the minimum capital to risk-weighted asset ratio required by bank regulators. The shock is normalized to 50 basis points, somewhat larger than the average change to requirements in the data, but a plausible benchmark for the size of change that could be contemplated in future (see section 4). Figure 2 shows the responses of banking system variables, along with pointwise 68% error bands. The initial impact of the shock falls on the aggregate capital ratio. As can be seen, there is an immediate increase this ratio of around 10 basis points, and it then continues to increase over a period of approximately 18 months. Surplus capital, having initially fallen, is therefore rebuilt fairly rapidly, and has returned to its baseline value within two years.

The effect of capital movements on bank lending is rapid and significant. Secured household lending growth falls by about 0.2% in a little over a year, and non-financial corporate lending growth falls by about 0.5%. The estimated responses we observe are therefore consistent with regulatory capital requirements being a binding constraint on aggregate bank lending. Loan growth stops falling roughly coincident with the return of the aggregate buffer to its pre-shock level. Because household secured and corporate categories attract high risk weights—50% and 100% respectively under Basel I—lower loan growth entails a higher risk-based capital ratio, other things equal.

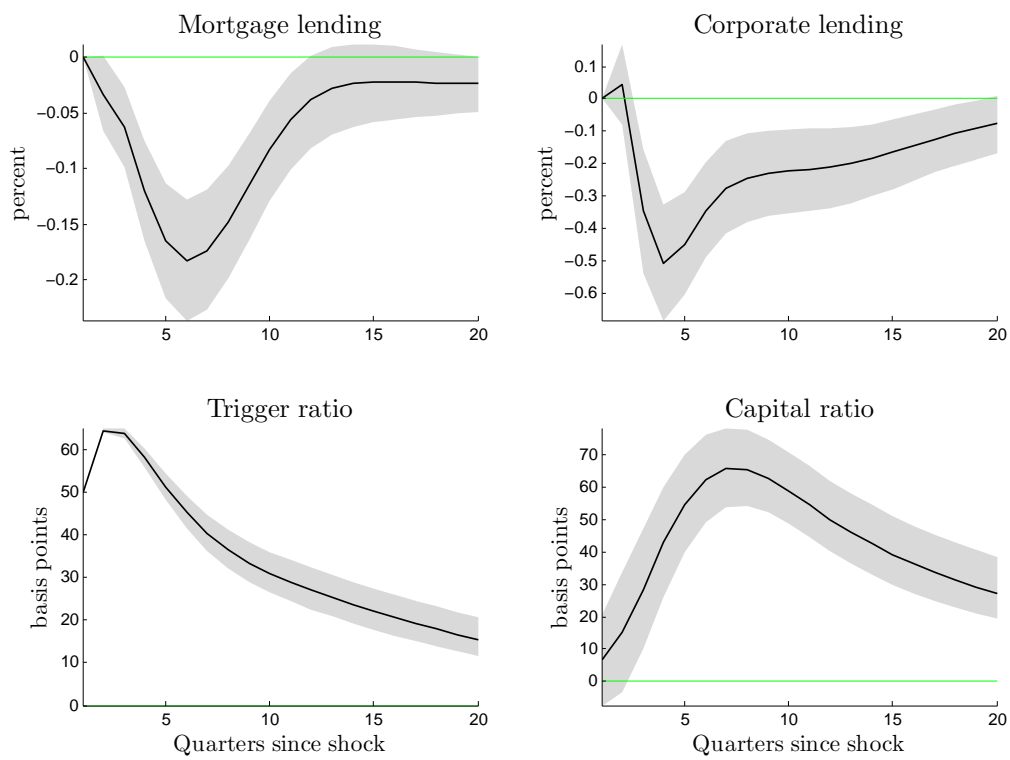


Figure 2. Banking system response to an unanticipated increase in aggregate capital requirements. *Note:* The panels depict the impulse response functions of aggregate lending and capital variables to an orthogonalized shock to the trigger ratio of 50 basis points. — Median response. The shaded bands represent pointwise 16 to 84 percentile error bands.

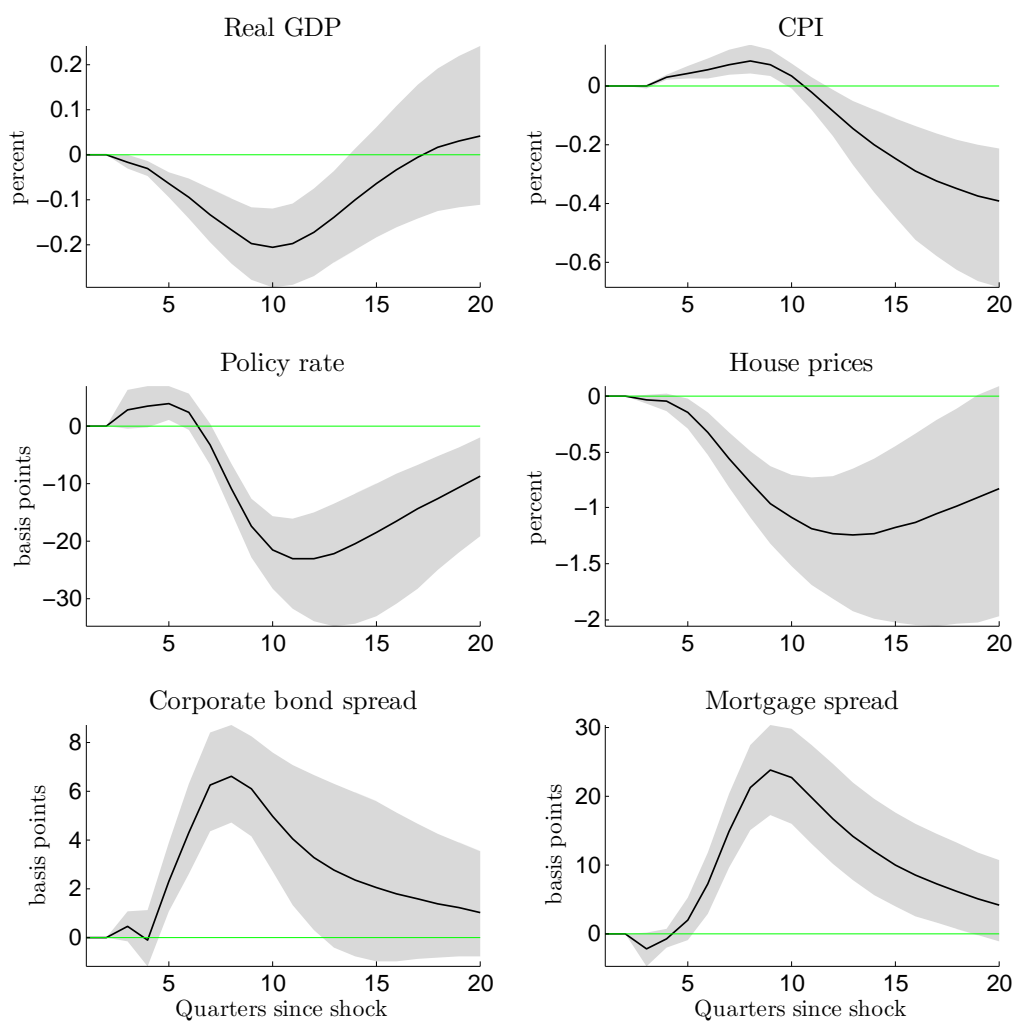


Figure 3. Macroeconomic response to an unanticipated increase in aggregate capital requirements. *Note:* The panels depict the impulse response functions of selected variables to an orthogonalized shock to the trigger ratio of 50 basis points. – Median response. The shaded bands represent pointwise 16 to 84 percentile error bands.

