

# Bank of England

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**Staff Working Paper No. 1,172**

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**Federico D'Amario, Sebastian De-Ramon and William B. Francis**

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Federico D’Amario,<sup>(1)</sup> Sebastian De-Ramon<sup>(2)</sup> and William B. Francis<sup>(3)</sup>

### Abstract

Strong bank capitalisation provides long-run financial-stability benefits. However, transitioning to higher capital levels may involve short-run costs. We analyse the effects of prudential capital changes on lending behaviour, macroeconomic outcomes, and banking competition using UK data within a structural VAR framework with sign and narrative restrictions. Narrative constraints draw on the UK regulator’s 2014–15 stress tests and the 2016 annual cyclical scenario. Impulse responses indicate that banks primarily adjust by reducing risk-weighted assets rather than raising new equity. Higher capital requirements entail negligible long-run costs, with modest short-run macroeconomic effects consistent with other VAR studies on bank capital. These impacts are driven by a contraction in lending and increase in spreads across sectors. We find that effects of altering prudential capital requirements are state dependent. Altering during recessions, as compared with expansions, amplifies short-run contractions, but these are more short-lived, with output recovering more quickly. Indicators of market power (Boone, HHI, Lerner) suggest that tighter capital requirements temporarily reduce banking competition.

**Key words:** Bayesian VAR models, narrative restrictions, financial stability, bank competition, state-dependent local projections.

**JEL classification:** C11, C32, E32, G21, G28.

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# 1 Introduction and Related Literature

The global financial crisis underscored the importance of stronger bank capital to reduce systemic risk and enhance financial stability. In response, many countries introduced macroprudential reforms, such as counter-cyclical capital buffers and stress testing, to ensure banks maintain sufficient capital to absorb shocks and continue lending throughout economic cycles. Empirical evidence demonstrates that higher capital requirements provides financial stability benefits, reducing both the frequency and the severity of systemic financial crisis (Fernandez-Gallardo, 2023). Cost-benefit analysis consistently find positive net present value for capital requirements. UK-specific analysis by Brooke et al. (2015) estimates that optimal Tier 1 capital ratios of 10-14% of risk-weighted assets yield significant welfare gains. These benefits materialize through multiple channels: reduced crisis probability, enhanced resilience during downturns, and lower output losses when crises do occur (Sufi and Taylor, 2022). Furthermore, macroprudential policies have proven effective even during financial booms and periods of accommodative monetary policy, making them an important tool for safeguarding financial stability (Fernandez-Gallardo, 2023).

While higher capital requirements can bolster financial stability in the long run, the actions banks take to satisfy these higher requirements can impose short-run costs on the economy, which must be weighed in the design of prudential capital policy. Indeed, there is evidence showing that in transitioning to higher levels of capitalization, banks reduce lending supply and increase lending rates (Basel Committee on Banking Supervision, 2019). This increase in borrowing costs can dampen economic output as it lowers household consumption and business investment. At the same time, however, appropriately designed capital requirements may also strengthen the resilience of banks (Admati et al., 2013), enhance market confidence in banks' solvency, and, in turn, lower funding costs (Noss and Toffano, 2016). Such mechanisms could improve banks' capacity to support lending, contrary to more sceptical perspectives.

The objective of this paper is twofold: (i) to examine the extent to which shocks<sup>1</sup> to bank capital requirements affect bank lending and macroeconomic activity and (ii) to provide measures of economic costs of such shocks that can help inform ongoing cost-benefit analyses and policy design work. Prudential regulators need to strike a balance between the costs and benefits of altering capital standards, and our paper makes a contribution to one part of the analysis informing that trade-off. These goals are not straightforward to address empirically and require that we overcome two key challenges. First, we need to account for the macroeconomic feedback loop between bank capital, lending, and the business cycle. Second, we must distinguish supervisory-driven capital shocks from other exogenous factors affecting bank capital, such as unexpected credit losses.

The literature has mainly addressed these challenges separately using two different approaches. One strand of literature has employed VAR models with timing or sign restrictions to identify bank capital shocks (e.g., Noss and Toffano, 2016; Mésonnier and Stevanovic, 2017; Meeks, 2017; Kanngiesser et al., 2020). Using sign restrictions, Noss and Toffano (2016) found that higher capital requirements reduce lending, especially during economic expansions, but have limited impact on GDP. Exploiting confidential United Kingdom regulatory micro-level data for identification, Meeks (2017) similarly finds that private, bank-specific capital requirement reduce credit growth, raise spreads, and dampen economic activity, particularly in the housing market. Other studies, such as Mésonnier and Stevanovic (2017); Kanngiesser et al. (2020), shift the focus from capital requirements to voluntary capital buffers (i.e., the excess capital banks hold above regulatory minima) to identify bank capital shocks. Mésonnier and Stevanovic (2017) and Kanngiesser et al. (2020),

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<sup>1</sup>We use the term shocks throughout as technical shorthand for unexpected changes to bank capital requirements, rather than abrupt or harmful events in the colloquial sense. In time series econometric frameworks, a shock is typically defined as the component of a movement that is unpredictable given the information set used in the model (i.e., after conditioning on observed predictors and systematic dynamics). This unpredictability matters because it separates genuinely new information from forecastable changes: if a disturbance were predictable, economic agents could adjust in advance and the observed comovements would partly reflect anticipation and pre-existing trends rather than the impact of a new impulse. Defining shocks as the unpredictable component therefore supports interpreting estimated responses as the effect of a distinct, newly-arriving impulse, rather than movements mechanically driven by predictable variation.

construct aggregate bank capital buffer measures for large, listed US and euro area banks, respectively. These measures are then incorporated into VAR models alongside key macro-financial variables. They find that declines in these buffers lead to reduced lending, higher spreads, and a shift away from risky assets, all of which slow economic activity.

These studies come with a key caveat. In particular, previous research shows that the use of sign restrictions alone can yield a wide set of structural parameters, some of which produce implausible implications for impulse responses, elasticities, or variance decompositions (Antolín-Díaz and Rubio-Ramírez, 2018). This limitation may have broader consequences for policy analyses.

To overcome the identification issues discussed above, several studies use micro-level data to isolate bank-specific capital requirements (e.g., Gropp et al., 2019; Mésonnier and Monk, 2015 ; Aiyar et al., 2016; De Jonghe et al., 2020; de Ramon et al., 2022). While more precise in the identification of prudential shocks, these studies lack the capacity to model the dynamic interaction between banks and the broader economy, focusing primarily on the impact on lending supply while overlooking macroeconomic effects. These features limit the use of these studies for quantifying the economic costs of prudential capital shocks.

A notable study that addresses both empirical challenges together is Conti et al. (2023). To improve identification, Conti et al. (2023) combine sign restrictions with an innovative set of restrictions based on two supervisory stress test events in Europe: the EBA 2011 Stress Test (ST) and the ECB 2014 Comprehensive Assessment (CA). Both events triggered unexpected increases in capital requirements for major Italian banks. This innovative approach, called narrative restrictions, enables more precise identifications by incorporating constraints related to the sign and contribution of specific shocks at particular dates, effectively narrowing the set of plausible models to be more consistent with historical evidence. This allows the authors to isolate supervisory shocks to capital more precisely and to test their impacts on lending supply and macroeconomic activity in Italy. They find that shocks to required capital persistently reduce risk-weighted assets and loan supply, which, in turn, leads to a temporary decline in GDP. Their historical decomposition indicates that the ST and CA increased Italian banks' Tier 1 capital ratio by 40 basis points. Their results also show that to achieve this higher ratio, banks reduced loan supply by up to 1.5 percent, which dampened GDP by 0.5 percent, in the two years after each supervisory shock.

We contribute to the literature examining the links between bank capital and economic activity by adapting the approach of Conti et al. (2023) using data from the United Kingdom. We estimate the effects of prudential capital shocks (PCS) on lending supply and macroeconomic activity using a Structural Vector Autoregression (SVAR) that incorporates components of the bank capital ratio alongside a range of macroeconomic, financial, and banking variables that influence bank capitalization. To identify prudential capital shocks, we use a combination of sign and narrative restrictions, an approach introduced by Antolín-Díaz and Rubio-Ramírez (2018) and applied in various contexts (e.g., Furlanetto and Robstad, 2019; Caggiano et al., 2021). Narrative restrictions enhance traditional sign restrictions by imposing additional constraints on the sign and timing of shocks based on historical events. These constraints ensure that the identified structural shocks and historical decompositions align with well-documented episodes, thereby improving identification precision compared to methods relying solely on sign or timing restrictions.

We use quarterly data for the UK banking sector and UK economy spanning more than thirty years, from 1991 to 2023. We base narrative restrictions on the UK supervisor's 2014 and 2015 stress tests and the 2016 annual cyclical scenario test, which strengthened capitalization in the UK. While UK banks knew these interventions were in the pipeline, the specific design features, hurdle rates and stress scenarios against which they would be judged were unknown until each test started. This timing supports the use of these supervisory interventions for narrative identification of prudential capital shocks in our study. In our setup, the use of narrative restrictions means that the restrictive capital shocks occurred in 2014:Q3, 2015:Q3 and in 2016:Q3.

An additional contribution of this paper is the evaluation of the non-linear effects of prudential policy

shocks on the UK economy, contingent on the state of the business cycle. Recent advances in empirical macroeconomics, which underscore the importance of non-linearities in understanding how structural shocks influence macroeconomic outcomes, motivate this extension. A central theme in this literature is the extent to which impulse response functions vary depending on the prevailing economic conditions.

To capture these non-linear dynamics, we employ state-dependent local projections, a methodological approach that has become essential for analyzing how policy effectiveness fluctuates across different phases of the business cycle. The literature provides robust evidence of state-dependent effects across various policy domains. For instance, in the context of fiscal policy, [Auerbach and Gorodnichenko \(2012, 2013\)](#) and [Ramey and Zubairy \(2018\)](#) find that government spending multipliers tend to be larger during recessions than in expansions. Similarly, [Candelon and Lieb \(2013\)](#) and [Alesina et al. \(2018\)](#) document significant variation in tax multipliers across economic states.

This state-dependence is also evident in monetary policy. Studies by [Santoro et al. \(2014\)](#), [Tenreiro and Thwaites \(2016\)](#), [Angrist et al. \(2018\)](#), [Barnichon and Matthes \(2018\)](#), and [Klepacz \(2021\)](#) show that the effects of monetary shocks differ markedly depending on the economic environment. [Caggiano et al. \(2014\)](#) also highlight similar patterns for uncertainty shocks, whose impacts vary between recessions and expansions.

Despite the widespread application of non-linear approaches to fiscal and monetary policy, their use in analyzing prudential policy remains limited. This paper seeks to address this gap by applying state-dependent local projections to examine how the effects of prudential capital shocks differ across the business cycle. This extension offers novel insights into the optimal timing and calibration of capital-based macroprudential interventions.

This study also extends its analysis beyond macroeconomic impacts to explore how prudential capital shocks influence competition within the banking sector. This perspective addresses a relatively underexplored area, as most existing research focuses on the reverse relationship – how bank competition affects financial stability. Our aim is to shed light on the impacts of prudential measures aimed at supporting financial stability on bank competition.

From a theoretical standpoint, capital-based macroprudential policies can influence bank competition through several interrelated channels, with often ambiguous effects. First, capital requirements typically raise regulatory compliance costs, which can have opposing effects on competition. On one hand, banks may compete more aggressively to offset margin reductions and maintain profitability, thereby intensifying competition. On the other hand, if these costs deter new entrants, incumbent banks may pass them on to customers through higher margins, reducing competitive pressure. Second, prudential requirements can act as entry barriers by imposing high initial capital thresholds on new banks. These barriers shield established institutions from new competition, especially when regulatory compliance involves institution-specific components or sophisticated risk management systems that entail significant fixed costs. Third, capital requirements can disproportionately burden smaller banks due to limited economies of scale and diversification opportunities. In contrast, larger banks can absorb these costs more efficiently. This asymmetry may lead to market consolidation, as smaller institutions become acquisition targets, potentially reducing the number of market participants and increasing concentration. Fourth, capital requirements may be more easily absorbed by large interest rate margins of large, dominant banks that enjoy market power, while smaller banks may have to adjust lending and deposit rates to sustain margins or even move to compete for higher-risk borrowers. If this is the case, then the effects on competition may appear muted. Fifth, capital requirements can restrict overall credit supply, generating mixed competitive effects. While constraints may open opportunities for non-bank financial intermediaries or fintech firms, they can also allow incumbent banks to charge higher spreads, particularly in markets with limited alternative funding sources. Finally, banks with capital buffers well above regulatory minimums often enjoy lower funding costs and greater capacity to hold riskier, higher-yielding assets. These advantages can enable them to expand market share at the expense of

less capitalized competitors, potentially leading to a bifurcated market structure.

Empirical evidence supports the notion that capital-based macroprudential policies influence banking competition, though effects vary by context. For example, [Scalco et al. \(2021\)](#) find that tightening capital-based macroprudential policies in Brazil reduces banking competition. Using stochastic frontier models, they show that instruments such as dynamic loan-loss provisions, capital surcharges for systemically important financial institutions (SIFIs), and leverage ratios increase banks' market power by raising the ratio of total revenue to total cost. The authors identify three primary channels for this effect: increased barriers to entry, rising operational costs, and reduced credit supply. [González \(2022\)](#) extends this analysis to a global context, examining eight macroprudential tools across 52 countries. His research shows that capital-based policies (dynamic loan-loss provisions, capital surcharges on SIFIs, and limits on leverage ratios) and tax-based macroprudential policies reduce bank competition, while loan supply and liquidity-based policies enhance it. Specifically, he finds that capital-based policies are associated with increases in the Lerner index, representing a significant decrease in competition. [Mirzaei and Moore \(2021\)](#) similarly analyze 58 countries and report that capital-related instruments, particularly leverage limits and dynamic provisioning, are positively and statistically significantly associated with the Lerner index, suggesting reduced competition. Collectively, these studies suggest that capital-based macroprudential policies aimed at promoting financial stability may also entail trade-offs for market competition, which can have further implications for policy analysis. Our study explores this issue in more depth.

Our analysis reveals several key findings regarding the effects of prudential capital shocks. First, banks tend to meet higher capital requirements primarily by reducing their risk-weighted assets rather than by raising new capital. A prudential capital shock normalized to generate a 1 percentage point increase in the Tier 1 ratio is decomposed as follows: it raises Tier 1 capital by approximately 0.50 percent over the first quarter and induces a more persistent reduction in RWAs of about  $-0.50$  percent lasting four to eight quarters. This adjustment mechanism leads to a contraction in lending volumes, with corporate lending experiencing a more pronounced decline of approximately 0.25 percent after six quarters, compared to a smaller reduction of about 0.05 percent in household secured lending after four quarters. The shock determines mild increases in the lending spreads to households and corporates of between 1 to 2 basis points. The impact on households, however, is more prolonged, lasting approximately eight quarters, while the increase on corporates dissipates after two quarters. As a result, this restriction in lending supply leads to a modest contraction in GDP, peaking at 0.2 percent after four quarters, and remaining in negative territory for around six to eight quarters. In general, our baseline results suggest that increasing capital requirements involves significant macroeconomic adjustments in the short run and non-significant costs in the longer run, potentially reflecting the mitigating impacts of monetary policy in response to a pullback in credit supply.

Our state-dependent analysis uncovers notable asymmetries across the business cycle. During recessions, prudential capital shocks tend to cause larger immediate economic contractions but are followed by quicker recoveries, likely due to enhanced market confidence in the stability of the banking sector. In contrast, during economic expansions, the negative effects are initially smaller but tend to persist for a longer period.

We also examine the impact of these shocks on banking sector competition using three key indicators: the Boone indicator, the Herfindahl-Hirschman Index (HHI), and the Lerner Index. The results consistently show that tighter capital requirements temporarily reduce competition. Specifically, the Boone indicator suggests that efficiency becomes less critical for profitability, while increases in the HHI point to greater market concentration. The Lerner Index indicates rising price-cost margins, suggesting that banks respond to higher capital costs by increasing lending rates – a dynamic consistent with a markup channel.

Using a historical decomposition, we evaluate the contribution of prudential capital shocks to the main variables in the model during stress tests. We find that these shocks induced banks to cut risk-weighted assets more than they bolstered Tier 1 capital, with the 2015 Concurrent Stress Test producing the largest effect, in absolute terms, among the three supervisory events considered. One quarter after the shock associated

with this event, Tier 1 capital rose by up to 0.80 percent and risk-weighted assets fell by as much as 1.39 percent, driving a Tier 1 ratio gain of nearly 34 basis points compared to its pre-shock level. Two quarters after the shock, credit spreads widened by up to 4.6 basis points for non-financial corporates and by 4.4 basis points for households, while corporate lending contracted by roughly 0.60 percent (versus just 0.06 percent for households). GDP declined by approximately 0.32 percent.

Our findings are robust to several sensitivity checks. These robustness tests include changing the timing of some narrative restrictions to align with micro-level data dynamics, truncating the sample before the COVID period to show that our main results are not sample dependent, and implementing perturbations of the sign restriction identification strategy to match those employed in the literature (Kanngiesser et al., 2020; Conti et al., 2023). Moreover, we demonstrate that the timing of our narrative restrictions is appropriate, as altering them to periods before stress test scenarios were announced produces wider credibility intervals. We also show that including COVID observations adversely affects statistical inference, justifying our approach of excluding quarters in 2020 and 2021 following Lenza and Primiceri (2020).

The remainder of this paper is organized as follows. Section 2 provides an overview of bank capitalization in the UK, including detailed information on the stress testing exercises we use for identification. Section 3 examines banking competition in the UK. Section 4 outlines our empirical framework, detailing our SVAR specification, identification strategy, and state-dependent local projections methodology. Section 5 presents our main results, including impulse response functions, state-dependent effects, and historical decomposition. Section 6 presents robustness checks, and Section 7 concludes.

## 2 Rationale for narrative restrictions

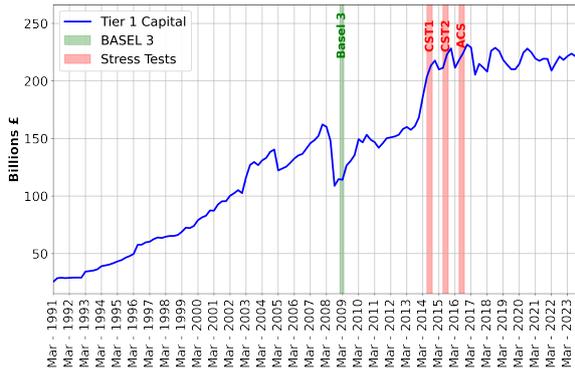
The purpose of this section is twofold. First, to provide context for our analysis of the economic effects of prudential shocks to bank capital, we briefly review the evolution of bank capitalization in the UK since the early 1990s. Second, we review three events that we use in the identification of prudential capital shocks with narrative restrictions: the UK PRA’s 2014 and 2015 Concurrent Stress Tests (CSTs) and the PRA’s 2016 Annual Cyclical Scenario (ACS) test. Each test raised supervisory expectations around bank solvency that had significant effects on bank capitalization.

### 2.1 Bank capitalization in the UK

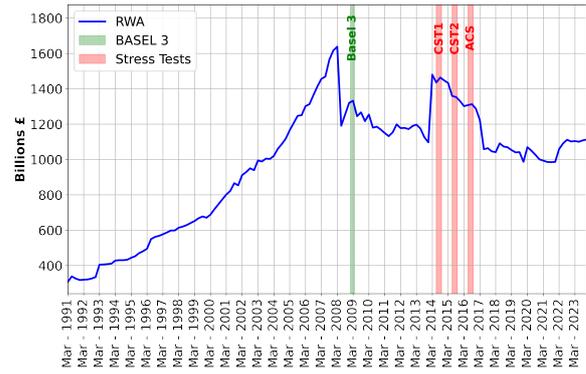
Figure 1 reports aggregate Tier 1 capital ratio and its components for all banks and building societies (hereafter ‘banks’) in the UK over the period 1991Q1 to 2023Q4.<sup>2</sup> The aggregate Tier 1 ratio reflects the (asset) weighted-average of all UK banks using data at the highest consolidated level. Key milestones marked on the charts correspond to significant regulatory events, including the initiation of discussions leading to Basel 3 adoption, and the three stress tests described earlier (and detailed below).

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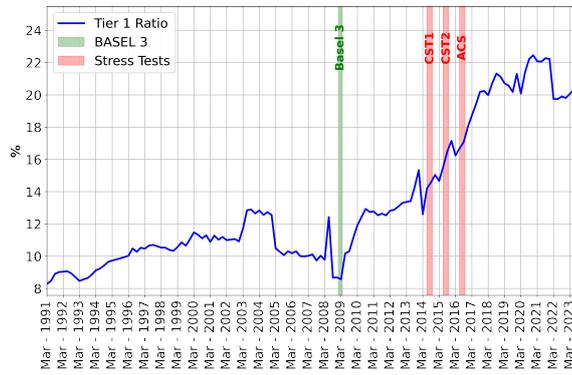
<sup>2</sup>The ratio of Tier 1 capital to total risk-weighted assets is a key regulatory measure of capital adequacy. Tier 1 capital consists of Common Equity Tier 1 (CET1), which includes common equity shares, stock surpluses from the issue of common shares, retained earnings, and accumulated other comprehensive income, together with Additional Tier 1 capital (AT1), i.e., instruments that are not common equity but that can count towards this tier. AT1 instruments include contingent convertible or hybrid securities that do not have a fixed term and that can be converted into equity when a trigger event happens. Risk-Weighted Assets are bank assets weighted by Basel risk-weights (or approved internal ratings-based approaches) that reflect their riskiness.



Tier 1 Capital



RWA



Tier 1 Ratio

Figure 1: The evolution of Total Tier 1 capital, RWA and their ratio for commercial banks and building societies in the UK.

*Note:* Quarterly data for the period 1991:Q1–2023:Q4. Red areas denote each episode considered for the narrative restrictions (2014:Q3 and 2015:Q3 for the Concurrent Stress Tests and 2016:Q3 for the Annual Cyclical Scenario); the green area denotes the start of the discussion that led to the adoption of the Basel 3 agreement (2009:Q1).

The figure shows a rapid increase (from 8% to 10%) in the overall capital adequacy ratio in the early 1990s. This increase is consistent with the general upturn in capital ratios documented in other developed countries following the implementation of the Basel 1 standards in 1991 (Jackson et al., 1999). The aggregate ratio rose modestly in the late 1990s (to around 12%) and remained relatively stable until the onset of the Global Financial Crisis in 2008. The initial sharp decline in Tier 1 capital during 2008 reflects the impact of the Global Financial Crisis (GFC), as banks incurred significant losses amidst market turmoil. A turning point occurs in 2009 with the start of Basel 3 discussions, encouraging banks to raise their capital levels to enhance resilience. In response, between 2009 and 2013, Tier 1 capital rose steadily, driven in large part by banks’ efforts to comply with the more stringent requirements under Basel 3. At the same time, RWAs exhibit a downward trend, suggesting that banks took steps to derisk as another way to meet the higher capital ratio standards under Basel 3.

In 2013, there is a noticeable increase in both capital and RWAs, likely related to the introduction of Capital Requirements Directive IV (CRD IV), the European implementation of Basel 3. From 2014 onward, the increase in Total Tier 1 Capital tapers off and displays moderate jumps around the stress tests conducted in the following three years. At the same time, RWAs display a clear downward trend starting in 2014. These dynamics result in a stepwise increase in the Tier 1 capital ratio.

These observations motivate our analysis of the economic costs associated with capital requirements, particularly focusing on the role of prudential capital shocks in driving these variables. The substantial increase in the Tier 1 capital ratio, driven largely by reductions in RWAs, may signal reduced credit availability, potentially exerting a negative impact on GDP.

