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Bank Lending Standards and the U.S. Economy

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Abstract

The provision of bank credit to firms and households affects macroeconomic performance. We use survey measures of changes in bank lending standards, disaggregated by loan category, to quantify the effect of changes in banks' attitudes toward lending on aggregate output, inflation, and interest rates. Bank lending to businesses is particularly important for macroeconomic outcomes, with peak effects on output of around half a percentage point after four quarters of the initial shock. These effects depend on the stage of the business cycle and the proximity of the short-term interest rate to its effective lower bound. The effects are larger when output is growing below trend and when the interest rate is away from its lower bound. We also find that the response of the economy to lending-standards shocks is asymmetric, with tightening shocks having larger effects on output.

JEL classification: E32, E44, G21.

Keywords: credit supply; macroeconomic activity; loan portfolio composition.

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1 Introduction

Bank lending conditions are generally considered an important consideration when evaluating the prospects for macroeconomic activity and the stance of monetary policy. During the July 26, 2023, post-FOMC press conference, Fed Chair Powell stated, *“The SLOOS has been telling us for more than a year that banking conditions are tightening. That process is ongoing, and that will restrain economic growth.”* A few minutes later, he underscored the multidirectional (endogenous) nature of the effects when he pointed out that *“an expected result of tightening interest rate policy is that bank lending conditions would tighten as well.”* In this paper, we aim to better understand the role that changes in bank lending standards play in the U.S. economy, explicitly accounting for possible endogeneity.

There is, by now, broad agreement about the critical importance of financial markets for macroeconomic outcomes. Banks, in particular, play a consequential role in the provision of credit to the U.S. economy. Accordingly, the economic literature has dedicated considerable attention to how banking conditions affect aggregate economic activity (see, for example, [Bernanke, 1983](#) for a classic reference).

The banking sector remains a significant portion of the U.S. financial system. At the end of 2019, 15% of assets in the domestic financial sector were located on the balance sheets of U.S. chartered depository institutions, with the participation increasing to 40% when narrowing the calculation to the provision of loans to economic agents. While these proportions tend to be lower relative to other advanced economies, they are still very significant; for many businesses and households, banks are their primary and, often, exclusive source of funding.

How important for the aggregate economy are changes in the provision of bank credit? This is a challenging question to answer because lending depends on multiple factors. Furthermore, feedback effects are likely to play an important role, as suggested in the quotes by Fed Chair Powell above: not only do banks influence the economy, but also the state of economic activity and policy impact the way banks evaluate lending opportunities (see also [Brunnermeier et al., 2021](#)). Therefore, identifying how banks’ attitudes toward lending affect

the performance of the economy requires careful empirical analysis.

In this paper, following [Lown and Morgan \(2006\)](#) and [Bassett et al. \(2014\)](#), we use canonical time-series techniques to empirically study how changes in banks' lending standards affect economic activity, inflation, and interest rates. We make three main contributions to this literature: first, we take a more granular approach regarding data construction and analysis, and in that way, trace the origin of the main macro effects to the behavior of bank lending to businesses or households separately; second, we study whether the response of the economy depends on the stage of the business cycle, the level and proximity of interest rates to their effective lower bound, and the direction of change in banks' attitudes toward lending; third, we provide a more complete assessment of the relative value of using the micro data to assess the macro effects of changes in lending standards.

For several decades now, the Federal Reserve has been consistently collecting survey data about banks' attitudes with respect to lending. The Senior Loan Officers Opinion Survey on Bank Lending Practices, or SLOOS, is a quarterly survey that includes information on lending standards, loan terms, and loan demand, to businesses and households. The survey defines *lending standards* as the processes that banks follow for approving or denying loan applications. *Loan terms* are the specific conditions included in those loan contracts that have already been approved. Aside from credit spreads and fees, the terms of loans include covenants, collateral requirements, and credit and maturity limits. In that way, changes in lending standards tend to capture variations in the extensive margin of lending, while changes in loan terms are more closely related to the intensive margin. Information on *loan demand* in the SLOOS captures surveyed banks' perceived changes in the demand for loans by their customers.

In principle, banks could adjust the pricing of loans to manage their exposure. Within the context of imperfect information, however, it has been long understood that interest rates are not sufficient to optimize the lending decision ([Stiglitz and Weiss, 1981](#); [Williamson, 1987](#)). Indeed, banks use multiple levers in the process of adjusting their lending—with, for example, collateralization requirements such as loan-to-value ratios playing an important

role. We focus on the changes in lending standards required by banks to approve applications, a key tool in loan decision-making. In our empirical analysis, we include direct measures of interest rates and the risk premium, as commonly reported in economic data, instead of using the survey information about these variables (loan terms) included in the SLOOS.¹

More broadly, we are interested in understanding how changes in the supply of bank credit affect the macroeconomy. Because the supply of credit is likely to respond to many of the same factors that drive the demand for credit, and economic activity more generally, there is a risk of introducing omitted-variable bias when trying to identify the effects of changes in credit supply. Furthermore, causation may run both ways, from lending standards to economic conditions and from economic conditions to lending standards. To address these issues, we follow the literature in using multiple identification methods, which then allow us to compare the results and discern those that are most robust.

Conveniently, the SLOOS includes bank-level loan demand information that can be helpful in the process of sorting out demand and supply effects. We follow [Bassett et al. \(2014\)](#) and use that loan demand data to help us identify exogenous changes in lending standards (net of effects that can be attributed to common factors affecting both demand and supply of bank loans, including reactions to changes in economic conditions). These exogenous changes allow us to describe, using standard tools such as impulse response functions, how key macroeconomic variables in the U.S. are impacted by changes in the supply of bank credit. Ultimately, we are interested in assessing all direct and indirect effects of changes in bank credit on the economy. To disentangle those effects from other confounding factors, it is critical to identify exogenous changes to lending standards.

The first step in our empirical analysis involves the construction of diffusion indexes for bank lending standards and for bank loan demand. We also use cross-sectional data on bank lending standards and loan demand conditions from the SLOOS, combined with bank-level balance sheet data from the Call Reports, and several macroeconomic variables,

¹[Lown and Morgan \(2006\)](#) find that measures of the average loan interest rate charged by banks do not significantly increase explanatory power once lending standards have been taken into account.

to construct a time series of aggregate exogenous shocks to bank lending standards for each of the main loan categories, namely commercial and industrial loans, commercial real estate loans, residential mortgages, and consumer loans. In doing this, we closely follow the pioneering work of [Bassett et al. \(2014\)](#). One main advantage of creating this shock series is that it allows us to investigate contemporaneous effects of changes in lending standards on the macroeconomy. The shocks series are also helpful for uncovering some of the state-contingent effects, as we explain below.

Using U.S. data between 1996 and 2021, we perform two main empirical exercises to assess the impact of changes in bank lending standards on macroeconomic performance—as captured by output growth, interest rates, and inflation. First, we specify a small-scale vector autoregressive (VAR) model and discuss the corresponding impulse response functions and the forecast error variance decomposition. We consider both a measure of overall lending standards (as in [Bassett et al., 2014](#)), and, separately, for loans to households and to businesses. We find that a tightening of overall lending standards reduces real GDP growth in the two years after the shock, with a peak effect after one year. We see that bank lending quickly drops in the quarters after the shock, which suggests a transmission channel from lending standards, to bank lending, to GDP growth. To dig deeper into the mechanisms at play, we identify shocks to lending standards for businesses and for households separately and show that only the former has significant effects on GDP growth and bank lending. In that sense, the effects we associate with overall lending standards seem to reflect mainly changes in lending standards *to businesses*.

Our variance decomposition analysis confirms that business lending standards are three times more important than household lending standards for explaining the variance in real GDP growth. Business lending standards also account for an important portion of the variance of the federal funds rate, particularly at long time horizons. Additionally, we find significant feedback effects, where real GDP growth explains a significant portion of the variation in business lending standards, and less so of household lending standards.

To further understand what drives the effects of changes in lending standards on the

macroeconomy, we conduct a second exercise which allows for asymmetries in the responses, conditional on the state of the economy. Specifically, we use Threshold VARs (TVARs) to accommodate the possibility that effects depend on various states of the economy: (1) the state of the business cycle, as measured by the level of GDP relative to trend; (2) the level of the interest rate and its proximity to its effective zero lower bound; (3) whether the economy experiences a tightening or an easing shock to lending standards. We find that the effects of a tightening shock to standards are significant when GDP is below trend and when interest rates are away from their effective lower bound. It is also the case that only tightening lending standards have a clear-cut and significant effect on economic output, while the effect on inflation is more nuanced.

Overall, we conclude that lending standards tend to meaningfully affect bank lending and GDP growth, and these effects are mainly driven by the response of the economy to *tightening* in lending standards *to businesses* when the level of GDP is below trend and the interest rate is away from its effective lower bound. The effect on inflation is relatively muted, but we do observe a tendency of interest rates to move to accommodate (and counteract) the tightening in standards (by falling), but this is naturally most operative when the interest rate has room to fall (it is sufficiently away from the lower bound).

The rest of the paper is organized as follows. The next paragraphs provide a brief review of the literature, and Section 2 describes the data. Section 3 explains the construction of the diffusion indexes, how we use the cross-sectional data to produce a sequence of exogenous lending-standards shocks, and a description of the VAR specifications we use in the empirical exercises of the following sections. Section 4 studies how shocks to lending standards in the business and household sectors affect the macroeconomy, and Section 5 studies potential asymmetries of these effects. Section 6 investigates several robustness checks, and Section 7 concludes.

Related Literature: Our analysis builds on the work by [Lown and Morgan \(2006\)](#) and [Bassett et al. \(2014\)](#). The construction of bank lending standard indexes broadly follows [Bassett et al.](#)

(2014) but incorporates improvements introduced by [Glancy et al. \(2020\)](#) and used regularly at the Federal Reserve Board to increase the precision of the aggregate indicators of bank lending conditions.

Using SLOOS data, [Castro et al. \(2022b\)](#) study how lending standards affect bank lending behavior in the cross-section of banks.² They study C&I lending and find that a one-standard-deviation increase in their index (a tightening move) is associated with a 3.13 percentage point drop in C&I loan growth in the following year. An important distinction with our analysis is that they consider the impact of a move by a given bank to tighten credit conditions—relative to other banks in the same period (quarter). Here, instead, we focus on the effects in the macroeconomy of a *general* (across all banks) move to tighten bank lending standards (as in [Bassett et al., 2014](#), [Cavallo et al., 2024b](#), [Cavallo et al., 2024a](#) and others).

There is a closely related empirical and theoretical literature aimed at understanding the endogeneity of credit standards. Two recent examples are [Jimenez et al. \(2012\)](#) and [Swarbrick \(2023\)](#). Using data from the Spanish credit registry, [Jimenez et al. \(2012\)](#) study empirically how financial and economic conditions affect the willingness of banks to accept loan applications. They find that bank balance-sheet strength, in the form of liquidity and capital, play a meaningful role in that process.³ [Swarbrick \(2023\)](#) sets up a dynamic macroeconomic model where informational frictions introduce a role for probabilistic approval of loan applications. In the model, loan risk drives changes in lending standards and tend to amplify the effects of credit-risk shocks on economic activity. This is in line with evidence uncovered by [Castro et al. \(2022a\)](#) using SLOOS data for C&I lending, combined with indicators of loan performance. We share with these papers the ultimate objective of understanding the importance of bank credit for economic activity. Here, however, the main focus is on *exogenous shocks* to credit standards as a way to address the omitted-variables

²Instead of using only lending standards, these authors construct a summary index that reflects changes in both, lending standards and loan terms and conditions, as collected in the SLOOS.

³[Chodorow-Reich \(2014\)](#) also finds that firms' relationships with banks and the financial conditions of banks matter for understanding the flow of bank lending to firms in the U.S., specially smaller firms. See also [Baslandze et al. \(2023\)](#) for a recent estimate of the impact of credit supply shocks on net job creation by small and medium-sized firms.

problem and, in that way, disentangle the net impact that changes in bank credit supply can have on the economy.

There is also a large and growing empirical literature that uses bank, firm, and sometimes loan level data to study the importance of bank funding for economic activity (e.g., [Chodorow-Reich et al., 2022](#), [Ivashina et al., 2022](#), [Alfaro et al., 2021](#), [Jiménez et al., 2020](#)). Relative to our paper, this literature focuses on a more micro-oriented view of the possible mechanisms behind some of the macroeconomic effects identified in our study.

While our focus here will be on bank lending, there is an extensive literature studying the impact that the general supply of credit in the economy can have on macroeconomic outcomes. A good recent example of these efforts is [Gambetti and Musso \(2017\)](#). These authors estimate a structural time-varying VAR model with stochastic volatility using data for the U.S., U.K., and Europe. Instead of lending standards, as we use here, their data include loan volumes (not just from banks) and a measure of the average lending rate. This allows them to use a quarterly time series that goes back to 1980. Their identification strategy is also different than ours, as they use sign restrictions to identify various shocks according to predictions from theory. Similar to what we find here, [Gambetti and Musso \(2017\)](#) find that their identified credit supply shock impacts bank lending and GDP growth, although the responses they find for the U.S. are shorter-lived than the ones we estimate.

[Mumtaz et al. \(2018\)](#) refines the use of sign restrictions for identification and for understanding the impact of credit supply shocks on the macroeconomy. They also caution the interpretation of lending standard shocks as proxies for general credit supply shocks. In their study, using sign restrictions and the forecast error variance decomposition to identify a general credit supply shock in the structural VAR, they find that a shock that increases credit spreads by 10 basis points has a large and persistent negative impact on the economy, with credit growth declining by 0.8% and investment, consumption, and output growth all declining by meaningful amounts (2%, 0.4%, and 0.5%, respectively).

An important contribution to this broader empirical literature is the paper by [Barnichon et al. \(2022\)](#), which focuses on asymmetries in the response of the economy to positive and

negative financial shocks estimated using corporate bond prices. Specifically, these authors allow the empirical model to respond differently to favorable and unfavorable financial shocks and find that the latter have stronger and more persistent effects on the economy than the former. Our results are consistent with their findings in that our threshold VARs, by breaking the linearity in the standard specification, allow us to confirm that tightening shocks to lending standards are a lot more consequential for GDP growth than easing shocks.⁴

2 The Data

Our measure of lending standards comes from the SLOOS. The Federal Reserve conducts this quarterly survey with the purpose of monitoring lending conditions in the banking sector. The survey has been in place, in different forms, since 1964. However, for the purpose of this paper, we restrict attention to the period between 1996 and 2021, for which the data is available at the level of disaggregation that we are interested in exploiting here.

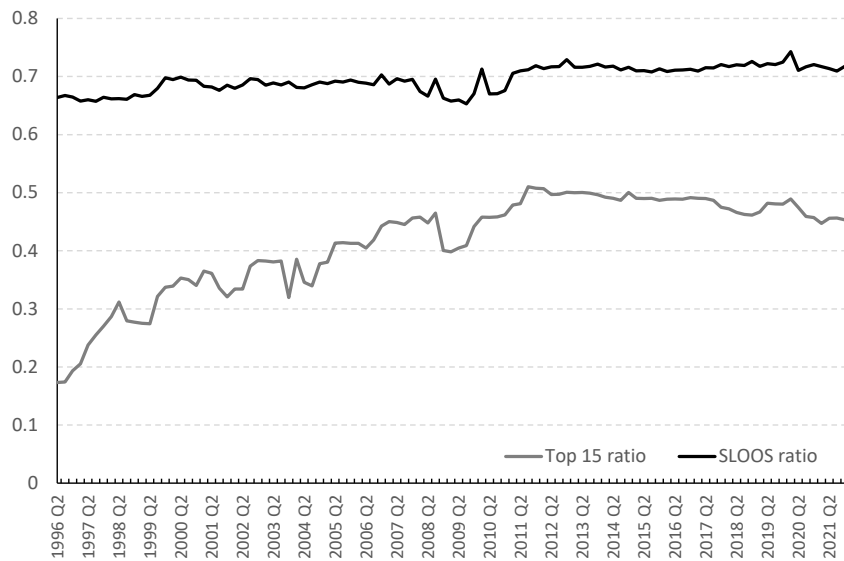
The SLOOS panel consists of a sample of up to 80 U.S. domestic commercial banks selected to be geographically diverse, mutually independent, and representative of a high proportion of lending volumes in each of the major bank lending areas.⁵ At the end of our sample period, in the fourth quarter of 2021, approximately 75 percent of assets in domestically chartered commercial banks were accounted for by SLOOS respondents, and each participating bank held at least two billion dollars in total assets. While bank participation is voluntary, response bias is unlikely to be a major limitation of the SLOOS as banks invited to join the panel nearly always agree to participate and, once included, consistently complete the survey.

As seen in Figure 1, the SLOOS sample of domestic commercial banks covers roughly

⁴Another set of papers in this general body of work dedicated to studying credit supply shocks is the one that exploits structural theoretical models to quantify the role of financial frictions and shocks on U.S. macroeconomic performance. A recent example is [Ajello \(2016\)](#).

⁵The SLOOS survey also contains information from U.S. branches and agencies of foreign banks. Following the previous literature, we do not include those responses in the main portion of our investigation.