Figure 3 summarises the responses of variables in the macroeconomic block. Aggregate real expenditure declines in response to tighter bank credit conditions, consistent with the existence of credit constrained and bank-dependent agents—a fundamental tenet of financial accelerator theories (see Bernanke and Gertler, 1995, for a survey of the evidence). Prices remain broadly flat for two years, whereafter they undergo a noticeable decline, bringing about a systematic easing in monetary policy. Changes in bank lending and in real expenditure propagate to broader financial conditions. Corporate spreads widen as bank credit supply contracts, which is consistent both with banks choosing to reduce high risk-weight assets by selling off corporate bonds, and with substitution by marginal bank borrowers into capital market funding. Consistent with a strong credit supply effect on the housing market, house prices decline by 1% relative to baseline, and arrears increase by approximately 0.05 percentage points (not shown). Mortgage spreads are initially flat, but after four quarters stay persistently above their pre-shock values.

These patterns are in line with the responses of the US economy to a bank credit supply shock reported in Bassett, Chosak, Driscoll, and Zakrajšek (2014). There a shock that produces a 4% decline in lending capacity (loans outstanding and unused commitments) raises corporate bond spreads by 40 basis points, and causes a fall of up to 0.7% in real GDP, with offsetting movements in monetary policy. Qualitatively, these movements closely resemble the regulation-induced supply shift we identify (although we lack data on loan commitments). On a long sample of UK data, Barnett and Thomas (2014) likewise estimate that a credit supply shock that reduces lending growth by 1% raises corporate bond spreads by a similar amount, and lowers GDP growth by up to 0.1%. Their findings indicate a slightly weaker pass-through from bank credit to aggregate expenditure than estimated here (but they report larger effects on a post-1992 sub-sample).

Variance decompositions show that the majority of the variation in the trigger ratio at horizons up to a year is the result of regulatory shocks. At the two year horizon, they account for about 16% of the variation in the capital ratio, and 2% of the variation in mortgage lending growth. But as large regulatory shocks were observed only infrequently, on average their contribution to fluctuations in the macroeconomy is very small. Historical decompositions, which trace the cumulative impact of structural shocks at each date, indicate that regulatory shocks made modest contributions to movements in aggregate variables, particularly in the mid-1990s. Figure 4 shows that in the absence of changes in capital requirements, mortgage spreads would have been some 15 basis points lower and corporate bond spreads around 5 basis points lower than was the case. Mortgage lending growth was reduced by 0.1 annual percentage points, and corporate lending by some 0.3 percentage points. These effects fed through to house prices, which were lower by up to 1% as a result (not shown). The largest

impact fell on the banking system capital ratio: it was 80 basis points higher in 1998 than in the absence of shocks, and 40 basis points lower in 2008.

In summary, we find that changes in regulatory capital requirements have real effects, consistent with the developing literature on the effects of financial shocks. Regulation was not, on average, an important source of aggregate fluctuations, but large regulatory shocks caused movements in mortgage and corporate bond spreads, house prices, and in particular the banking system capital ratio.

3.3 Feedbacks and financial accelerator effects

To better understand the transmission channels at play, in this section we unpick the full system responses described above using posterior simulations in which various endogenous variables are held constant at their baseline values by selectively setting coefficients to zero, as in Sims and Zha (1996).²⁴ Figure 5 indicates how the system responds in the absence of the financial accelerator mechanism, that is, holding mortgage and corporate bond spreads constant. For comparison, the baseline responses from figures 2 and 3 are shown as dash lines. In this case we see that the decline in aggregate expenditure is about half as large as in the baseline case where spreads rise: Higher credit spreads act to amplify the regulatory disturbance, as in the classical financial accelerator mechanism. Both firm-side and household-side financial accelerator effects appear to be important, as emphasised in Iacoviello (2005) for example.

It is noteworthy that figure 5 shows bank lending and bank capital variables responding similarly to the baseline case, indicating that feedbacks from spreads to the banking system are weak.²⁵ Feedbacks appear to be most important within the banking system itself. For example, if corporate lending is held constant, the responses of secured lending, spreads, house prices and real expenditure are all muted; if mortgage lending is held constant, the transmission to the real economy is close to nil, indicating the central role played by housing (see in particular Iacoviello and Minetti, 2008; Walentin, 2014).

Our second scenario involves holding the policy interest rate constant. The prolonged period that advanced economies, including the UK, have spent at the zero nominal interest rate bound since 2009 naturally raises the question of how tighter regulation might play out when monetary policy is constrained. Figure 6 shows that the constraint on monetary policy leads to amplified responses to tighter prudential policy. The main effects fall on the housing market.

²⁴These experiments are not intended to assess the plausibility of the implied restrictions, or to pose a counterfactual change in the structure of the economy (for which, see section 4). Rather, they are intended to highlight the role played by the dynamic responses of particular variables.

²⁵Perhaps surprisingly, this was also found to be the case when all macroeconomic variables were held constant. However, it does not follow that banking variables are not impacted by other, macroeconomic shocks.



Figure 4. Historical contribution of regulatory shocks to path of selected variables. *Note:* The panels depict the difference between the actual path of each variable, and the path that would have been followed if regulatory shocks had be zero. – Median path. The shaded bands represent pointwise 16 to 84 percentile error bands.