The aggregate ratio fell at the time of the GFC to around 8.6%, but then recovered steadily in the immediate aftermath of the GFC as steps were taken to shore up solvency positions. Since 2009, the aggregate Tier 1 capital ratio increased from 8.5% to almost 19% by the end of 2023, with a modest decline evident during the Covid period 2019-2020. The persistent upturn in the aggregate Tier 1 capital starting in 2009 corresponds with negotiations that led to the adoption of more stringent capital standards under Basel 3 at the end of 2010. These revised standards, targeted to begin in 2014, mandated increases in both the quantity and quality of capital. In response, from 2009 to 2014, aggregate Tier 1 capital increased by roughly 63 percent (£80 billion).

Because this increase came on the heels of one of the most notable and publicly deliberated regulatory changes in global bank capital standards, it is most likely the case that it reflected banks' anticipation of such reforms and the need to improve capital positions. Practically, this means that this period of time is not useful for identifying a prudential capital shock following a narrative restriction approach. This approach requires that we determine a specific period in which an unanticipated shock happened.

## 2.2 Stress testing in the UK

To help in that direction, we rely on three unique periods of supervisory interventions, discussed in turn below, that were generally unanticipated: the UK PRA's Concurrent Stress Tests (CST) in 2014 and 2015 and its Annual Cyclical Scenario (ACS) test in 2016. While the PRA announced its intention to conduct such tests in 2013, the nature and severity of the stress scenarios under which banks would be assessed were not known to the banks at that time. This supports their use for identifying prudential capital shocks using a narrative framework.

### 2.2.1 UK PRA 2014 Concurrent Stress Test

The UK PRA conducted its first concurrent stress test of the UK banking system in 2014. This stress test was significant as it marked the beginning of regular concurrent stress testing by the PRA to assess the resilience of major UK banks and the banking system more broadly to severe economic scenarios.<sup>3</sup> While the PRA had announced its plans to undertake such testing in 2013, the exact nature of the testing and the scenarios that banks would be subject to were not announced until March 2014. The 2014 CST evaluated banks' balance sheets as of December 2013, and results were published in December 2014. The 2014 CST evaluated banks against several severe economic scenarios, including (i) a deep economic recession; (ii) a global economic downturn; (iii) a housing market crash; and (iv) a market stress. The results of the test revealed capital shortfalls in three of the eight participating banks. As a result, banks raised approximately £13 billion to address the identified capital shortfalls and strengthen their financial positions.<sup>4</sup>

### 2.2.2 UK PRA 2015 Concurrent Stress Test

The PRA's 2015 CST built on the framework established in 2014. To ensure that banks had sufficient time to prepare, analyse, and respond to the demands of the test, the PRA released its stress scenarios in December 2014. The PRA launched the CST in March 2015, subjecting banks' balance sheets as of December

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<sup>3</sup>The 2014 CST covered eight major UK institutions: Barclays, The Co-operative Bank, HSBC, Lloyds Banking Group, Nationwide, The Royal Bank of Scotland Group, Santander UK and Standard Chartered. These banks account for over 80% of PRA-regulated banks' lending to the real economy.

<sup>4</sup>See [Bank of England \(2014\)](#), Stress testing the UK banking system: 2014 results

2014 to several different adverse scenarios.<sup>5</sup> The key scenarios tested included: (i) a global recession; (ii) a UK property market shock; (iii) a financial market turmoil; and (iv) a sharp interest rate rise. Banks submitted their results by mid-2015, with the PRA evaluating and providing ongoing feedback during this period. The PRA released its final assessment in December 2015, which found shortfalls at two institutions. This prompted banks to raise almost £7 billion of Tier 1 capital by the end of 2015.<sup>6</sup>

### 2.2.3 UK PRA 2016 Annual Cyclical Scenario

The PRA conducted its 2016 stress test under a new annual cyclical scenario framework that systematically adjusted the severity of the test based on the PRA’s assessments of risk levels across markets and regions. The PRA announced stress scenarios in March 2016, banks submitted results and PRA assessed and provided feedback, including any required actions to strengthen capital positions over the next several months. The PRA published results in November 2016, which indicated that three major UK banks needed to improve their capital positions. In response, banks’ Tier 1 leverage positions were improved by the issuance of Tier 1 instruments worth over £7 billion in 2016 during the first three quarters of the year, taking the total stock to around £30 billion.<sup>7</sup>

## 3 Bank Competition in the UK

Evaluating the competitive implications of macroprudential policies is critical for comprehensive policy assessment. While capital-based macroprudential instruments effectively promote financial stability, their effects on market competition remain theoretically ambiguous, as they operate through multiple interconnected channels with potentially offsetting effects. These policies may intensify competitive behavior as banks seek to maintain profitability despite regulatory costs or alternatively enable institutions to transfer compliance burdens to consumers via increased pricing. Furthermore, prudential requirements may create market access impediments that shield incumbent players, asymmetrically affect smaller institutions potentially driving industry concentration, generate opportunities for alternative financial intermediaries, or confer strategic advantages upon financially robust banks. Given this theoretical ambiguity, empirical examination of competition effects is essential to inform regulatory calibration and ensure policymakers account for the complete implications of prudential interventions.

This section provides a brief overview of the evolution of bank competition in the UK by presenting in Figure 2 the evolution of three established competition measures. These indicators enable us to examine the various channels previously described and will be employed in our empirical framework. In particular, the first competition indicator used is the Boone Indicator [Boone \(2008\)](#). This measure reflects the elasticity of profits to banks’ efficiency, proxied by marginal costs (as a percentage of total revenue). As competition intensifies, the relative profitability of firms becomes more sensitive (i.e., larger in absolute value) to cost differences, making the Boone Indicator a robust measure of competitive pressure. The second competition measure employed is the Lerner Index [Lerner \(1934\)](#). This index captures market power and reflects the price-cost margin for all UK banks. Higher values of the Lerner Index point to higher market power and lower competition, as they signify a larger gap between prices and costs. Finally, we use the Herfindahl Hirschman Index (HHI) [Hirschman \(1964\)](#). This index is computed as the sum of the squared market shares of all firms in the market, based on loans, given our study’s interest in lending impacts. Higher values of the HHI indicate a more concentrated market, suggesting less competition. All these indicators are derived from micro-level data utilizing the Historical Banking Regulatory Database (HBRD) of the Bank of England [de Ramon et al. \(2017\)](#). Appendix E describes in detail how these indicators are constructed.

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<sup>5</sup>The 2015 CST covered the same institutions with the exception of the Co-operative Bank.

<sup>6</sup>See [Bank of England \(2015\)](#), Stress testing the UK banking system: 2015 results.

<sup>7</sup>See [Bank of England \(2016\)](#), Stress testing the UK banking system: 2016 results

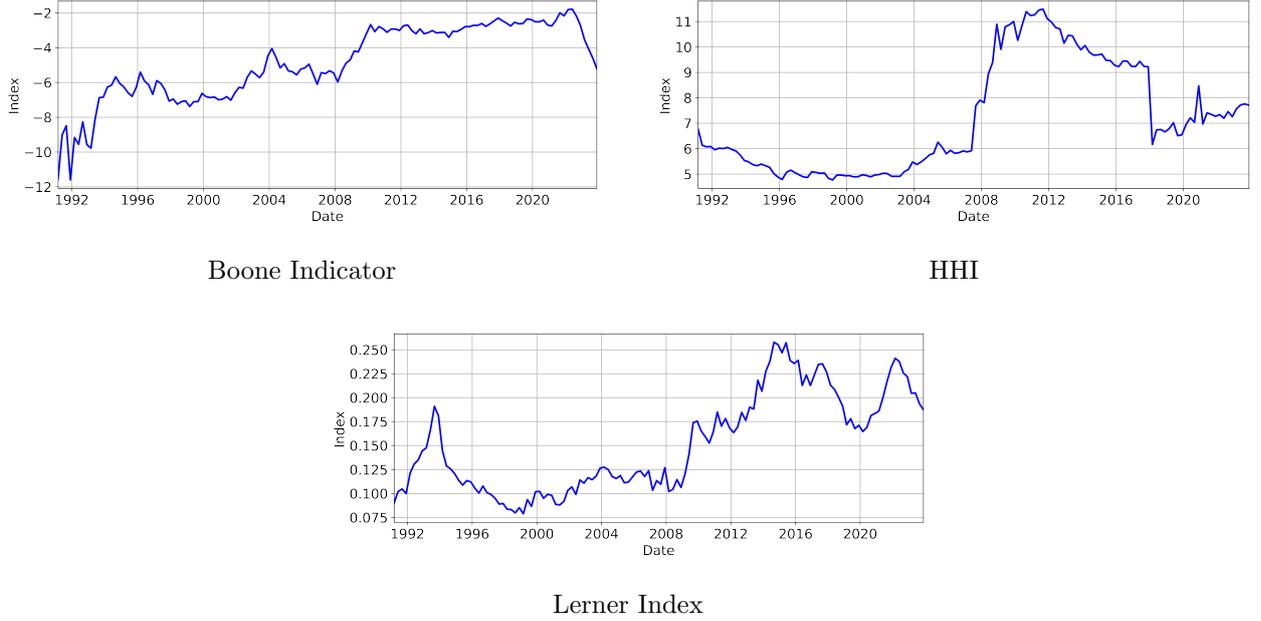


Figure 2: The evolution of competition measures in the UK.

*Note:* Quarterly data for the period 1991:Q1–2023:Q4.

Starting from the upper left panel of Figure 2, we see that the Boone Indicator exhibits a clear trend. From the beginning of our sample, the indicator steadily moves toward zero, indicating that the relative profitability of firms has become less sensitive to cost differences. Equivalently, efficiency differences have had a diminishing impact on market shares and profitability, indicating a reduction in competition.

The HHI for UK banking reveals a clear trend of increasing market concentration throughout our sample. During the 1990s and early 2000s, asset concentration levels remained relatively low, indicating nonconcentrated markets. The financial crisis triggered further concentration, with total assets moving into the “high-concentration” region after 2008, reflecting additional mergers (Lloyds-HBOS, Santander UK acquisitions). Although concentration levels began to decrease after 2010, the HHI measure indicates a more concentrated market compared to earlier periods.

The Lerner Index, measuring market power through price markups, shows varying levels of competition throughout the period. Market power increased noticeably during 1998-2015, followed by a slight reduction in 2016-2020.

## 4 Empirical Framework

### 4.1 Model

To evaluate the impact of a prudential capital shock on the UK economy and banks’ competition, we rely on a structural vector autoregression (SVAR). To introduce this model, we start from its reduced-form representation:

$$\mathbf{y}_t = \sum_{l=1}^p \mathbf{A}_l \mathbf{y}_{t-l} + \mathbf{c} + \mathbf{u}_t, \quad t = 1, \dots, T, \quad \mathbf{u}_t \sim \mathcal{N}(0, \Sigma) \quad (1)$$

where  $\mathbf{y}_t$  is an  $n \times 1$  vector of endogenous data,  $\mathbf{A}_l$  are  $p$  matrices of dimension  $n \times n$ , and  $\mathbf{c}$  is a vector of constant terms.  $\mathbf{u}_t$  is an  $n \times 1$  vector of reduced-form residuals following a multivariate normal distribution.  $\Sigma$  is an  $n \times n$  symmetric positive definite variance-covariance matrix, with variance terms on the diagonal

and covariance terms off-diagonal.

In standard impulse response analysis, a key issue arises from the fact that shocks are often correlated, as the residual covariance matrix ( $\Sigma$ ) is generally non-diagonal. This makes the causal interpretation of the effects of estimated shocks on the variables meaningless, as shocks typically arise together. SVARs resolve this by decomposing the shocks into orthogonal components, allowing for a clearer interpretation of the dynamic responses to independent disturbances. We can rewrite (1) in its structural form:

$$D_0 \mathbf{y}_t = \sum_{l=1}^p D_l \mathbf{y}_{t-l} + \mathbf{F} + \boldsymbol{\varepsilon}_t, \quad t = 1, \dots, T, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(0, \mathbf{\Gamma}) \quad (2)$$

where  $\boldsymbol{\varepsilon}_t$  is a vector of structural innovations with diagonal variance-covariance matrix  $\mathbf{\Gamma}$ . This implies that shocks in  $\boldsymbol{\varepsilon}_t$  are mutually orthogonal, making it possible to assume structural shocks are uncorrelated and arise independently. The mapping between (2) and (1) is given by:

$$\mathbf{D} = D_0^{-1}, \quad \mathbf{A}_l = \mathbf{D} D_l, \quad \mathbf{c} = \mathbf{D} \mathbf{F}, \quad \text{and} \quad \mathbf{u}_t = \mathbf{D} \boldsymbol{\varepsilon}_t.$$

The structural matrix  $\mathbf{D}$  is defined as  $\mathbf{D} = h(\Sigma) \mathbf{Q}$ , where  $h(\cdot)$  is any continuously differentiable function of symmetric positive definite matrices such that  $h(\Sigma) h(\Sigma)' = \Sigma$ , such as the Cholesky factor often used in practice.  $\mathbf{Q}$  is an orthogonal matrix such that  $\mathbf{Q} \mathbf{Q}' = \mathbf{I}_n$  to preserve the SVAR property.

We estimate our model following the approach proposed in [Antolín-Díaz and Rubio-Ramírez \(2018\)](#), employing a Jeffrey’s conjugate prior. Moreover, the identification procedures rely on traditional sign and zero restrictions ([Uhlig, 2005](#) and [Arias et al., 2018](#)). In particular, these identification strategies restrict the response of a variable to a specific structural shock to be positive, negative, or zero. Each such restriction, set by the VAR model user, can be applied over any number of impulse response function periods, which need not be the same across restrictions.

We fine-tune this restriction following the methodology of narrative restrictions proposed by [Antolín-Díaz and Rubio-Ramírez \(2018\)](#). Their approach allows researchers to exploit historical, external events (narratives) to identify structural shocks by constraining the timing, magnitude, or direction of their effects based on real-world observations, ensuring more credible identification of causal relationships. In this work, we employ a set of narrative restrictions that constrain the sign of the  $j$ th shock at  $s_j (t_1, \dots, t_{s_j})$ , expressed as:

$$\mathbf{e}'_{j,n} \boldsymbol{\varepsilon}_{t_v} \geq 0 \quad \text{for} \quad 1 \leq v \leq s_j. \quad (3)$$

where  $\mathbf{e}'$  is the  $j$ th column of  $\mathbf{I}_n$ .

## 4.2 Data and Specification

The baseline VAR specification includes eleven variables and four lags (i.e.,  $n = 11$  and  $p = 4$ ). Our estimation sample consists of quarterly data spanning from 1991:Q1 to 2023:Q4, thereby including the COVID-19 period. The unprecedented economic shock during the pandemic potentially affects inference on UK Real GDP, as between Q1 2020 and Q2 2020, UK real GDP contracted by approximately 20 percent (the largest quarterly decline on record) exhibiting volatility several times greater than any pre-pandemic period. To address this analytical challenge, we follow the insights from [Lenza and Primiceri \(2020\)](#), who demonstrate that introducing period-specific scaling factors can effectively absorb the volatility spike during extreme events such as the initial pandemic quarters. However, they also establish that for purposes of obtaining unbiased VAR parameter estimates (as opposed to density forecasting under extreme volatility) simply excluding pandemic-era observations produces virtually identical posterior distributions for the coefficients compared to their comprehensive scaling approach. Since our analysis focuses exclusively on parameter estimation, we accordingly exclude observations’ quarters from 2020 and 2021 from our estimation sample.

For comparative purposes, we present structural impulse response functions that include the COVID-19 period in the Appendix D.4.

The variables included in our model are closely related to those used in the main papers on VAR literature dealing with prudential capital shocks (Noss and Toffano, 2016, Meeks, 2017, de Ramon and Straughan, 2017, Kanngiesser et al., 2020, Conti et al., 2023).<sup>8</sup> We consider the level of Tier 1 capital for UK commercial banks and building societies, as well as their risk-weighted assets (RWA). Including the numerator and denominator separately is essential for shock identification, as detailed in Conti et al., 2023. Additionally, we include both lending spreads and volumes for households and private non-financial corporations (PNFCs) in our model. Using lending volumes that are not risk-weighted mitigates concerns that our results could be distorted by banks reshuffling their balance sheets to optimise risk-weighted assets and obtain more favourable regulatory treatment, rather than reflecting genuine changes in credit supply.

The impact of a prudential capital shock may differ across credit market segments due to varying levels of customer riskiness. To capture these differences, we include the outstanding amount of Household M4 secured lending and PNFCs M4 lending,<sup>9</sup> along with their respective interest rate spreads, calculated as the difference between deposit and lending rates.

We include UK real GDP and the consumer price index as standard determinants of the business cycle. Following Noss and Toffano (2016), we include a measure of banks’ profitability relative to the overall market, which we refer to as the bank beta. This variable is calculated as the ratio of the UK FTSE Banks Index to the overall FTSE All-Share Index. Additionally, we include the Bank of England Base interest rate.

To account for bank competition, we employ the three competition proxies described in Section 3, estimating the VAR with each proxy separately. This approach provides a comprehensive understanding of how prudential policy shocks influence competition from different perspectives.<sup>10</sup> By including the Boone indicator, HHI and, Lerner index we capture distinct dimensions of competition: profit sensitivity to cost differences, market power through price-cost margins, and overall market concentration.

In all the models, spreads, ratios, and competition proxies are employed in levels, while the other variables are included in logarithms.

### 4.3 Identification

We identify prudential capital shocks (PCS) combining zero-sign restrictions and narrative restrictions (following Antolín-Díaz and Rubio-Ramírez, 2018). Table 1 outlines the sign restrictions used to identify the effects of a tightening in prudential capital requirements.

Table 1: Identification of prudential capital shocks (PCS): sign restriction.

Response	Tier 1 <sub>t</sub>	PNFC Spread <sub>t</sub>	Household Spread <sub>t</sub>	RWA <sub>t</sub>	Household Lending <sub>t</sub>	PNFC Lending <sub>t</sub>	Bank Profitability <sub>t</sub>	π <sub>t</sub>	Base Rate <sub>t</sub>	GDP <sub>t</sub>	Competition Proxy <sub>t</sub>
$t = 0$	+	+	+	-	-	-	-	0			

Note: +/ - /0 denote sign and zero restrictions on impact ( $t = 0$ ). Blank table entries denote unconstrained IRFs. π<sub>t</sub> stands for CPI inflation. Competition Proxy stands for *Boone<sub>t</sub>*, *Lerner<sub>t</sub>* or *HHI<sub>t</sub>*.

A key restriction underlying our identification strategy is that a prudential capital shock has opposite effects on the numerator (Tier 1 capital) and the denominator (RWAs) of the risk-based capital ratio. The

<sup>8</sup>We report in Appendix A the time series charts of the variables employed in the model.

<sup>9</sup>Household M4 secured lending consists mainly of mortgages, home equity loans, and remortgaging, where individuals borrow against their residential properties. These loans are secured because the house or property acts as collateral, meaning the lender can repossess it if the borrower defaults. PNFCs M4 lending includes commercial property loans, asset-backed business loans, and secured credit lines provided to private non-financial corporations. These loans are secured because they are backed by business assets such as commercial properties, machinery, or inventory, which lenders can claim if the company fails to repay.

<sup>10</sup>See Appendix E for details on how each competition is measured.

intuition behind this identification approach is that banks respond to tighter prudential capital standards by increasing Tier 1 capital (e.g., by issuing new capital or restricting dividends and increasing earnings retention) and by reducing RWAs. This restriction is crucial for disentangling prudential capital shocks from other shocks that may also affect banks’ capitalization. It also means that through their impacts on RWAs, such shocks drive a reduction in lending supply, implying that loan volumes decrease and loan spreads increase.<sup>11</sup> Unlike PCS, other shocks typically exhibit a positive co-movement between the two components of the capital ratio. This is because capitalization is influenced by both business cycle dynamics and financial developments (Conti et al., 2023). For instance, a negative shock to the economic outlook may lead to a spike in loan defaults, necessitating higher provisions that erode banks’ earnings and, in turn, capital levels. Banks often respond by reducing their lending supply and other assets, resulting in a decline in RWAs. Conversely, favourable financial market conditions can yield unexpected gains from asset holdings, enhancing bank capital. To the extent that positive macroeconomic developments drive increased loan demand, RWAs increase, thus contributing to the positive association between capital and RWAs.

As for the negative restriction in the bank profitability, following an increase in regulatory capital requirements is justified primarily by the constrained ability of banks to engage in profitable lending activities and the rise in funding costs. This sector-specific reduction in profitability is introduced to differentiate the effects of a capital requirements shock from those of a broader negative shock to the overall macroeconomic outlook. Consequently, an increase in regulatory capital requirements is also expected to result in a negative shock to bank equity prices relative to the performance of the UK equity market as a whole.

The zero restriction on impact for CPI inflation is imposed to distinguish the shock from restrictive monetary policy shocks.<sup>12</sup> Furthermore, the response of the BoE base rate is left unrestricted, as no strong theoretical foundations are available to justify a specific response. Real GDP and competition proxies are also left unrestricted, as they are variables of primary interest.

To refine the identification of prudential capital shocks, we leverage three historical events, as discussed in the previous section: the CSTs of 2014 and 2015 and the first ACS test of 2016. Between 2014 and 2016, these tests prompted several banks to take measures to strengthen their capital positions. The stress test framework adopted by the PRA follows an eleven-month cycle, with banks’ prior year-end accounts serving as the data cut-off point. Stress scenarios and guidance are published at the beginning of Q2, banks submit their responses by the end of Q2 or early Q3, and the results, along with policy decisions, are released in December. Based on these facts and on the structure of the stress testing procedure, Table 2 presents the narrative restrictions scheme:

Table 2: Identification of Prudential Capital Shock (PCS): Narrative restrictions.

<b>Dates and signs of the shock</b>	
CST 2014	PCS > 0 in 2014:Q3
CST 2015	PCS > 0 in 2015:Q3
ACS 2016	PCS > 0 in 2016:Q3

We impose that the prudential capital shock exhibited a positive sign in the third quarters of 2014, 2015, and 2016, when banks adjusted their capital structures to comply with the requirements of the stress test. We adopt an agnostic stance regarding whether these events were the primary drivers of Tier 1 capital evolution and, consequently, do not impose any restrictions on their magnitude or contribution.

<sup>11</sup>To account for the possibility that adjustments in bank balance sheet variables may occur gradually, as suggested by Conti et al. (2023), we employ an alternative identification strategy as a robustness check. In this specification, the restrictions on Tier 1 capital, RWA, corporate lending, and household lending are imposed not only on impact but also through period  $t = 1$ . Results are reported in Appendix D.

<sup>12</sup>As robustness checks we estimate the model without restricting the response of headline inflation as in Känngiesser et al. (2020). We report the estimated IRF in Appendix D.

Narrative restrictions play a critical role in constraining structural parameters to align the identified shocks with the historical narrative of the episodes under study. Using sign restrictions alone can generate unrealistic range of structural parameters, resulting in implausible implications for impulse response functions (Antolín-Díaz and Rubio-Ramírez, 2018). Combining sign and narrative restrictions helps address this limitation. In the subsequent section, we will demonstrate how the imposition of these restrictions together enables us to exclude cases that satisfy the sign restrictions but imply a loosening of capital requirements on those dates, which contradicts the established narrative accounts.

#### 4.4 Non-Linear Effects

As explained in the introduction, recent empirical macroeconomics literature highlights the importance of non-linearities in estimating the effects of exogenous shocks on variables of interest. In our case, we aim to evaluate the non-linear effects of the prudential capital shock estimated from the SVAR model, represented as  $\varepsilon_{t,PCS}$ , on UK real GDP and each of the competition proxies discussed in the previous sections. To achieve this, we employ a variant of the Local Projections (LP) approach (Jordà, 2005, 2009) to estimate the state-dependent impulse response functions of GDP and competition proxies to a PCS.