Figure 1: Ratio of total loans in SLOOS banks and the banking system.



Note: The black line corresponds to the ratio of total loans in domestic commercial banks surveyed in the SLOOS and total loans in all domestic commercial banks. The gray line is the ratio of loans in the top 15 largest banks (by assets) in the SLOOS and total loans in all SLOOS banks.

70 percent of all the loans in domestic commercial banks in the U.S. This ratio has been consistently at that level since the beginning of our sample period. We also compute the share of loans in the SLOOS banks that is accounted for by the top 15 banks by assets. This share increased steadily in the first half of our sample period but has been relatively stable at around 50 percent since the end of the global financial crisis. This pattern is consistent with the more general consolidation trends in the U.S. banking system, with the largest banks gaining share during the 2000s and levelling off during the 2010s (McCord and Prescott, 2014).

The SLOOS survey asks participating banks to report changes to lending standards during the survey period by category of loans using the following general template:

“Over the past three months, have your bank’s credit standards for loans in category k changed?”

Banks answer these questions subjectively using a scale from 1 to 5, with lower num-

bers indicating movement in the direction of tightening lending standards, and higher numbers corresponding to easing. The middle of the scale indicates that standards remain mostly unchanged over the survey period. Because banks rarely characterize changes in standards using the most extreme labels on either end, we define categorical variables for each loan category k as follows:

$$I_{it}[k] = \begin{cases} -1 & \text{if bank } i \text{ reported easing standards for category } k \text{ in quarter } t \\ 0 & \text{if bank } i \text{ reported no change in standards for category } k \text{ in quarter } t \\ 1 & \text{if bank } i \text{ reported tightening standards for category } k \text{ in quarter } t \end{cases}$$

Note that, relative to the survey, this definition effectively inverts the scaling so that increases in the lending standards index will indicate tightening. This inversion is mainly done for expositional reasons, following the previous literature.

Table 1 provides a list of the categories k under consideration. Each category belongs to one of four main groups of loan categories in the SLOOS data: C&I, CRE, Consumer Credit, and RRE.

To construct the corresponding weights for each category, for each bank, we use loan data from the Call Reports, which are collected quarterly for supervisory purposes. We also use call report data to construct an adjusted series for lending standards, as we explain below. The variables involved in the adjustment of standards are described in the appendix.

For the estimation of our medium-size macroeconomic VARs, we use standard variables such as real GDP growth, unemployment, inflation, and the real federal funds rate. In some cases, following [Bassett et al. \(2014\)](#), we also include a measure of the credit spread developed by [Gilchrist and Zakrajšek \(2012\)](#) (GZ) and a measure of growth of core lending capacity for the banking system.⁶

Figure 2 shows the macroeconomic variables, aside from the lending standard indexes,

⁶Core lending capacity is computed as the sum of core loans outstanding and the corresponding unused commitments. We use annualized quarter-over-quarter changes of real GDP and core lending capacity, while realized inflation is the year-over-year percent change in core PCE.

Table 1: Data Information: Loan Categories and groups

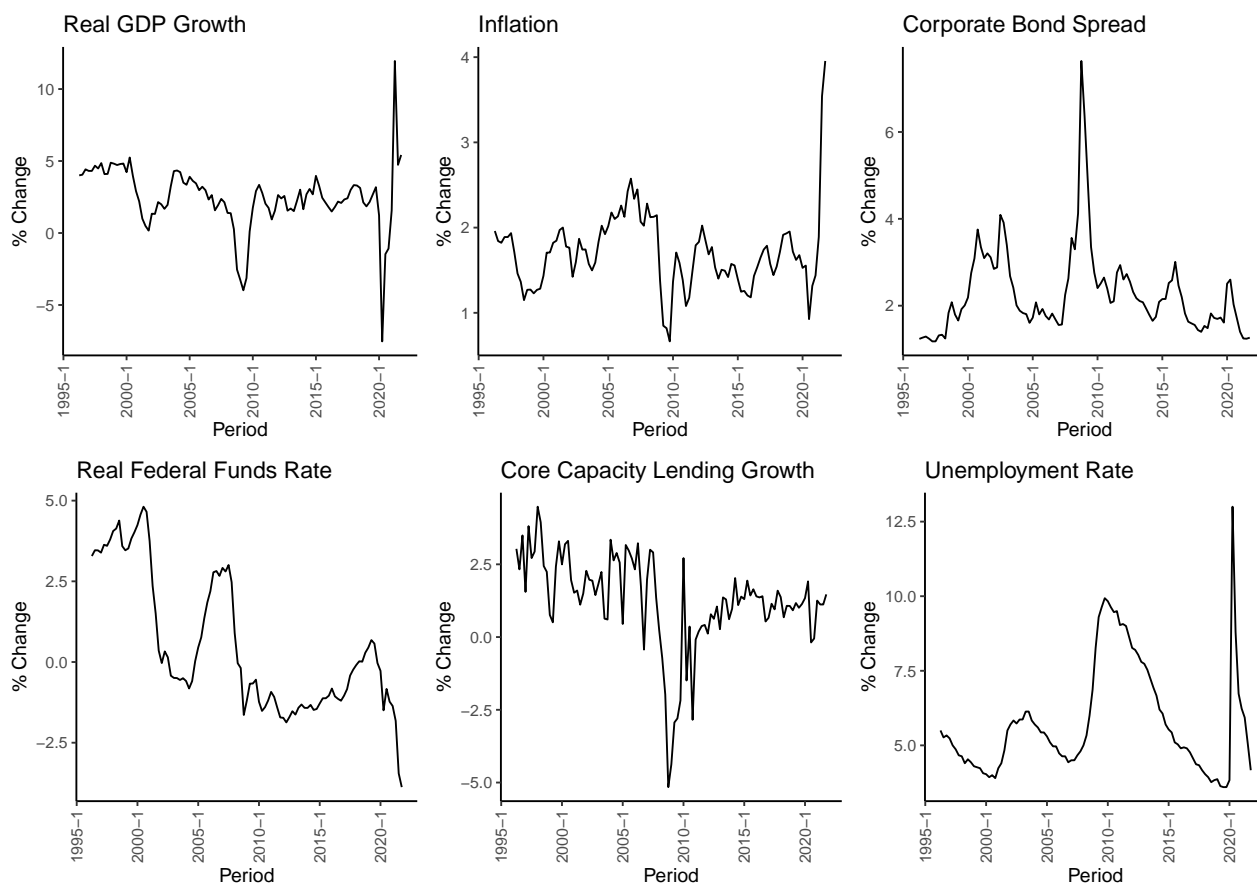
	Our Sample Period
C&I	
Large C&I	1996 Q1 - 2021 Q4
Small C&I	1996 Q1 - 2021 Q4
CRE	
All	1996 Q1 - 2013 Q3
Construction & Land Development	2013 Q3 - 2021 Q4
Non-Farm/Non-Residential	2013 Q3 - 2021 Q4
Multifamily	2013 Q3 - 2021 Q4
RRE	
All Residential Mortgage Loans	1996 Q1 - 2014 Q4
GSE-eligible Mortgages	2015 Q1 - 2021 Q4
Jumbo Qualified Mortgages	2015 Q1 - 2021 Q4
Non-Jumbo Qualified Mortgages	2015 Q1 - 2021 Q4
CONS	
Credit Card	1996 Q1 - 2021 Q4
Consumer excluding Credit Cards	1996 Q1 - 2011 Q1
Auto Loans	2011 Q2 - 2021 Q4
Consumer excluding Credit Card and Auto	2011 Q2 - 2021 Q4

Notes: The level of aggregation in the SLOOS data changed over time. The table provides the categories available and the time periods when they are available within our sample period. As in the text, the loan categories are organized by groups: commercial and industrial (C&I), commercial real estate (CRE), residential real estate (RRE), and consumer loans (CONS). Between 2007 and 2015, the SLOOS collected information for different categories of residential mortgages, but limitations on the bank balance-sheet information does not allow us to fully exploit that level of desegregation.

used in our VARs. The COVID shock in 2020:Q1 is clearly an outlier in macroeconomic terms. For this reason, for our benchmark cases, we estimate the model using data up to 2019:Q4. Alternatively, we could deal with the COVID period by implementing the volatility correction proposed by [Lenza and Primiceri \(2020\)](#). However, as these authors explain, if inference is the sole goal of the VAR estimation—as it is in our study—then simply excluding the COVID shock from the sample will have the same effect as their solution approach, while introducing less noise. In the robustness section, we present the estimation including the COVID period and discuss the impact on our results.⁷

⁷We also use the [Lenza and Primiceri \(2020\)](#) correction and find our results to be qualitatively robust to

Figure 2: Macroeconomic data used in VARs



Notes: Data are quarterly from 1996:Q1 through 2021:Q4. Realized inflation is the year-over-year percent change in core PCE. Real GDP growth and core lending capacity are presented as annualized quarter-over-quarter changes. All data are shown in percent. Shaded areas indicate recession periods as dated by the National Bureau of Economic Research.

Sources: Real GDP growth and core PCE are from the U.S. Bureau of Economic Analysis; the unemployment rate is from the U.S. Bureau of Labor Statistics; the GZ spread is from the Federal Reserve Board; and the real federal funds rate and core lending capacity are based on data from the Federal Reserve Board and authors' calculations.

Before we describe the empirical design, it is worth highlighting a few differences with the data used in [Bassett et al. \(2014\)](#), which we otherwise intend to replicate and extend. First, our sample period starts in 1996:Q1, instead of 1991:Q4, and goes all the way to 2021:Q4, instead of only until 2012:Q3, as it does in [Bassett et al. \(2014\)](#). The specific questions about standards for consumer lending are available beginning in 1996:Q1, which including and correcting for the COVID shock.

is why our sample period starts after 1991. Furthermore, as is clear from Table 1, the level of disaggregation by categories within the main groups of loans in the SLOOS data only becomes significant later in the period. Given that we add many more years at the end of the sample period, and to the extent that the methodology pursued here—and in [Bassett et al. \(2014\)](#)—is intended to exploit such disaggregation, it makes sense to start the sample period for this study later, in 1996.

Another relevant difference with the data employed in [Bassett et al. \(2014\)](#) is that we use responses by all the banks in the survey instead of restricting to banks that are publicly traded. As a result, we are not able to use stock valuations in our study, and we instead use profitability measures that are available for all banks in the sample. As part of the robustness exercises in Section 6, we restrict our sample to the group of largest banks (all of them publicly traded), and show that results are similar in that case.

3 Lending Standards and Their Effects

The first step in our empirical strategy is to construct an aggregate index of the state of lending standards in the banking system. For this, we use the responses of individual banks appropriately weighted by the proportion of total bank lending that they hold in their respective balance sheets.

We are interested in assessing how changes in lending standards affect economic outcomes. However, the index of bank lending standards we construct is likely affected by conditions in the economy, the demand for bank lending, and other various factors (such as general perceptions of risk in financial markets), creating endogeneity issues. Our next step involves addressing these issues.

Generally speaking, we need to isolate exogenous fluctuation (shocks) to lending standards that are not just reflecting the response to other forces driving bank lending, such as changes of the aggregate demand for credit in the economy. One traditional way to deal with this problem in macroeconomics is to use a VAR, which combined with minimal

structural assumptions, extracts shocks to the variables of interest. We call this the “macro approach” (pioneered by [Lown and Morgan, 2006](#) in the context). The relative simplicity of this method comes with some costs. In particular, disciplining the selection of identifying assumptions is a complicated matter, with no unique correct answer ([Ramey, 2016](#)). In some cases, those assumptions meaningfully restrict the possibilities that can be accommodated to better explain the data.

More recently, [Bassett et al. \(2014\)](#) propose an innovative approach that combines a VAR with an initial process of adjustment to the index of lending standards using individual-bank level data. We refer to that way of adjusting for endogeneity as the “micro approach” (see Subsection 3.2). An advantage of this approach is to allow the researcher to consider the possibility that exogenous changes in lending standards may affect the macroeconomy contemporaneously when specifying the macro VAR model.

For running our macro VARs, we follow [Lown and Morgan \(2006\)](#) and [Bassett et al. \(2014\)](#) and impose minimal structural assumptions during the estimation process by using a standard Cholesky decomposition on the residuals’ variance-covariance matrix to discipline the contemporaneous impact of shocks.⁸

3.1 Constructing the Lending Standards Index

The first step in our empirical strategy is to build indexes of changes in lending standards for different groups of categories and for the composite of overall bank lending activity. By taking advantage of the granular data in the construction of these indexes, we weight each bank’s response by that bank’s lending volume in each corresponding category ([Glancy et al., 2020](#)). This weighting approach allows us to capture more accurately the extent to which

⁸[Mumtaz et al. \(2018\)](#) find that using sign restrictions result in stable and realistic VAR estimations when studying credit supply shocks—based on Monte Carlo experiments. However, sign restrictions only lead to set identification, and these sets can be quite wide, even when robust and agnostic priors are used (see e.g., [Baumeister and Hamilton, 2015](#)). [Mumtaz et al. \(2018\)](#)—in the spirit of [Uhlig \(2004\)](#) and [Kilian and Murphy \(2012\)](#)—also test a specification where they choose an impact matrix that maximizes the contribution of credit supply shocks to the forecast error variance. Since analyzing the relative importance of different lending standard shocks is a key aspect of our study, we forgo this approach and take a narrower interpretation of the shocks (not as proxies for general credit supply shocks, which is the perspective taken in [Mumtaz et al., 2018](#)).

each reported change in standards affects the total bank-lending activity in the economy.⁹

Based on these indexes for each category, we compute the change in lending standards for the group c of categories as the weighted average:

$$\Delta S_{cit} = \sum_{k \in c} w_{c,i,t-1}(k) * I_{c,i,t}(k), \quad (1)$$

where $w_{c,i,t-1}(k)$ is the fraction of bank i 's credit portfolio on group c that is accounted for by loans in category k , with $k \in c$, according to the call report of bank i at the end of quarter $t-1$. Weighting by category is necessary for constructing our indexes because each category has its own SLOOS questions. To construct the overall lending-standards index, we aggregate across groups using the same weighting approach.

Each of these indexes is a diffusion index that takes continuous values between negative 1 and 1 and can be interpreted as the net proportion of type- c loans in bank i 's balance sheet for which the bank reported tighter lending standards.

We then aggregate indexes across banks using the same loan-based weighting approach:

$$\Delta S_{ct} = \sum_{i \in c} w_{c,i,t-1} * \Delta S_{cit}, \quad (2)$$

where $w_{c,i,t-1}$ is the fraction of total loans on SLOOS respondents' balance sheets that are held by bank i in all the categories in group c at the end of quarter $t-1$. Figure 3 plots in black ΔS_{ct} for each of the four major groups of loan categories. For each group of lending category, the plots line up well with qualitative accounts of credit conditions during the sample period and highlight that the Global Financial Crisis of 2007-2009 (GFC) was preceded by a substantial tightening of lending standards for real estate lending, which was then followed by tightening in other loan categories.

⁹For each group of categories, except for RRE, the weights are computed using the lending of each bank in each lending category. The call report data does not include the set of categories for RRE that would be consistent with the SLOOS data, so we follow Glancy et al. (2020) in approximating fixed weights across all banks and only using the categories with significant weights. Also, as in Glancy et al. (2020), we exclude home equity lines of credit from the calculations of the residential real estate index.