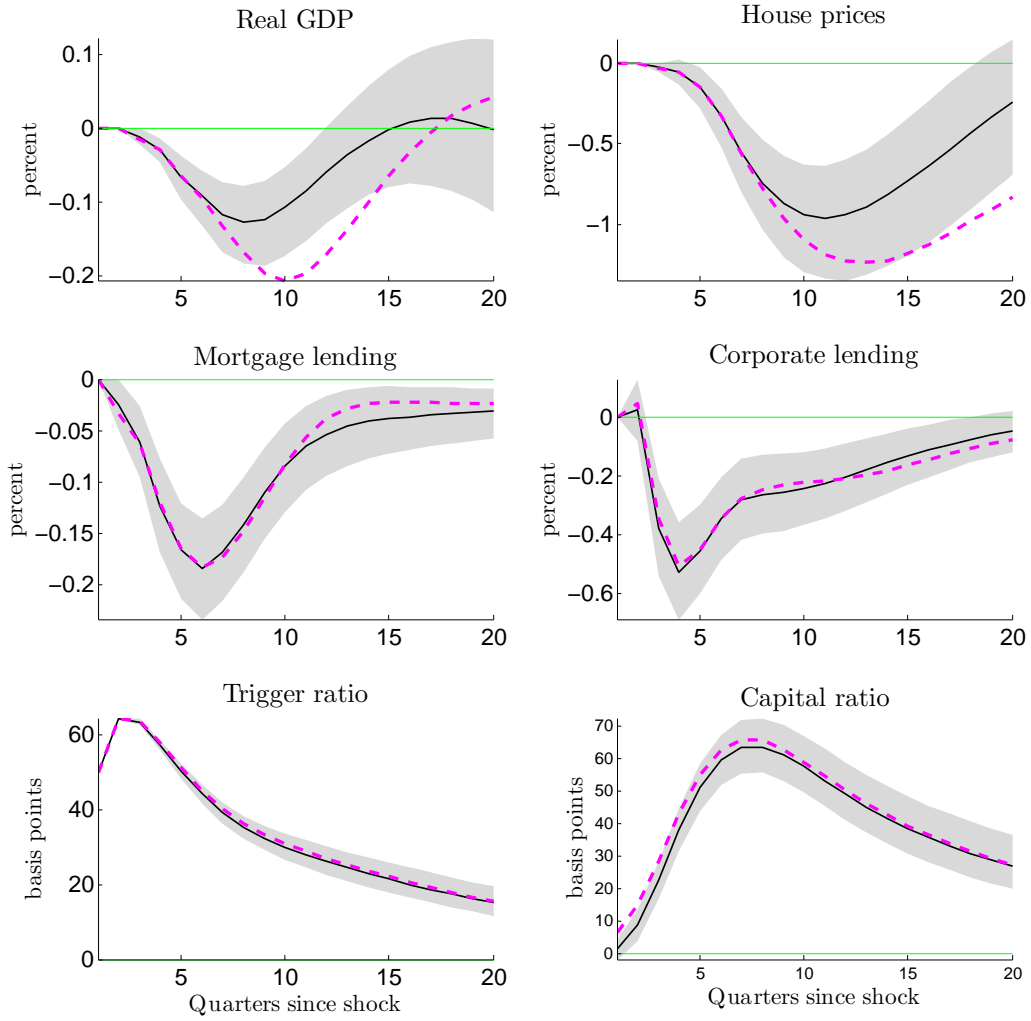


Figure 5. Responses to an unanticipated increase in aggregate capital requirements holding credit spreads constant. *Note:* The panels depict the impulse response functions of selected variables to an orthogonalized shock to the trigger ratio of 50 basis points, with mortgage and corporate bond spreads held constant. – Median response. – – Unrestricted impulse-response function (see figures 2 and 3). The shaded bands represent pointwise 16 to 84 percentile error bands.

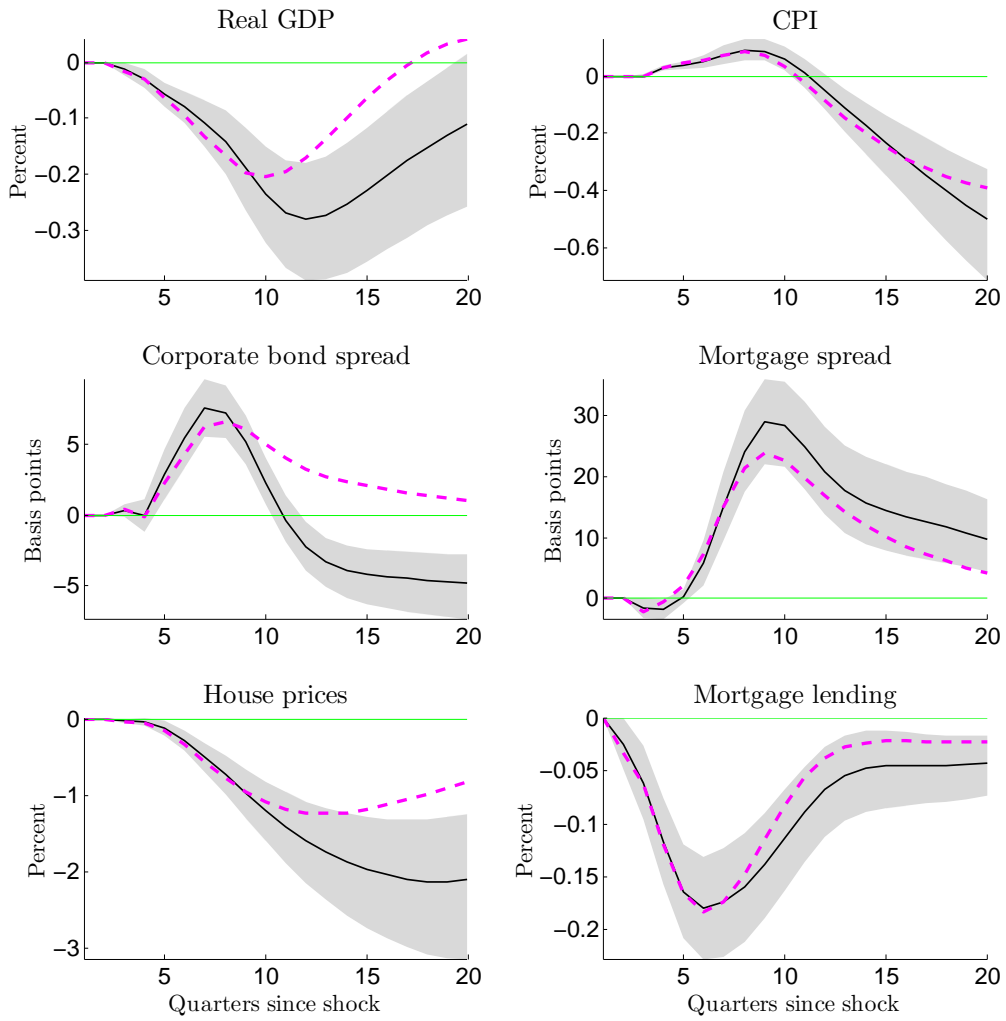


Figure 6. Responses to an unanticipated increase in aggregate capital requirements holding policy rate fixed. *Note:* The panels depict the impulse response functions of selected variables to an orthogonalized shock to the trigger ratio of 50 basis points, with the short term nominal interest rate held fixed. — Median response. - - Unrestricted impulse-response function (see figures 2 and 3). The shaded bands represent pointwise 16 to 84 percentile error bands.