To trace out how our estimated policy shock,  $\varepsilon_{t,PCS}$ , affects a scalar variable  $y_{t+h}$  differently in expansions versus recessions across horizons, we run the following set of state-dependent LP for each horizon  $h$ :

$$y_{t+h} = f(Z_{t-1}) [\beta_{E,h}\varepsilon_{t,PCS} + \phi'_{E,h}\mathbf{X}_{t-\ell}] + (1 - f(Z_{t-1})) [\beta_{R,h}\varepsilon_{t,PCS} + \phi'_{R,h}\mathbf{X}_{t-\ell}] + \eta_{t+h} \quad (4)$$

Here,  $\varepsilon_{t,PCS}$  denotes our estimated prudential capital shock at time  $t$ , and  $y_{t+h}$  is the outcome variable  $h$  periods ahead. The vector  $\mathbf{X}_{t-\ell}$  contains all control variables. The function  $f(Z_{t-1})$  is a continuous state variable that takes values near 0 when the economy was in expansion (state E) at  $t - 1$  and near 1 when it was in recession (state R). The coefficients  $\beta_{E,h}$  and  $\beta_{R,h}$  capture the horizon- $h$  impulse response of  $y$  to a one-unit shock in expansions and recessions, respectively, while  $\phi_{E,h}$  and  $\phi_{R,h}$  govern how the controls  $\mathbf{X}_{t-\ell}$  enter in each state. Finally,  $\eta_{t+h}$  denotes the error term.

An advantage of using state-dependent local projections over state-dependent structural vector autoregressive models relates to their computational simplicity. Estimating impulse responses in state-dependent VAR models via numerical methods is generally more computationally intensive compared to using least squares for state-dependent local projections. Additionally, local projection estimators have the benefit of not requiring the estimation of equations for variables other than the outcome variable of interest. Finally, unlike state-dependent VAR models, state-dependent local projections can be estimated without the need to specify the process governing transitions between states. We estimate model (4) using OLS. We use a control set ( $\mathbf{X}_{t-\ell}$ ), which includes variables employed in the VAR up to lag 2 including the dependent variable. To account for potential heteroskedasticity and autocorrelation in the residuals, we compute the standard errors using the HAC (heteroskedasticity and autocorrelation consistent) correction with lags equal to the number of horizon when constructing the confidence intervals.

To build our state variable we follow the method proposed in Auerbach and Gorodnichenko (2012). In particular,  $Z_{t-1}$  is a standardized seven quarter centred moving average of UK real GDP year-on-year growth. We date the variable  $t - 1$  to avoid contemporaneous feedback of policy actions with respect to when the economy is in a recession or expansion.  $f(\cdot)$  is a logistic function with a scale parameter  $\gamma = 8.5$ . The calibration ensures that, using the threshold  $f(Z_t) > 0.8$  (the same threshold chosen by Auerbach and Gorodnichenko, 2012 to classify recessions) the economy is in recession for approximately one-quarter of our sample period, consistent with OECD-based recession indicator for the UK. The key advantage of using this measure is that it allows us to leverage our state variable, enabling the inclusion of the entire sample for estimation. This is particularly significant given the relatively small size of our sample. In contrast, employing a simple dummy variable to represent recession periods would have necessitated the removal of

many observations, limiting the robustness and comprehensiveness of the analysis.

Figure 3 displays the evolution of our state variable  $f(Z_t)$  for the World GDP throughout the estimation sample.

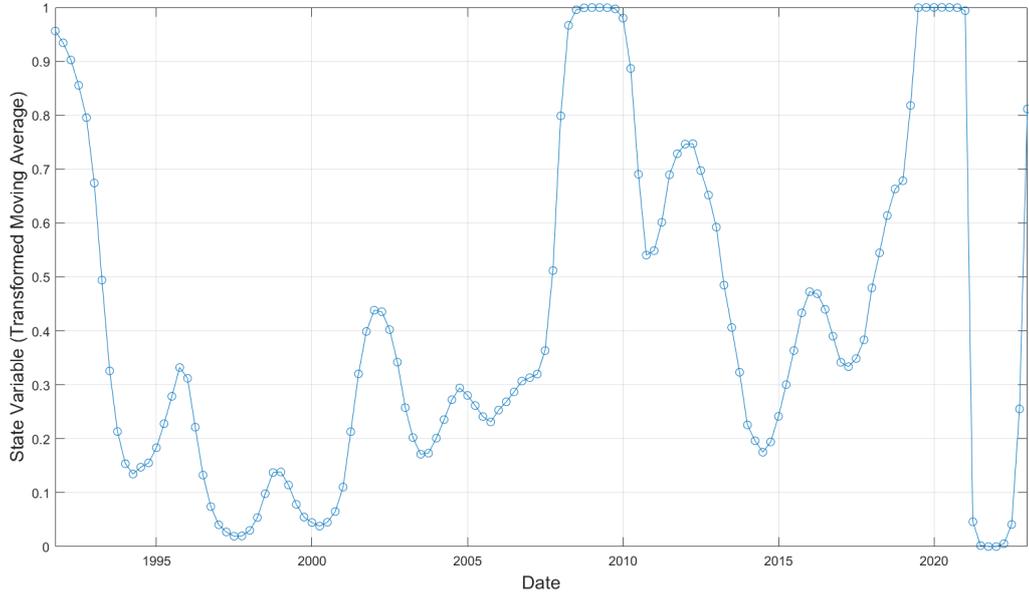


Figure 3: State variable  $f(Z_t)$

During this period, our state-variable rises sharply toward one in four distinct episodes of economic stress. The first spike in early 1991 coincides with the UK’s early-1990s recession, followed by a pronounced peak in late 2008 and early 2009 at the height of the Global Financial Crisis. A more prolonged elevation appears between mid-2011 and early 2013 during the Euro-area sovereign-debt turmoil, and a final, very sharp surge occurs in 2020 Q1 as the UK plunged into recession under COVID-19 lockdowns. The fact that each of these peaks aligns neatly with well-known downturns gives us confidence that  $f(Z_t)$  accurately tracks the business cycle and hence that its smoothly varying “weight” in our state-dependent local projections correctly shifts the estimated impulse responses between expansionary and recessionary regimes.

## 5 Results

In this section, we first present the contribution of narrative restrictions in identifying prudential capital shocks. We then report the estimated structural impulse response functions derived from the baseline VAR model discussed in the previous section. Finally, the section concludes with an analysis of the estimated nonlinear dynamic effects of a prudential policy shock.

### 5.1 Contribution of narrative restrictions

Figure 4 presents the posterior distribution of the estimated structural shock for the dates where narrative restrictions are imposed.

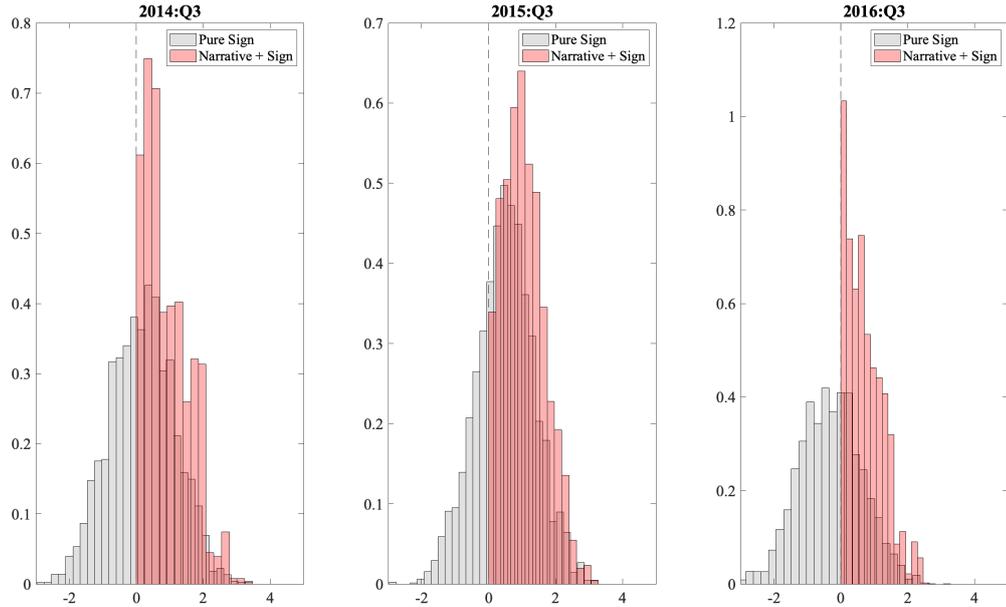


Figure 4: Prudential Capital Shock: narrative vs. pure sign restrictions.

*Note:* The left panel plots the posterior distribution of the Prudential Capital Shock for 2014:Q3, corresponding to the 2014 CST. The central panel plots the posterior distribution for 2015:Q3, corresponding to the 2015 CST while the last corresponds to 2016 ACS. The grey bars refer to the identification obtained with pure sign restrictions, while the light red bars refer to the identification obtained with narrative sign restrictions.

As mentioned above, narrative restrictions constrain the structural parameters so that the identified structural shocks align with the established narrative account of specific events, which, for our case, correspond to three supervisory stress tests. For the three dates where we imposed the restriction that a positive prudential capital shock occurred, i.e., 2014:Q3 for the 2014 CST (left-hand panel), 2015:Q3 for the 2015 CST (central panel), and 2016:Q3 for the first ACS (right-hand panel), the figure compares the posterior distribution of the structural shock under the baseline identification (light red histograms, including narrative restrictions) with that under a specification relying solely on sign restrictions (grey histograms). The results show that, on these dates, sign restrictions alone leave the shock only weakly identified: the posterior places substantial probability on both positive and negative shocks, resulting in wider and less informative impulse responses. This does not indicate that the sign-restricted posterior is “incorrect”; rather, it reflects the lack of date-specific information on the direction of the shock. Narrative restrictions incorporate such information, drawn from supervisory assessments, and therefore sharpen identification and yield impulse responses with narrower credibility intervals compared to those derived under pure sign-restrictions identification. To illustrate the importance of narrative restrictions for identification, we compare the structural impulse responses obtained using sign restrictions alone with those obtained using narrative restrictions in Appendix C.

## 5.2 Impulse Response Functions

Figure 5 illustrates the responses of the macro-financial variables included in the model, normalized to reflect a 100 basis points increase in Total Tier 1 capital ratio upon impact.

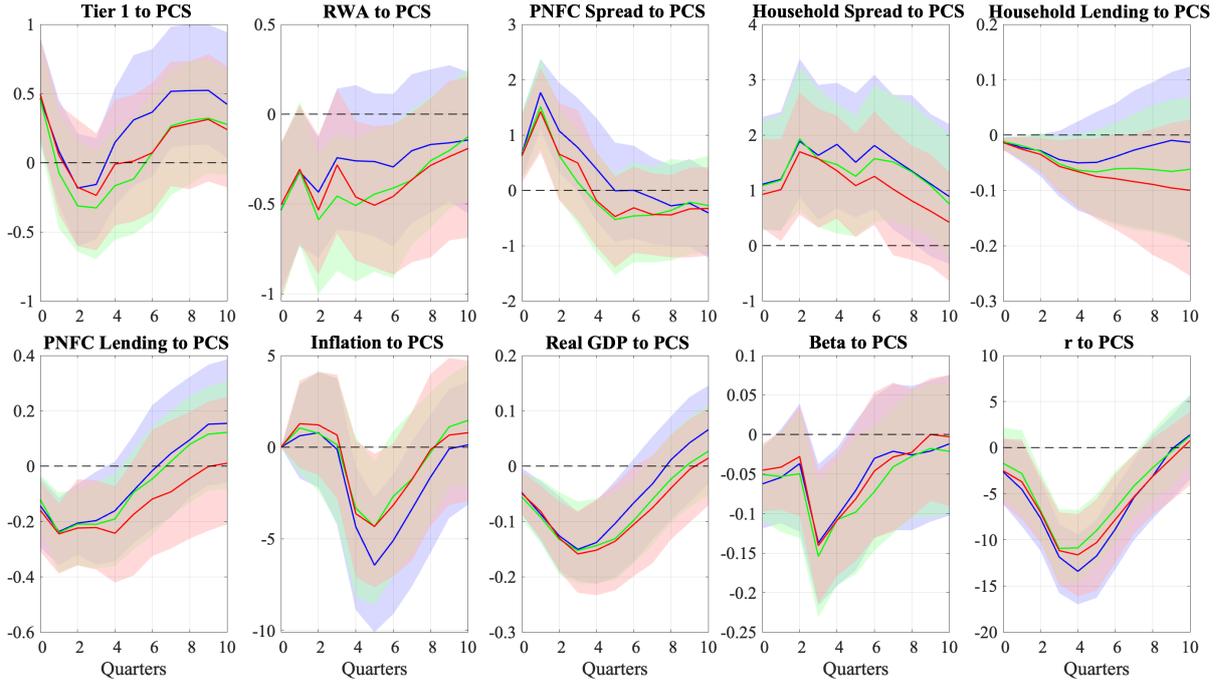


Figure 5: IRFs of macro-financial variables to a Prudential Capital Shock

*Note:* The blue, red, and green lines represent the medians of the posterior distributions obtained by combining sign and narrative identification, estimated using the Boone, Lerner, and HHI dataset, respectively. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding all quarters in 2020 and 2021. Units of measurement are as follows: Tier 1, RWA, Household and PNFC lending, and Real GDP are expressed in percentage changes; PNFC and Household spreads, interest rate and inflation are expressed in basis points; Bank Beta is expressed in units.

The figure shows that a Prudential Capital Shock has an immediate and significant effect on the level of Tier 1 capital at 0.50 percent; however, the impact is short-lived, lasting for less than two quarters. At the same time, the shock determines a like reduction (-0.50 percent) in RWA which is more persistent, lasting between four to eight quarters depending on the nature of competition. The reduction in RWA reflects a modest decline in lending to households (of around 0.05 percent) that lasts for about four quarters, and a larger decline in lending to corporates (of roughly 0.25 percent) that persists for slightly longer at around four to six quarters. The impact on lending spreads is positive for both sectors, though there are notable differences. The shock determines mild increase of between 1 to 2 basis points for households and corporates; however, the impact on households is more prolonged, lasting approximately eight quarters, while the increase on corporates dissipates after two quarters. The more acute impact on corporate lending, which garner relatively higher regulatory risk weights compared with household mortgages, is consistent with banks focusing on reducing relatively higher risk-weighted assets to meet higher ratio requirements.<sup>13</sup>

These impacts confirm that prudential capital shocks drive contractions in the supply of credit. This contraction, in turn, has significant negative macroeconomic effects in the short-run, which fade away in the long-run. The IRFs show that during the first year after the shock, GDP contracts by almost 0.2 percent. The adverse impacts last for six to eight quarters, depending on the nature of competition, after which they become non-significant. Simultaneously, this process results in a short-term reduction in banks' profitability relative to overall market profitability: the bank beta falls by almost 0.20 during the first three quarters, but then recovers after six to eight quarters.

It is important to emphasize that our analysis focuses on a generalized prudential capital shock, which

<sup>13</sup>This result is consistent with papers analyzing the macroeconomic effects of prudential capital shocks, such as Meeks (2017), de Ramon and Straughan (2017), Kanngiesser et al. (2020), and Conti et al. (2023).

might impact banks of different sizes in distinct ways. Such differential effects could, in turn, have implications for competition. Our analysis integrating competition allows us to shed light on the impacts.

In Figure 6, we present the estimated impulse response functions for each competition proxy utilized in our analysis.

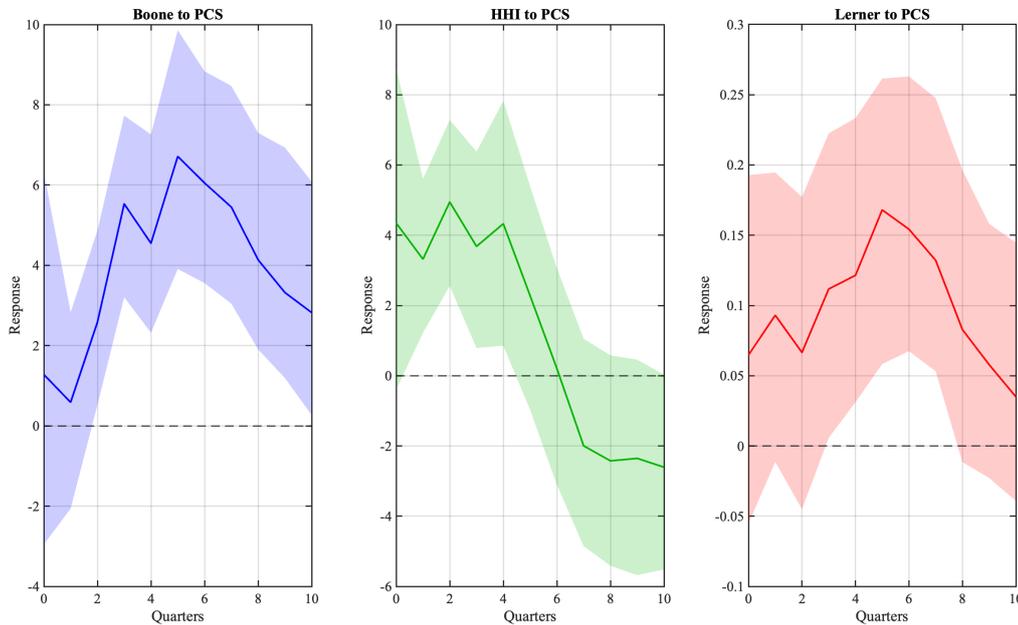


Figure 6: IRFs of competition proxies to a Prudential Capital Shock

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative identification. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding all quarters in 2020 and 2021. Scales are in units.

The left panel illustrates the response of the Boone indicator to a prudential capital shock, displaying a temporary increase that peaks within five quarters and dissipates after approximately ten quarters. For the Boone indicator, this movement is consistent with a temporary reduction in competition following a PCS.

While we do not examine the determinants of this shift, this result aligns with theoretical insights regarding differential impacts across banks. Specifically, large incumbent banks, typically operating with minimal regulatory capital and functioning as price leaders, are more likely to respond to higher regulatory capital costs by raising lending rates, reflecting a shift toward a more expensive funding mix. In contrast, smaller banks, maintaining higher voluntary capital surpluses but operating with smaller profit margins, are less directly impacted by the shock. Nevertheless, as price takers, these smaller banks might also raise lending rates, slightly improving their profit margins but significantly reducing lending volumes. Consequently, competition diminishes as relatively inefficient banks experience an increased share of total profits, consistent with the observed Boone indicator response.

The central panel, depicting the HHI, initially shows a short-term increase in market concentration following the capital shock, subsequently declining after approximately two years. This increase in concentration can be explained by the differential lending responses of banks of varying sizes. Larger incumbent banks are able to pass higher regulatory capital costs to borrowers more effectively, maintaining their market positions, while smaller banks reduce their lending volumes due to tightened margins and decreased competitiveness. This phenomenon contributes to the temporary elevation in concentration measures such as HHI.

Finally, the right panel presents the response of the Lerner index, indicating an increase in price-to-cost

margins roughly one to two years after the shock, suggesting reduced competition. This result aligns closely with the “markup channel”, where banks, particularly larger incumbents, respond to increased capital costs by raising lending rates, thereby increasing their markups. Smaller banks, despite operating with higher voluntary capital buffers, follow suit as price takers, contributing to the generalized increase in lending spreads. However, smaller institutions experience greater adverse impacts on lending volumes, reinforcing the market power of larger banks and thus reducing competition.

In summary, our empirical findings are consistent with theoretical predictions regarding how generalized prudential capital shocks affect competition through differential responses by banks of varying sizes. The mark-up channel is particularly relevant, driving increased lending rates, reduced volumes (among smaller banks), and thereby reducing overall market competitiveness as measured by the Boone indicator, HHI, and Lerner index. These dynamics emphasize the importance of carefully considering competition effects in the design and implementation of capital-based macroprudential regulations.

### 5.3 State Dependent Impulse Response Functions

The state-dependent impulse response functions of real GDP to a prudential capital shock, depicted in the Figure 7, reveal significant asymmetries between recessionary and expansionary states.

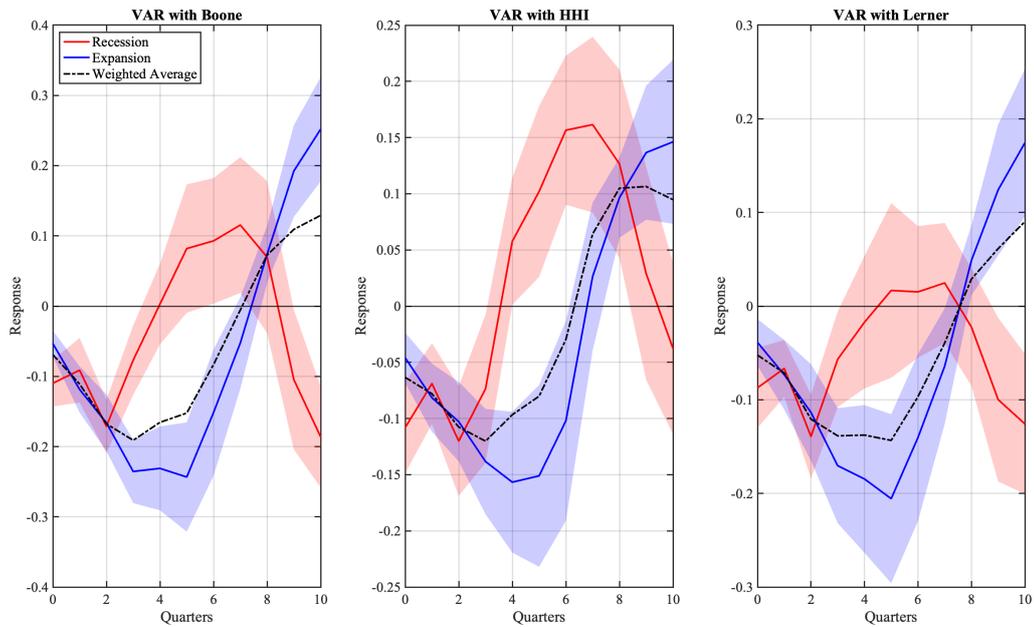


Figure 7: State-Dependent IRFs of Real GDP to a Prudential Capital Shock

*Note:* Starting from the left, the first subfigure presents the state-dependent IRF of real GDP using the Boone dataset. The center figure reports similar IRFs using the HHI dataset, while the far-right figure reports IRFs using the Lerner dataset. In each, the red line represents the median response during recessionary periods, while the blue line captures the median response during expansionary periods. The shaded areas correspond to the 68% confidence intervals. The black dashed line represents the weighted average of responses during recessions and expansions. The weights are determined by the rule  $f(Z_t) > 0.8$ , according to which the economy is in a recession 28% of the time and in an expansion 72% of the time. The weighted average serves as a robustness check, as it should recover the median estimated IRF from the VAR model. Scales are in percentage changes.

During recessions, represented by the red lines, the real GDP response is generally negative on impact, initially larger in magnitude compared to expansions, indicating a more severe immediate economic con-

traction following the prudential capital shock. The peak negative effect is observed almost immediately or within the first 1–2 quarters. Moreover, GDP tends to recover more quickly from the shock, with responses moving towards positive territory within about 6–8 quarters. In contrast, during expansions, the initial impact on GDP is smaller in magnitude compared to recessions, but the negative effect persists, gradually worsening and reaching its maximum after approximately 5–6 quarters. The recovery from the shock is slower, showing persistent negative effects or delayed recovery.