3.2 A Micro Approach to Endogeneity

To adjust for the endogeneity in lending standards, the "micro approach" uses a dynamic fixed effects regression for the cross-section of banks in the SLOOS dataset. The regression also includes some aggregate and bank-specific factors that may be affecting loan demand. The SLOOS data includes (confidential) bank level information on the perceived evolution of demand for loans in a given quarter. The change in the assessment of loan demand conditions in category c by each bank i at time t , denoted ΔD_{cit} , is also used as a control in the adjustment regression.¹⁰

Specifically, we regress ΔS_{cit} on a set of relevant aggregate and bank-specific variables as follows:

$$\Delta S_{cit} = \beta_1 \Delta S_{ci,t-1} + \beta_2 \Delta D_{cit} + \lambda_1' E_{t-1} [m_{t+4} - m_t] + \lambda_2' * f_t + \theta' Z_{i,t-1} + \phi_i + \epsilon_{cit}, \quad (3)$$

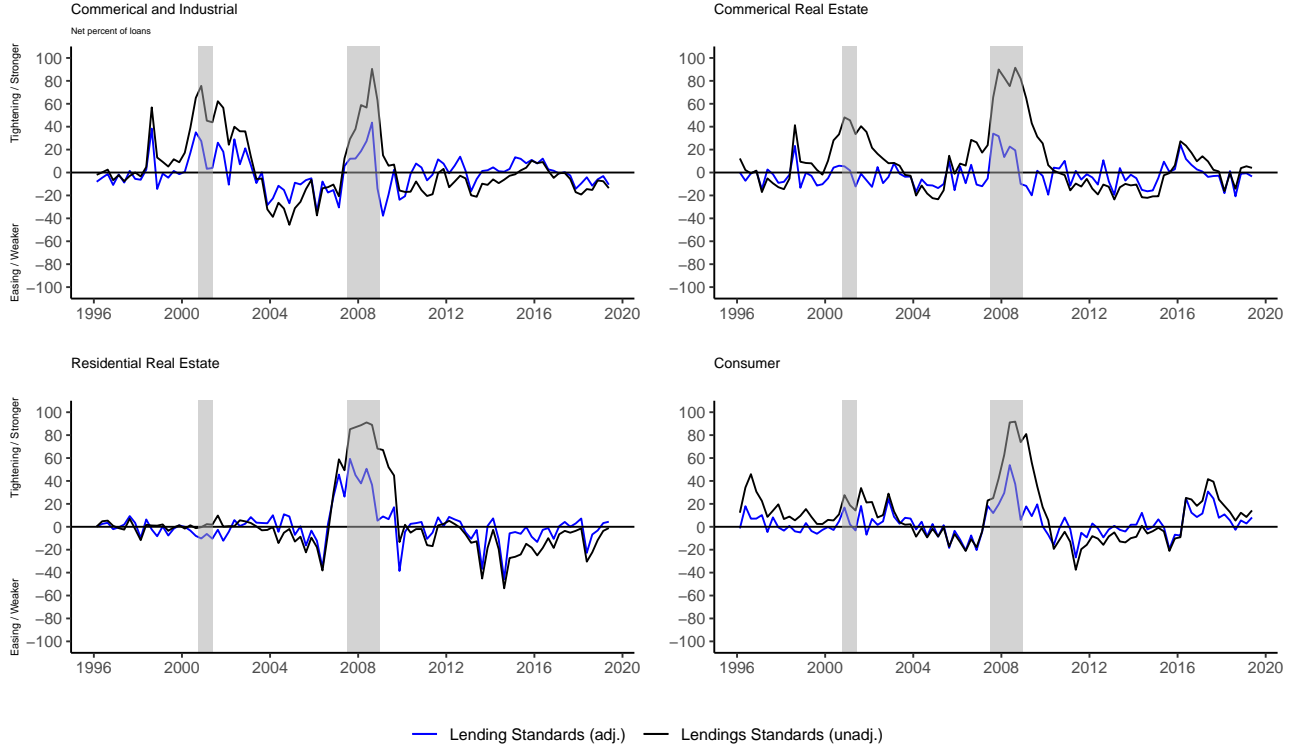
where m_t is a vector of macroeconomic variables, f_t is a vector of variables characterizing risk attitudes, and Z_{it} is a vector of bank-specific controls. Table 6 in Section 6.4 includes the regression results for the case of overall (i.e., across all categories) lending standards, where the dependent variable is ΔS_{it} . We provide a detailed description of the variables used as controls in the appendix.

Changes in bank lending tend to persist for multiple quarters as seen in the black lines in Figure 3. By including a lagged version of the dependent variable and bank fixed effects ($\phi_i, i = 1, \dots, N$), we control for this cyclical momentum as well as any time-invariant factors at the individual bank level that may affect the way SLOOS respondents report changes in their credit policies.

For our benchmark calculations, we restrict the sample period to exclude the COVID period in the estimation of these micro-based adjustments. We want to avoid the possibility that the coefficients in regression (3) become overly influenced by outlier observations that

¹⁰We construct the bank-level demand indexes following the same steps as in the construction of the lending standards indexes.

Figure 3: Adjusted and unadjusted lending standards by group of categories



Notes: Sample period is from 1996:Q1 to 2019:Q4. Shaded areas indicate recession periods as dated by the National Bureau of Economic Research.

Sources: Federal Reserve Board Senior Loan Officer Opinion Survey on Bank Lending Practices; Consolidated Reports of Condition and Income, FFIEC 031/041/051

occurred during the onset of the pandemic. We revisit this issue in the robustness section. With the regression results on hand, we appropriately weight the estimated residuals ϵ_{cit} to create a measure of changes in bank lending standards that is purged from contemporaneous macroeconomic and bank-specific factors, including perceived changes in loan demand. In particular, we have:

$$\Delta S_{c,t}^a = \sum_i^{N_{ct}} w_{c,i,t-1} * \hat{\epsilon}_{cit}, \quad (4)$$

where N_{ct} is the number of respondent banks in quarter t answering questions about a loan category in group c , and $w_{c,i,t-1}$ is the ratio of loans in all categories of group c at bank i relative to the total lending in group c for the full sample of respondent banks, measured at the end of the previous quarter.

The series of *adjusted* lending standards for each broad group of loan categories is plotted in blue in the four panels of Figure 3. Adjusted lending standards suggests that credit supply tightens for consumers and business as the economy nears or enters a recession. This pattern is more visible for real estate during the GFC but less evident in the 2001 recession. In turn, credit eases again late in the recession or early in the expansion. Interestingly, we also see that credit supply tightened noticeably early in RRE as the economy approached the GFC, which seems consistent with events at the time.

Our adjusted lending standards indicators are constructed in a similar way (although not exactly the same) as the one used by Bassett et al. (2014) in their VAR framework. Because this measure is already purged from the influence of factors that may also be simultaneously affecting the demand for credit, it can be introduced first in the ordering within the VAR. In other words, these previously identified shocks to the supply of bank credit can be used to capture their contemporaneous impact on other macroeconomic variables, importantly including GDP.

3.3 A Macro Approach to Endogeneity

As we are mainly interested in the impact of changes in lending standards on the aggregate economy, it seems reasonable to contemplate using the VAR estimation to directly control for some of the endogeneity in lending standards. Does this traditional approach produce comparable results to the micro approach? Indeed, Bassett et al. (2014) compare their novel approach with an alternative obtained by estimating a VAR using the unadjusted index of lending standards and other macro variables.

Some of the macroeconomic variables used by Bassett et al. (2014) to adjust standards in the micro approach do not appear in their VAR macro approach alternative. Two of these variables, namely the unemployment rate and the diffusion index of loan demand obtained from the SLOOS data, seem particularly relevant. As these variables are used in the micro approach to address endogeneity, a more accurate comparative assessment with the macro

approaches requires that we also include those variables in the VAR that uses unadjusted lending standards.

To compute the index for aggregate credit demand conditions (ΔD_t), we proceed the same way that we computed the aggregate for lending standards in equation (2). Using this approach, we can also construct indexes for lending standards and credit demand across all groups of categories by taking a weighted average of the index for each group, using the ratio of loans in each group relative to total loans in all groups as weights.

To assess the relative performance of the micro and macro approach to endogeneity, we consider three alternative estimations in expression (5): a VAR using adjusted lending standards (Alternative 1); the version of the VAR with unadjusted lending standards considered by [Bassett et al. \(2014\)](#) (Alternative 2); and a VAR that includes unadjusted lending standards and the other variables in Alternative 2 plus two additional macro variables: unemployment and the index of credit demand (Alternative 3).

$$\mathbf{Y}_t^1 = \begin{bmatrix} \Delta S_t^a \\ \Delta GDP_t \\ \Delta CoreCapacity_t \\ \pi_t \\ GZSpread_t \\ RealFedFunds_t \end{bmatrix} \quad \mathbf{Y}_t^2 = \begin{bmatrix} \Delta GDP_t \\ \Delta CoreCapacity_t \\ \pi_t \\ GZSpread_t \\ RealFedFunds_t \\ \Delta S_t \end{bmatrix} \quad \mathbf{Y}_t^3 = \begin{bmatrix} \Delta GDP_t \\ Unemp_t \\ \Delta D_t \\ \Delta CoreCapacity_t \\ \pi_t \\ GZSpread_t \\ RealFedFunds_t \\ \Delta S_t \end{bmatrix} \quad (5)$$

Alternative 1
Alternative 2
Alternative 3

In Alternative 1, the change in adjusted lending standards appears first in the order of the VAR. The presumption is that *adjusted* lending standards have already been purged from any endogenous component, leaving only the exogenous shock to standards, which is not affected contemporaneously by any of the other variables in the VAR.¹¹ In alternatives 2 and

¹¹Ordering the exogenous shocks to lending standards first in the system is analogous to estimating the

3, instead, *unadjusted* lending standards appear last in the order of the VAR. The idea here is that we intend to extract from the changes in lending standards any contemporaneous (endogenous) impact that other macro variables might have on the behaviour of banks. For that reason, having unadjusted lending standards last in the order of the VAR is the most conservative approach to extracting all endogeneity in the process of identifying an exogenous shock to standards.

Given that the main interest here is on the effect of changes in bank lending standards on the macroeconomy, the order of the other macro variables is not critical for the results. Our ordering generally follows the previous literature. We discuss alternative orderings in the robustness section.

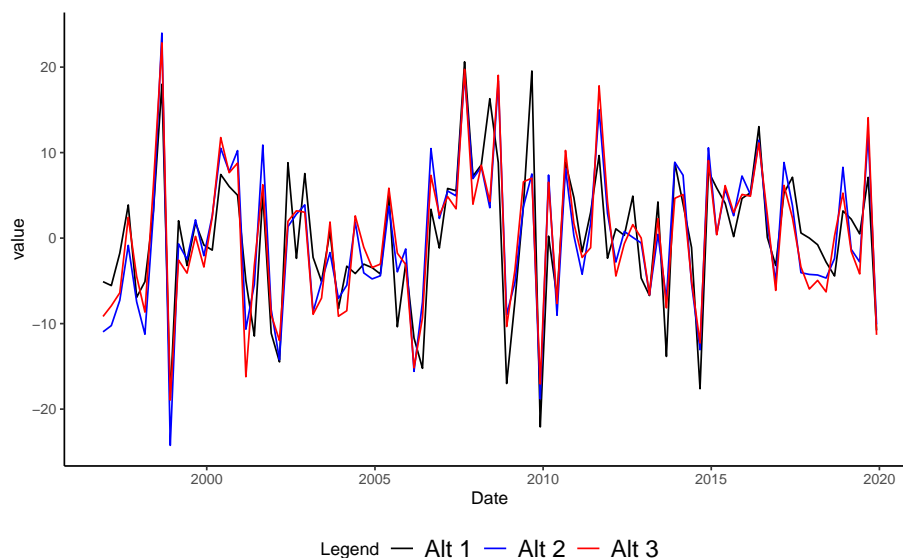
3.4 Overall Lending Standards and the Macroeconomy

In this section, we present and compare the results from estimating the three different alternatives described in expression (5). We use the index of lending standards aggregated across all banks and all categories, which we call the index of “overall” lending standards. The sample period excludes the COVID event and hence goes from 1996:Q1 until 2019:Q4.

Figure 4 plots the sequence of shocks to overall lending standards extracted by using each of the three alternatives. It seems evident from the figure that the identified shocks are very similar to each other. Our expectation was that including additional variables in Alternative 3 would bring the residual closer to that from Alternative 1, since those additional variables played a role in extracting the shock in Alternative 1 but not in Alternative 2. In other words, the residual from Alternative 3 should predominantly lie between alternatives 1 and 2. While this is happening for many periods, it is not uniformly the case.

To complement the figure, Table 2 presents the correlation between the residuals from the three alternatives. The shocks extracted using alternatives 2 and 3 are very similar, and the residuals from Alternative 2 are actually slightly more correlated with the residuals from Alternative 1. The main takeaway from this table is that the extra information used in VAR as a proxy-SVAR or IV-VAR (Plagborg-Møller and Wolf, 2021).

Figure 4: Residuals from the alternative models



Notes: The black line corresponds to the residuals for adjusted lending standards in Alt 1 of the VARs. The blue line is the residuals for unadjusted lending standards for Alt 2 and 3, respectively. The sample period is from 1996:Q1 to 2019:Q4.

Alternative 3 does not make a considerable difference in the signal extraction process. In other words, aggregate loan demand and the unemployment rate do not seem to affect the lending standards index in any significant way.

Table 2: Correlations of residuals from alternatives 1, 2, 3 and overall adjusted standards

	Alternative 1	Alternative 2	Alternative 3
Alternative 1	1		
Alternative 2	0.859	1	
Alternative 3	0.843	0.971	1
ΔS_t^a	0.795	0.674	0.670

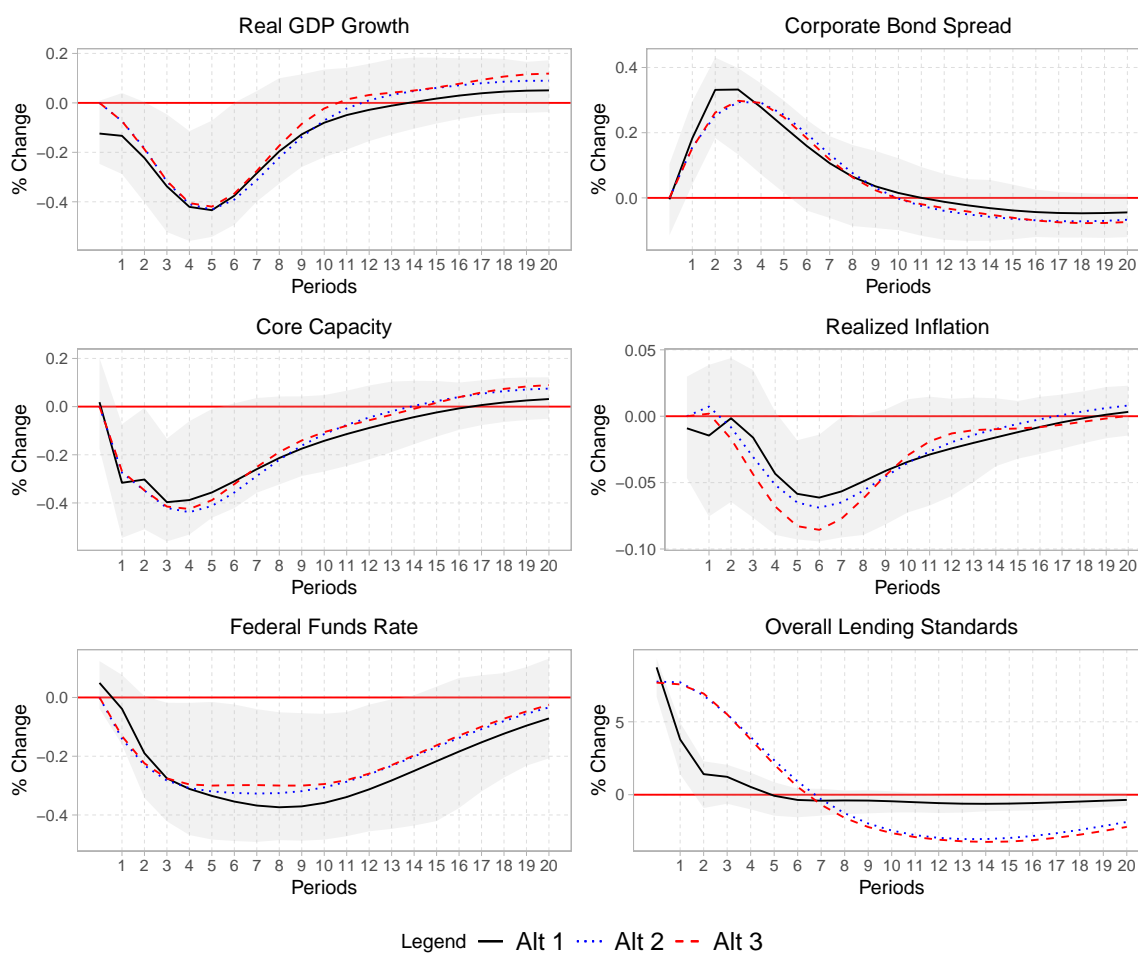
Note: Sample period is from 1996:Q1 to 2019:Q4.

We now study the impulse responses to shocks in overall lending standards corresponding to each of the three alternative VARs in expression (5). As Figure 5 shows, when overall lending standards tighten, output growth falls for a year and only recovers ten to twelve quarters after the shock. All three estimation methods produce similar responses, with

Alternative 1 showing an immediate impact on output that cannot be accommodated by the other two alternatives, by assumption. The impulse response for core lending capacity suggests the transmission channel for the shock, with bank lending falling abruptly after the lending standards shock, which gets reflected in output after two or three quarters.

Similarly, inflation and interest rates respond in the standard way, given the fall in output growth. But it is worth highlighting that the effect on inflation of a tightening in the supply of credit by banks is relatively subdued. Corporate bond spreads, on the other hand, widen noticeably as bank lending tightens.

Figure 5: Orthogonal impulse response functions: Shock to overall lending standards



Notes: The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on alternative 1 (in black). Alternative 1 uses a 1 SD shock to ΔS_t^a , and alternatives 2 and 3 use a 1 SD to ΔS_t . All models are estimated using 2 lags. The sample period is 1996:Q2 to 2019:Q4.

The inclusion of core bank lending capacity makes virtually no difference for the estimation of the impulse responses of output, inflation, and the interest rate (see the figure in the appendix). Including it, however, allows us to gain some insight into the mechanics of the propagation of the shocks.

The bottom panel of the figure shows that fluctuations in lending standards display considerable persistence (with shocks dissipating only after six or seven quarters—blue and red lines in the figure). It is also useful to see that our measure of shocks to lending standards obtained using the micro adjustment approach (and used to estimate Alternative 1, the black line in the figure) has, as expected, little-to-no persistence, which suggests that the micro adjustment does a good job isolating the shock component of lending standards.