House prices decline by around 2% four years out versus 1%, and arrears (not shown) also rise strongly. Around 5bps are added to mortgage spreads, likely the result of the higher credit risk associated with rising arrears, and the impact on mortgage lending growth is modestly negative. From a stabilisation perspective, the most significant finding is that the decline in aggregate expenditure in response to tighter prudential policy is around 50% larger when policy rates are constant compared to the baseline.

4 A macroprudential counterfactual

It is now widely recognized that pre-2008 bank regulation was excessively focused on individual institutions, and failed to act on build-ups of system-wide risk. The macroprudential approach to regulation explicitly takes into account trends in the financial sector that pose such risks, in particular rapid growth in aggregate bank credit (for an overview, see Hanson, Kashyap, and Stein, 2011). Basel III introduces a new regulatory tool, the countercyclical buffer (CCB), to address these macroprudential concerns. The CCB, which applies to all banks, is a variable requirement on the common equity ratio of up to 2.5%. It is one of the macroprudential tools given to national regulatory authorities in recent EU-wide legislation, known as Capital Regulation Directive or CRD IV, to be phased in from 2016 in Europe.²⁶ For the meantime, it remains untested and its effects largely unknown. An important question for policymakers is the extent to which changes to the required countercyclical buffer will lead to changes first in banking system capital ratios, and second in aggregate credit growth and wider economic conditions. Answering these questions is hard because there has so far been no direct application of the CCB, nor many concrete indications of exactly how policymakers plan to apply it. However, the previous sections have shown how variation in microprudential capital requirements led to variation in banking system capital ratios that exerted some influence on the macroeconomy, and so it is tempting to try to extrapolate from the old regime in the hope of learning something about the new one.

In order to provide some indicative evidence on the effect of a countercyclical macroprudential capital requirement, the remainder of this section reports on the results of a counterfactual simulation exercise employing the model developed above. The basic idea is straightforward. We use the VAR to recover the time series of structural shocks that hit the economy over the sample period. Then taking the proposed macroprudential policy instrument to be the trigger ratio, we modify the corresponding equation in the VAR to introduce some counterfactual feedback from financial conditions (to be specified) to system wide bank capital requirements. We then ask how the paths followed by the endogenous variables of the system change when the

²⁶Tarullo (2013) notes that the CCB was also included in the implementation of Basel III by US authorities in summer 2013, but that there too its possible use is not planned for several years hence.

model is simulated using the same exogenous structural shocks as the driving force, but with the counterfactual equation setting the aggregate required capital ratio.

The principal objection to the counterfactual analysis just described is that it falls foul of the Lucas (1976) critique, as it takes the remaining structural relations in the VAR to be invariant to the introduction of the macroprudential policy. If private agents do take changes to bank regulation into account when forming expectations of future policy, the results may be in error. However, there are reasons to proceed, albeit with some care. In the specific context of risk-based capital regulation, which was itself a novel policy tool in 1990, it is not clear that agents would have even formulated an estimate of what the ‘usual’ policy response would be; in this sense, deviations from the estimated rule, particularly over the early part of the sample, are unlikely to cause Lucas-type concerns. In weighing the merits of this exercise, it is also important to recognize that a consensus view on what constitutes a correctly specified and fully structural model that can accommodate macroprudential policy analysis is not currently in evidence in the profession, although several variants of candidate DSGE models for this purpose have already been mentioned (see footnote 5). In the meantime, some indication of the effects of the countercyclical buffer can contribute to the formulation of policy.

We do not know the precise form policy on countercyclical macroprudential capital buffers will take in practice, but for the purposes of this exercise we rule out threshold effects, non-linearities, and reaction to indicators other than those included in the model as it stands (e.g. the results of banking system stress tests such as the Federal Reserve’s SCAP). In other words, we limit the scope of the counterfactual macroprudential policies we consider to those taking the form of a linear feedback rule on macroeconomic and financial variables.

4.1 Feedback on the credit gap

A useful benchmark exercise is to examine how policy would be set if it mechanically followed the aggregate private sector credit-to-GDP gap set out by the Basel Committee on Banking Supervision (2010b).²⁷ The credit gap is intended as a common reference point, against which judgemental decisions on precise instrument settings will be made. The feedback rule used in the simulation has the trigger ratio depend on the moving average of current and lagged credit gaps:

$$\text{trig}_t = \theta^{\text{gap}} \frac{1}{3} (\text{credgap}_t + \text{credgap}_{t-1} + \text{credgap}_{t-2}) + \hat{\beta}' \mathbf{w}_t + v_t^{\text{trig}} \quad (5)$$

where \mathbf{w}_t contains the lending and capital variables from the estimated prudential policy equation, and $\hat{\beta}$ are their estimated coefficients, see table 3. The reason for including this term is

²⁷The credit gap is the difference between the ratio of a broad measure of credit to GDP, and a one-sided HP filtered estimate of its trend. The baseline model is re-estimated to include this variable within the macro block.