The differences on impact can be related to the fact that during recessions, financial and economic fragility is higher. Banks, firms, and households typically have weakened balance sheets, reduced capital buffers, and heightened uncertainty. Thus, the tightening of prudential capital requirements quickly translates into a contraction in lending, investment, and economic activity, generating an immediate negative shock to GDP. Furthermore, the faster recovery observed during recessions can be related to the fact that economic downturns often prompt aggressive monetary and fiscal policy responses, cushioning the initial negative impacts and fostering quicker recoveries. Moreover, during recessions, increased regulatory capital acts as a clear signal that banks are becoming safer and more robust, reducing fears of bank failures and financial contagion. This signaling effect boosts investor, consumer, and business confidence, facilitating a quicker recovery after the initial shock. At longer horizons (beyond two years), the state-dependent responses in both regimes are close to zero and the confidence bands widen substantially. The slight renewed decline of real GDP in recessions after about 8 quarters should therefore be interpreted as a small fluctuation around the long-run baseline, rather than as evidence of a second, distinct downturn. Non-monotonic IRFs of this kind are common in state-dependent VAR and local-projection applications and often reflect a combination of richer dynamics and sampling variability, especially for recession states where the number of observations is more limited. The weighted average responses represented in the subfigures closely approximates the real GDP impulse response functions estimated via the linear VAR in Figure 5. This check confirms the consistency of our state-dependent approach with the linear VAR specification while simultaneously revealing the distinct economic dynamics that characterize different regimes. Overall, these results suggest the importance of state-contingent prudential regulation and to utilize capital tools to explicitly signal stability and boost confidence during crises. On the other hand, results suggest employing gradual, proactive adjustments during expansions to mitigate prolonged negative GDP impacts.

Figure 8 presents the state-dependent impulse response functions for our three competition proxies following a prudential capital shock, highlighting substantial differences between recessionary and expansionary periods.

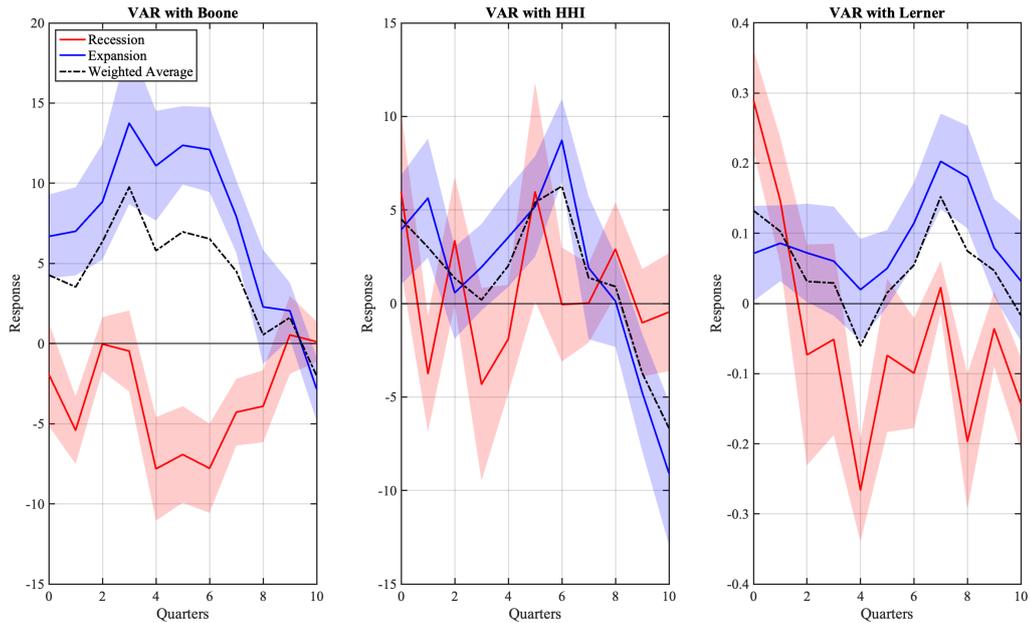


Figure 8: State-Dependent IRFs of Competition proxies to a Prudential Capital Shock

*Note:* The left panel presents the state-dependent IRF of the Boone Indicator, the central panel displays the IRFs for the HHI, and the right panel shows the results for the Lerner Index. The red line represents the median response during recessionary periods, while the blue line captures the median response during expansionary periods. The black dashed line represents the weighted average of responses during recessions and expansions. The weights are determined by the rule  $f(Z_t) > 0.8$ , according to which the economy is in a recession 28% of the time and in an expansion 72% of the time. The weighted average serves as a robustness check, as it should recover the median estimated IRF from the VAR model. Scales are in units.

For the Boone indicator (left panel), we observe a stark asymmetry: during expansions, competition worsens considerably as shown by the pronounced positive response, peaking approximately after 3-4 quarters. In contrast, during recessions, competition actually improves temporarily as indicated by the negative values, before gradually returning to baseline. This dichotomy suggests that during expansions, larger banks can more effectively leverage their market position to increase lending rates and maintain profit margins when faced with higher capital requirements. Meanwhile, in recessions, when credit demand is already constrained, the relationship appears reversed. This can be due to the tight interest rate margins during recessions so profits become more sensitive to cost differences and the most efficient firms gain advantage.

The HHI response (middle panel) exhibits considerable volatility in both states but reveals that concentration increases more persistently during expansions due to a prudential capital shock. The recessionary response shows higher oscillations with less persistent effects, suggesting that market concentration is less affected during economic downturns to a PCS. The expansion-state response demonstrates that increased capital requirements during good economic times allow larger incumbents to strengthen their market position over approximately 6-7 quarters, after which concentration begins to normalize.

The Lerner index (right panel) shows perhaps the most pronounced state-dependent behaviour. During expansions, banks gradually increase their price-to-cost margins, with the effect becoming most significant around 7-8 quarters after the shock. This indicates banks can steadily expand their markups when economic conditions are favourable. Conversely, during recessions, there is an initial sharp increase in markups that quickly reverses and becomes negative, suggesting that while banks may attempt to pass on capital costs immediately, tight interest rate margins and decreased loan demand during recessions ultimately compress banks' markup. The weighted average responses (dashed lines) approximate our linear VAR results,

confirming methodological consistency while revealing the rich heterogeneity that linear models conceal.

These state-dependent patterns highlight the importance of considering economic conditions when implementing prudential capital regulations, as their competitive effects differ substantially across regimes. During expansions, prudential measures may inadvertently strengthen the position of larger banks and reduce competition, while during recessions, the competitive landscape exhibits more complex and volatile dynamics.

## 5.4 Historical Decomposition

In this subsection, we describe the contribution of the estimated prudential capital shock to the dynamics of the endogenous variables across the three stress test episodes used to define narrative restrictions. Appendix B presents the historical decomposition figures for all stress tests and competition proxies employed in the VAR. The red lines represent the median of the counterfactual path obtained by excluding all other shocks except the prudential capital shock. The shaded bands depict the 68% credible set, while the black line shows the change in each variable, net of the deterministic component (see Kilian and Lütkepohl, 2017). For a concise summary of the historical decomposition results, we present the key findings in Table 3. Appendix B presents the detailed results computed using each competition proxy, as summarized in Table 5.

Table 3: Evaluation of the effects of PCS during stress tests episodes through historical decomposition.

Episode	CST 2014	CST 2015	ACS 2016
<b>Tier 1 (%)</b>	0.51–0.64	0.43–0.80	0.40–0.49
<b>RWA (%)</b>	–0.69 to –0.91	–1.09 to –1.39	–0.42 to –0.56
<b>Tier 1 Ratio (bps)</b>	18–20	24–34	14–16
<b>GDP (%)</b>	–0.21 to –0.25	–0.25 to –0.32	–0.04 to –0.05
<b>PNFC Spread (bps)</b>	2.2–3.6	2.5–4.6	0.5–0.6
<b>HH Spread (bps)</b>	1.3–4.2	2.9–4.4	0.8–1.0
<b>PNFC Lending (%)</b>	–0.34 to –0.55	–0.50 to –0.63	–0.11 to –0.14
<b>HH Lending (%)</b>	–0.02 to –0.06	–0.05 to –0.06	–0.01

*Note:* The impacts on TT1, RWA, and their ratio are computed after one quarter for CST1 and CST2, while the effects on the other endogenous variables are evaluated after two quarters. For the ACS, the effects on all variables are evaluated on impact, as they are not statistically significant in subsequent periods. The range of values reflects the three competition proxies employed.

There are a couple things worth highlighting up front. First, our historical decomposition provides a very similar picture regardless of the competition proxy included. In all three cases, the PCS contributed to an increase in Tier 1 capital and a decline in RWA. Using the counterfactual paths of Tier 1 capital and RWA, we can isolate the contribution of PCS to their movements. For example, during the first concurrent stress test (CST1), one quarter after the narrative restriction was imposed (2014 Q4), PCS contributed to an increase in Tier 1 capital of 0.51–0.64 percent, and a reduction in RWA of 0.69–0.91 percent, depending on the competition proxy used in the VAR. The same exercise for the second concurrent stress test (CST2) shows that, one quarter after the shock (2015 Q4), PCS increased Tier 1 capital by 0.43–0.80 percent and decreased RWA by 1.09–1.39 percent. Finally, for the annual cyclical scenario we evaluate the contribution of PCS on impact (2016 Q3). Here, the shock had a smaller effect: Tier 1 rose by 0.40–0.49 percent and RWA fell by 0.42–0.56 percent.

Second, these impacts led to moderate increases in the Tier 1 ratio in all three cases. We compute the resulting change in the Tier 1 ratio following Conti et al. (2023). We start from the actual levels of Tier 1,

RWA, and their ratio one quarter before each shock (i.e. 2014 Q2, 2015 Q2, and 2016 Q2), which were:

- **CTS1 (2014 Q2):** Tier 1 = 203,701.1 £Mln; RWA = 1,435,491 £Mln; ratio = 14.19 %.
- **CTS2 (2015 Q2):** Tier 1 = 211,355.7 £Mln; RWA = 1,359,706 £Mln; ratio = 15.54 %.
- **ACS (2016 Q2):** Tier 1 = 218,189.9 £Mln; RWA = 1,307,509 £Mln; ratio = 16.687 %.

We then apply the PCS contributions to derive counterfactual Tier 1 and RWA levels one quarter after the shocks for CTS1 and CTS2 (and on impact for ACS), compute the new ratio, and compare it to the pre-shock ratio.<sup>14</sup> The resulting increases in the Tier 1 ratio due to PCS are:

- **CTS1:** 18.44 to 20.34 basis points.
- **CTS2:** 23.82 to 34.42 basis points.
- **ACS:** 13.60 to 16.45 basis points.

In general, the first key finding is that prudential capital shocks induce banks to reduce risk-weighted assets to a greater extent than they boost Tier 1 capital. Furthermore, the gap between the counterfactual and actual capital ratios shows that the second concurrent stress test had the strongest impact in absolute terms, followed by the first concurrent stress test and then the annual cyclical scenario. These, in turn, produced differential effects on credit spreads and lending volumes, as depicted in Table 3.

For example, the effect of the shock evaluated after two quarters on the private non-financial corporations' credit spread ranges from 3 to 4.6 basis points for the second concurrent stress test and from 2.2 to 3.6 basis points during the first concurrent stress test. Similarly, the impact on mortgage spreads ranges from 2.5 to 4.3 basis points during the second concurrent stress test and from 1.26 to 4.22 basis points during the first concurrent stress test.

Beyond credit spreads, the prudential capital shock also had a considerable impact on lending volumes. In particular, private non-financial corporations' lending contracted more significantly than household lending across all stress test scenarios. During the second concurrent stress test, private non-financial corporations' lending declined in a range from 0.5 to 0.63 percent, while household lending was only marginally affected, with reductions ranging between 0.05 and 0.06 percent. A similar pattern is observed in the first concurrent stress test, where private non-financial corporations' lending declined between 0.34 and 0.55 percent, while household lending contracted between 0.02 and 0.06 percent. The annual cyclical scenario resulted in the mildest lending contractions, with private non-financial corporations' lending decreasing by up to 0.14 percent and household lending by no more than 0.01 percent.

Ultimately, these effects culminate in a measurable impact on gross domestic product of 0.25-0.32 percent during the second concurrent stress test, 0.21-0.25 percent during the first concurrent stress test after two quarters, and very little impact during the annual cyclical scenario, with only 0.04-0.05 percent on impact.

Overall, these effects are broadly in line with those reported in the VAR literature on bank capital shocks. Table 4 presents our IRF-based estimates of the impact of PCS on GDP, PNFC lending, and spreads alongside those from the main VAR studies, and also compares the stress-test effects obtained via

<sup>14</sup>As a practical example for CTS1: the PCS contribution to Tier 1 in 2014 Q4 was 0.51 percent. Starting from the actual Tier 1 in 2014 Q2 of 203701.1 (in £ Mln), the counterfactual Tier 1 is

$$203701.1 \times (1 + 0.51/100) = 204737.94.$$

Similarly, starting from the actual RWA of 1 435 491, the counterfactual RWA is

$$1\,435\,491 \times (1 - 0.91/100) = 1\,422\,406.50.$$

Hence the counterfactual Tier 1 ratio is

$$\frac{204737.94}{1\,422\,406.50} = 14.39\%,$$

versus the pre-shock ratio of 14.19%, for an increase of 14.39% - 14.19% = 0.20% (i.e. 20.34 basis points).

historical decomposition with those presented in [Conti et al. \(2023\)](#). For comparability, we normalize the shock to a 50 basis points increase in each paper’s primary capital metric. Our estimates lie clearly within the range of the other five contributions, especially those for the UK and [Conti et al. \(2023\)](#), which employs the same capital ratio and identification strategy.

Table 4: The impact of bank capital shocks: a comparison (All effects are scaled to a 50 basis points increase in the primary capital metric used to transmit the shock).

Reference	Country	Evaluation after...	Real GDP (%)	PNFC lending (%)	PNFC spread (bps)
<a href="#">Noss and Toffano (2016)</a>	UK	2 quarters	-0.3 <sup>a</sup>	-1.0	N/A
<a href="#">Meeks (2017)</a>	UK	6 quarters	-0.1	-1.3	2
<a href="#">Mésonnier and Stevanovic (2017)</a>	US	4 quarters	-0.7	-3.0	30 <sup>b</sup>
<a href="#">Kanngiesser et al. (2020)</a>	EA	on impact	-0.6	-1.2 <sup>c</sup>	10
<a href="#">Conti et al. (2023)</a>	Italy	2 quarters	-0.1	-0.12	3
<b>This paper</b>	UK	3 quarters	-0.1	-0.12 <sup>d</sup>	1 <sup>d</sup>
<i>Conti et al. (2023) (historical decomposition)</i>					
2011 EBA stress test	Italy	8 quarters	-0.6	-1.9	25
2014 ECB comprehensive assessment			-0.6	-1.4	19
<b>This paper (historical decomposition)</b>					
2014 CST		2 quarters	-0.52 to -0.67	-0.86 to -1.48	5.63 to 8.94
2015 CST	UK	2 quarters	-0.45 to -0.53	-0.88 to -1.05	5.11 to 6.69
2016 ACS		on impact	-0.07 to -0.14	-0.33 to -0.45	1.60 to 1.91

*Note:* <sup>a</sup> Denotes not significant estimate. <sup>b</sup> Impact after 2 quarters. <sup>c</sup> Impact after 4 quarters. <sup>d</sup> Impact after 1 quarters. The upper panel of the table compares IRF results across studies, while the bottom panel compares results derived from historical decomposition. The primary capital metrics used to transmit the shock in each paper are as follows: [Noss and Toffano \(2016\)](#) use the capital-to-asset ratio; [Meeks \(2017\)](#) uses the trigger ratio; [Mésonnier and Stevanovic \(2017\)](#) and [Kanngiesser et al. \(2020\)](#) use the capital buffer; and [Conti et al. \(2023\)](#) use Tier 1 / RWA.

## 6 Robustness

This section shows how our results are robust to a number of perturbations of the baseline model. Specifically, we conduct robustness checks utilizing micro-level bank data and adjusting the choice of narrative restrictions. Additionally, we reduce the estimation period up to 2019Q4, as the ad-hoc removal of COVID-related observations from the sample could influence the estimated impulse response functions. Moreover, Appendix D provides additional robustness checks, showing the results under perturbations to the identification strategy and the inclusion of COVID-19 observations.<sup>15</sup>

### 6.1 Choice of the narrative restriction

To test the sensitivity of our main findings to the choice of narrative restrictions, we analyzed micro-level regulatory data for the banks involved in each stress test. We observed that the third quarter of each year generally exhibited the most significant changes compared to the previous quarter, with the notable exception of the 2014 CST. In this case, banks significantly altered their Tier 1 capital levels in the second quarter. Specifically, Co-op Bank increased its Tier 1 capital by 37 percent compared to the previous quarter, Lloyds reported a 21 percent increase, and RBS raised its Tier 1 capital by 32 percent. In light of this, we re-estimate the model imposing the narrative restriction for the 2014 CST on 2014:Q2. Figure 9 presents the posterior distribution of the estimated structural shock for the dates where narrative restrictions are

<sup>15</sup>In particular, Appendix D.1 shows that the results are unchanged after allowing inflation to respond freely on impact, as in [Kanngiesser et al. \(2020\)](#). Appendix D.2 demonstrates that accounting for gradual adjustment (as in [Conti et al. \(2023\)](#)) when imposing sign restrictions on balance sheet data also leaves the dynamics of lending, spreads, GDP, and competition proxies unchanged. Appendix D.3 shows that imposing narrative restrictions prior to the publication of stress test scenarios results in wider credibility intervals. Finally, Appendix D.4 shows that including COVID-era observations significantly affects statistical inference, thus justifying our approach of excluding the quarters in 2020 and 2021, following [Lenza and Primiceri \(2020\)](#).

imposed. The narrative identification presented in this section effectively eliminates scenarios in which an easing of prudential policy would have been estimated when relying solely on sign restrictions.

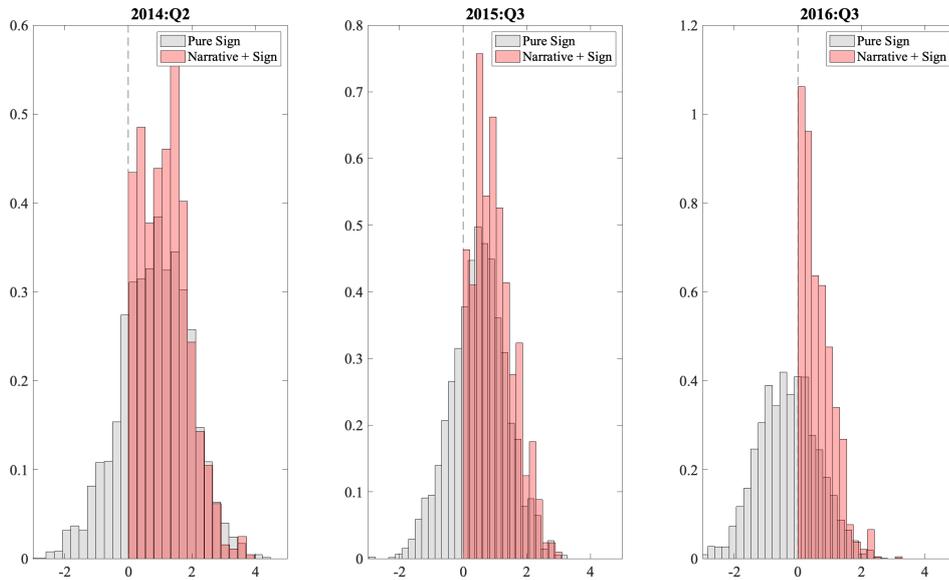


Figure 9: Robustness of Prudential Capital Shock: narrative vs. pure sign restrictions.

*Note:* The left panel plots the posterior distribution of the Prudential Capital Shock for 2014:Q2, corresponding to the 2014 CST. The central panel plots the posterior distribution for 2015:Q3, corresponding to the 2015 CST while the last corresponds to 2016 ACS. The grey bars refer to the identification obtained with pure sign restrictions, while the light red bars refer to the identification obtained with narrative sign restrictions.

Figures 10 and 11 report the estimated IRFs of the macro-financial variables and competition proxies, respectively, to a prudential capital shock estimated imposing the first narrative restriction on 2014:Q2. As in Figure 5 the responses are scaled to reflect a 100 basis points increase in Total Tier 1 capital ratio upon impact. The charts indicate that the estimated responses are closely aligned with those obtained from the baseline model. Specifically, the estimated median responses of Real GDP, competition proxies, and the remaining variables exhibit a high degree of similarity to those of the baseline specification, both in terms of their overall shape and magnitude. These findings provide strong support for the robustness and validity of our baseline model.

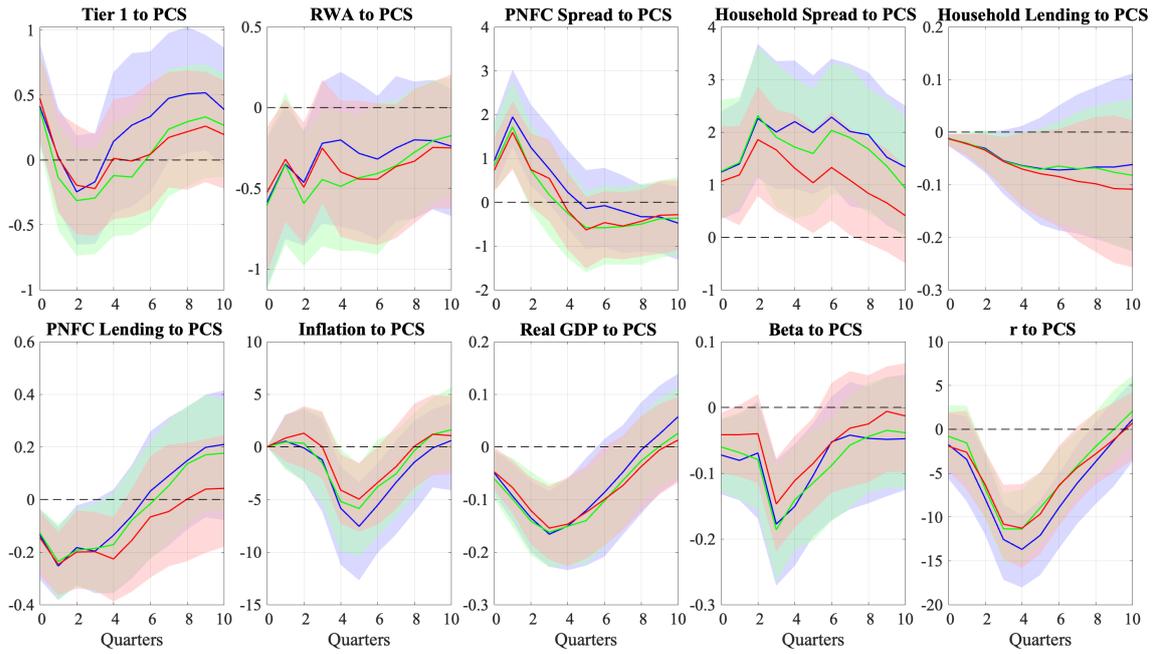


Figure 10: IRFs of macro-financial variables to a Prudential Capital Shock with alternative narrative restrictions.

*Note:* The blue, red, and green lines represent the medians of the posterior distributions obtained by combining sign and narrative identification (the first narrative restriction is imposed on 2014:Q2), estimated using the Boone, Lerner, and HHI dataset, respectively. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 5.