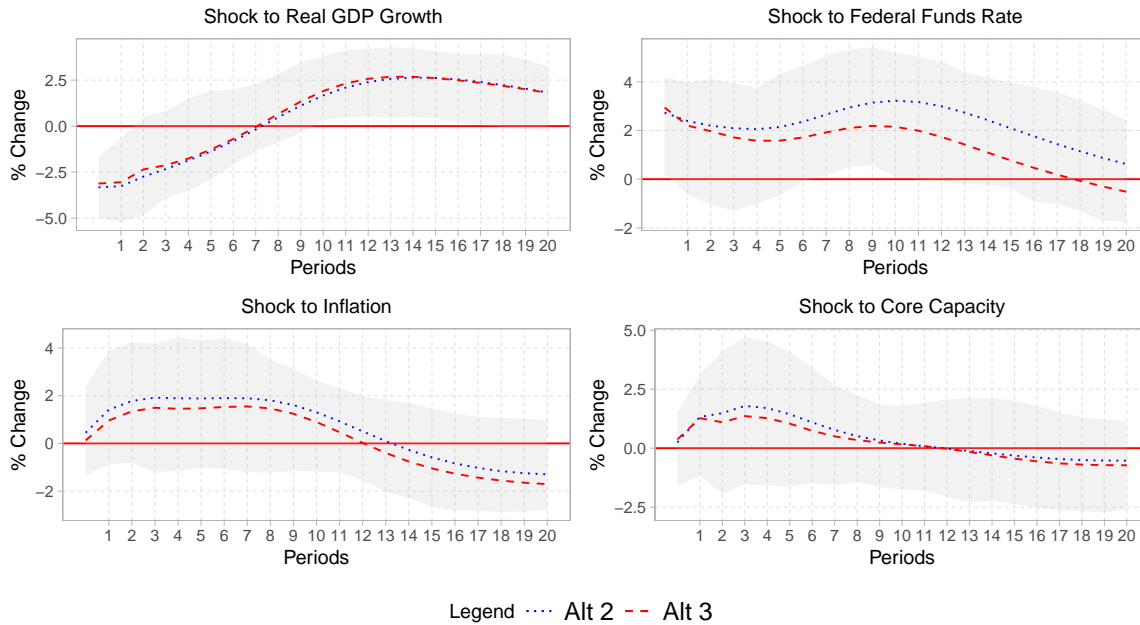
With the estimation under Alternative 3, we also obtain an impulse response for unemployment and loan demand (see the appendix). As expected, unemployment increases as output growth falls. Loan demand (as perceived by banks) falls after the shock to standards, but the response is relatively mild. Interestingly, demand actually recovers and becomes positive after ten quarters, when the effect on output of the shock is almost fully dissipated.

It is also clear from Figure 5 that all three alternatives produce very similar impulse response functions. Aside from the contemporaneous effect on output estimated under Alternative 1 (which is not statistically significant), the rest of the effects are basically the same across alternatives. One interpretation of these results is that the micro adjustment does not produce significantly different outcomes when it comes to understanding the macroeconomic effects of changes in lending standards. As we explain in the appendix, since for macroeconomic purposes we aggregate lending standards (adjusted or not), the process of aggregation tends to minimize the role of the idiosyncratic cross-sectional variation removed by the micro approach. As a result, the *aggregated* unadjusted lending standards capture very similar macroeconomic consequences to the adjusted ones.

3.5 Other Shocks' Impact on Overall Lending Standards

Our VARs also produce estimates for the effects of shocks to other variables on the macroeconomy and, importantly, on the evolution of lending standards. Figure 6 plots the impulse response functions for lending standards; one panel for each of the main macro shocks: (1) output growth, (2) interest rates, (3) inflation, and (4) core lending capacity. Note that in this figure, we do not plot the impulse response under Alternative 1 since lending standards in that case are represented by the (exogenous) shock to lending standards which results, by design, in no systematic response to other macro shocks.

Figure 6: *Impact of other shocks on overall lending standards*



Notes: The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on alternative 2 (in blue). All models are estimated using 2 lags. The sample period is 1996:Q2 to 2019:Q4.

A shock to output growth tends to ease lending standards on impact, but lending standards revert back after about a year and begin to tighten after seven quarters. Shocks to the real rate of interest and the inflation rate both induce a persistent tightening of lending standards. It is not surprising that banks tend to tighten lending standards when interest rates increase, as it becomes harder for creditors to repay their debts. Regarding the inflation

shock, as it turns out, the identified shock driving an increase in inflation also results in a drop of output growth and a drop in interest rates. These responses suggest that aggregate supply shifts are behind those inflation shocks and that the central bank accommodates them with a drop in interest rates. The combination of all these effects initially push lending standards to tighten (although the effect is not significant and starts reverting after a few quarters).

[Lown and Morgan \(2006\)](#) emphasize that, in their data, innovations to the amount of lending done by banks eventually translate into a tightening of lending standards. They interpret this as an indication of credit cycle dynamics, where there are feedback effects from standards to loans and back to standards. A loosening in lending standards increases lending (as implied by [Figure 5](#)), but eventually the increase in lending triggers an adjustment toward tighter lending standards.

The findings in [Figure 6](#) are consistent with the credit-cycle interpretation. A positive shock to output growth, for example, tends to initially drive banks to loosen lending standards but after about a year and a half, standards start tightening. Similarly, a shock to core lending capacity (bottom-right panel) tends to induce a persistent tightening in lending standards.

4 Lending Standards for Businesses and Households

We now turn to gaining a deeper understanding of the impact of shocks to lending standards on the macroeconomy. In principle, we could proceed by estimating the effect of changes in lending standards separately for each of the four main groups of loan categories. However, [Table 3](#) suggests a possible further grouping of these categories. Given that C&I and CRE are highly correlated and the correlation of consumer loans and RRE is relatively high as well, particularly for the micro-adjusted data (second panel in the table), we adopt two supra-groups: lending to business (C&I and CRE) and to households (CONS and RRE).

It is interesting to observe that the correlation of unadjusted lending standards among

Table 3: *Correlations of lending standards between groups of categories*

For ΔS_{ct}	C&I	RRE	CRE	CONS
C&I	1			
RRE	0.505	1		
CRE	0.768	0.766	1	
CONS	0.588	0.694	0.701	1

For ΔS_{ct}^a	C&I	RRE	CRE	CONS
C&I	1			
RRE	0.160	1		
CRE	0.553	0.383	1	
CONS	0.311	0.449	0.262	1

Note: Sample period is from 1996:Q1 to 2019:Q4.

the two real estate groups of categories is relatively high, but falls considerably for the adjusted series. This suggests that the high correlation in standards across real estate categories is driven in non-trivial ways by endogenous factors (the response of standards to common macroeconomic factors). Since all our estimation alternatives intend to control for endogeneity, the relevant correlation to consider for grouping categories is the one that abstracts from this endogeneity. Our choice of supra-groups of categories is consistent with this logic.

In the robustness section, we include an analysis of each of the four groups of categories separately. That analysis, in fact, provides further support for grouping categories the way we do here, which translates into a valuable gain of parsimony without any significant loss. [Glancy et al. \(2020\)](#) also adopt this form of aggregation as a productive way to summarize the data.

To adjust lending standards at the supra-groups level, we run a separate panel regression for each of the two supra-groups, following the same approach as in expression (3). Figure 7 plots the unadjusted and the adjusted time series of the index of lending standards.

Standards tightened during recessions, and it is clear from the figure that during those times, endogeneity plays a meaningful role in driving the lending standard decisions of banks. Interestingly, for the 2008 recession both lending standards, for business and for households, tightened in comparable ways. The effect on business lending of the 2001 recession appears particularly strong.

Figure 7: *Unadjusted and adjusted lending standards for supra-groups*



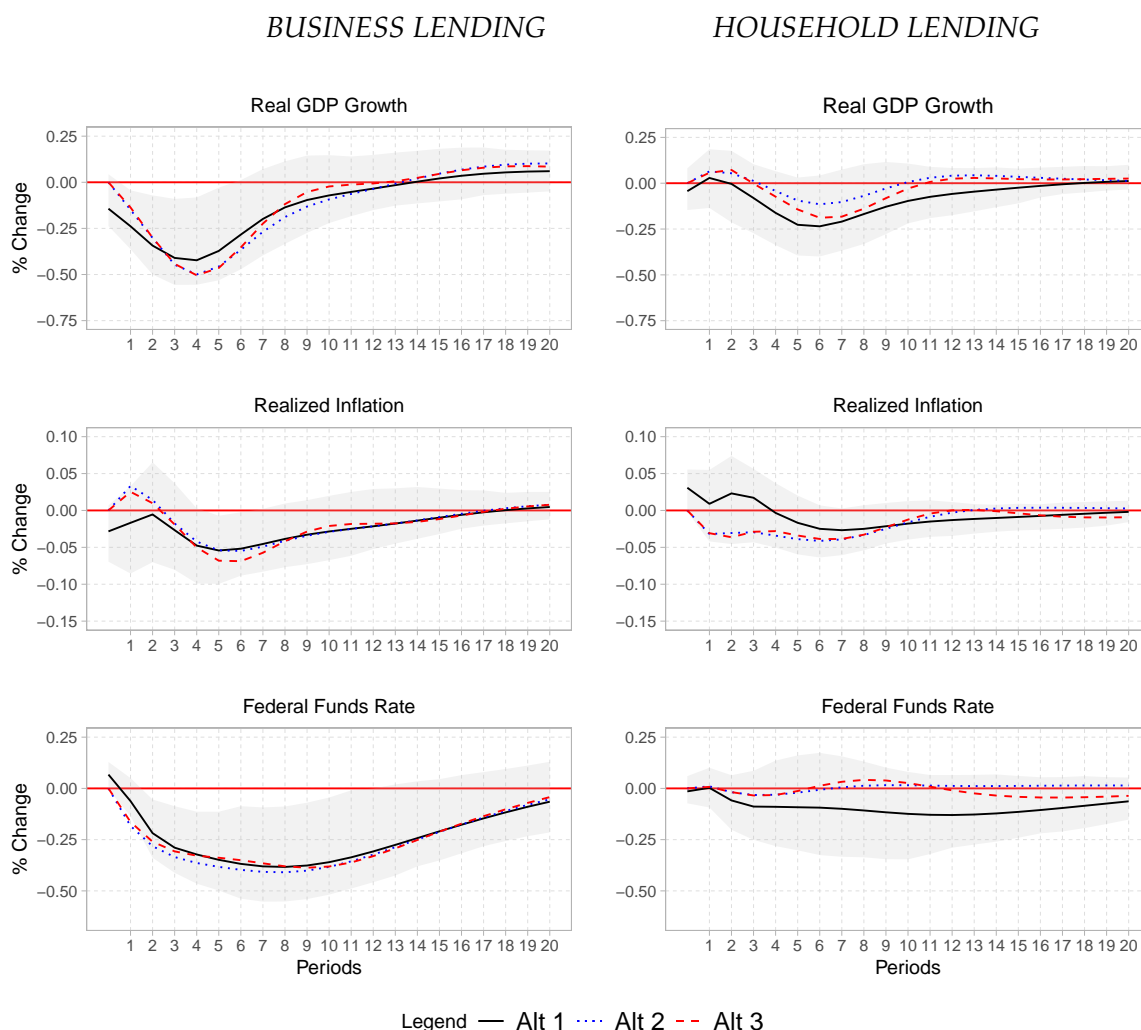
Notes: The plot on the left is for standards in business lending (BUS), and the right panel is for standards in lending to households (HOUS). In each figure, the black and blue lines represent standards for the FULL sample of SLOOS banks. The red line shows adjusted standards for the top 15 SLOOS banks in our sample, for future reference (see Section 6.2).

We estimate three VARs corresponding to the three alternative approaches introduced in expression (5), but we now include two separate indexes for lending standards: one for business lending and one for household lending. Having two components of lending standards in the VAR brings up a new issue: which of the two components is to appear first in the order? In our benchmark specification, we have business standards coming right before household standards in the VAR order, but in the appendix we include the impulse responses when that ordering is reversed. Results are effectively unchanged.¹²

Figure 8 plots the impulse responses functions for our benchmark specification. We

¹²Going back to expression (5), we replace ΔS by ΔS^{BUS} and ΔS^{HOUS} in those specifications, maintaining the general ordering of variables. When implementing Alternative 1, the micro approach, we run separate panel regressions: one for business and one for household lending standards.

Figure 8: Orthogonal impulse response functions: Shock to business and household lending standards

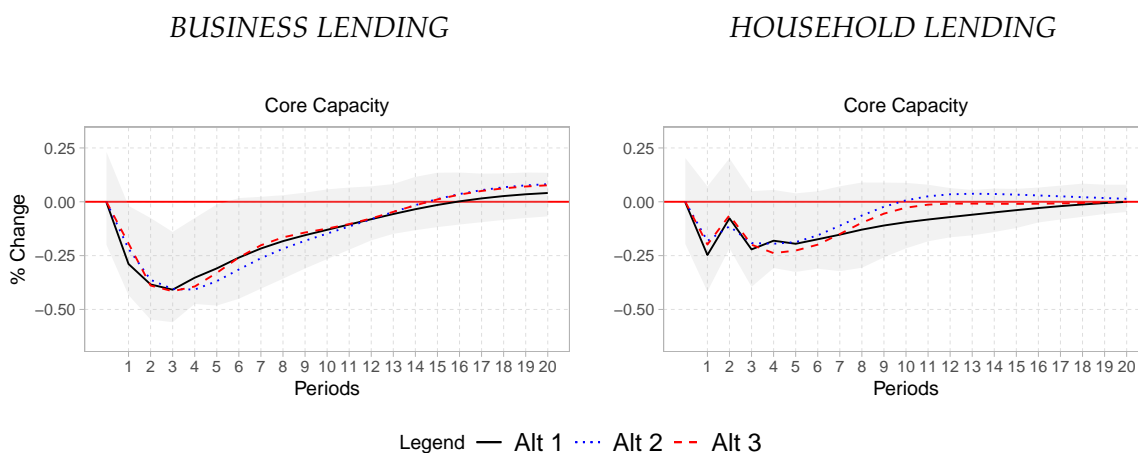


Notes: The left column corresponds to the effect of a 1 SD shock to business lending standards and the right column a 1 SD shock to household lending standards. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on alternative 1 (in black). All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

include the main macroeconomic variables: output, inflation, and the interest rate and consider, side by side, a one standard deviation shock to lending standards for business (on the left) and for households (on the right). It is clear from the plots that the shock to business lending has the more significant effect over output and other macroeconomic variables. In fact, the bootstrap confidence intervals suggest that the effect of a shock to household lending standards is not statistically different from zero at all horizons.

This impulse response functions suggest that the effects we observed in Figure 5 are mainly driven by the tightening of business credit, with the tightening of credit to household minimally reinforcing those effects. Confirming our prior assessment, we see in Figure 9 that lending to businesses takes a significant dive after the shock, presumably driving the macroeconomic effects captured in Figure 8. Lending to households, on the other hand, responds much less to a shock to household credit supply.

Figure 9: *Impact on bank core lending capacity of a shock to business/household lending standards*



Notes: The left panel corresponds to the effect of a 1 SD shock to business lending standards and the right panel a 1 SD shock to household lending standards. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on alternative 1 (in black). All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

4.1 The Relative Importance of Bank Credit Supply Shocks

An important and related question to consider is how much of the variability in the main macroeconomic variables included in our VARs can be attributed to the different shocks at different forecast horizons, and in particular, how much lending standards drive this variability. To this end, Table 4 presents the forecast error variance decomposition for real GDP growth, inflation, and the fed funds rate of a VAR estimated using the adjusted series for business and household lending standards (our Alternative 1). The table provides this decomposition at different horizons, as indicated with the variable h in the second column.

In most cases, after approximately 2 years ($h = 8$), the variance decomposition settles down and becomes a good approximation of the unconditional variance decomposition of these variables. The entries on the table represent the percentage contribution of each of the shocks to the h -quarters-ahead forecast error variance for each of the three variables in the first column. The entries in each row should sum to 100% (after accounting for rounding).