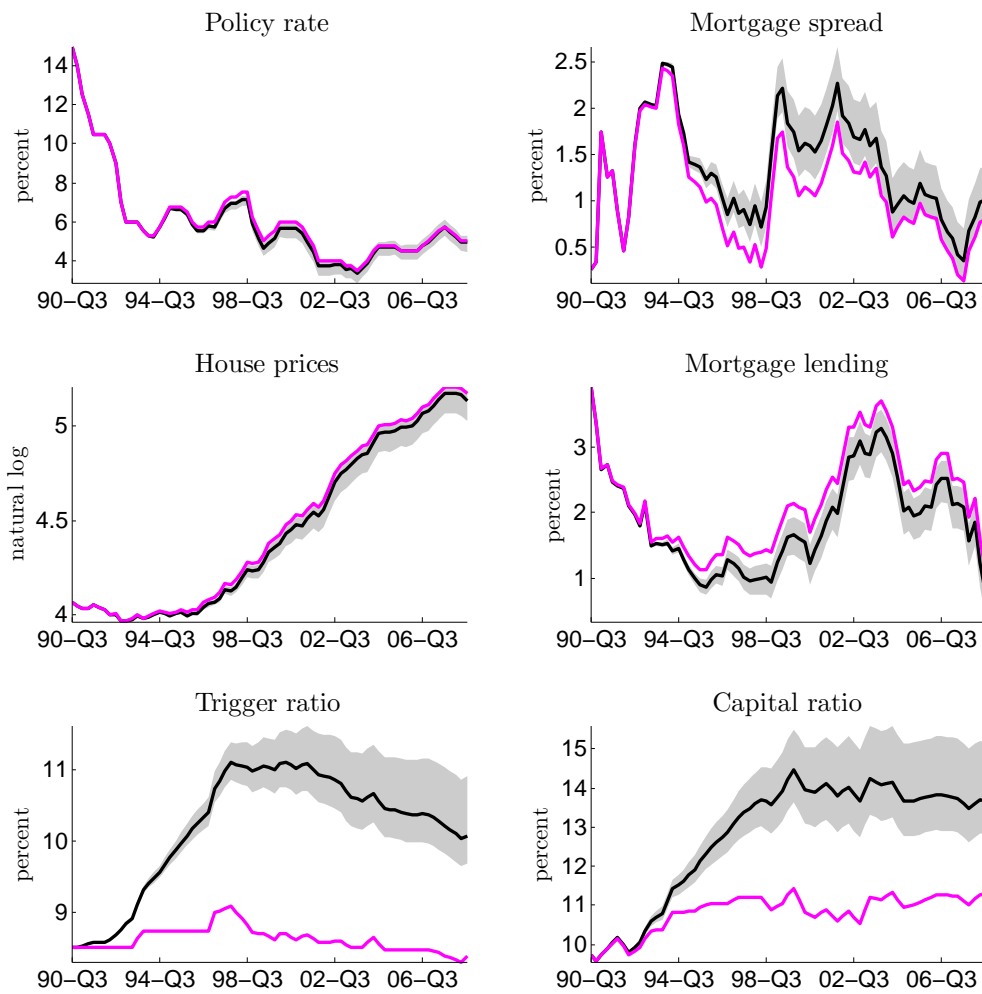


Figure 7. Simulated paths for macroeconomic and banking variables under a counterfactual macroprudential rule responding to the credit-to-GDP gap. *Note:* Solid black line – median path under counterfactual rule; solid pink line – data. The shaded bands represent pointwise 16 to 84 percentile error bands.

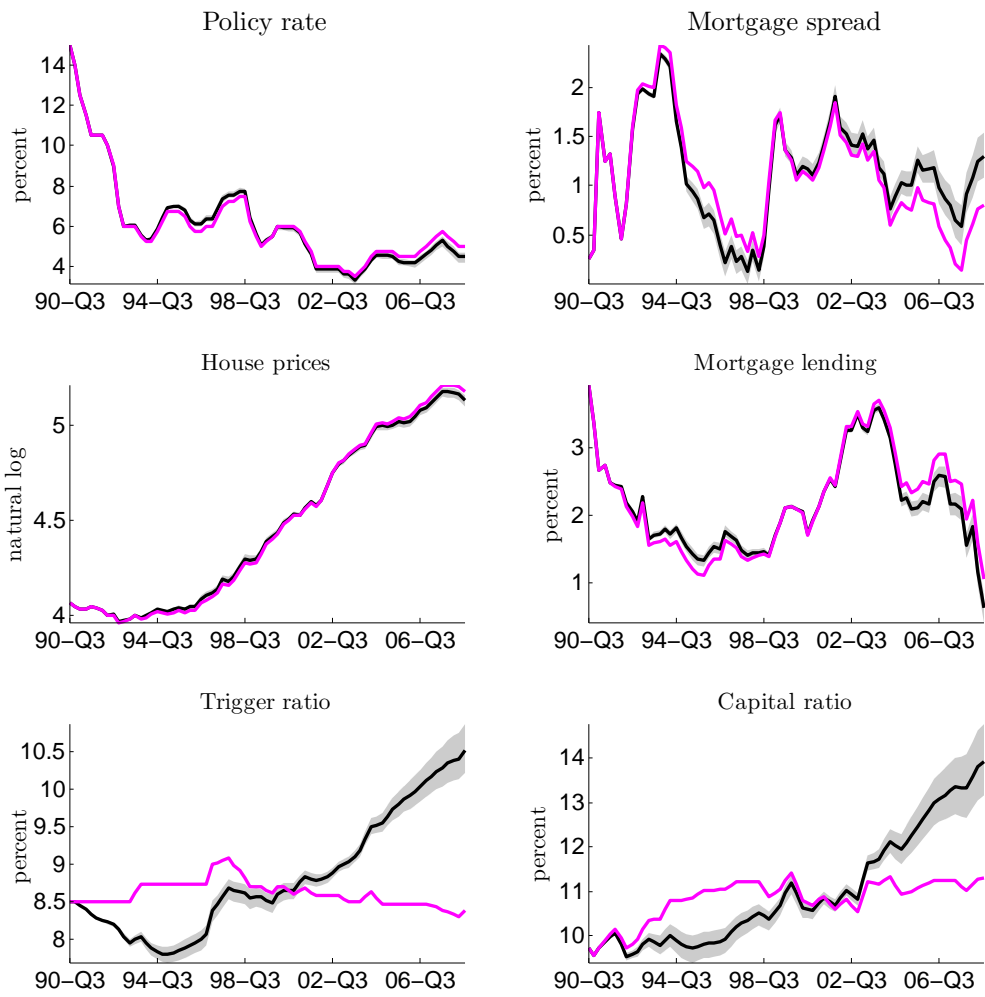


Figure 8. Simulated paths for macroeconomic and banking variables under a counterfactual macroprudential rule responding to house price acceleration. *Note:* Solid black line – median path under counterfactual rule; solid pink line – data. The shaded bands represent pointwise 16 to 84 percentile error bands.

Table 3. Estimated policy reaction function

<i>Variable</i>	posterior mode	HPD interval	
		min	max
trigger	8.84	7.67	10.0
mortgage lending (-1)	-1.08	-4.54	2.38
corporate lending (-1)	-0.84	-1.43	-0.25
trigger (-1)	11.2	9.71	12.7
capital ratio (-1)	0.17	0.14	0.20
mortgage lending (-2)	2.86	2.39	3.33
corporate lending (-2)	0.70	0.60	0.80
trigger (-2)	-3.36	-3.84	-2.89
capital ratio (-2)	0.11	0.09	0.14

Table shows posterior estimates of $(\mathbf{a}_i^T, \mathbf{f}_i^T)^T$ for $i = P$, the equation for trigger, under the baseline identification scheme. The first column indicates the mode of the marginal posterior densities. The min and max columns show the lower and upper bounds of the $100(1 - \alpha)\%$ highest probability density set, respectively, with $\alpha = 0.1$.

so that when $\theta_{\text{gap}} = 0$, every simulated path coincides exactly with the realized path in the data. Because we consider only linear rules, our exercise does not map precisely into the settings for the capital buffer recommended by the BCBS. Nevertheless, the exercise can illustrate the general behavior of the macroeconomy under the scheme.

The simulation reported in figure 7 has θ_{gap} set to $1/8$, which ensures that the range of variation in the counterfactual capital requirement is broadly in line with the 2.5% limits laid down in Basel III. It is immediately noticeable that capital requirements are raised substantially until 1999, relative to what was actually observed, and then fall back. This pattern mirrors movements in the credit gap. A result of these movements is that the simulated path for the actual capital ratio also lies materially above its observed path. By the end of the sample period in 2008, the system-wide tier 1 capital ratio is close to 14%, about 3 percentage points above what was observed. The counterparts to higher capital ratios are consistently lower growth in mortgage lending, and higher mortgage spreads, which make house prices a shade lower than otherwise. The apparent drawback with (5) is that by raising capital requirements during the deleveraging phase of the credit cycle, when the credit gap is still high but lending growth is falling, it acts to amplify the decline in credit. Exactly this concern was raised by Repullo and Saurina (2012) on the basis of simple correlation analysis for a sample of developed economies. The rule considered next appears to have better stabilisation properties.