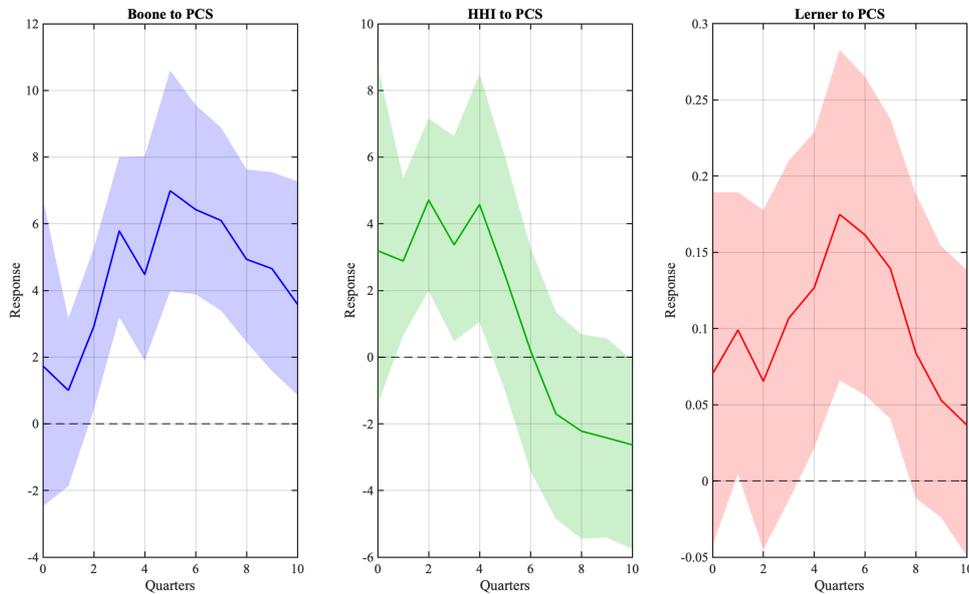


Figure 11: IRFs of competition proxies to a Prudential Capital Shock with alternative narrative restrictions.

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative identification (the first narrative restriction is imposed on 2014:Q2). The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 6.

Figures 12 and 13 present the estimated state-dependent local projections for real GDP and the competition proxies, respectively, based on the alternative narrative restrictions discussed in this section. In these cases as well, the responses remain consistent with those reported in Figures 7 and 8, thereby reinforcing the robustness of our main findings.

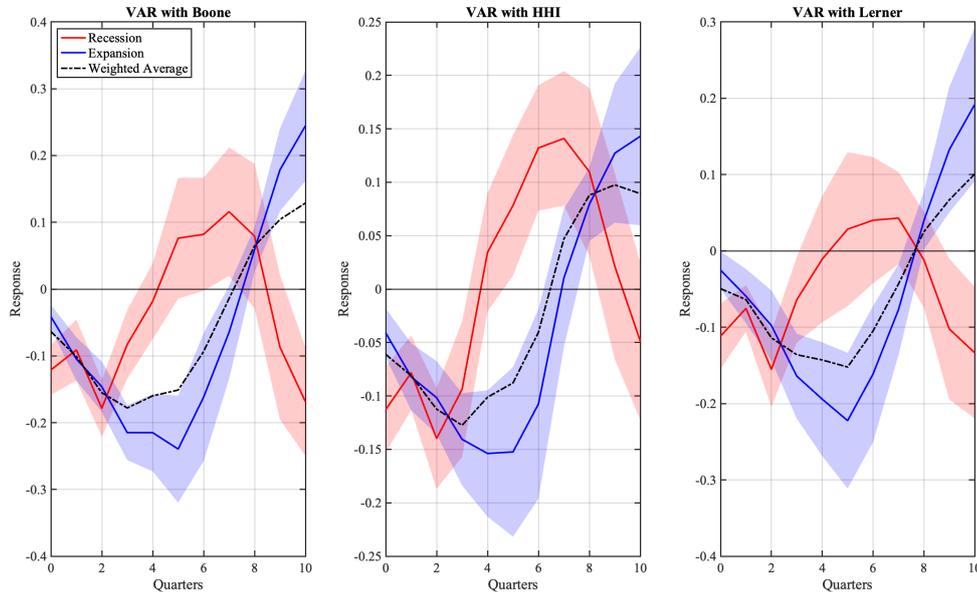


Figure 12: State-Dependent IRFs of Real GDP to a Prudential Capital Shock with alternative narrative restrictions.

*Note:* The first subfigure presents the state-dependent IRF of real GDP using the Boone Dataset. The second subfigure shows the IRFs estimated with the HHI dataset, and the third subfigure illustrates the results obtained using the Lerner dataset. Structural shocks are obtained imposing the first narrative restriction on 2014:Q2. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. (For interpretation of the references to colours and unit of measures in this figure refer to Figure 7)

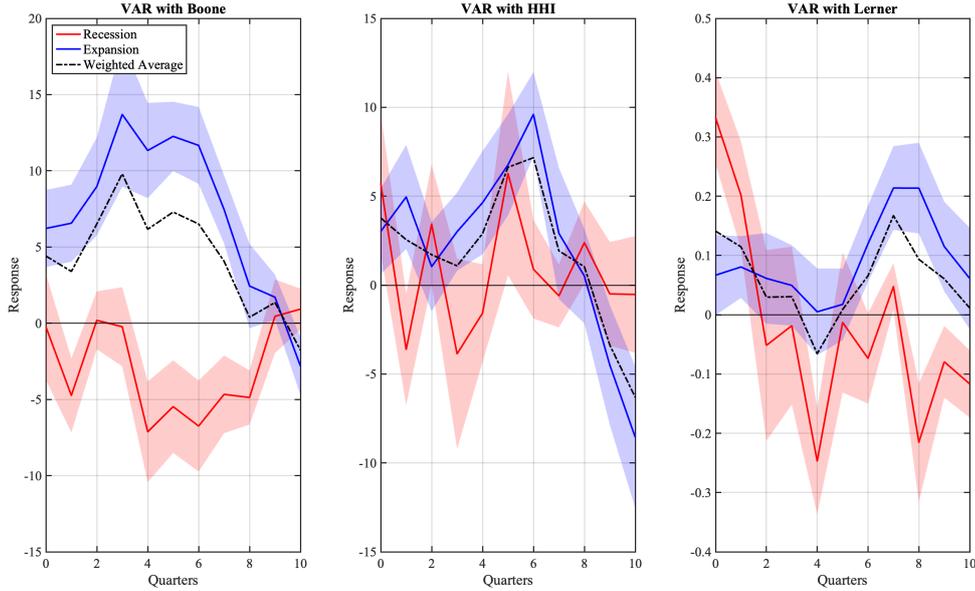


Figure 13: State-Dependent IRFs of Competition Proxies to a Prudential Capital Shock with alternative narrative restrictions.

*Note:* The left panel presents the state-dependent IRF of the Boone Indicator, the center panel displays the IRFs for the HHI, and the right panel shows the results for the Lerner Index. Structural shocks are obtained using the first narrative restriction, imposed on 2014:Q2. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. (For interpretation of the references to colours and unit of measures in this figure refer to Figure 8)

To validate the timing and logic of our narrative restrictions, we conduct an additional robustness check by applying the same positive prudential capital shock constraints to the first quarters of 2014, 2015, and 2016 instead of the third quarters. This exercise is essential for supporting our identification strategy, because in Q1 the narrative mechanism should not yet be active: stress scenarios and guidance are released in Q2/Q3, and banks have not received regulatory signals that would trigger capital or balance sheet adjustments. We report the results of this check in Appendix D.3. Although theory indicates that narrative restrictions should improve identification precision, imposing them in Q1 yields substantially wider credibility intervals for all macro-financial variables, reflecting reduced rather than enhanced estimation accuracy. This counterintuitive finding implies that using Q1 as a narrative restriction does not align with the actual prudential policy transmission mechanism, thereby reinforcing our original approach.

## 6.2 End of sample

In this subsection, we present the results obtained by truncating the sample at 2019:Q4, as excluding observations from the COVID-19 period may affect the estimates, particularly in the context of local projections.

Figures 14 and 15 display the estimated structural impulse response functions for macroeconomic and competition-related variables, respectively.

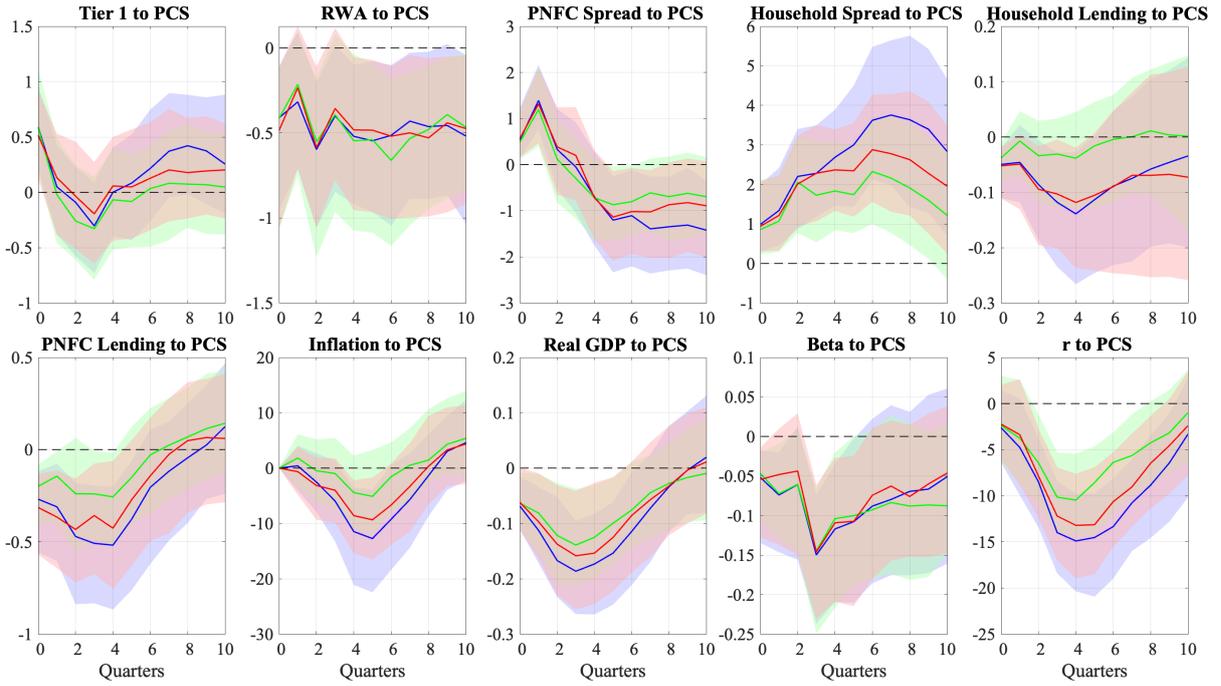


Figure 14: IRFs of macro-financial variables to a Prudential Capital Shock with truncated sample.

*Note:* The blue, red, and green lines represent the medians of the posterior distributions obtained by combining sign and narrative identification, estimated using the Boone, Lerner, and HHI dataset, respectively. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2019:Q4. For interpretation of unit of measures refer to Figure 5.

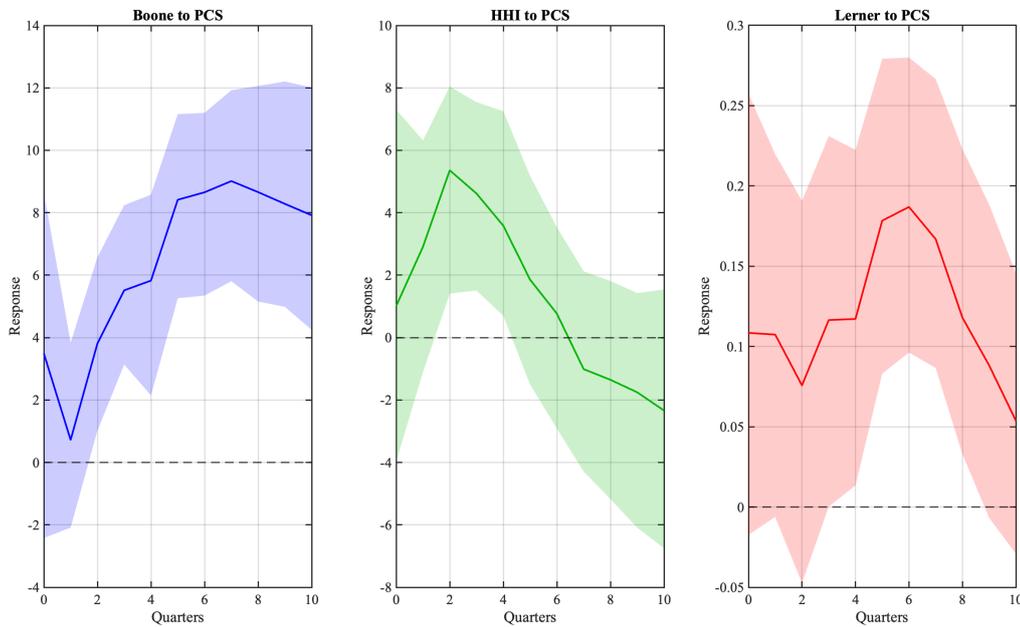


Figure 15: IRFs of Competition proxies to a Prudential Capital Shock with truncated sample.

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative identification. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2019:Q4. For interpretation of unit of measures refer to Figure 6.

Overall, the results remain broadly consistent with those of the baseline model, although some notable differences emerge. First, the estimated response of RWAs to a PCS exhibits greater persistence, remaining negative for up to seven quarters following the shock. Household lending shows a stronger negative response, particularly in the VAR specifications using the Boone and Lerner indices. As a result, the response of real GDP is slightly larger in magnitude, with a peak decline of approximately 0.2 percent. Regarding the competition proxies, the only notable deviation is a more persistent effect of the shock on the Boone indicator. Overall, these findings further support the validity of the baseline identification strategy.

Figure 16 shows the estimated state-dependent local projection of Real GDP in this robustness scenario.

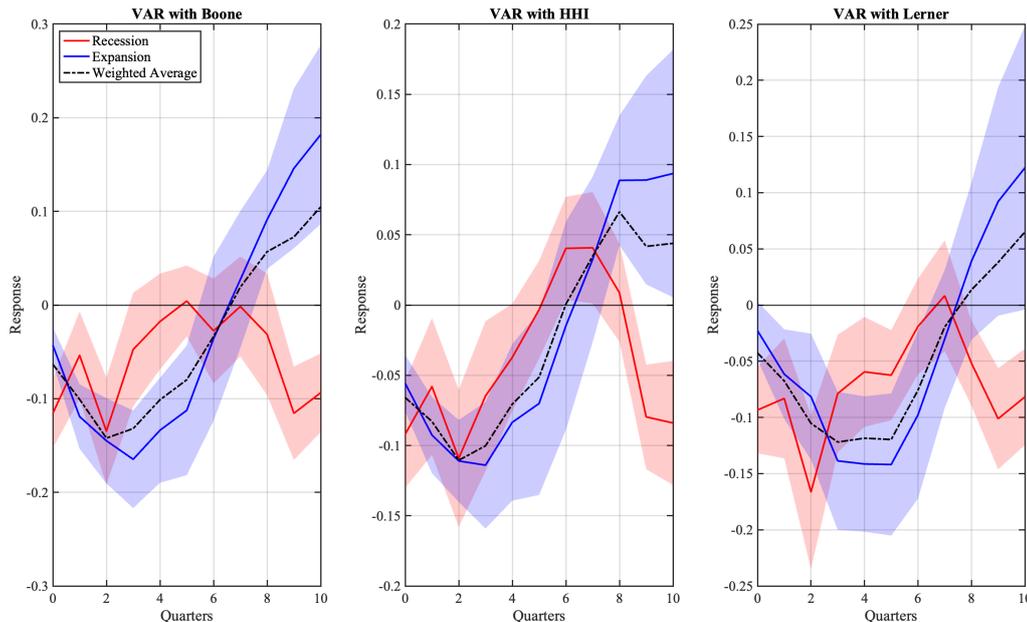


Figure 16: State-Dependent IRFs of Real GDP to a Prudential Capital Shock with truncated sample.

*Note:* The first subfigure presents the state-dependent IRF of Real GDP using the Boone Dataset. The second subfigure shows the IRFs estimated with the HHI dataset, and the subfigure on the right illustrates the results obtained using the Lerner dataset. The estimation sample spans from 1991:Q1 to 2019:Q4. (For interpretation of the references to colours and unit of measures in this figure refer to Figure 7)

Also in this case results closely align with the baseline model. Under this test, the results align closely with the baseline model, with one minor exceptions. We note a slightly more persistent, negative effect of the impact of the PCS during recessions, especially in the case of the VAR with the Lerner index. Also in this robustness exercise, the recovery of GDP during recessions is faster than the one during expansions, corroborating the interpretations presented in section 5.3.

Figure 17 presents robustness checks for our state-dependent impulse response functions of competition proxies, largely confirming our main findings while revealing some important differences.

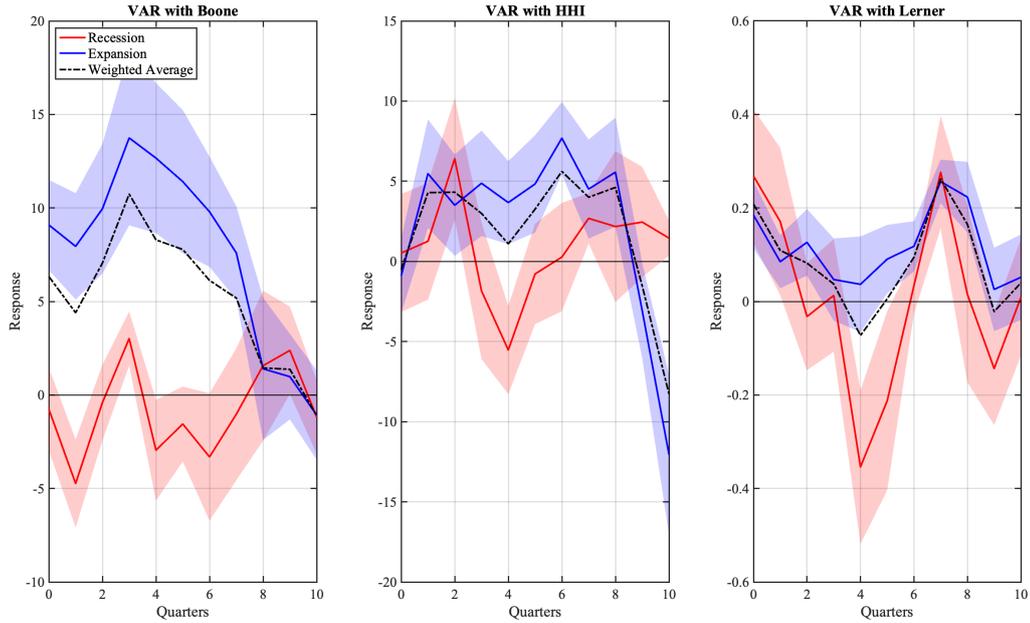


Figure 17: State-Dependent IRFs of Competition proxies to a Prudential Capital Shock with truncated sample.

*Note:* The first subfigure presents the state-dependent IRF of Boone Indicator. The second subfigure shows the IRFs estimated with the HHI dataset, and the rightmost subfigure illustrates the results obtained using the Lerner dataset. The estimation sample spans from 1991:Q1 to 2019:Q4. (For interpretation of the references to colours and unit of measures in this figure refer to Figure 8)

For the Boone indicator (left panel), the response in expansionary states remains strongly positive, whereas the recession-state response is notably closer to zero compared to the baseline results. This suggests a more muted competition-enhancing effect of prudential capital shocks during downturns, indicating that under alternative specifications, the differential impact across economic states may be less pronounced than initially estimated.

For the HHI (central panel), the overall pattern of more persistent concentration effects during expansions is preserved, thereby supporting our main conclusion regarding market structure dynamics.

The most pronounced divergence appears in the results for the Lerner index (right panel). While the expansion-state response continues to show a gradual increase in markup power, the recession-state response now features a pronounced positive peak around quarter seven, closely resembling the expansion response. This convergence implies that banks' pricing power in response to prudential shocks may eventually reach similar levels across states of the economy, albeit through different adjustment trajectories. Notably, a significant negative peak persists around quarters four and five during recessions, reinforcing the notion that compressed interest rate margins and weakened loan demand in downturns may temporarily reduce banks' markup.

## 7 Conclusions

We examine the effects of prudential capital shocks (PCS) on lending supply, bank competition and economic output. Using a structural vector autoregression (SVAR) with sign and narrative restrictions, we identify structural shocks to bank capital requirements, exploiting the UK PRA's 2014 and 2015 Concurrent Stress Tests and the 2016 Annual Cyclical Scenario as defining, narrative events. Combining sign and

narrative restrictions helps fine-tune parameter restrictions in a SVAR framework and avoid potentially implausible elasticities and IRFs that can otherwise occur when relying only on sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018). This approach offers a way to account for feedback effects among bank capital, lending, competition and the economy, while at the same time disentangling prudential shocks from other exogenous determinants of bank capital (e.g., unexpected losses).

Studies evaluating the effects of bank capital requirement shocks have generally only been able to consider feedback effects or prudential capital shocks separately (e.g., Mésonnier and Monks, 2015; Noss and Toffano, 2016; Meeks, 2017; Kanngiesser et al., 2020; Gropp et al., 2016). A key exception is Conti et al. (2023), who tackle the two issues simultaneously by using a combination of sign and narrative restrictions. We contribute to this line of research in two ways. First, we account for bank competition, which can determine banks' ability to pass on the costs of prudential shocks to borrowers and the broader economy. Second, we account for possible non-linearities in the macroeconomic impact of prudential capital shocks. We do this by using local projections (Jordà, 2005, 2009) that depend on state of economic cycle.

We employ quarterly data for the UK economy spanning the period 1991 to 2023. We base our narrative restrictions on three supervisory episodes: the PRA's 2014 and 2015 Concurrent Stress Tests and the PRA's 2016 Annual Cyclical Scenario test. Each determined increases in Tier 1 capital of UK banks of £13, £7 and £7 billion, respectively.

Overall, our results suggest that higher capital requirements generate non-significant costs in the long run, with some economically modest macroeconomic adjustments in the short run. Our findings indicate that prudential capital shocks lead to statistically significant adjustments in bank balance sheets, with increases in Tier 1 capital accompanied by more substantial reductions in RWAs. This pattern suggests that banks primarily respond to higher capital requirements by reducing risky assets rather than raising new capital, consistent with theoretical predictions. The responses of lending volumes and spreads reveal important sectoral differences, with corporate lending experiencing more pronounced contractions (around 0.25 percent) compared to household secured lending (approximately 0.05 percent). These differences likely reflect the higher risk weights associated with corporate lending, making it a more effective target for banks seeking to improve their capital ratios.

Regarding macroeconomic impacts, our baseline model estimates a modest contraction in UK real GDP, with a peak decline of about 0.2 percent following a shock that increases the Tier 1 capital ratio by 100 basis points. Overall, these estimates are broadly in line with those reported in the VAR literature on bank capital.

Our state-dependent analysis reveals significant asymmetries in these effects across the business cycle. During recessions, prudential capital shocks generate larger immediate economic contractions but lead to faster recoveries, likely due to enhanced market confidence in bank stability. In contrast, during expansions, the negative effects on GDP are initially smaller but more persistent, suggesting that gradual implementation of capital requirements during economic upswings may be preferable.