Table 4: Forecast error variance decomposition for Alternative 1 of the VAR

Forecast error in	Forecast horizon h	Percentage of variance, h periods ahead, accounted for by innovations in						
		BUS	HOU	RGDP	CC	INF	CBS	FFR
RGDP	1	5.5	0.5	94.0	0.0	0.0	0.0	0.0
	2	10.8	0.4	84.6	1.9	1.8	0.6	0.0
	3	16.6	0.2	63.9	5.2	10.7	3.3	0.1
	4	20.8	0.5	47.1	4.5	21.4	5.6	0.1
	8	26.2	6.1	28.8	3.6	29.0	6.1	0.1
	12	26.0	7.6	27.8	3.7	28.7	6.0	0.2
	20	25.6	7.7	27.2	3.7	28.7	5.8	1.3
INF	1	2.7	3.2	1.8	0.0	92.3	0.0	0.0
	2	1.6	1.5	0.8	3.8	89.8	1.5	1.0
	3	1.2	1.6	0.7	6.9	82.7	4.3	2.5
	4	1.6	1.7	0.7	9.7	76.2	6.6	3.5
	8	8.4	2.5	0.8	10.2	63.3	9.2	5.7
	12	10.6	3.4	1.2	9.6	59.9	9.1	6.2
	20	11.1	3.8	1.3	9.4	59.0	9.1	6.3
FFR	1	4.5	0.2	7.8	0.9	30.6	0.4	55.7
	2	3.2	0.1	7.0	0.4	29.1	0.2	60.0
	3	11.2	0.7	7.3	0.9	22.9	0.5	56.6
	4	17.3	1.4	8.0	1.7	17.9	0.5	53.2
	8	29.3	2.1	11.9	2.2	11.2	0.3	43.0
	12	34.9	3.1	13.2	2.2	11.8	0.6	34.2
	20	36.5	4.7	13.3	2.3	13.7	1.0	28.5

Notes: Forecast error variance decomposition for real GDP, realized inflation, and the federal funds rate. The variance decomposition is constructed via Cholesky decomposition, using quarterly data from 1996:Q2 to 2019:Q4. All variances are reported as percent of the total error variance at horizon h attributed to each given shock.

As we see in the table, shocks to business and households lending standards account for a third of the variance in real GDP growth after two years. However, most of the effect comes from changes in bank lending standards for business, with household lending standards contributing very little at short horizons and only reaching 7.6% after three years. Interestingly, lending standards to businesses appear to play a significant role in explaining

fluctuations of the fed funds rate, even if the effects on inflation are relatively moderate. In fact, at horizons longer than a year, bank lending standards to business becomes the second most important driver of the variability in the fed funds rate—second only to the fed funds rate itself.

Table 5: Forecast error variance decomposition for Alternative 3 of the VAR

Forecast error in	Forecast horizon h	Proportions of forecast error variance h periods ahead accounted for by innovations in									
		RGDP	Unemp.	BUS _{<i>d</i>}	HOUS _{<i>d</i>}	CC	INF	CBS	FFR	BUS _{<i>s</i>}	HOUS _{<i>s</i>}
BUS _{<i>s</i>}	1	14.3	0.0	6.3	0.7	0.3	1.3	8.8	4.3	64.0	0.0
	2	13.7	3.4	8.5	1.1	4.5	0.8	6.8	2.7	56.8	1.6
	3	12.9	4.8	6.7	2.1	5.4	0.9	7.1	2.2	55.4	2.4
	4	13.2	5.5	6.0	2.7	5.5	0.8	7.2	2.1	53.4	3.5
	8	12.9	5.8	5.4	4.1	6.1	0.9	6.9	3.6	49.5	4.8
	12	14.7	5.2	5.2	4.5	5.4	0.9	6.6	5.0	48.2	4.2
	20	18.3	4.6	4.6	4.0	4.6	1.2	6.8	4.3	48.0	3.6
HOUS _{<i>s</i>}	1	3.7	2.1	0.1	0.1	0.0	1.5	1.8	5.7	4.0	81.0
	2	4.6	1.9	0.3	0.8	0.4	2.9	1.4	3.5	9.3	74.8
	3	6.2	3.0	0.7	2.9	0.4	4.7	1.0	2.5	13.4	65.2
	4	6.6	4.4	0.7	5.6	0.5	6.0	1.1	2.0	15.6	57.4
	8	6.6	6.2	0.5	15.0	0.7	11.0	2.1	1.5	13.2	43.3
	12	6.7	5.3	0.5	19.0	0.6	13.2	2.3	1.9	13.4	37.1
	20	11.2	4.2	1.3	16.2	0.9	10.9	3.5	1.7	20.4	29.9

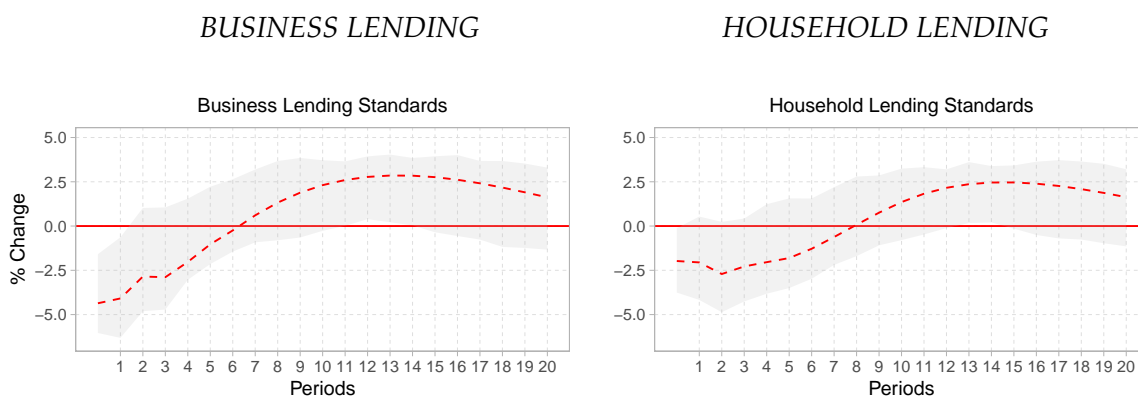
Notes: Forecast error variance decompositions for business (BUS) and household (HOUS) bank lending standards. The variance decompositions are constructed via Cholesky decomposition, using quarterly data from 1996:Q2 to 2019:Q4. All variances are reported as percent of the total error variance at horizon h attributed to each given shock.

Under Alternative 1, the specification uses lending standards that are adjusted using micro and macroeconomic data and then appear first in the order of variables for the VAR. This specification is not well-suited to think about feedback effects from macroeconomic conditions onto lending standards; i.e., how much changes in lending standards are the response to changes in real GDP and, more broadly, the general macroeconomic outlook. To get a perspective on this issue, we use our estimation based on Alternative 3 to compute the forecast error variance decomposition of bank lending standards for both businesses and households.¹³ The results are presented in Table 5.

¹³Table 7 in the appendix provides the forecast error variance decomposition for the main macroeconomic variables based on Alternative 3 and confirms that results are similar to those reported in Table 4.

We see in the table that real GDP growth explains a significant portion of the fluctuations on lending standards, particularly for businesses. For households, this effect of output over standards is present, but much more subdued. Business lending standards, on the other hand, seem to affect household lending standards considerably after a few quarters. On the demand side, household demand for bank lending appears to be a more important driver of lending standards to households, in the medium term, relative to the role of business demand for lending standards to business, even though at shorter horizons, business lending standards appear more responsive to changes in demand shocks.

Figure 10: *Impact on lending standards of a shock to real GDP growth*



Notes: The left panel corresponds to the effect of a 1 SD shock to output growth on business lending standards, and the right column is the effect on household lending standards of the same shock. The shaded area represents bootstrap 90% confidence intervals from 250 iterations. The VAR includes 2 lags. The sample period is 1996:Q2 to 2019:Q4.

To complement this information, in Figure 10, we plot the impulse response of lending standards to a shock to output growth corresponding to the VAR used to produced Table 5 (Alternative 3). We can see in the figure that a positive shock to output growth tends to initially loosen business lending standards with a reversal after seven to ten quarters. The effect of GDP shocks on household lending standards show a similar pattern but is much smaller and mostly insignificant.

In general, these results suggest sizable feedback effects: a tightening in business lending standards tends to drive a slowdown on real GDP growth after a few quarters, which

eventually induces further tightening of those standards, in that way reinforcing the initial shock.

5 Asymmetric and State-Dependent Effects

In this section, we look deeper into the nature of the effects that changes in bank lending standards can have on the macroeconomy. We consider two possibilities: (1) that the effects are different depending on the state of the economy; and (2) that the effects are asymmetric, with positive shocks affecting the economy differently than negative shocks (Barnichon et al., 2022).

5.1 Empirical Framework

The basic approach is based on the VAR we used before, although we now allow the matrix of VAR coefficients to be state contingent. In particular, we adopt a threshold VAR specification, or TVAR, similar to that in Section 18.3 of Kilian and Lütkepohl (2017).

Denote by Θ the matrix of coefficients for a given VAR specification, and let S be the set of mutually exclusive and predetermined economic states s under consideration. At each time t , the economy will be in one of these states—more formally, for each time t in the sample period, the state of the economy $s(t) = s$ for some $s \in S$. In the estimation, we let the matrix Θ change when the state changes. For this methodology to be operational, of course, the number of possible states in S has to be relatively small to be able to have sufficient data periods associated with each of the possible states.

It is useful to think of each state as associated with a different “regime.” We use a relatively simple criteria to determine the economy’s regime at each point in time. These criteria are based on patterns of the data that are not necessarily part of the VAR specification. Given our short sample period, we will restrict the number of states or regimes to just two and the number of lags in the VAR to just one.¹⁴

¹⁴In fact, for all the TVAR exercises that follow, the BIC minimizing number of lags was always equal to one.

This generalized, regime-contingent VAR can be written concisely as:

$$Y_t = \Theta_{s(t-1)} Y_{t-1} + \Sigma_{s(t-1)} u_t, \quad u_t \sim \mathcal{N}(\mathbf{0}, I), \quad (6)$$

where, for all t in the sample period, $s(t-1) = s$ for some $s \in S$, and the model allows the distribution of shocks Σ to be influenced by the state s , as well. Persistence and propagation are, of course, also influenced by the state via the state-contingent matrix Θ . Note that the model subsumes the non-state-dependent VAR and, if the data generating process is not meaningfully state-dependent, then the estimation will show no significant differences across states.

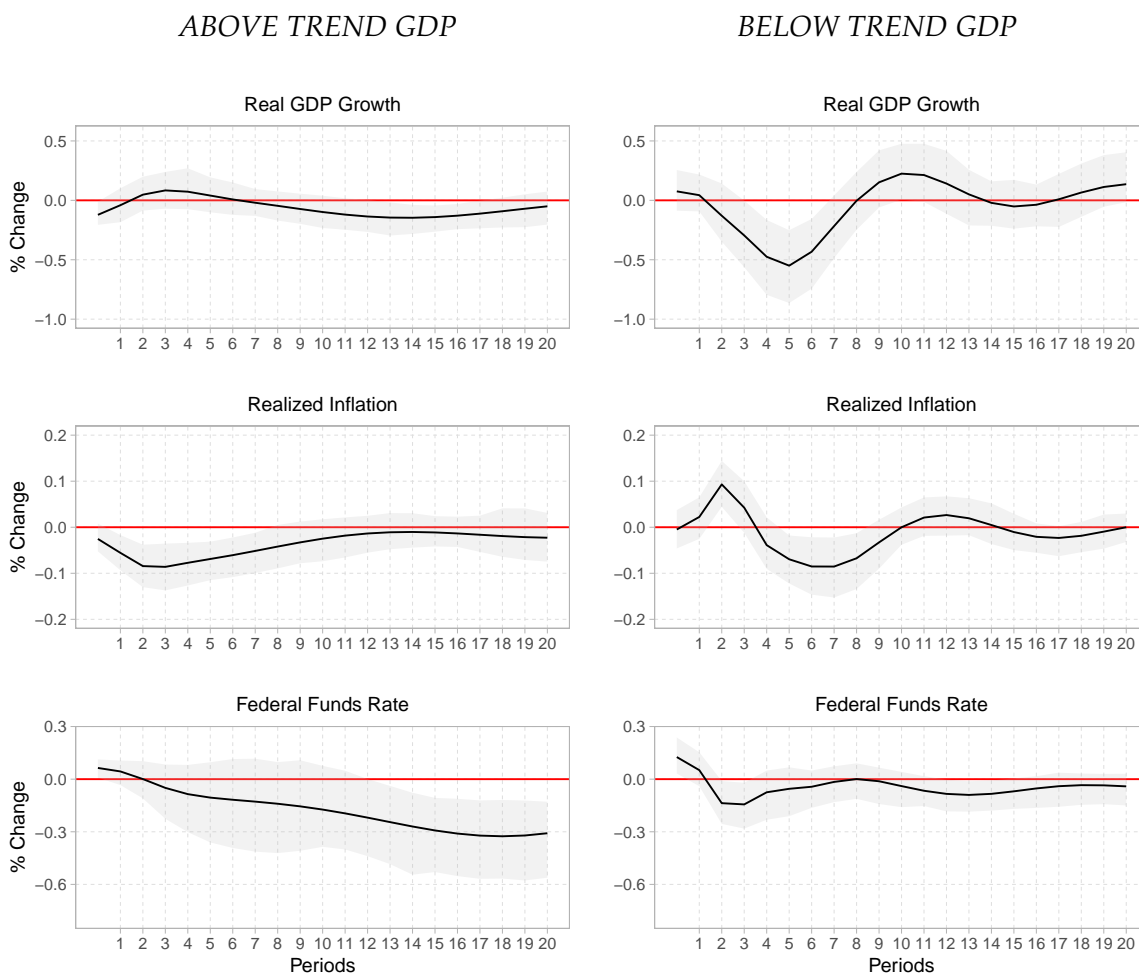
Our main objective here is to deepen our understanding of the economic mechanisms driving the effects of changes in lending standards on the macroeconomy. This will motivate the choice of the set of states S and is also the reason why we proceed with a simple (and easily interpretable) TVAR model, instead of using a smooth-transition or a regime switching VAR. Similarly, when we plot impulse responses, we will assume that the economy does not switch regimes in the subsequent periods after the shock. For the purpose of forecasting, it would be more appropriate to consider generalized impulse response functions, which are more demanding in terms of the amount of data needed to obtain acceptable identification.

5.2 The State of the Business Cycle

In this section, we consider the case when the set S has two elements capturing the state of the business cycle. For our baseline estimation, we use the *level* of output, relative to trend, as the criterion for defining the states. That is, one state relates to periods when output is above its long-run trend, and the other state when output is below trend. We use Hamilton's method to determine the trend in GDP ([Hamilton, 2018](#)), and we say that output is above (below) trend when the four-quarters moving average of the detrended series is positive (negative) for at least two consecutive quarters. For our sample period, there are sixty-one quarters with output above trend and thirty-four quarters with output below trend.

Figure 11 plots the resulting state-contingent impulse response functions. It is clear from the figures that most of the impact on output growth from shocks to lending standards comes from times when output is below trend. The effects on inflation and interest rates are much more subdued.

Figure 11: *Orthogonal impulse response functions: Shock to overall lending standards*



Notes: Based on the estimation of alternative 1, the plots correspond to the effect of a 1 SD shock to lending standards that happens when real GDP is above trend (left column) and below trend (right column). The shaded area represents bootstrap 90% confidence intervals from 250 iterations. All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

We also verify that the effect on GDP growth of a tightening in standards when output is below trend occurs in conjunction with a contraction in banks' core lending capacity (see the figure in the appendix). As before, this suggests a mechanism where banks tighten

standards, credit falls, and output consequently reflects the fact that loans become harder to come by.

When output is above trend, our impulse response functions indicate that adjustments in banks' lending standards do not have much impact on GDP growth. This could be reflecting the fact that a tightening of bank credit during an expansion does not significantly affect access to credit for productive activities, given that other non-bank alternatives can fill the void. Interestingly, though, Figure 11 suggests that a tightening in lending standards can have a significant (negative) effect on inflation when output is above trend. And in that case, the fed funds rate eventually accommodates the tightening shock with a persistent decrease that commences after about a year of the initial shock and lasts for several years.

These impulse response functions also suggest that the ability of interest rates to respond to the tightening of lending standards may play a role in how lending standards impact GDP growth. With this in mind, we now turn our attention to the case when we allow parameters in the VAR to depend on the level of interest rates.

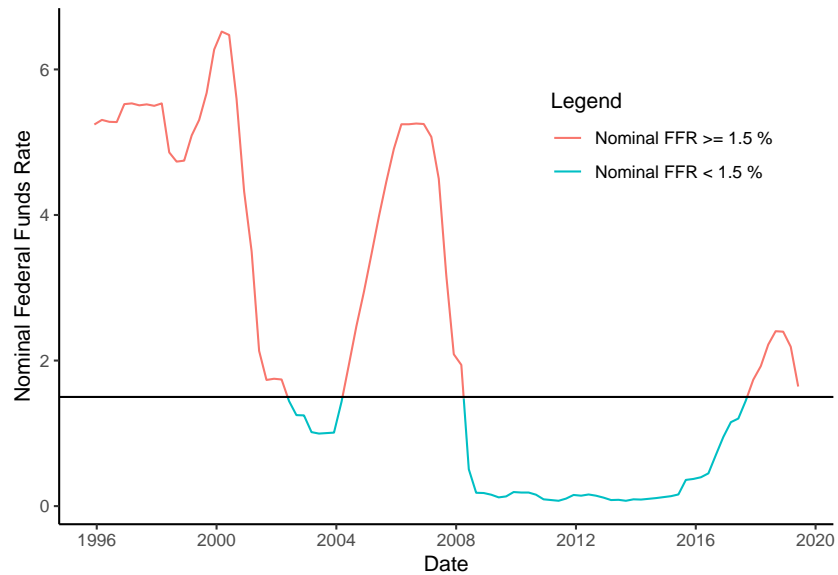
5.3 High and Low Interest Rate Periods

We now consider the case when, again, S has two elements, according to the level of the nominal interest rate. The idea is to assess whether shocks to lending standards affect the economy differently when there is a greater probability of having a binding zero lower bound on interest rates.