4.2 Feedback on housing

The second counterfactual policy we construct focuses on housing finance. It is parameterized so that the trigger is raised when house prices are accelerating, and when spreads are falling:

$$\text{trig}_t = \theta^{\text{hp}} \Delta^2 \ln \text{housep}_t - \theta^{\text{spr}} \left(\text{spr}_t - \frac{1}{2} [\text{spr}_{t-1} + \text{spr}_{t-2}] \right) + \hat{\beta}' \mathbf{w}_t + v_t^{\text{trig}} \quad (6)$$

where again $\hat{\beta}' \mathbf{w}_t$ is the estimated systematic component. In the simulation, θ^{hp} is set to 3/4, and θ^{spr} is set to 1/5.

The effects of the simulated macroprudential policy are shown in figure 8. The simulated paths are not, in most cases, radically different from those that were actually observed. The most noticeable difference is in the policy instrument itself: the trigger ratio is lower throughout the 1990s, as policy attempts to ease conditions in the mortgage market. The counterfactual trigger ratio was around 50 basis points lower than the historical ratio during this period. Simulated capital ratios are therefore also somewhat lower. There are indications that this policy would have stabilized the housing market somewhat. First, under the simulation, mortgage lending growth is higher through the mid-1990s; second, log house prices (shown in levels for clarity) are marginally higher in this period, and mortgage spreads are 20 basis points or so lower.

The picture alters as we move into the 2000s. Now the counterfactual trigger ratio is higher than the observed one, as are capital ratios. This tends to depress mortgage lending growth; by the mid-2000s it is close to a 1/4 percentage point lower than was the case in reality. Spreads were also higher under the counterfactual policy, and house prices were lower. Throughout this period, there is barely any impact on growth in GDP (not shown). A key reason for this is the endogenous response of monetary policy. As can be seen from the figure, monetary policy was marginally tighter through the period in the 1990s when the counterfactual macroprudential policy was easier; and it was marginally looser through the mid-2000s when the macroprudential policy was tighter. The model predicts no contradiction in this particular mix of policies. Monetary policy is able to stimulate the broad economy at the same time that macroprudential policy damps down mortgage lending and raises bank capital ratios.

5 Sensitivity to priors and identifying assumptions

5.1 Sensitivity to priors

This section reports on the results of using several variants of our baseline prior in which the pre-sample and bank-level information used in estimation is selectively altered. The exercise involves varying the hyperparameter controlling the prior tightness on the banking and macroeconomic blocks of the model.²⁸ At one extreme, a ‘tight’ prior results in posterior esti-

²⁸The parameter λ_2^j in Appendix B.

mates that put most weight on micro-level data (in the case of the banking block) or 1975-1989 macroeconomic data (in the case of the macro block). At the other extreme, a 'loose' prior results in posterior estimates that put most weight on the 1989-2008 aggregate data. A fully uninformative or 'diffuse' prior produces rather poorly determined estimates, due to the large number of parameters in the model.

The first alternative we checked was to vary the tightness of the micro prior. The results are shown in figure 9. The qualitative shapes of the responses are broadly similar to those of the baseline model (solid line), but with loose prior settings the quantitative results are markedly different. The main effect of reducing the weight on bank-level information is to make the median responses of lending growth to an innovation in trigger larger, and in the case of mortgage lending, more volatile. The main cause appears to be the very persistent responses in the trigger and capital ratios; indeed, the capital ratio 'overshoots' the rise in trigger somewhat, leading to persistently higher capital buffers. This possibility seems somewhat implausible, and mainly reflects the lower precision of the estimates: error bands (not shown) on all variables widen considerably, supporting the notion that useful information on the response of lending to changes in capital is contained in the micro data. With tight prior settings, the responses are pulled towards those estimated from micro data. The declines in mortgage and corporate lending growth are slightly lower than in the base case, leading to smaller declines in aggregate real expenditure and house prices.

The second alternative was to vary the weight on pre-1990 data, while keeping the prior weight assigned to bank-level data the same as in the baseline. With a 'tight' prior, the estimated relationship between aggregate lending and other macroeconomic variables is weakened slightly, while retaining the same qualitative shape. There is a smaller fall in GDP, and a smaller rise in arrears; on the other hand, mortgage spreads appear to be slightly more responsive. Setting a 'loose' prior results in roughly the opposite: a larger fall in GDP, a larger rise in arrears, a smaller rise in mortgage spreads. However, once more estimates become much less precise.

In summary, the prior sensitivity analysis reported on here has revealed the importance of taking into account both pre-sample and bank-level information in estimation. Pre-sample information allows for sharper estimates of the responses of macroeconomic variables to changes in lending, without much altering the average responses. The micro data helps to provide a coherent characterization of the link between capital and lending.

5.2 Sensitivity to identifying assumptions

In section 2.2 the reasoning behind our baseline identification scheme was laid out. In this section, we test the sensitivity of the results presented above to adopting two polar alternative identifications for the policy equation. The first alternative is to adopt a standard recursive