A novel contribution of our research lies in examining the effects of prudential capital shocks on bank competition. Using three distinct measures, the Boone indicator, the Herfindahl-Hirschman Index, and the Lerner Index, we find consistent evidence that tighter capital requirements temporarily reduce banking sector competition. The Boone indicator results suggest that efficiency becomes less important for profitability following a prudential capital shock, while increases in the HHI point to greater market concentration. Similarly, the Lerner Index indicates higher price-cost margins, consistent with the "markup channel" through which banks-particularly larger incumbents-respond to increased capital costs by raising lending rates. These findings align with theoretical predictions that capital-based regulations can disproportionately burden smaller institutions, potentially contributing to increased market power for larger banks.

The state dependent analysis reveals significant asymmetric effects of prudential capital shocks on banking competition across economic regimes. During expansions, competition measures deteriorate more

substantially as larger banks leverage their market position to maintain profits when facing higher capital requirements. Conversely, during recessions, competitive dynamics become more volatile, with efficiency playing a greater role in determining market outcomes as profit margins tighten.

Our historical decomposition analysis reveals that the 2015 Concurrent Stress Test had the strongest impact among the three stress test episodes, increasing Tier 1 capital by up to 0.8 percent while decreasing RWAs by up to 1.39 percent, resulting in approximately 30 basis points increase in the Tier 1 capital ratio. The economic consequences included increases in lending spreads of up to 4.6 basis points for corporations and 4.3 basis points for households, along with reductions in lending volumes and a GDP contraction of about 0.3 percent.

Our baseline results prove highly robust across a range of alternative specifications. First, re-estimating the model by imposing the 2014 CST narrative restriction in Q2 (reflecting actual micro-level bank data adjustments), yields median IRFs for GDP, competition measures, and all other variables that closely match the baseline impulse responses in both shape and magnitude. Second, imposing narrative restrictions on the first quarters of for each stress test, produces substantially wider credibility intervals and IRF magnitudes that conflict with established literature, confirming our identification strategy.<sup>16</sup> Third, truncating the estimation sample to 2019 Q4 (i.e., excluding 2020–21) produces virtually identical IRFs for macroeconomic and competition variables, verifying that our ad-hoc removal of COVID-era quarters does not drive our conclusions. Fourth, allowing headline inflation to respond freely on impact and imposing two-quarter restrictions on balance-sheet variables (consistent with gradual adjustment) also leaves the core dynamics of lending, spreads, GDP, and competition proxies unchanged.<sup>17</sup> By contrast, including 2020–21 observations dramatically alters several key responses underlining why COVID-era quarters are excluded in our baseline.<sup>18</sup> Collectively, these checks bolster confidence that our main findings are not artefacts of specific identification choices, sample periods, or variable restrictions.

Several policy implications emerge from our analysis. First, our evidence on the state-dependent, asymmetric economic effects of capital regulation continues to support policymakers' consideration of the state of the business cycle when setting capital policy. Second, the potential competition effects of capital regulations that we document also support the role secondary competition objectives play in ensuring that policymakers continue to afford attention to competition implications of their decisions.<sup>19</sup> Third, the differential sectoral impacts suggest that targeted macroprudential tools might be more effective than broad capital requirements in addressing specific risks without unduly constraining economically important lending. Finally, our estimates of the macroeconomic and banking-sector effects of prudential capital shocks should be interpreted within a broader welfare trade-off. While higher requirements can entail transitional adjustments, the evidence indicates that stronger prudential regulation reduces crisis risk and mitigates the output costs when crises occur, supporting a positive social valuation of resilience.

A number of important questions on the economic impacts of capital regulation remain outstanding and could benefit from ongoing research. For example, future research could delve deeper into the heterogeneous impacts of prudential policies across various bank categories and borrower segments, particularly examining effects on small- and medium-sized enterprises. Additionally, investigating potential non-linearities in both the sign and magnitude of prudential shocks would provide valuable insights into regulatory transmission mechanisms.

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<sup>16</sup>Detailed results are shown in Appendix D.3.

<sup>17</sup>Detailed results are shown in Appendix D.1 and D.2.

<sup>18</sup>Detailed results are shown in Appendix D.4.

<sup>19</sup>The impacts of competition on stability remain unresolved empirically. Results from empirical studies provide varying degrees of support for the views that competition can both strengthen and weaken stability. Zigravova and Havranek (2016), for example, use meta-data analysis to examine almost 600 empirical estimates from 31 studies of the competition-stability link and find no definitive evidence on the connection one way or the other.

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# A Data Baseline Model

Variables in Billions £

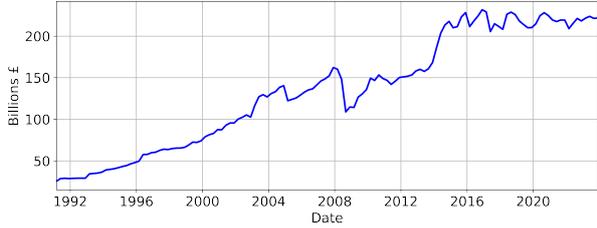


Figure 18: Tier 1 Capital

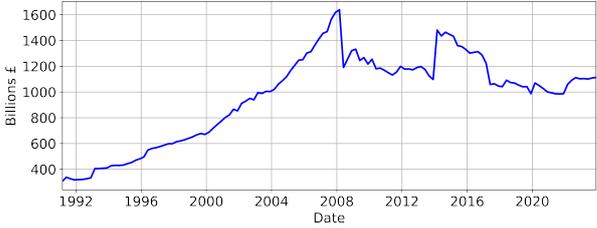


Figure 19: RWA

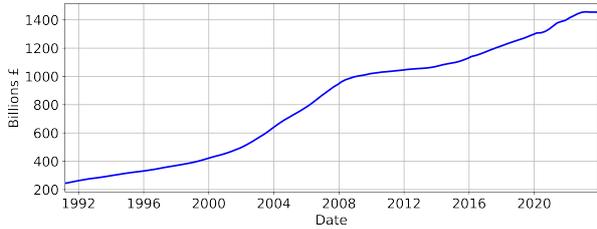


Figure 20: HH M4 Secured Lending



Figure 21: PNFCM4 Lending

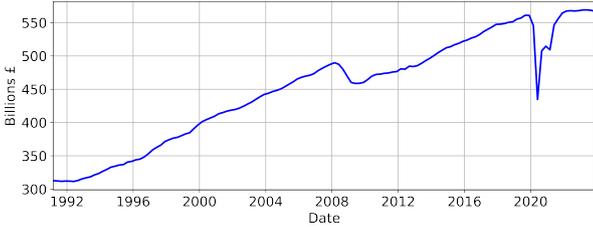


Figure 22: Real GDP

### Variables in Percentages

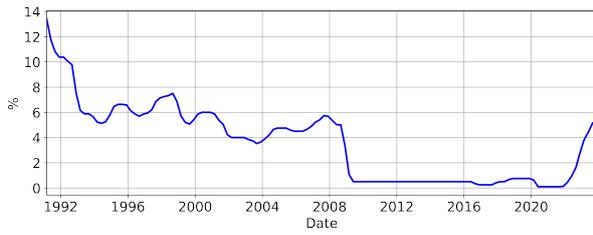


Figure 23: Bank of England Base rate

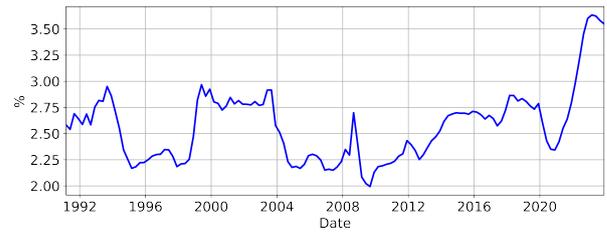


Figure 24: Corporate Spread

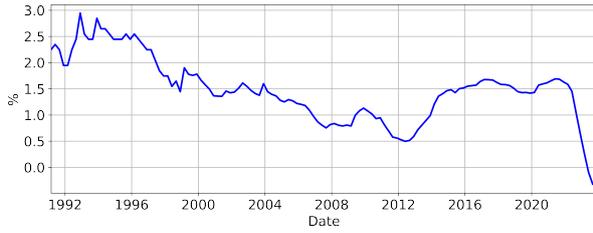


Figure 25: Mortgage Spread

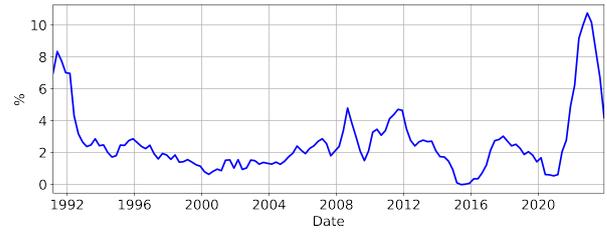


Figure 26: Inflation

### Variables Indices

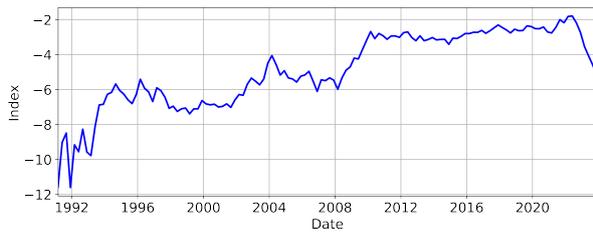


Figure 27: Boone

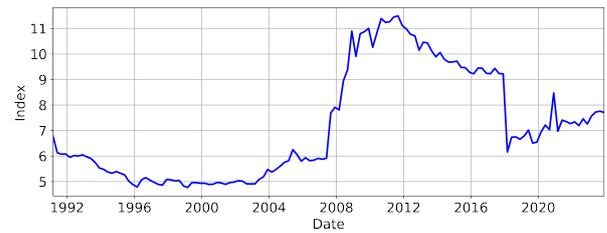


Figure 28: HHI

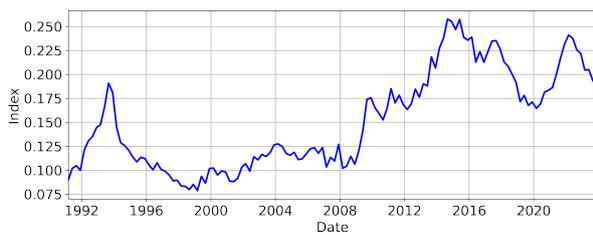


Figure 29: Lerner Index

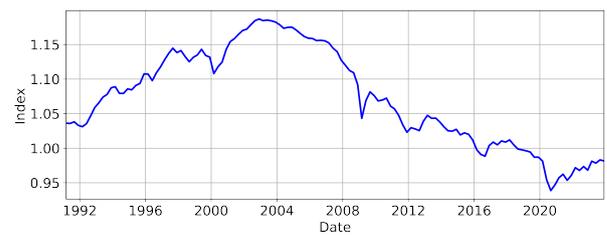


Figure 30: Bank Beta

## B Historical Decomposition in Details

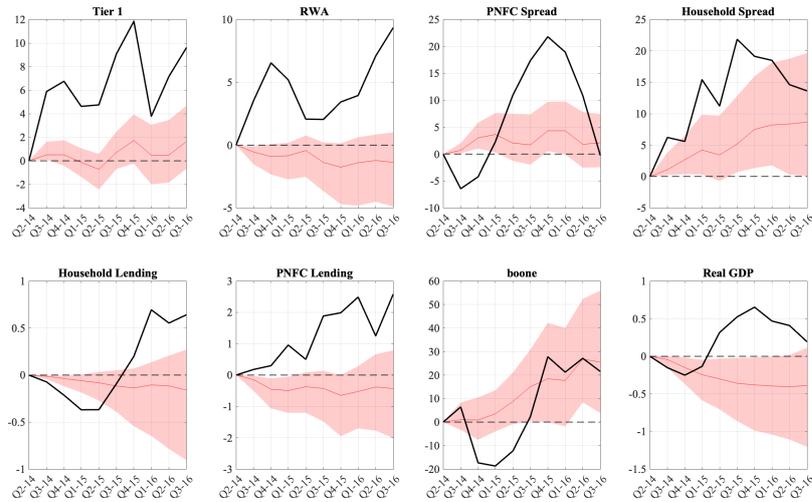


Figure 31: Historical decomposition from VAR with Boone - CST1

*Note:* The black line represents the observed unexpected change in the displayed variable around the time of the Stress Test. The red lines show the median counterfactual path obtained by excluding all structural shocks except the PCS. The light red bands indicate 68% credible intervals around the median. For interpretation of unit of measures refer to figures 5 and 6.

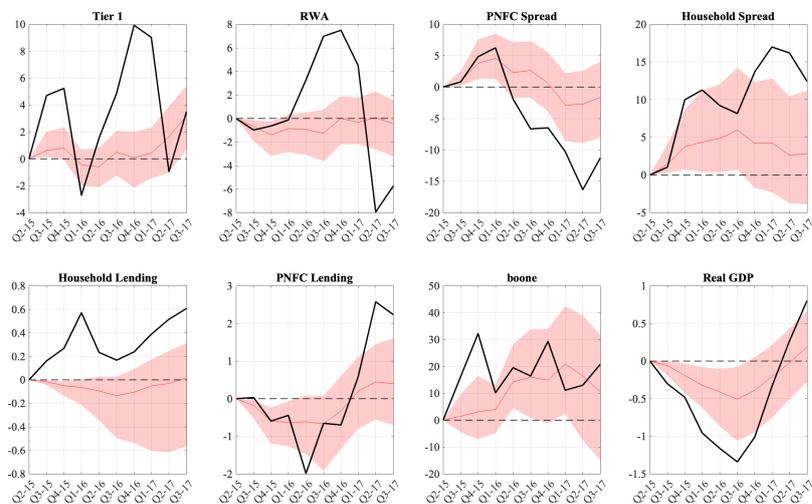


Figure 32: Historical decomposition from VAR with Boone - CST2

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

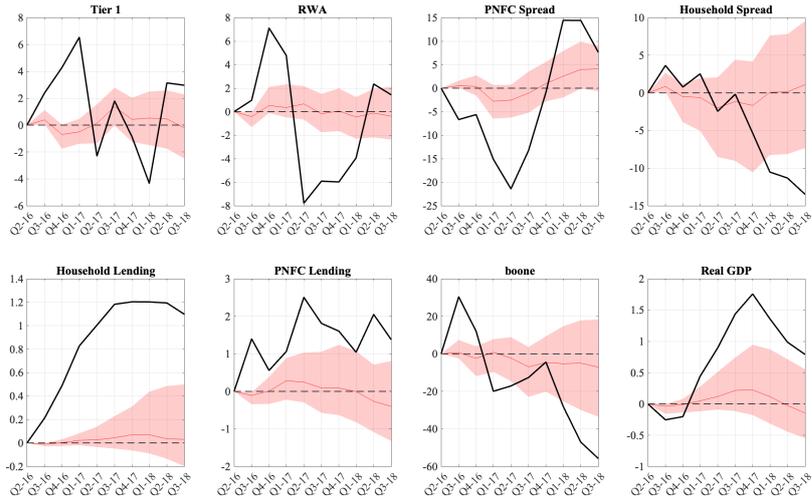


Figure 33: Historical decomposition from VAR with Boone - ACS

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

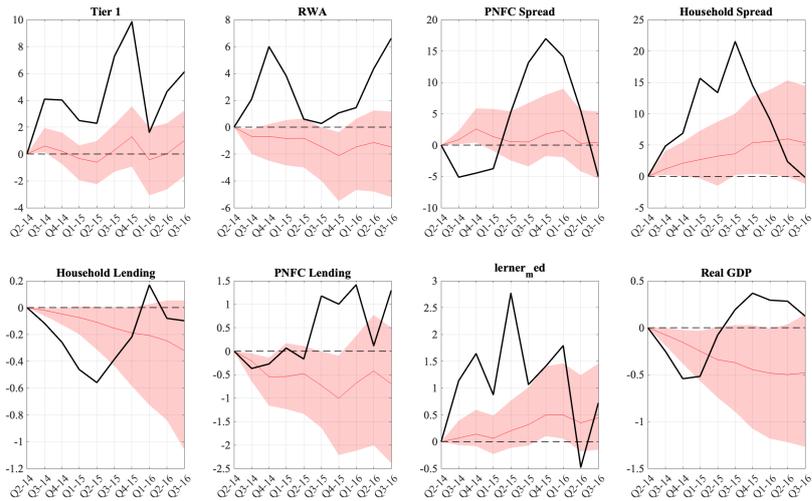


Figure 34: Historical decomposition from VAR with Lerner - CST1

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

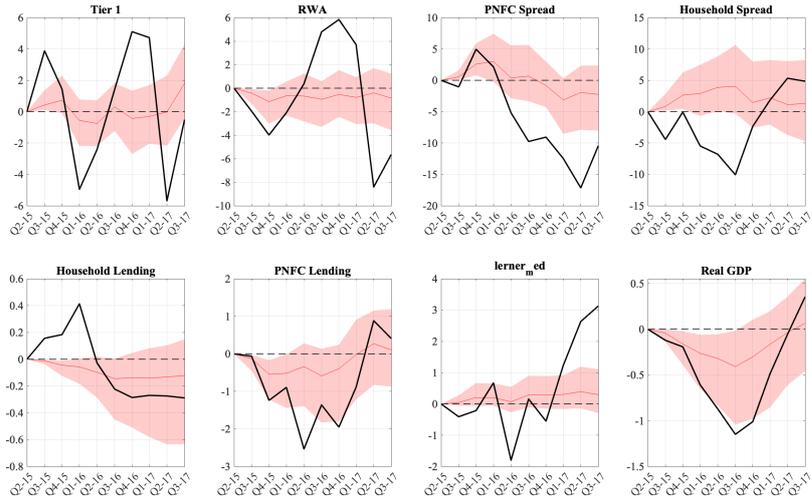


Figure 35: Historical decomposition from VAR with Lerner - CST2

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

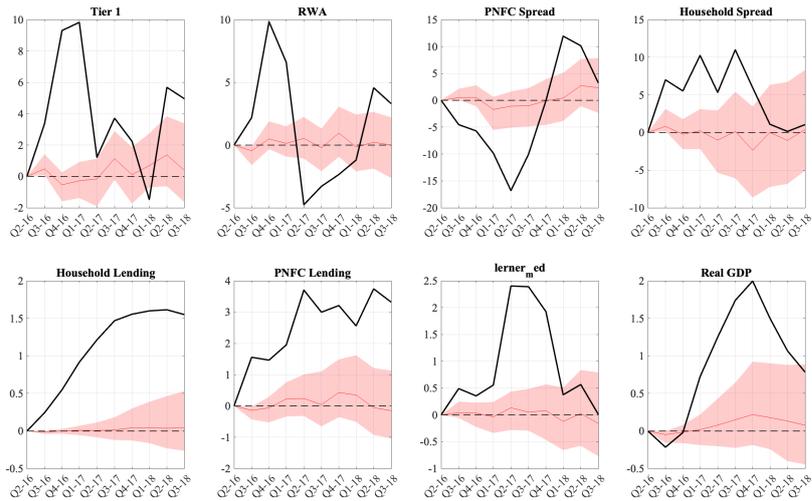


Figure 36: Historical decomposition from VAR with Lerner - ACS

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

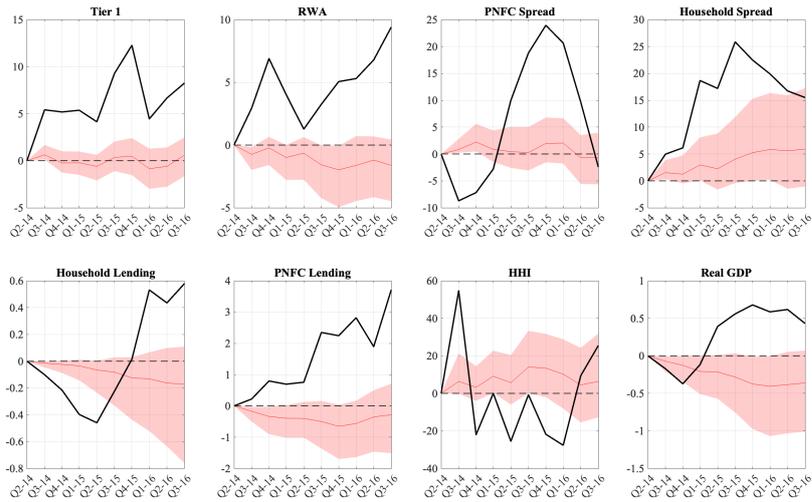


Figure 37: Historical decomposition from VAR with HHI - CST1

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

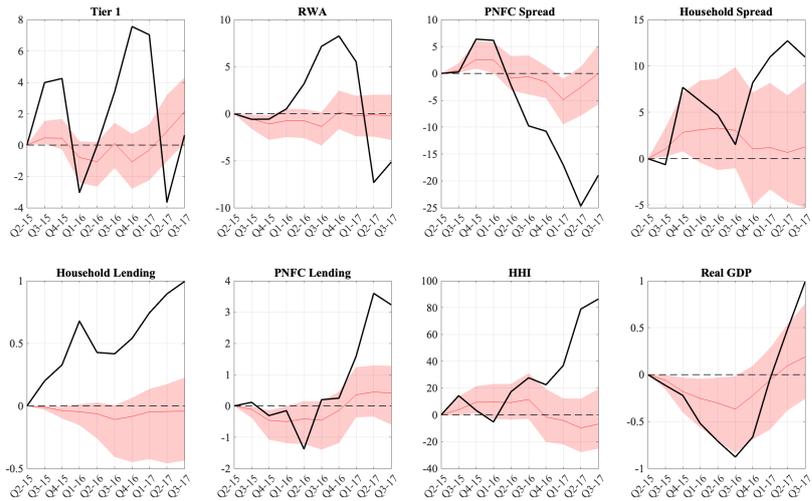


Figure 38: Historical decomposition from VAR with HHI - CST2

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

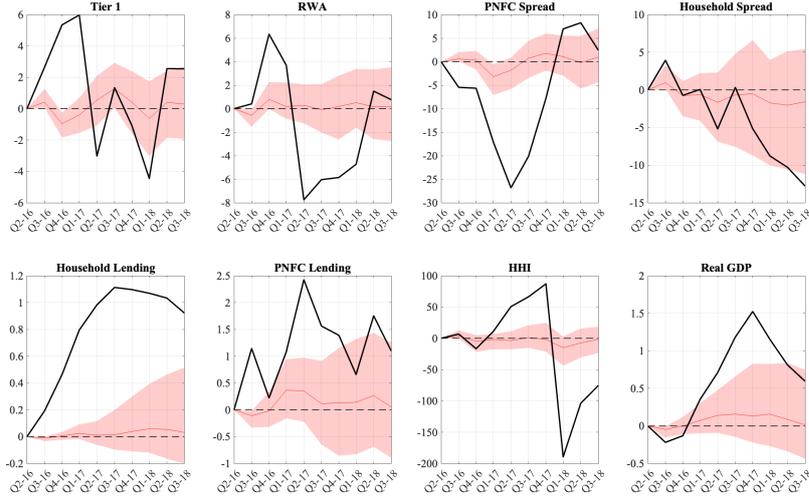


Figure 39: Historical decomposition from VAR with HHI - ACS

*Note:* For interpretation of lines and colors, see Figure 31, for unit of measures refer to figures 5 and 6.

Table 5 reports the detailed historical decompositions results computed for each competition proxy.

Table 5: Evaluation of the effects of PCS during stress tests episodes through historical decomposition.