We set the threshold for the fed funds rate at 1.5 percent and designate the low interest rate state as the one including all quarters when the rate is below the threshold. Figure 12 shows the split of our sample period according to these two states. We have forty-six low interest rate quarters and forty-nine high interest rate periods. Results are similar when we set the threshold at 1 percent, but the split of the data is more balanced when using the 1.5 percent threshold.

Figure 13 plots the impulse response functions for the main macro variables in response

Figure 12: High and low interest rate states



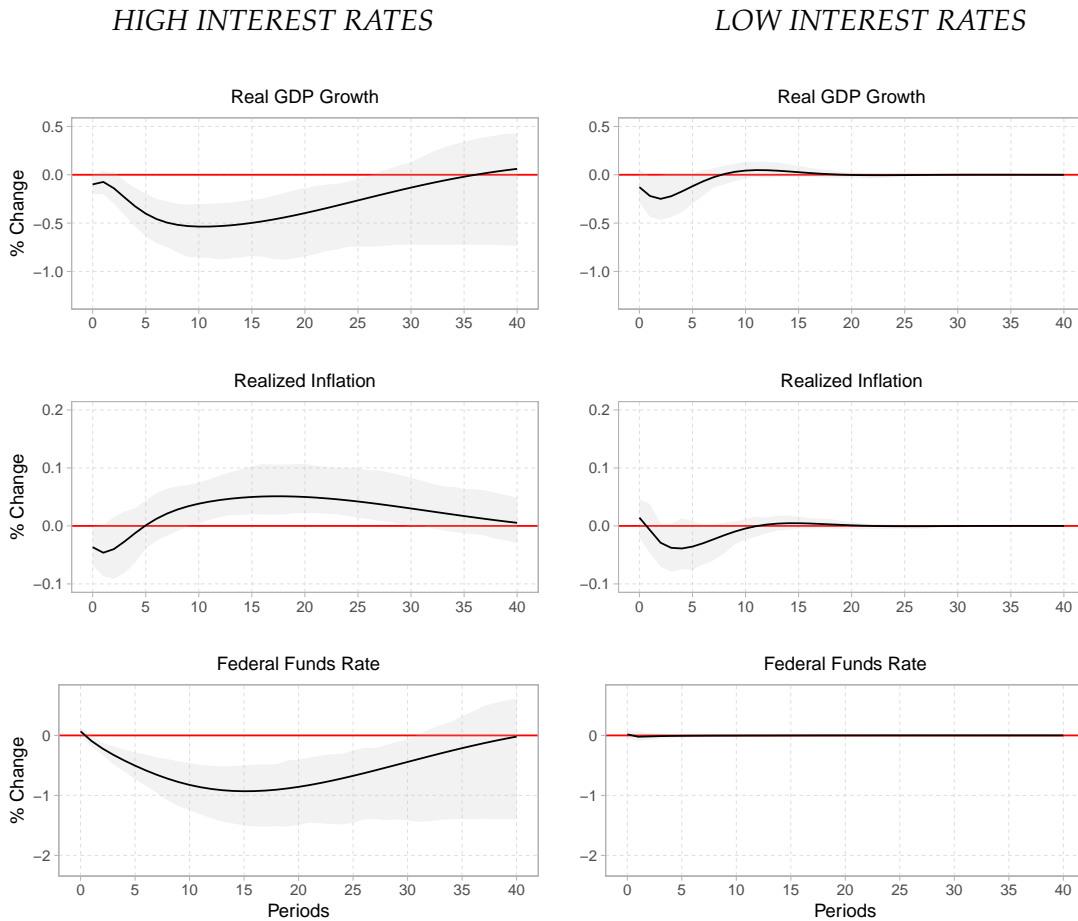
Notes: The red color indicates quarters when the nominal federal funds rate was higher than our 1.5% threshold, and the blue indicates when it was below. Sample period is from 1996:Q1 to 2019:Q4.

to a tightening shock to lending standards. We extend the horizon to forty quarters to capture the full span of the effect. The effect on output growth of a tightening of lending standards is significant during high-rate periods and very persistent. Interest rates fall and inflation increases in reaction to such a shock. During low interest rate periods, on the other hand, the effect on output growth and inflation are insignificant. Naturally, the fed funds rate seems highly insensitive to lending-standards shocks in the low-rate regime, presumably because there is not much room to accommodate the shock by lowering rates in such situation.

5.4 Asymmetric Effects of Positive and Negative Shocks

Finally, we estimate a model where we allow the VAR parameters to be contingent on the sign of the shock in our adjusted overall lending standard series. More specifically, S has two elements, one denoting the state when the shock to lending standards is positive and one when the shock to lending standards is negative. As before, we allow for changes

Figure 13: *Orthogonal impulse response functions: Shock to overall lending standards*



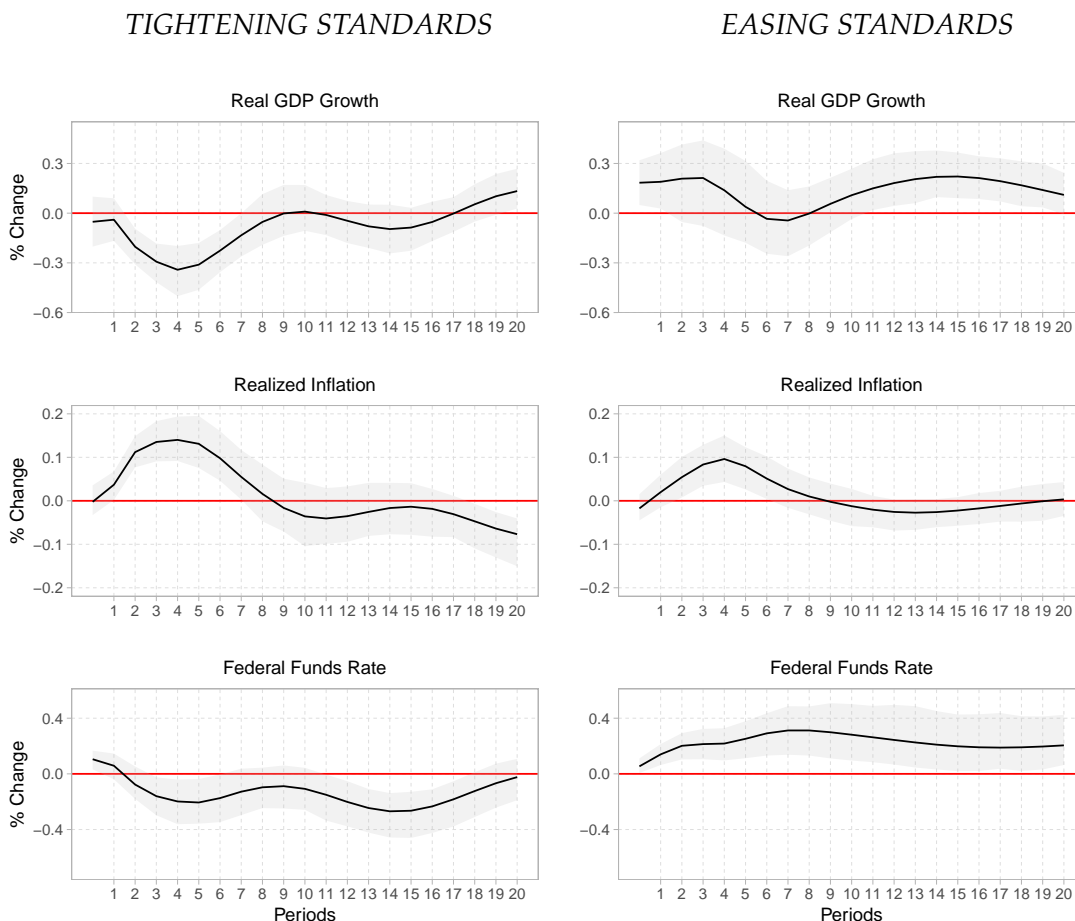
Notes: Based on the estimation of Alternative 1, the plots correspond to the effect of a 1 SD shock to lending standards that happens when the nominal fed funds rate is below 1.5% (left column) and above 1.5% (right column). The shaded area represents bootstrap 90% confidence intervals from 250 iterations. We use 1 lag in the estimation. The sample period is 1996:Q2 to 2019:Q4.

in the state only when the shock is of the same sign for at least two consecutive periods (to reduce high frequency switches that are unlikely to represent meaningful economic effects).

Notice that for this exercise, it is critical to have the *adjusted* lending standards of Bassett et al. (2014), which is a representation of the exogenous shocks to standards. This allows us to directly classify changes in the adjusted series as negative and positive shocks and use that classification of regimes to then estimate state-contingent parameters for the VAR. In contrast, the VARs in alternatives 2 and 3 of expression (5) above use the unadjusted lending standards and obtain the sequence of shocks as a byproduct of the VAR estimation. Such

endogeneity would make conditioning on the sign of the shock much less straightforward (Barnichon et al., 2022).

Figure 14: *Orthogonal impulse response functions: Shock to overall lending standards*

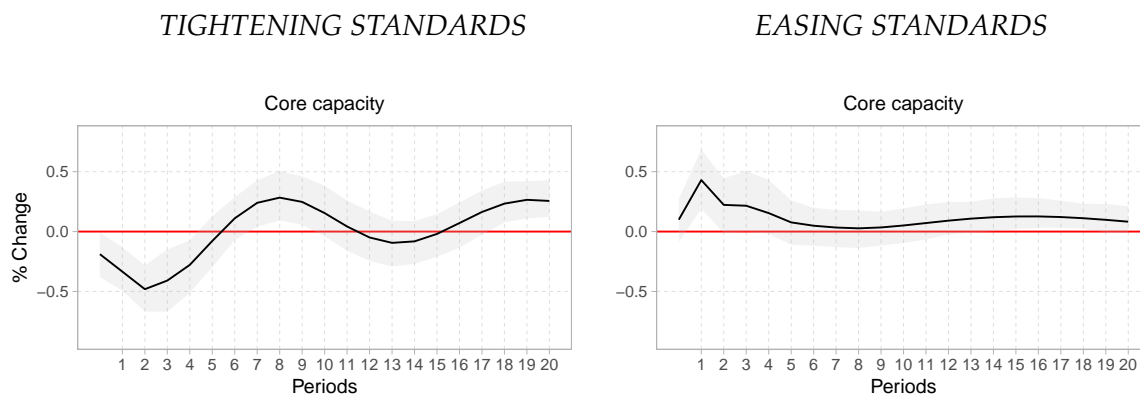


Notes: Using the VAR in Alternative 1, the plots correspond to the effect of a 1 SD positive (tightening) shock to lending standards (left column) and a 1 SD negative (easing) shock to lending standards (right column). The shaded area represents bootstrap 90% confidence intervals from 250 iterations. All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

Figure 14 plots the impulse responses of the main macroeconomic variables to a one standard deviation shock to overall lending standards. On the left panel, we plot the response to a positive (tightening) shock to lending standards, and on the right panel, we plot the responses to a negative (easing) shock to standards. A tightening shock has a negative and significant impact on GDP growth after four quarters and a contemporaneous effect on inflation that tends to revert itself after two or three quarters. Easing shocks

to standards, on the other hand, have a more subdued effect on output growth, mostly statistically insignificant, and a gradual and long-lasting effect on inflation and the interest rate, increasing both for several quarters.

Figure 15: *Impact on bank core lending capacity of a shock to lending standards*



Notes: Using the VAR in Alternative 1, the plots correspond to the effect on bank core lending capacity of a 1 SD positive (tightening) shock to lending standards (left column) and a 1 SD negative (easing) shock to lending standards (right column). The shaded area represents bootstrap 90% confidence intervals from 250 iterations. All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

Figure 15 shows that the movement in GDP growth is also consistent with the effect that standards have on banks' core lending capacity. In particular, a tightening shock to lending standards tend to lower bank lending, consistent with the transmission of the shock from bank lending to output.

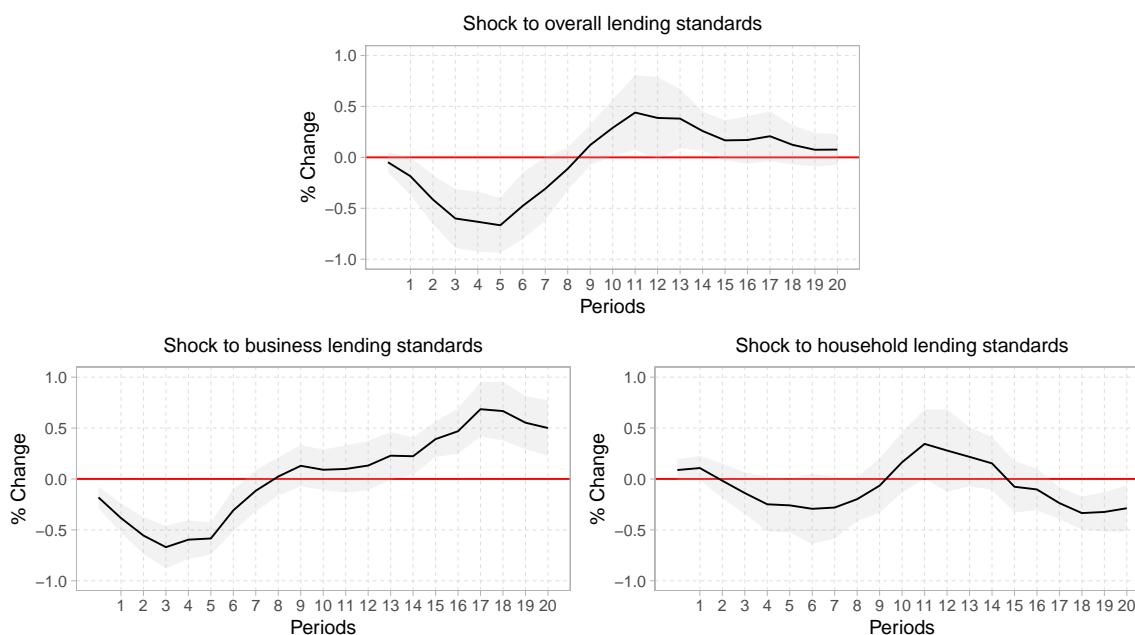
6 Robustness

In this section, we conduct several robustness exercises that reinforce and expand the range of our results. Given the findings so far and the nature of the exercises we do here, we focus mostly on overall lending standards as the leading example. Similar results can be obtained with more disaggregated series for lending standards.

6.1 Local Projections

To compare with much of the previous literature and to be able to assess the implications of pursuing a micro or macro approach in controlling for endogeneity, we have used standard VARs for most of our analysis so far, complemented with timing restrictions for identification. While our estimates are minimally sensitive to the specific number of lags used in the VARs, it is still possible that when we use the adjusted lending standards in the estimation, the impulse responses we obtain from a VAR could be biased (Li et al., 2024). With this in mind, we follow Cavallo et al. (2024a) and use local projections to assess the robustness of our findings.

Figure 16: Impact of a shock to lending standards using local projections



Notes: Using local projections based on adjusted lending standards, the plot shows the response of GDP growth to a 1 SD positive (tightening) shock to lending standards (overall and for businesses and households, separately). The shaded area represents 90% confidence bands where standard errors have been Newey-West adjusted. The sample period is 1996:Q2 to 2019:Q4.

Figure 16 shows the impact that a shock to adjusted lending standards has on output growth when using local projections as the estimation method (Jordà, 2005). We see that real GDP growth declines as much as 0.6 percent after a one standard deviation shock to

overall adjusted lending standards, with the peak effect occurring around five quarters after the shock. This result is very much in line with the results we obtained using VARs in Figure 5. Furthermore, the figure shows a very clear disparity between the effect of a shock to business lending standards and a shock to households lending standards, with most of the effect on output coming from changes in lending standards for businesses. This, again, supports the robustness of our previous results using VAR (as presented in Figure 8).