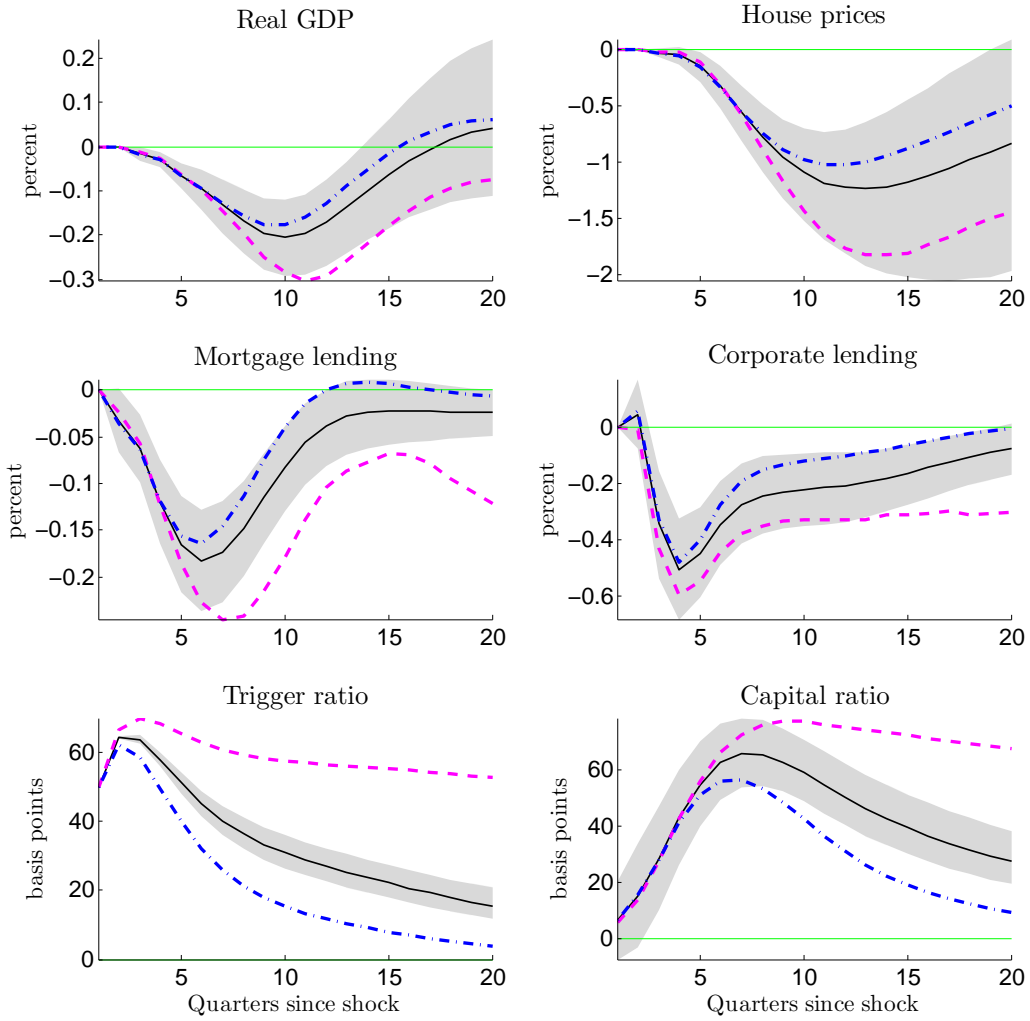


Figure 9. The effect on impulse-response functions of bank-level information. *Note:* The panels depict the median estimated impulse response functions of selected variables to an orthogonalized shock to the trigger ratio of 50 basis points, when the micro prior given in section 2.3.1 is applied according to : – baseline settings; – – a ‘loose’ setting; – · – a ‘tight’ setting. The shaded bands represent pointwise 16 to 84 percentile error bands under the baseline settings.

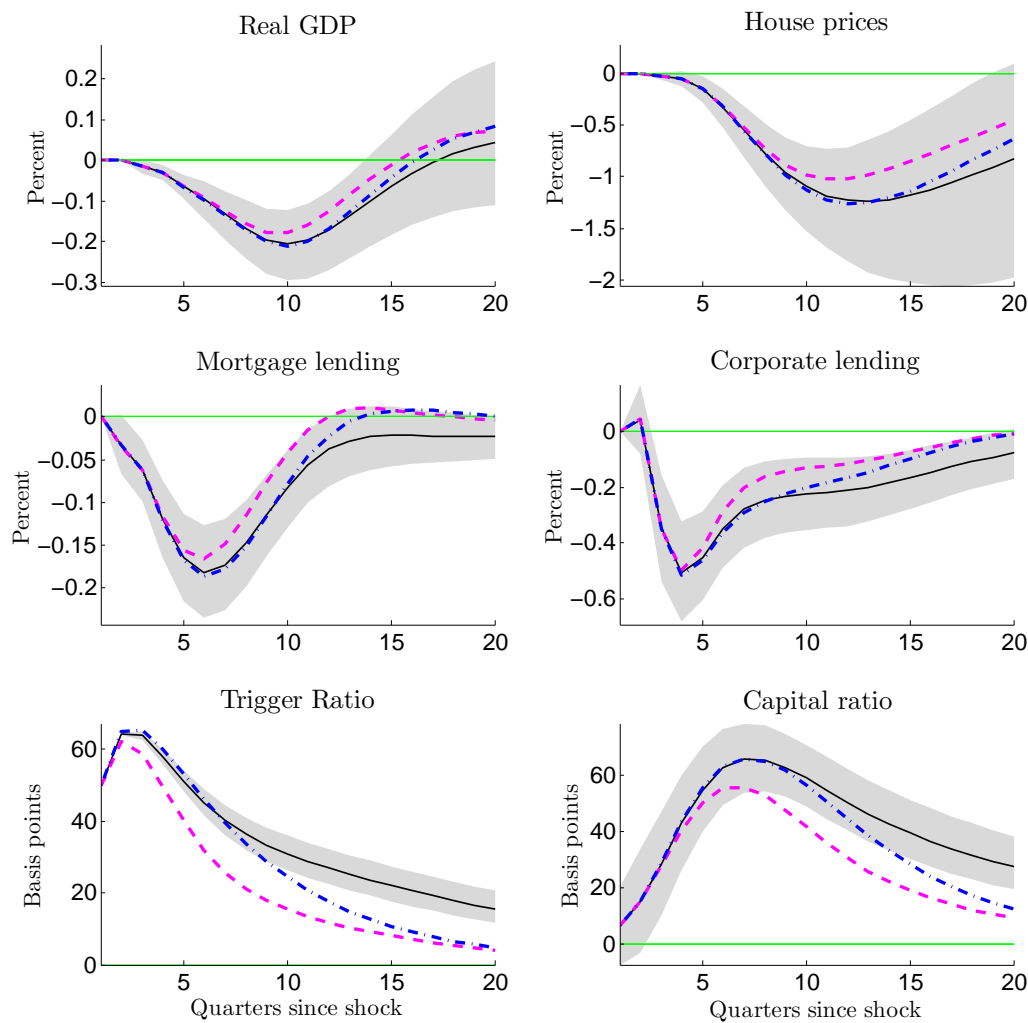


Figure 10. The effect on impulse-response functions of different identifying assumptions. *Note:* The panels depict the estimated impulse response functions of selected variables to an orthogonalized shock to the trigger ratio of 50 basis points. – Median response under baseline identification. - - Median response when trigger responds to all macro and lending variables. - - - Median response when trigger is exogenous. The shaded bands represent pointwise 16 to 84 percentile error bands under the baseline identification.

Table 4. Alternative identification

Impact matrix \mathbf{A}					Lag matrix \mathbf{F}_ℓ				
<i>Variables</i>	M	B	K	P	<i>Variables</i>	M	B	K	P
M	×	×	×	×	M	×	×	×	×
B		×	×	×	B	×	×	×	×
K			×		K		×	×	×
P			×	×	P		×	×	×

Note: An \times indicates position of non-zero coefficient blocks in the \mathbf{A} and $\mathbf{F}_\ell, \ell = 1, \dots, p$ matrices in equation (1). M – macroeconomic variables; B – bank lending variables; K – system-wide capital ratio; P – prudential policy variable (trigger ratio).

assumption, with the trigger ratio ordered second-to-last (so that actual capital is allowed to respond to regulation within period), see table 4. Under this scheme, policy can respond to macroeconomic variables contemporaneously and at lags. The second alternative is to have the trigger ratio depend only on its own lags. Prudential policy is then set independently from any aggregate variable (although not from idiosyncratic bank-level factors, which appear as shocks to the trigger ratio).