VAR with Boone											
	Impact on TT1 (%)	Counterfactual Tier 1 (Mln £)	Impact on RWA (%)	Counterfactual RWA (Mln £)	Counterfactual Ratio (%)	Difference from Actual (Bps)	Impact on GDP (%)	Impact on PNFC Spread (Bps)	Impact on HH Spread (Bps)	Impact on PNFC Lending (%)	Impact on HH Lending (%)
CST1	0.51	204737.94	-0.91	1422406.50	14.39	20.34	-0.25	3.64	4.22	-0.49	-0.06
CST2	0.80	213039.36	-1.39	1340846.88	15.89	34.42	-0.32	4.61	4.36	-0.63	-0.06
ACS	0.40	219051.75	-0.42	1302064.53	16.82	13.00	-0.04	0.52	0.84	-0.11	-0.01
VAR with HHI											
	Impact on TT1 (%)	Counterfactual Tier 1 (Mln £)	Impact on RWA (%)	Counterfactual RWA (Mln £)	Counterfactual Ratio (%)	Difference from Actual (Bps)	Impact on GDP (%)	Impact on PNFC Spread (Bps)	Impact on HH Spread (Bps)	Impact on PNFC Lending (%)	Impact on HH Lending (%)
CST1	0.64	204997.86	-0.75	1424792.29	14.39	19.76	-0.21	2.22	1.26	-0.34	-0.02
CST2	0.43	212266.64	-1.09	1344953.19	15.78	23.82	-0.25	2.51	3.12	-0.50	-0.05
ACS	0.42	219106.30	-0.56	1300186.95	16.85	16.45	-0.05	0.56	0.97	-0.11	-0.01
VAR with Lerner											
	Impact on TT1 (%)	Counterfactual Tier 1 (Mln £)	Impact on RWA (%)	Counterfactual RWA (Mln £)	Counterfactual Ratio (%)	Difference from Actual (Bps)	Impact on GDP (%)	Impact on PNFC Spread (Bps)	Impact on HH Spread (Bps)	Impact on PNFC Lending (%)	Impact on HH Lending (%)
CST1	0.60	204929.42	-0.69	1425620.56	14.37	18.44	-0.25	2.58	2.12	-0.55	-0.05
CST2	0.73	212888.87	-1.14	1344205.35	15.84	29.33	-0.26	3.00	2.90	-0.52	-0.06
ACS	0.49	219252.05	-0.46	1301558.53	16.85	15.79	-0.05	0.50	0.82	-0.14	-0.01

*Note:* The impact on TT1, RWA, and their ratio is computed after one quarter for CST1 and CST2, while the effects on the other endogenous variables are evaluated after two quarters. For the ACS, the effects on all variables are evaluated on impact.

## C The importance of Narrative Restrictions

In this section, we contrast the structural impulse responses derived from sign restrictions alone with those incorporating narrative restrictions. For clarity, Figure 40 displays the IRFs of the macro-financial variables (both with and without narrative restrictions) for the VAR model estimated using only the Boone indicator. The conclusions are analogous for models estimated with the other competition proxies.

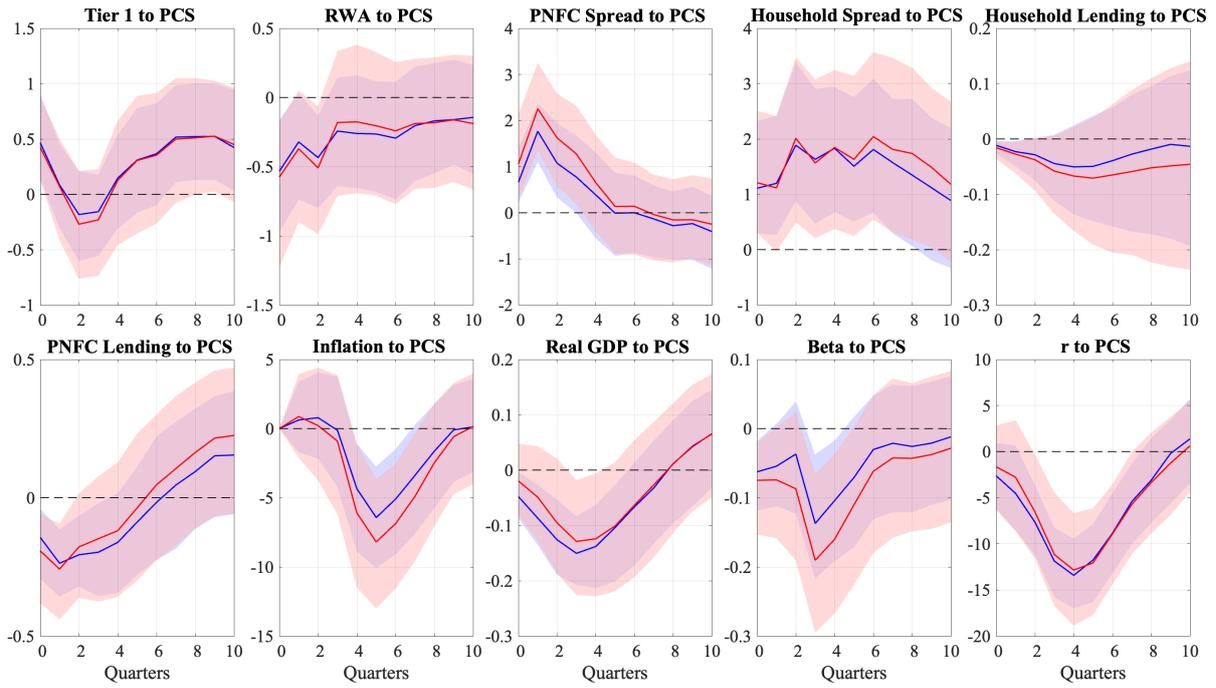


Figure 40: IRFs of macro-financial variables to a Prudential Capital Shock: narrative vs pure sign restriction.

*Note:* The blue (red) lines represent the medians of the posterior distributions obtained by combining sign and narrative (using a pure sign restrictions) identification, estimated using the Boone Indicator. The corresponding light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 5.

Figure 40 demonstrates that incorporating narrative restrictions yields substantially tighter credibility intervals compared to relying solely on sign identification. Additionally, Figures 41 and 42 present a more detailed account of the responses of real GDP and the competition proxies, estimated using each competition measure.

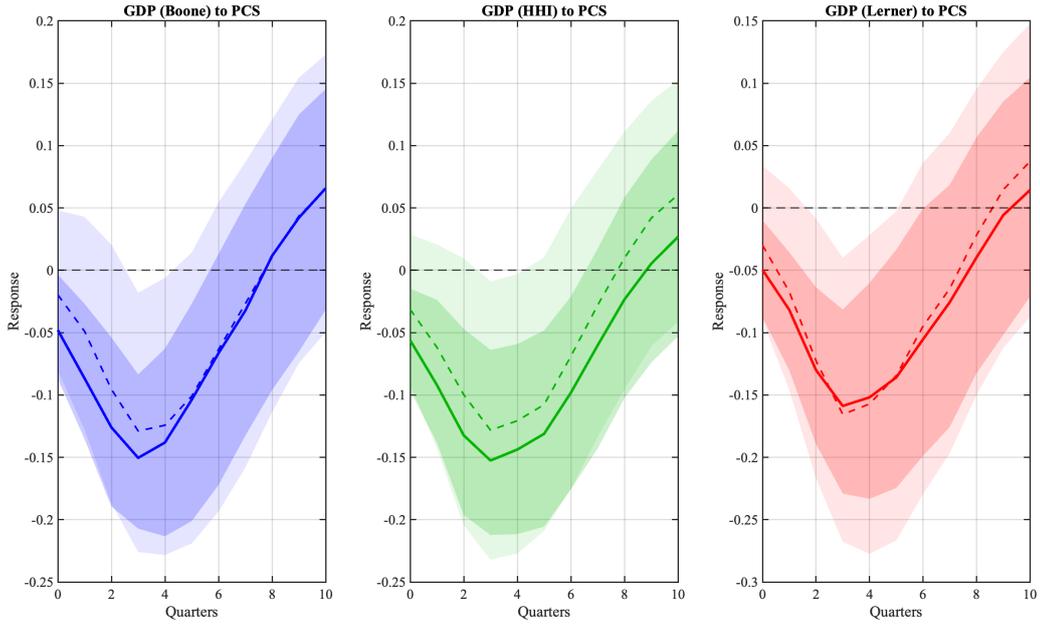


Figure 41: IRFs of real GDP to a Prudential Capital Shock: narrative vs pure sign-restriction.

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative (using a pure sign restrictions) identification. The shaded (light shaded) areas correspond to the 68% confidence bands combining sign and narrative (using a pure sign restrictions) identification. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 5.

Under pure sign restrictions, the IRFs are somewhat milder, especially in the VARs estimated with the Boone and HHI proxies, whereas combining sign and narrative restrictions yields markedly tighter credibility intervals. As expected, narrative information both amplifies the detected impact and reduces uncertainty.

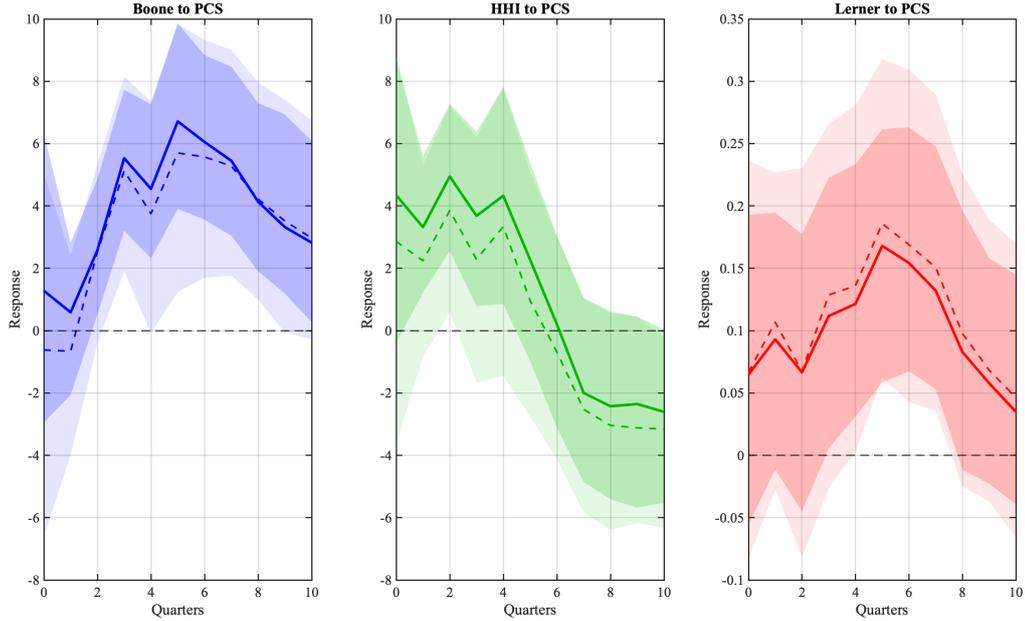


Figure 42: IRFs of Competition Proxies to a Prudential Capital Shock: narrative vs pure sign-restriction.

The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative (using a pure sign restrictions) identification. The shaded (light shaded) areas correspond to the 68% confidence bands combining sign and narrative (using a pure sign restrictions) identification. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 6.

For all three competition measures, the median IRF without narrative restrictions closely tracks the median obtained when narrative information is included. However, under pure sign identification, the credibility bands are appreciably wider. In the Boone and HHI VARs, these wider bands span substantially milder effects (i.e., they include near-zero or weak responses), whereas in the Lerner VAR they also admit the possibility of considerably stronger responses.

## D Further Robustness

### D.1 Unrestricted Response of Inflation

In this section, we present an alternative identification of a prudential capital shock as a further robustness check. Specifically, Table 6 shows an identification strategy that differs from the baseline in Section 4.3 by leaving the response of inflation unrestricted on impact. This approach is consistent with [Kanngiesser et al. \(2020\)](#), who remain agnostic about the immediate effect of a prudential capital shock on inflation.

Table 6: Robustness Identification: Unrestricted Inflation response.

Response	Tier 1 <sub>t</sub>	PNFC Spread <sub>t</sub>	Household Spread <sub>t</sub>	RWA <sub>t</sub>	Household Lending <sub>t</sub>	PNFC Lending <sub>t</sub>	Bank Profitability <sub>t</sub>	$\pi_t$	Base Rate <sub>t</sub>	GDP <sub>t</sub>	Competition Proxy <sub>t</sub>
$t = 0$	+	+	+	-	-	-	-				

Note: +/- denote sign restrictions on impact ( $t = 0$ ). Blank table entries denote unconstrained IRFs. Competition Proxy stands for  $Boone_t$ ,  $Lerner_t$  or  $HHI_t$ .

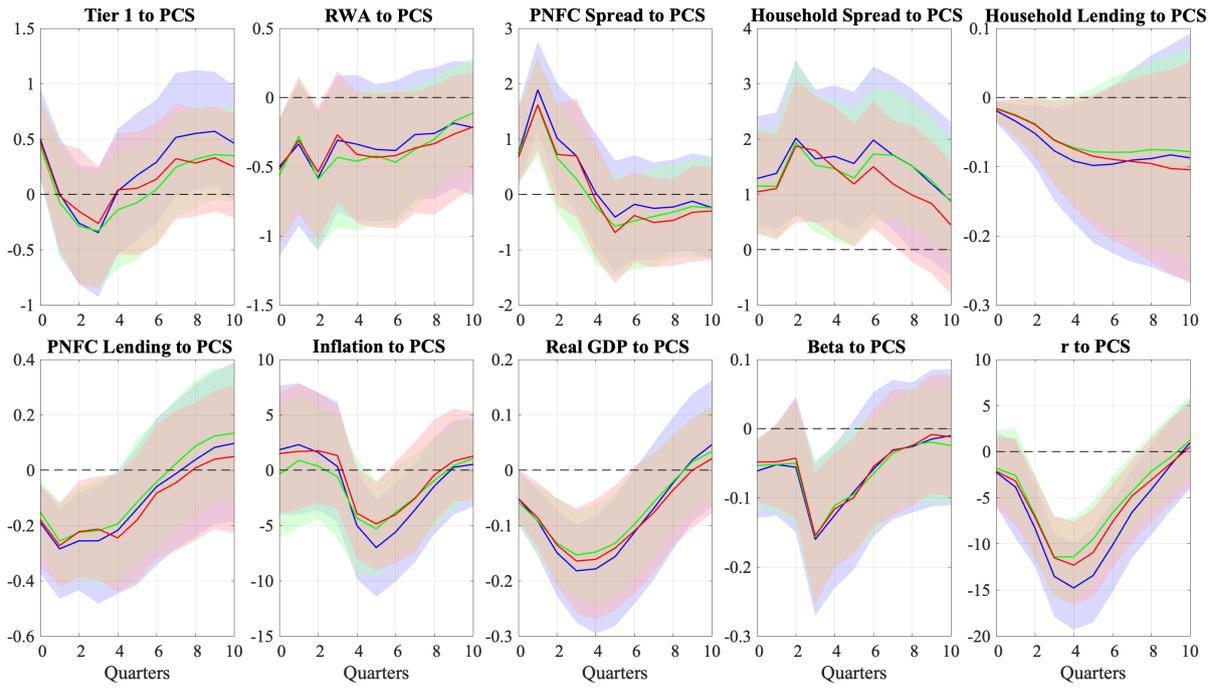


Figure 43: IRFs of macro-financial variables to a Prudential Capital Shock with unrestricted inflation response.

*Note:* The blue, red, and green lines represent the medians of the posterior distributions obtained by combining sign and narrative identification, estimated using the Boone, Lerner, and HHI dataset, respectively. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 5.

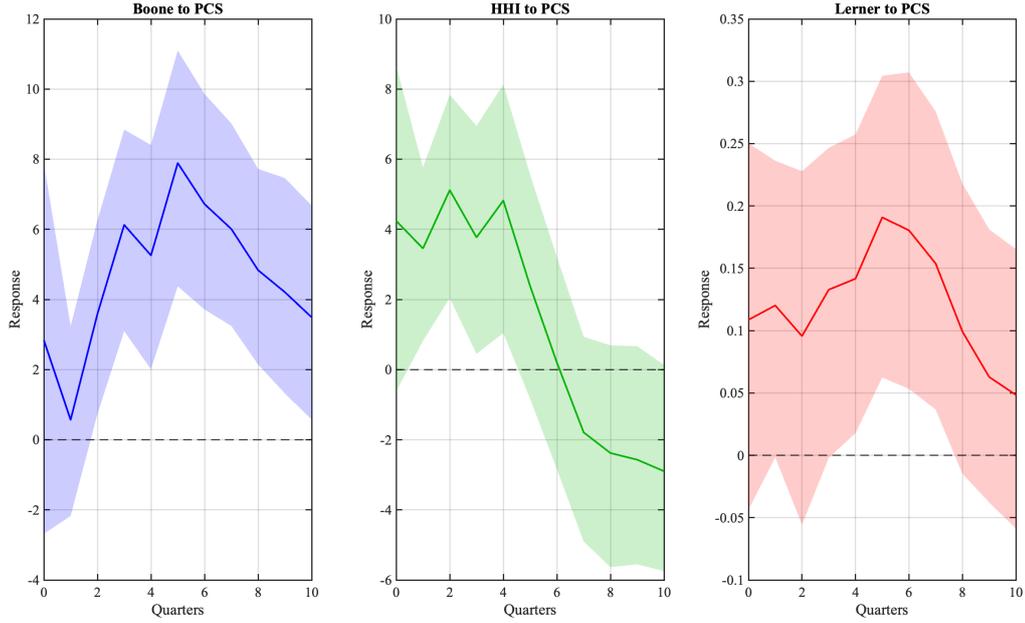


Figure 44: IRFs of Competition Proxies to a Prudential Capital Shock with unrestricted inflation response.

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative identification. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 6.

Figures 43 and 44 show that results are unchanged in this alternative specification.

## D.2 Accounting for balance sheet adjustment

A further robustness check involves restricting the response of the balance sheet variables used in the model for one additional period beyond the impact. This approach is consistent with Conti et al. (2023), who argue that changes in these variables occur gradually, implying that the effects of the shock are spread over two periods. Table 7 reports this alternative identification strategy, in which Tier 1 capital, RWA, and lending volumes are constrained also at time  $t = 1$ .

Table 7: Robustness Identification: Two Periods restrictions for balance sheet variables.

Response	Tier 1 <sub>t</sub>	PNFC Spread <sub>t</sub>	Household Spread <sub>t</sub>	RWA <sub>t</sub>	Household Lending <sub>t</sub>	PNFC Lending <sub>t</sub>	Bank Profitability <sub>t</sub>	$\pi_t$	Base Rate <sub>t</sub>	GDP <sub>t</sub>	Competition Proxy <sub>t</sub>
$t = 0$	+	+	+	-	-	-	-	0			
$t = 1$	+			-	-	-					

*Note:* +/ - /0 denote sign and zero restrictions on impact ( $t = 0$ ) and one quarter ahead ( $t = 1$ ). Blank table entries denote unconstrained IRFs. Competition Proxy stands for  $Boone_t$ ,  $Lerner_t$  or  $HHI_t$ .

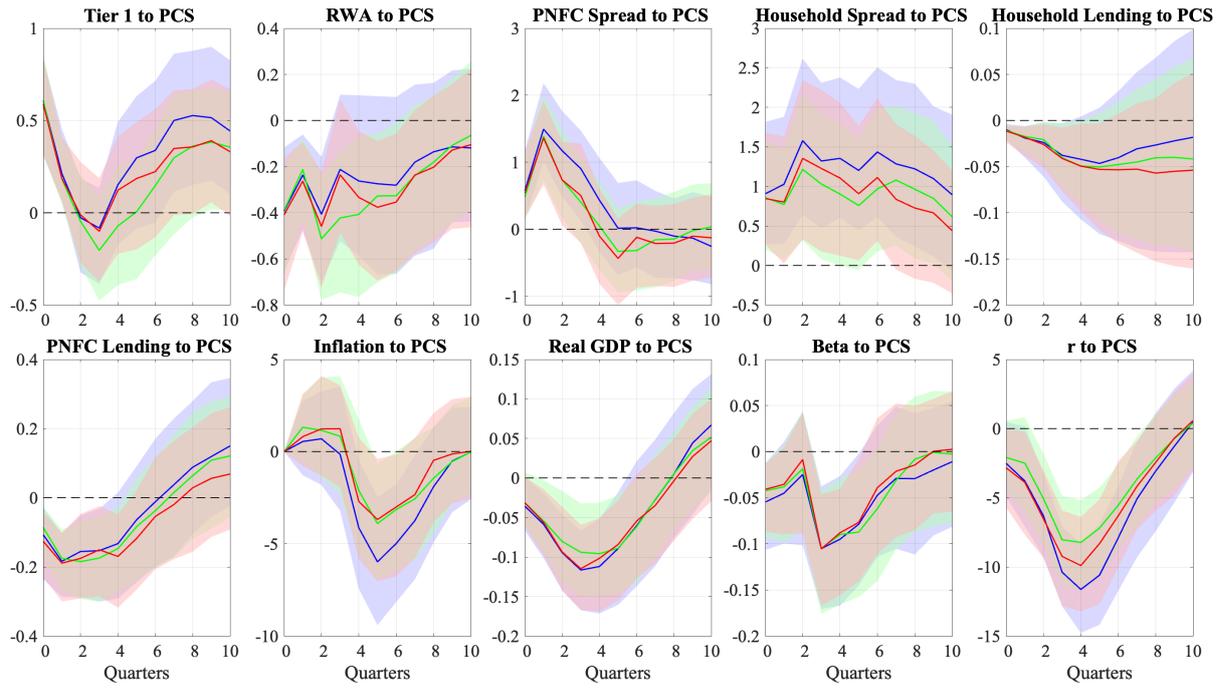


Figure 45: IRFs of macro-financial variables to a Prudential Capital Shock with two periods restrictions for balance sheet variables.

*Note:* The blue, red, and green lines represent the medians of the posterior distributions obtained by combining sign and narrative identification, estimated using the Boone, Lerner, and HHI dataset, respectively. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 5.

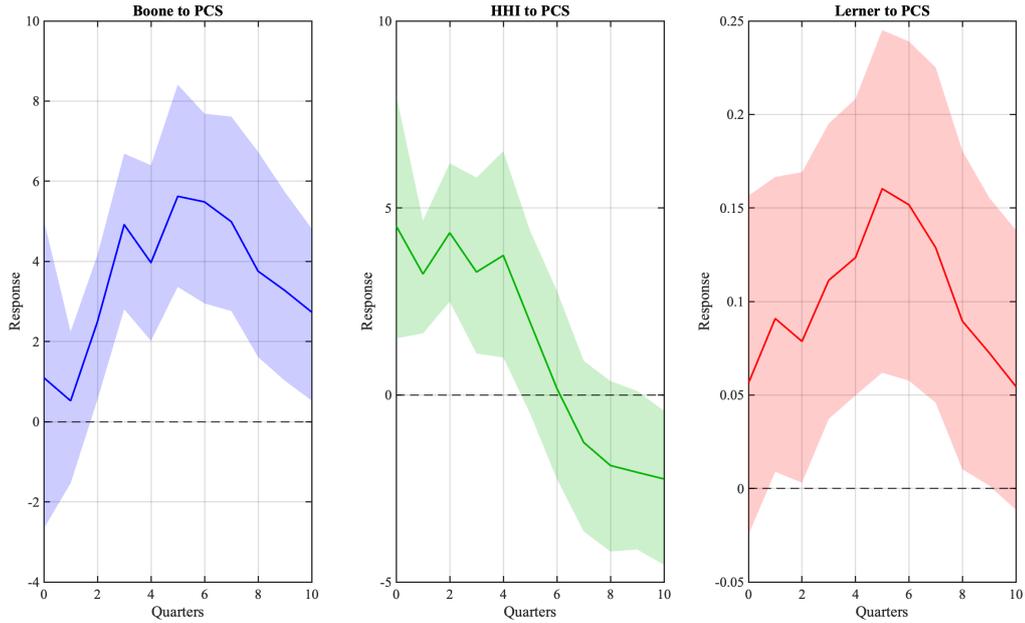


Figure 46: IRFs of Competition proxies to a Prudential Capital Shock with two periods restrictions for balance sheet variables.