6.2 The Role of Large Banks

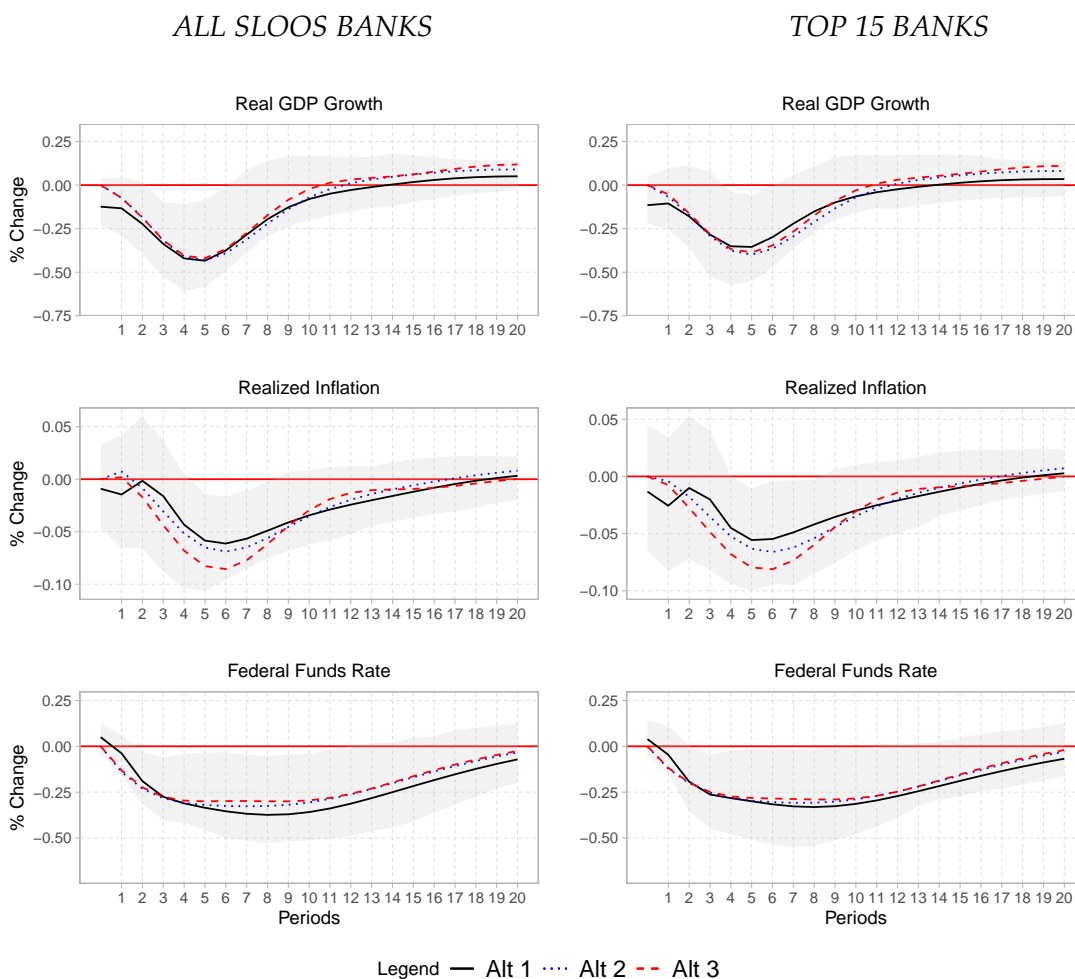
The banking industry is highly concentrated. In this section, we re-do our estimation procedures with a sub-sample of the SLOOS banks: the top 15 banks when ranked by asset size. In each quarter, we select the largest 15 banks in the SLOOS sample. Some of the banks rotate in and out of the sub-sample (and of the SLOOS sample, as well), making the data an unbalanced panel. Over our sample period, 22 different banks are at some point in the top 15 sub-sample, which suggests rotation is not very prevalent.

It is interesting to note, first, that the index for adjusted lending standards using the full SLOOS sample is very similar to the index that only uses the top 15 largest banks in the sample. Indeed, this is the case even if we split the categories into the two natural supra-groups, lending to businesses and to households. This is clear from comparing the blue and red lines in Figure 7.

Perhaps not surprisingly, then, the effect on the macroeconomy is very similar when we consider the lending standards of the top 15 banks instead of the full SLOOS sample. To see this, Figure 17 plots the impulse responses from a tightening of overall lending standards by the top 15 largest SLOOS banks. We also include the impulse responses from the full sample of banks (as in Figure 5), for easier comparison. It seems evident from the figure that most of the macroeconomic impact of a shock to lending standards comes from the activity of the largest banks. This is of course mainly the result of focusing on aggregate effects: when assessing the impact of bank lending standards on GDP, inflation, and monetary policy,

the activity of large banks is critical given the high levels of concentration within the U.S. banking industry. However, it is also evident from Figure 17 that some of the effects are not captured by the decisions of the top 15 banks, and for some sectors of the economy, the medium and small banks likely play an important role.

Figure 17: Orthogonal impulse response functions: Sub-sample of large banks



Notes: The left column uses the estimation that includes all domestic banks in the SLOOS sample, and the right column uses the one for the sub-sample of the top 15 banks by assets. The impulse response functions correspond to the effect of a 1 SD shock to overall lending standards. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black). All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

In the appendix, we include the impulse response functions from separately estimating the effects of changes in lending standards to businesses and households. The effect of

a tightening in lending standards is again very similar regardless of whether the index includes all SLOOS banks or just the top 15 (see Figure 29 in the appendix).

Understanding the disparate role of smaller and larger banks is also important because shocks to the banking sector may not affect all banks equally. During the recent events that resulted in the liquidation of several regional U.S. banks in March 2023, deposits flowed from smaller to larger banks, giving larger banks a more favorable position to possibly increase lending, while smaller banks were experiencing the opposite.¹⁵

With this in mind, we also run a VAR where we separate standards for the top 15 banks and for the rest of the banks, but we include them both in the estimation. While lending standards for the two groups often move together, the correlation during our sample period is 0.66, so there is some variation worth exploring (see Figure 31 in the appendix). As a result of running this exercise, we determine that a shock to the lending standards of those banks outside of the top 15 indeed has meaningful effects on output, independently of the shock to lending standards of the top 15 (see Figure 30 in the appendix). Interestingly, the effects on inflation are more pronounced from the shock to the smaller banks, while the effects on the fed funds rate are comparable.

6.3 Including the COVID Period

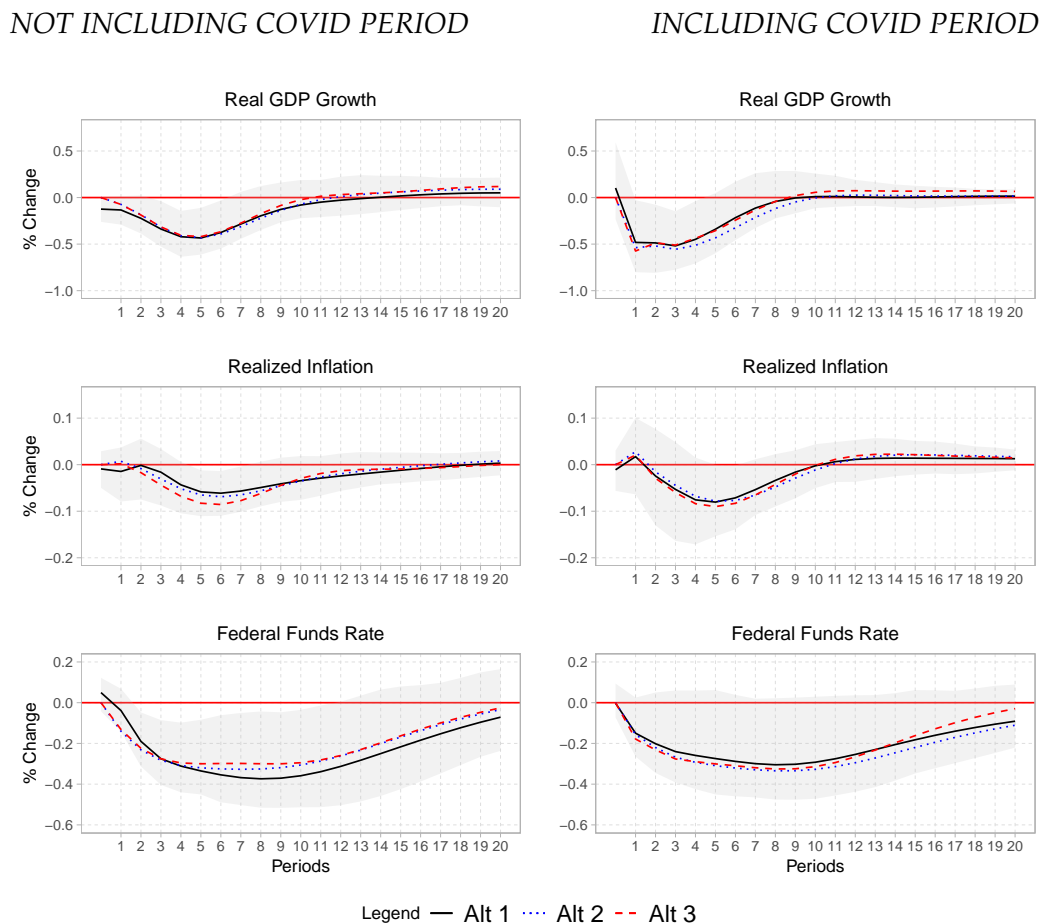
Our data sample includes the years 2020 and 2021, a period where all macroeconomic variables were strongly impacted by the COVID pandemic (see Figure 2). For this reason, in most of our calculations, we left the period of the pandemic out of the estimation. However, it is worth assessing whether our results would change dramatically when taking that period into account.

To that end, Figure 18 presents the impulse response functions for the main macroeconomic variables, output, inflation, and interest rates of a shock to overall lending standards. The three panels on the right are presented to facilitate the comparison, but they are the same as the ones we presented in Figure 5. The panel on the left of the figure shows the

¹⁵Cavallo et al. (2024b) discuss in more detail the recent evolution of bank lending standards.

same impulse responses but now estimated using the sample period that extends until the fourth quarter of 2021 and hence includes two years of pandemic times.

Figure 18: *Orthogonal impulse response functions: Shock to overall standards*



Notes: The "NO COVID" sample period goes from 1996:Q2 to 2019:Q4. The period "INCLUDING COVID" goes from 1996:Q2 to 2021:Q4. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black). Alternative 1 uses a 1 SD shock to ΔS_t^a , and alternatives 2 and 3 use a 1 SD to ΔS_t . All models are estimated using 2 lags.

The patterns in the impulse response functions are similar when including the COVID period. While the impact on GDP growth of a shock to overall standards appears to be larger when using the longer sample period (including COVID), the accuracy of the estimation represented by the confidence intervals is lower in that case. This makes sense given the significant noise added to the estimation that results from including the pandemic

period in the sample. Multiple effects unrelated to the variables included in the VAR affected macroeconomic outcomes during that time and are captured mainly as noise in our estimation.

Overall, we conclude from these figures that for the purpose of our study, excluding the pandemic period should not be a source of concern. If anything, by reducing the level of noise in the data, the exclusion of the COVID period provides confidence that the effects we identified are consistently present in the economy.

6.4 The Role of Bank-Level Adjustments

Going back to the micro approach introduced in Section 3.2, we assess the relative value of including bank-level information in the panel regressions. Table 6 presents three regression specifications: The panel regressions in columns A and B are similar to column C, but with a more limited set of controls. In column A, the regression only includes the lagged change in standards and the change in loan demand (as reported in the SLOOS). The regression in column B includes these two explanatory variables and a set of macroeconomic and financial variables that are common across all banks. Finally, column C includes all the variables in column B plus a set of bank-specific variables that are meant to capture the performance of each bank at each point in time. All three regressions include bank-level fixed effects.

The regression in column C was used in the benchmark specification to construct the time series of adjusted lending standards. Based on comparing the values of the R-squared for each of the regressions (see Table 6), it seems clear that bank-specific variables do not add significant explanatory power (comparing column B with C). Indeed, the p-value for an exclusion test of the bank-specific variables in regression C is higher than 10 percent (see the test with super-index "b" at the bottom of the table. In contrast, macroeconomic and aggregate financial variables are jointly significant in explaining the behaviour of banks' lending standards, as seen in the exclusion tests with super-index "a" at the bottom of the

Table 6: Factors affecting changes in banks' overall lending standards (all banks)

Dependent variable: quarterly bank-level overall lending standards, ΔS_{it}

	A		B		C	
	Est.	(S.E.)	Est.	(S.E.)	Est.	(S.E.)
Lagged Qtly. Change in Standards	0.528***	(0.016)	0.399***	(0.017)	0.358***	(0.018)
Qtly. Change in Loan Demand	-0.102***	(0.010)	-0.071***	(0.010)	-0.073***	(0.011)
Economic outlook: Real GDP			1.516*	(0.855)	1.877*	(0.951)
Economic Outlook: Unemployment			22.251***	(1.764)	23.790***	(2.093)
Economic Outlook: 3-Month Treasury			-2.125*	(1.109)	-1.859*	(1.102)
Economic Outlook: 10-Year Treasury			1.247	(1.652)	0.333	(2.194)
Yearly Change in Real GDP			-2.301***	(0.382)	-2.339***	(0.411)
Yearly Change in Unemployment			1.278*	(0.670)	1.387*	(0.761)
Qtly. Change in EBP			9.039***	(1.154)	9.365***	(1.165)
Qtly. Change in Real FF Rate			-3.635***	(0.476)	-3.704***	(0.483)
Qtly. Change in VIX			-0.229**	(0.102)	-0.248**	(0.103)
Qtly. Change in NIMs					-0.969	(0.736)
Qtly. Change in LLPs					1.380	(1.062)
Bank Size					-0.150	(0.838)
ROA					3.058*	(1.599)
Share of Core Loans					0.142*	(0.083)
Share of Core Deposits					0.082	(0.111)
Observations	6151		6106		6106	
$Pr > W^a$			0		0	
$Pr > W^b$					0.1627	
R^2	0.318		0.385		0.387	

Standard errors in parentheses

In the table, the symbol * stands for $p < .10$, ** stands for $p < .05$, and *** stands for $p < .01$

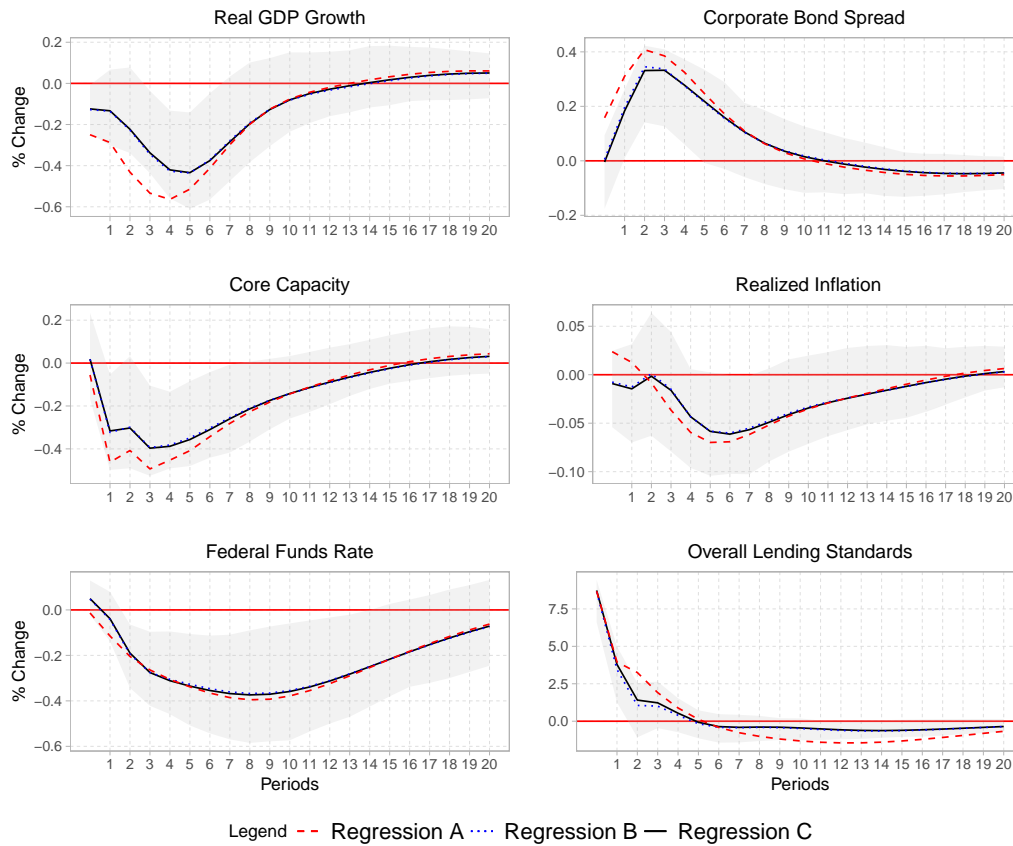
Notes: Sample period: 1996:Q3–2019:Q4; No. of banks = 115. The dependent variable in each specification is ΔS_{it} , which is the diffusion index of change in overall lending standards at bank i in quarter t . The variables aimed at capturing the economic outlook are defined as the expected four-quarter ahead change (i.e., $\mathbb{E}_{t-1}[y_{t+4} - y_t]$). Bank size is the log of total bank assets, and the share of core loans and deposits is expressed as a share of total bank assets. For the definition of other variables, see the data appendix. OLS estimates are under the column headings “Est.” We report robust standard errors clustered at the bank level under the column headings “(S.E.)” All specifications include bank fixed effects (not reported).

The super-index “a” indicates the p -value for the exclusion test of common macroeconomic and financial explanatory variables; the super-index “b” indicates the p -value for the exclusion test of bank-specific explanatory variables.

table.