Figure 10 plots the median responses of selected variables under the baseline identification, along with pointwise error bands, and compares them with the median responses under the two alternative identifications. The qualitative shape of the responses is similar in all cases. The size of the responses in output, lending and house prices is also broadly similar, although when policy is allowed to respond to macroeconomic variables the adverse effects of the shock are somewhat ameliorated. As can be seen from the bottom row of the figure, the reason is that the trigger ratio falls back towards its pre-shock value marginally faster. However, this turns out not to be due to significant feedback effects from macroeconomic variables to the trigger ratio: The $100 \times (1 - \alpha)\%$ highest probability density credible set for the parameters in the policy equation contains zero for every variable aside from the trigger and capital ratios for $\alpha = 0.1$. Moreover, setting to zero all the responses of non-capital variables does not alter the shape of the response of the trigger ratio to a policy shock. In short, our estimates of the prudential policy rule do not reveal any systematic response to macroeconomic variables, lending support to the over-identifying restrictions used to obtain the baseline results.

6 Conclusions

This paper has demonstrated that variation in microprudential capital requirements at individual banks, when aggregated, caused changes in aggregate expenditure, asset prices and credit supply under the Basel I and II regimes in the UK. An increase in the required capital ratio was estimated to have persistent and negative effects on household and corporate lending growth,

consistent with the existence of binding regulatory constraints at the system level. Lower credit growth was found to exert downward pressure on GDP, with wider corporate bond and mortgage spreads acting to amplify the initial impulse through a financial accelerator channel. The results add to the growing literature on the real effects of financial disturbances.

The paper also offered a counterfactual analysis of the type of macroprudential capital tool introduced under Basel III. Simulations of the structural VAR model developed in the paper indicated that a macroprudential rule that mechanically tracked the credit-to-GDP gap, an indicator proposed by the BCBS, would have produced greater fluctuations in credit than a rule that reacted to house price acceleration and mortgage spreads. Of course, a full analysis of such tools requires the development of a suitable DSGE model. A good model should be capable of reproducing the main features of the empirical behavior described here.

A caveat that future research aimed at informing counter cyclical macroprudential policy should address is that there are conditions under which the market constraint on banks is binding, and the regulatory constraint is slack. Changes in counter-cyclical macroprudential buffers may then have little effect (at least, not through the direct channels operative during the period studied here). This suggests that modeling non-linear effects, as in Mitnik and Semmler (2013), may be of importance.

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A Aggregation from bank-level data

Table A.1. Data sources

Series	Sample	Source	Notes
Log real GDP	1975:1-2008:3	ONS	-
Log CPI	1975:1-2008:3	ONS	-
Official Bank rate	1975:1-2008:3	Bank of England	Bankstats, Table G
Log house prices	1975:1-2008:3	ONS	Mix adjusted, all dwellings
Log arrears	1975:1-2008:3	Council of Mortgage Lenders, ONS	% of outstanding mortgages > 6 months in arrears
Credit gap ^a	1975:1-2008:3	Bank of England	FPC countercyclical buffer guide
Mortgage spread	1975:1-2008:3	Council of Mortgage Lenders, Oxford Ec.	Average, all floating rate mortgages, over Bank rate
Corp. bond spread	1975:1-2008:3	Global Financial Data	Average investment-grade yield over 10 year gilts
Aggregate (a) lending and capital			
Secured lending ^b (a)	1975:1-2008:3	Bank of England	Bankstats, Table A
PNFC lending ^{bc} (a)	1975:1-2008:3	Bank of England	Bankstats, Table A
Trigger ratio (a)	1989:4-2008:3	See Appendix A	From Trigger ratio (b)
Capital ratio (a)	1989:4-2008:3	See Appendix A	From Capital ratio (b)
Bank-level (b) lending and capital			
Secured lending (b)	1989:4-2008:3	FSA/BoE	Reporting form BE
PNFC ^c lending (b)	1989:4-2008:3	FSA/BoE	Reporting form BE
Trigger ratio (b)	1989:4-2008:3	FSA/BoE	-
Capital ratio (b)	1989:4-2008:3	FSA/BoE	Quarterly data interpolated from semi-annual obs.

^aNot included in baseline model.

^bAdjusted for securitisations and loan transfers.

^cPrivate Non-Financial Corporations.

B Details of prior specification

Following Sims and Zha (1998), the prior distribution of the parameters is specified in terms of a marginal prior $p(\mathbf{a})$ and a conditional prior $p(\mathbf{f}|\mathbf{a})$ (lowercase letters understood to stand for the corresponding vectorized uppercase matrices). Both distributions are normal, and independent across equations. Their prior means are given in (3). Beliefs about the structural parameters \mathbf{F} are derived from priors over the reduced form behavior of the time series; to see this, note that as $\mathbf{F} = \mathbf{B}\mathbf{A}$, conditional on \mathbf{B} the prior (3) has mean $\mathbf{f} = (\mathbf{I} \otimes \mathbf{B})\mathbf{a}$ with independence across structural equations. Sims and Zha impose a Litterman-type belief that \mathbf{y}_t follows a multivariate random walk, in which case $\mathbf{B} = \mathbf{I}$.

The unrestricted prior covariance and conditional covariance matrices are set in a standard way, with the sole complication that we allow for two distinct blocks of variables, along the lines of table 1: macroeconomic (M) and bank related (B, K, P). The standard deviation of elements in \mathbf{a}_i is given by

$$\frac{\lambda_1}{\sigma_i}$$

and the conditional standard deviation of elements in \mathbf{f}_i is given by:

$$\frac{\lambda_1 \lambda_2^j}{\sigma_i \ell^{\lambda_3}}, \quad j = \text{M or B, K, P.}$$

In each case the scale factor σ_i is an estimate of the standard deviation of the residuals from a p th order univariate autoregression in the i th variable. The hyperparameters can be understood as follows:

λ_1 sets the overall tightness of prior beliefs; it is set to 0.1.

λ_2^j sets the tightness of prior beliefs around the dynamics implied by $\underline{\mathbf{P}}$; the baseline setting is 0.05 for both blocks. Under the ‘loose’ prior, it is set to 0.20, and under the ‘tight’ prior to 0.001.

λ_3 controls the rate at which prior variance shrinks with lag length ℓ ; it is set at 2.

λ_4 controls the conditional standard deviation of the intercept, set to $\lambda_0^j \lambda_4$, with λ_4 a large number.

The derived prior under the restrictions in table 1 is given by Waggoner and Zha (2003, eq. 10).