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative identification. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 6.

Figures 45 and 46 show that results are unchanged with this alternative identification strategy.

### D.3 Narrative restrictions on the first quarter

To validate the timing and economic rationale underlying our narrative restrictions, we conduct a robustness test by imposing the same positive prudential capital shock restrictions on the first quarters of 2014, 2015, and 2016 instead of the third quarters. This robustness check is crucial for establishing the credibility of our identification strategy, as Q1 represents a period when the narrative mechanism should not operate as stress scenarios and guidance are not yet published (occurring in Q2/Q3), and banks have not received the regulatory signals that would prompt capital and/or balance sheet adjustments.

Figure 47 displays the IRFs of the macro-financial variables (both with and without narrative restrictions imposed on Q1) for the VAR model estimated using only the Boone indicator. The conclusions are analogous for models estimated with the other competition proxies.

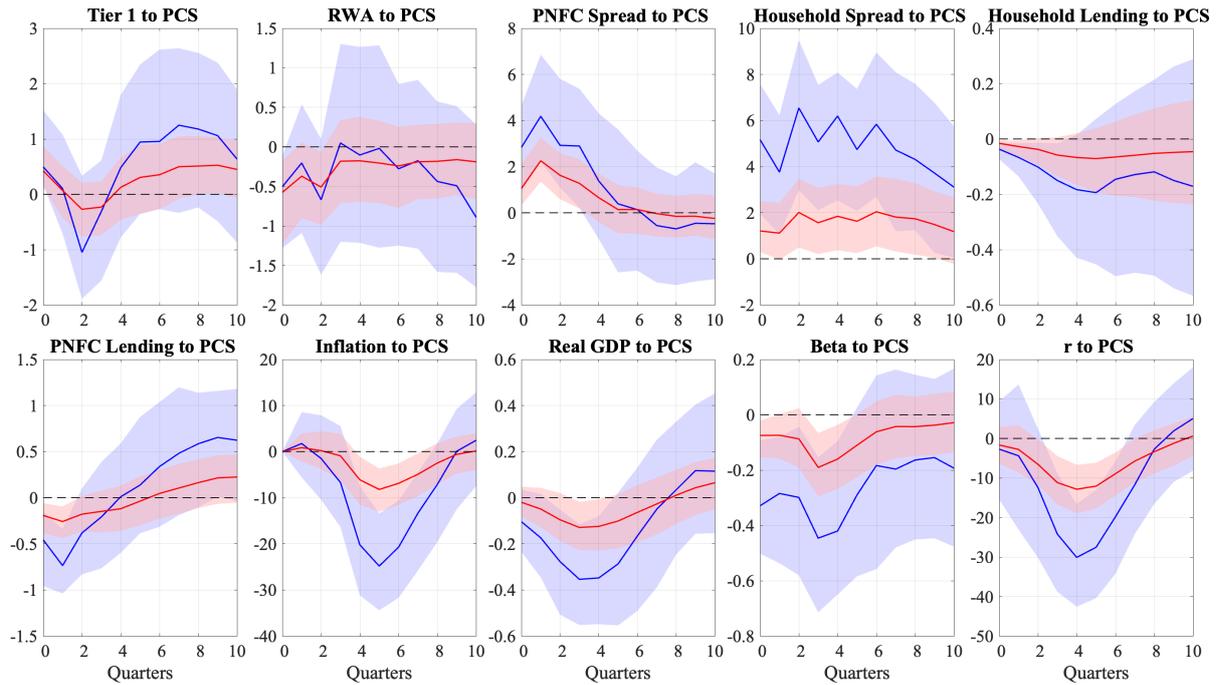


Figure 47: IRFs of macro-financial variables to a Prudential Capital Shock: narrative imposed on Q1 vs pure sign-restriction.

*Note:* The blue (red) lines represent the medians of the posterior distributions obtained by combining sign and narrative (using a pure sign restrictions) identification, estimated using the Boone Indicator. The corresponding light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 5.

Figure 47 shows that contrary to the theoretical expectation that narrative restrictions should improve identification precision, imposing restrictions on Q1 produces substantially wider credibility intervals across all macro-financial variables. This deterioration in estimation precision suggests that the Q1 timing fails to capture genuine prudential policy transmission, as banks would not yet have received the regulatory signals necessary to prompt capital adjustments. Furthermore, while the impulse response functions maintain qualitatively similar shapes to those obtained under our baseline Q3 restrictions, their magnitudes are considerably larger and inconsistent with the established empirical literature on prudential policy effects. Finally, Figures 48 and 49 provide detailed evidence that these conclusions hold robustly for the responses of real GDP and the competition proxies, with results estimated using each respective competition measure.

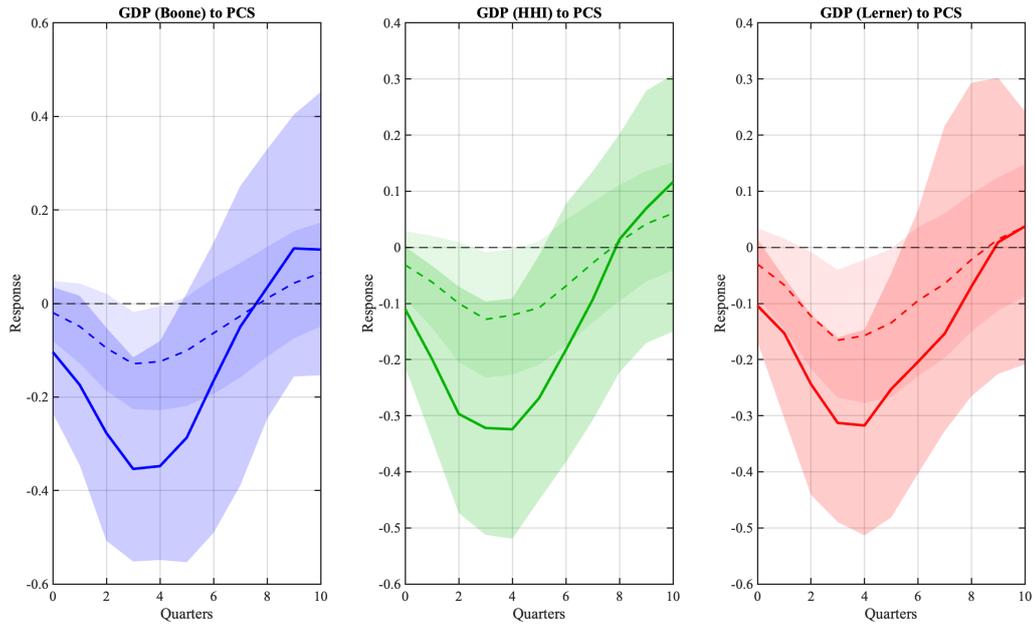


Figure 48: IRFs of real GDP to a Prudential Capital Shock: narrative imposed on Q1 vs pure sign-restriction.

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative (using a pure sign restrictions) identification. The shaded (light shaded) areas correspond to the 68% confidence bands combining sign and narrative (using a pure sign restrictions) identification. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to 5.

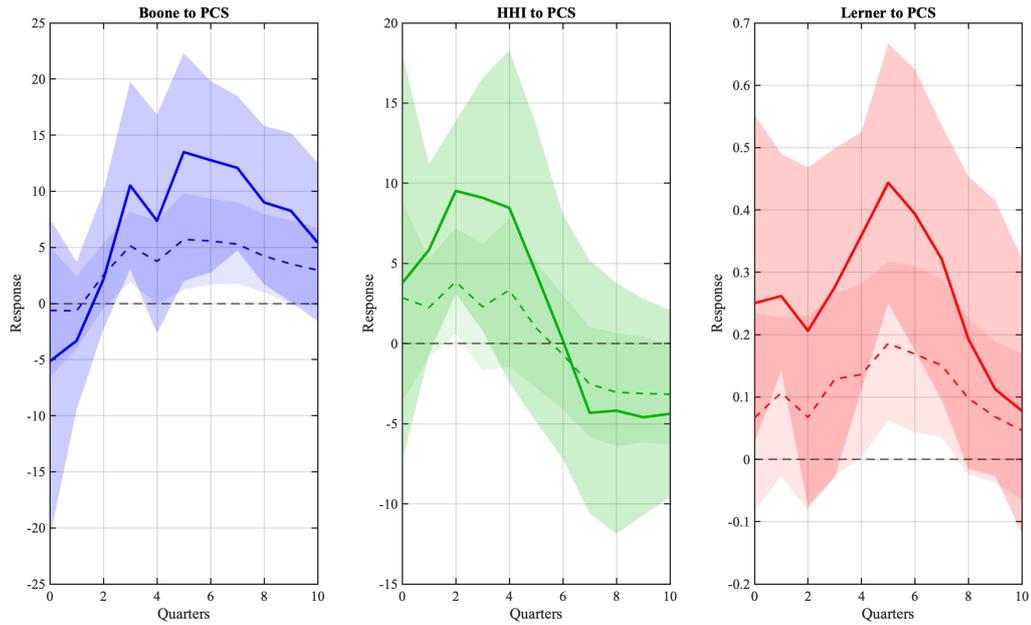


Figure 49: IRFs of Competition Proxies to a Prudential Capital Shock: narrative imposed on Q1 vs pure sign-restriction.

The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative (using a pure sign restrictions) identification. The shaded (light shaded) areas correspond to the 68% confidence bands combining sign and narrative (using a pure sign restrictions) identification. The estimation sample spans from 1991:Q1 to 2023:Q4 excluding quarters in 2020 and 2021. For interpretation of unit of measures refer to Figure 6.

#### D.4 Inclusion of COVID-19 observations

In this subsection, we present results obtained by incorporating COVID-19 observations, specifically including quarters from 2020 and 2021, demonstrating how the inclusion of this exceptional period can significantly affect statistical inference. Figures 50 and 51 display the estimated structural impulse response functions for macroeconomic and competition-related variables, respectively.

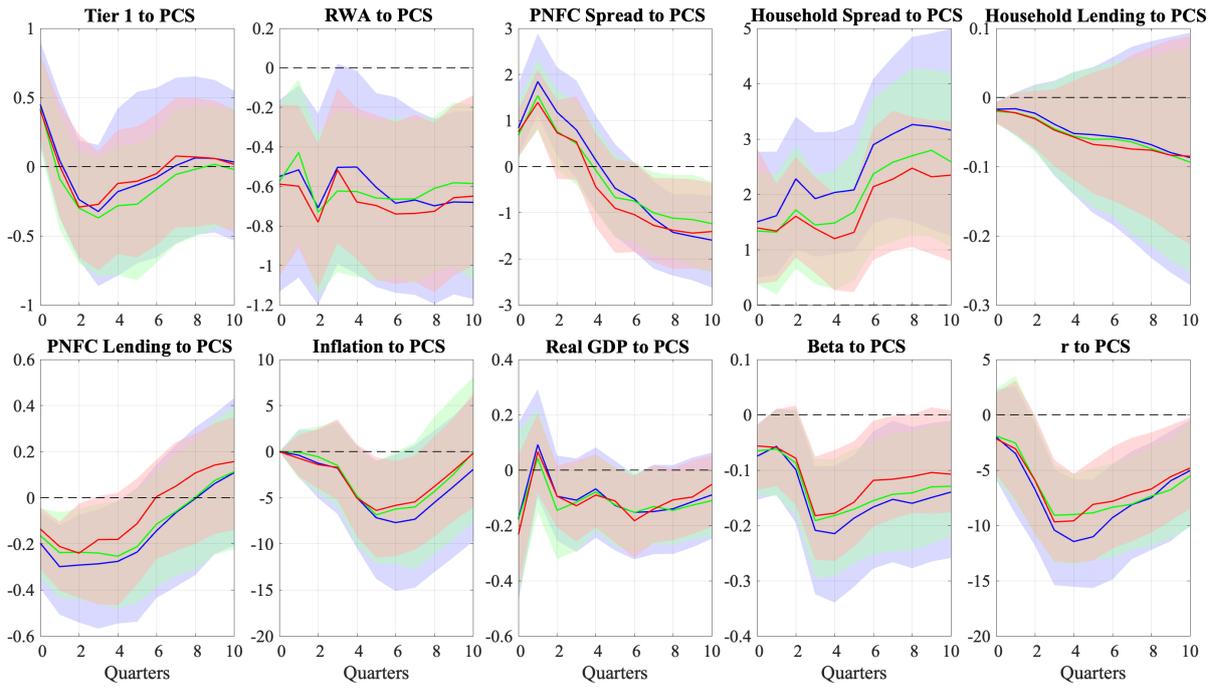


Figure 50: IRFs of macro-financial variables to a Prudential Capital Shock including COVID-19 quarters.

*Note:* The blue, red, and green lines represent the medians of the posterior distributions obtained by combining sign and narrative identification, estimated using the Boone, Lerner, and HHI dataset, respectively. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4. For interpretation of unit of measures refer to Figure 5.

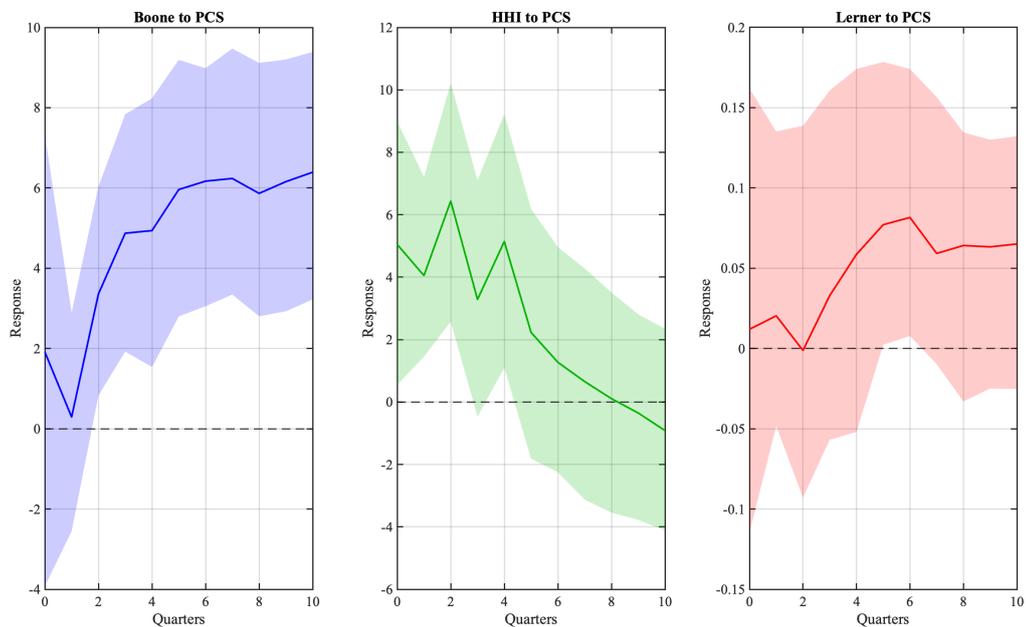


Figure 51: IRFs of Competition proxies to a Prudential Capital Shock including COVID-19 quarters.

*Note:* The solid lines represent the medians of the posterior distributions obtained by combining sign and narrative identification. The light shaded areas correspond to the 68% confidence bands. The estimation sample spans from 1991:Q1 to 2023:Q4. For interpretation of unit of measures refer to 5.

The responses of key variables are substantially altered by the inclusion of COVID quarters, with several notable departures from our baseline findings. Most strikingly, the RWA response exhibits a persistent negative trajectory, remaining statistically significant and below zero throughout the entire 10-quarter horizon. Similarly, the household spread response displays a monotonically increasing pattern over time, contrasting sharply with the baseline specification. The real GDP response loses statistical significance across most horizons, though it exhibits a counterintuitive positive sign at the initial horizon. Among the competition measures, the Boone indicator shows a continuously increasing response throughout the entire forecast horizon, suggesting a persistent reduction in competition that differs markedly from the baseline results. These findings underscore that the VAR estimates are highly sensitive to the inclusion of the COVID-19 period, thereby justifying our ad-hoc procedure of removing quarters from 2020 and 2021 observations from the baseline analysis.

## E Constructing measures of competition

This appendix describes in more detail the three measures of competition used in this study and how we estimated each of them. The measures are constructed from balance sheet, income and expenditure data reported by individual (i.e., non-group) banking entities (commercial banks and building societies) operating in the United Kingdom that are authorised and directly regulated by the UK Prudential Regulation Authority. Non-group data represent more closely activities undertaken within the domestic UK banking markets. We also include UK incorporated subsidiaries of international banks operating in the UK loan and deposit markets.

### The Boone Indicator

The Boone indicator measures competition from an efficiency perspective. The measure relies on the output-reallocation effect: any increase (decrease) in competition intensity will lead to a relative increase (decrease) in output by the most efficient firms. We measure output as variable profits, and proxy efficiency as the log of the average variable costs and control for other factors that influence variable profits (equation 5).

$$\pi_{i,t} = \alpha_t + \beta_t \ln(c_{i,t}) + \Phi X_{i,t} + \eta_{i,t} \quad (5)$$

where  $\pi_{i,t}$  is variable profits for firm  $i$  and time  $t$ ,  $c_{i,t}$  is average variable costs,  $X_{i,t}$  are other control variables and  $\eta_{i,t}$  is the error term. The Boone indicator is given by  $\beta_t$ , which is estimated for each time period  $t$  using interactions between average variable costs and a time-fixed effects dummy variable.

We measure variable profits as the ratio of total revenue less variable costs (interest paid, staff expenditure, other variable costs including occupancy) to total assets. Average variable costs are variable costs scaled by variable revenue derived directly from current activity (interest received, foreign exchange receipts, investment income, fees and other charges). The control variables include average risk on balance sheet, provisions, Tier 1 capital, the loans-to-assets ratio, the proportion of retail funding, other non-interest earning assets and balance sheet size. We also include lagged changes in the deposits-to-assets ratio for each bank as a proxy for the change in banks' competitive strategy building deposit market share [Klemperer, 1995](#). In the presence of consumer switching costs, deposit-takers can temporarily increase deposit interest rates to increase their customer base and expand their balance sheets. This strategic behaviour increases average variable costs, and hence the estimate of the elasticity of variable profits but is not related to changes in the efficiency of the firm. Consequently, without adjusting for this behaviour, estimates of the Boone indicator will not reflect the period-by-period change (e.g., less negative when competition increases) than that implied by the underlying efficiency of the firm [de Ramon et al., 2018](#). To avoid distortions from quarterly volatility,

we annualised quarterly data; to eliminate the effects of outliers, we winsorised all variables at the first and 99th percentiles.

While our approach to estimating the Boone indicator is consistent with the literature, there are subtle differences related to, among other things, regression setup and sample characteristics, that mean our Boone indicator is not directly comparable with those reported in other sources. For example, in estimating its measure of the Boone indicator (reported in the [World Bank \(2019\)](#)), the World Bank uses marginal costs as opposed to average costs (which we use). Several studies also rely on data from Bankscope (e.g., [Schaeck and Cihak \(2014\)](#); [van Leuvensteijn et al. \(2011\)](#); [Liu and Wilson \(2013\)](#); [Beck et al. \(2013\)](#)). Despite providing a rich set of bank-level information, this database is less frequent (annual only) and omits information on small and rural institutions (i.e., that do not publish financial statement information) and on banks that operate as subsidiaries of a larger, foreign institution domiciled in another country. Our estimation includes more frequent (quarterly) information on all such institutions, which, although adding to the insights on competition, complicates comparisons with other studies' measures.

## The Lerner index

The Lerner index measures the price–cost margin for individual firms over time, and a central tendency measure (e.g., average or median) across all firms in a market or industry (at each point in time) is used as a proxy for market power and competition. The values of the index reflect theoretical outcomes from the competitive process: under perfect competition the index is zero as the output price (marginal revenue) equals marginal cost, and economic profits are zero. The Lerner index is positive as a firm's market power increases and price rises above marginal cost in a Cournot static (quantity-setting) oligopoly model.

We follow a well-established approach to estimating the index (e.g., [Berger et al. \(2009\)](#); [Fernández de Guevara et al. \(2007\)](#)). The Lerner index ( $L_{i,t}$ ) is computed as the ratio of the difference in the output price ( $P$ ) and marginal cost ( $MC_{i,t}$ ) to the output price:

$$L_{i,t} = \frac{P_{i,t} - MC_{i,t}}{P_{i,t}} \quad (6)$$

The output price is calculated as interest and non-interest revenue per unit of total output (proxied by total assets). The marginal cost  $MC_{i,t}$  is not directly observable, either for the firm or for a particular product supplied by the firm. The marginal cost is derived empirically from the parameters of an estimated total cost function which is generally of the form:

$$\begin{aligned} \ln(c_{i,t}) = & \alpha_0 + \alpha_1 \ln(Q_{i,t}) + \frac{1}{2} \alpha_2 (\ln(Q_{i,t}))^2 + \sum_{j=1}^3 \beta_j \ln(w_{j,i,t}) \\ & + \frac{1}{2} \sum_{k=1}^3 \sum_{j=1}^3 \alpha_{kj} \ln(w_{k,i,t}) \ln(w_{j,i,t}) + \sum_{j=1}^3 \delta_j \ln(w_{j,i,t}) \ln(Q_{i,t}) \\ & + \lambda_1 E_{i,t} + \frac{1}{2} \lambda_2 E_{i,t}^2 + \theta_1 T + \theta_2 T^2 \\ & + \sum_{j=1}^3 \lambda_j T \ln(w_{j,i,t}) + \Phi' X_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (7)$$

where  $c_{i,t}$  is the total cost for firm  $i$  at time  $t$ ,  $Q_{i,t}$  is total output, the  $w_{j,i,t}$  are input costs,  $E_{i,t}$  is equity capital,  $T$  is a time trend,  $X_{i,t}$  contains other relevant control variables and  $\varepsilon_{i,t}$  is the error term. We identify three input costs common to the literature for the financial sector: staff (labour) costs, physical capital (buildings and other business costs) and funding (interest paid on deposits). The marginal cost is then calculated as the derivative of total cost with respect to output:

$$MC_{i,t} = \frac{\partial c_{i,t}}{\partial Q_{i,t}} = \left( \alpha_1 + \alpha_2 \ln(Q_{i,t}) + \sum_{j=1}^3 \delta_j \ln(w_{j,i,t}) \right) \frac{c_{i,t}}{Q_{i,t}} \quad (8)$$

The Lerner index calculated for each bank  $i$  ranges from 0 to 1, with values approaching 1 indicating increasing levels of market power (wider margins) on the part of the firm. We derive the Lerner index from estimates of the total cost function shown in equation 7. Variables used in the specifications have been winsorised at the first and 99th percentiles to reduce the impact of outliers. We also impose homogeneity of inputs so that the elasticity of all cost inputs sum to one by using funding costs as a numeraire. The estimated model parameters are robust to the inclusion of different controls.

## The Herfindahl–Hirschman Index

The HHI is a relative measure of concentration, calculated as the sum of each bank’s share in a market squared:

$$HHI = \sum_{i=1}^N s_i^2 \quad (9)$$

where  $s$  is the market share of the bank in a particular market and  $N$  is the total number of firms in the industry. Bank shares are calculated on a scale between zero and 100 such that a monopoly industry will have an HHI of 10,000 while increasingly atomised industry will have an HHI approaching zero. We follow other papers from the literature (e.g., Beck et al. (2006); Berger et al. (2009); Anginer et al. (2014)) and compute the HHI for UK loans of UK deposit takers. We recognise that the HHI is not a direct proxy for competition, but it is useful in providing comparisons with previous studies and in helping evaluate the results from the other competition measures.