We can use the residuals in each of the three regressions to construct alternative time series of adjusted lending standards. In Figure 19, we present the impulse response functions under Alternative 1, where we use the three different regression specifications in Table 6 to construct adjusted lending standards. As expected, the adjusted lending standards that

Figure 19: *Orthogonal impulse response functions: Shock to overall adjusted lending standards*



Notes: All three sets of impulse response functions are the result of implementing Alternative 1, each with a different definition of adjusted lending standards. The impulse functions are the reaction of each variable to a 1 SD shock to ΔS_t^a . The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on the impulse response functions (in black) that result from using specification C of the panel regression. All VARs are estimated using 2 lags. The sample period is 1996:Q2 to 2019:Q4.

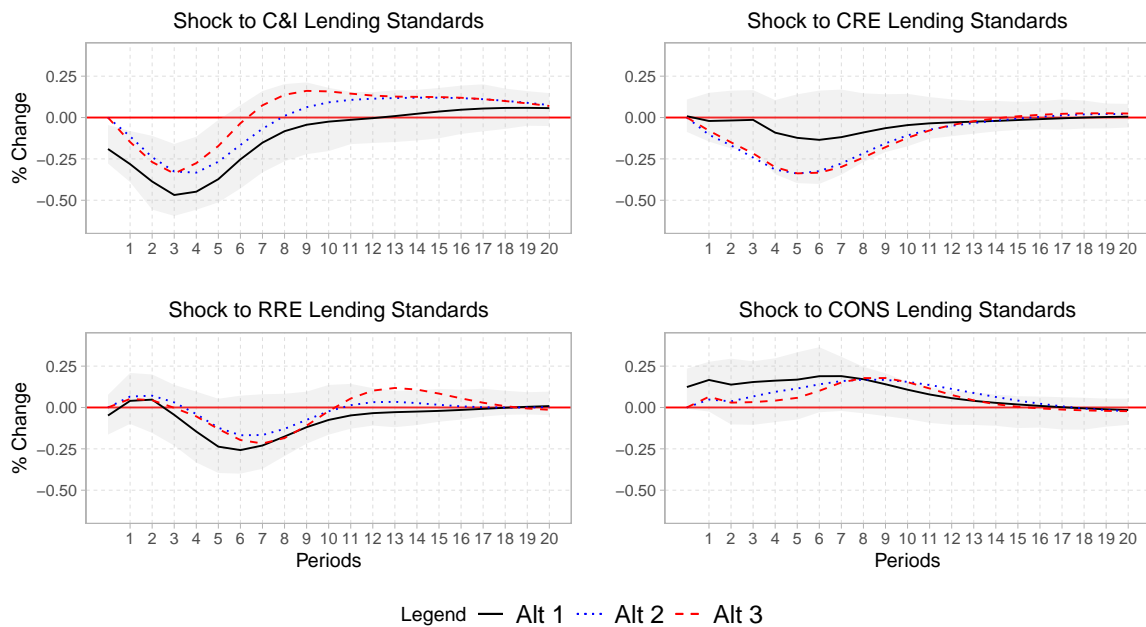
result from columns B and C produce very similar impulse response functions, while the adjustment produced by column A gives results that suggests a stronger effect of standards on output, core capacity, and credit spreads. Overall, however, results are comparable in all three cases.

These findings are interesting because they suggest that the key source of endogeneity for lending standards comes from the influence that macroeconomic factors have on banks' attitudes toward lending. Idiosyncratic factors, on the other hand, seem to be playing much less of a role given our ultimate focus on aggregate outcomes (see Appendix A.3).

6.5 Further Disaggregation: Four Groups of Categories

In this section, we consider four broad categories of loans and how changes in lending standards for each of those four categories affect the macroeconomy (Cavallo et al., 2024a). This further disaggregation allows us to gain a deeper understanding of the effects discussed in the previous sections. In particular, Figure 20 suggests that changes in standards for C&I loans are the main drivers behind the impact of business lending standards on GDP growth. While we only plot the impulse response function for output growth, results are similar in the case of inflation and interest rates.

Figure 20: *Orthogonal impulse response functions for real GDP growth: Shock to lending standards in each main loan categories*

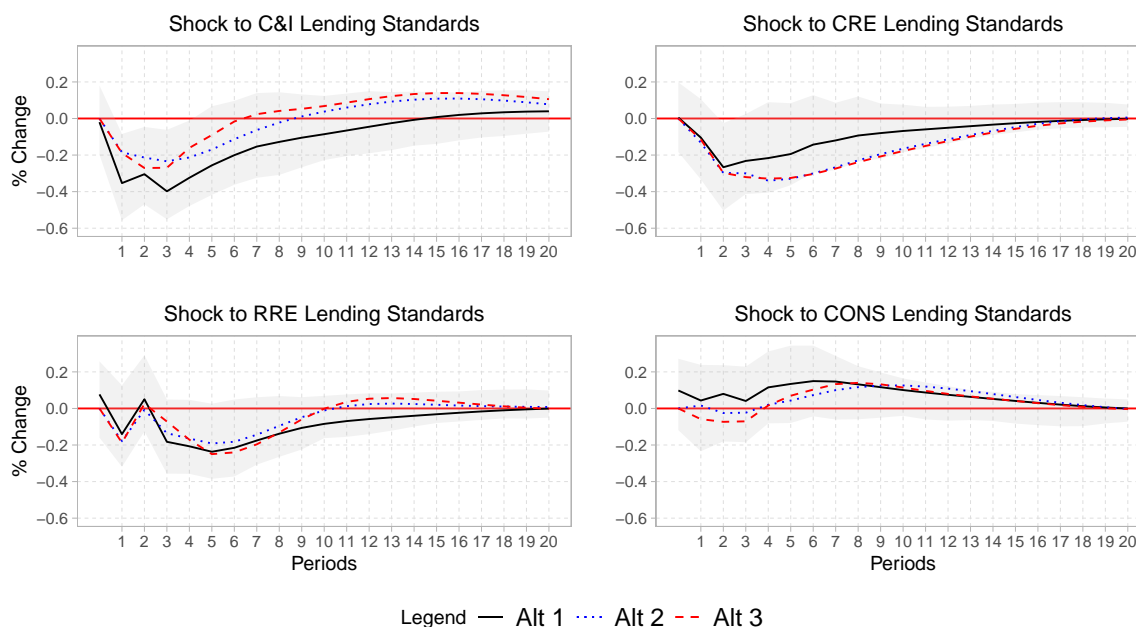


Notes: *The impulse response functions correspond to the effect on real GDP growth of a 1 SD shock to lending standards on C&I, CRE, RRE, and consumer loans. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black). All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.*

Interestingly, when we use unadjusted lending standards in alternatives 2 and 3 to estimate our VAR, lending standards for CRE loans also appear to have meaningful effects on output. The lending standards on residential real estate and consumer loans do not

impact output significantly regardless of the way we estimate their effects. These findings are in line with our conclusion that the main macroeconomic impact of changes in lending standards comes from their effects on business lending.

Figure 21: *Orthogonal impulse response functions for core lending capacity: Shock to lending standards in each main loan categories*



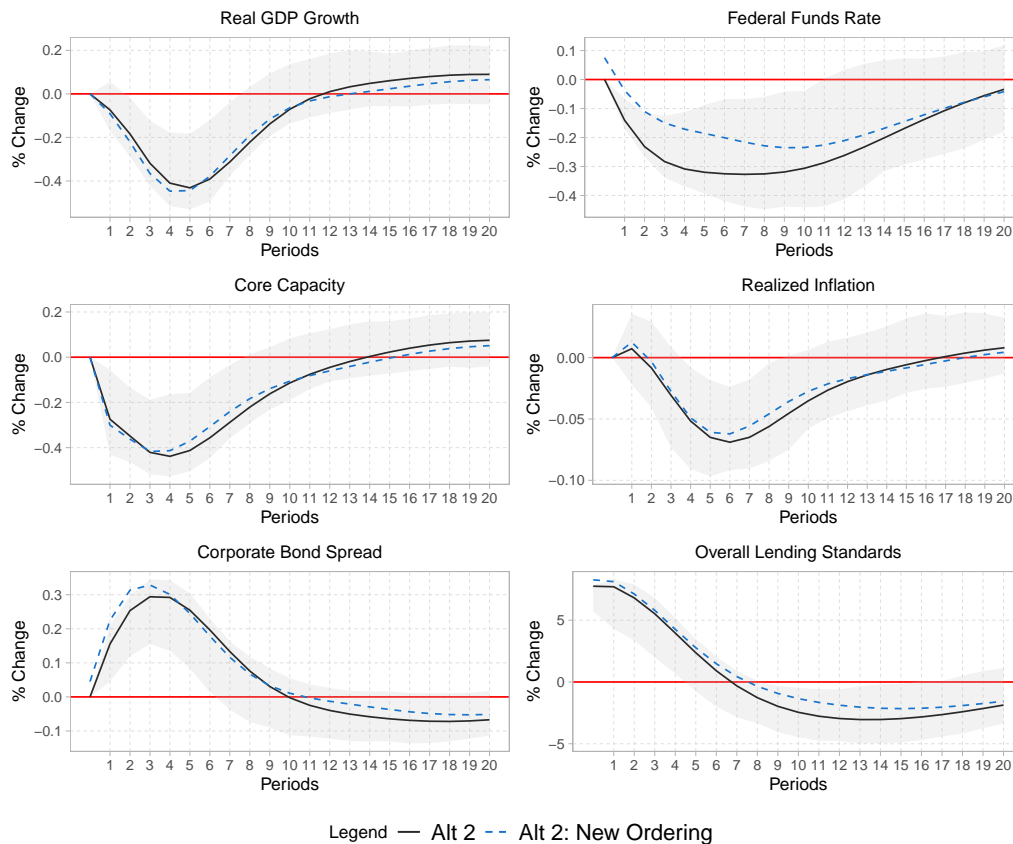
Notes: *The impulse response functions correspond to the effect on bank core lending capacity of a 1 SD shock to lending standards on C&I, CRE, RRE, and consumer loans. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black). All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.*

To complement these findings, Figure 21 shows the impulse response for bank core lending capacity of a lending-standards shock to each of the four main loan categories. Supporting the interpretation that the transmission of the shock to lending standards goes from reduced bank lending to lower GDP growth, we see that the drop in output growth is largest in those cases when core lending capacity also falls the most. And, again, most of the significant effects come from the impact on business lending.

6.6 Identification and the Ordering of Variables in the VAR

Following Gilchrist and Zakrajšek (2012), the study by Mumtaz et al. (2018) advocates for a different ordering of variables in the VARs. In particular, the new order allows interest rates to react contemporaneously to credit shocks. To assess the impact on our findings of variations in the identification assumptions, we consider a VAR that uses the same variables as in Alternative 2—see expression (5)—but under the following order: output growth, core capacity growth, inflation, *changes in overall lending standards*, GZ credit spread, and the real fed funds interest rate.

Figure 22: Orthogonal impulse response functions: Shock to overall lending standards under alternative ordering of variables



Notes: The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 2: old ordering (in dark blue). Both impulse responses are for a 1 SD shock ΔS_t . The models are estimated using 2 lags. The sample period is 1996:Q2 to 2019:Q4.

Figure 22 compares the impulse response functions of a shock to overall bank lending standards for all the variables in Alternative 2 under the old and new ordering. As is clear from the figures, the new ordering (in dashed light blue) permits contemporaneous effects of the shock to standards on the fed funds rate and the corporate bond spread. While these contemporaneous effects appear statistically significant, they are small in an economic sense, and in general, all impulse response functions under the new ordering of variables are very similar to those under the old ordering. We find this evidence, hence, supportive of the robustness of our results.

7 Conclusion

In this paper, we worked to better understand the role of bank lending standards in the U.S. economy. We produced three main findings: one methodological and the other two about the economic mechanisms at play in the data. Methodologically, we find that using micro data to adjust for endogeneity produces relatively small differences when comparing with the more traditional macro VAR approach. This finding is important because in many instances, the bank-level data is not readily available to the researcher. Our study suggests that this should not be seen as an insurmountable limitation.

One clear advantage of the micro data adjustment of bank lending standards is the possibility of bringing in, in that way, extra information (such as bank-level cross-sectional data) to address the questions at hand. This is specially valuable given the limited data that can be brought to bear in this context. In particular, good, comprehensive, and consistent data on aggregate lending standards is relatively recent. For the purpose of this paper, for example, we can go back only to 1996, given our interests on high-level disaggregation by categories of credit. However, since 1996, the U.S. economy has experienced only three main business cycles, and the interaction between the financial system and the economy is heavily influenced by the events in 2008, which was a very special historical episode.

The lack of an extensive sample period also limits the number of variables that can

be included in a VAR without compromising accuracy in the estimation. In principle, as the time series on standards becomes longer and the sample period covers a broader set of macroeconomic outcomes, the VAR approach to the identification of lending-standards shock can produce encouraging results, as hinted by the exercises provided here. In the meantime, however, using the micro data to complement the analysis, to the extent possible (given that some of the data remain confidential), is a valuable approach to consider.

In terms of the economics captured by our data, we see that a *tightening* of lending standards can have significant negative impact on output growth, with the peak effect about five quarters after the shock. We also see that this impact is much larger when standards tighten for business lending, relative to when they tighten for household lending. Furthermore, much of the effect captured in the aggregate data comes from the impact that a tightening of lending standards has on bank lending capacity and real GDP when interest rates are away from their effective lower bound and when output is below its long-run trend. If, instead, lending standards are easing, or output is above trend, or interest rates are close to their lower bound, then lending standards do not appear to have significant effects on the U.S. economy.

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A Appendix

A.1 Monetary Policy Shocks in our Sample Period

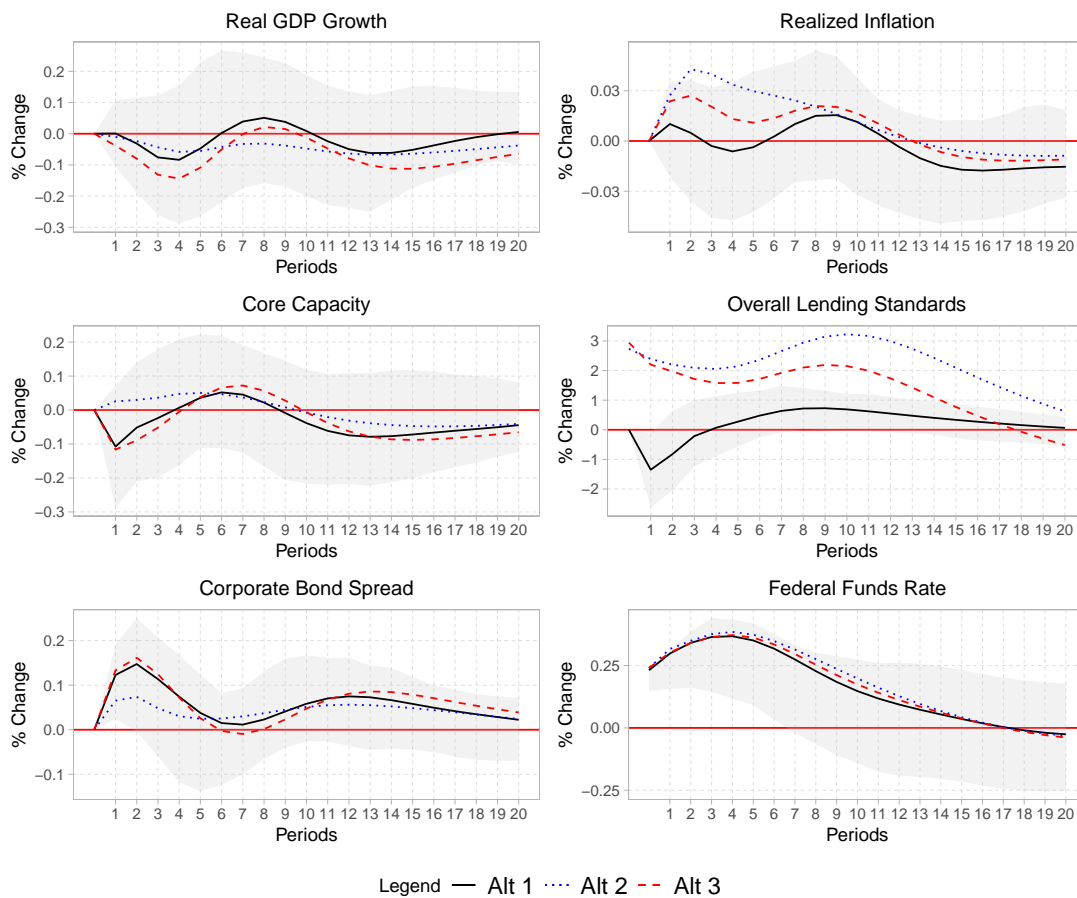
To better understand the information content of our sample and selected endogenous variables, we study the response of the economy to a monetary policy shock in our empirical specifications. Monetary policy shocks have been widely studied in the literature, making this a good benchmark for assessing the information content in our data. We start by estimating impulse response functions for the main macroeconomic variables of a shock to the real interest rate using our baseline specifications—alternatives 1 to 3 in expression 5, where shocks are being identified using short-run timing assumptions (i.e., a Cholesky decomposition).

As shown in Figure 23, a one standard deviation increase in the real federal funds rate tends to reduce output growth, although the effect is small and not statistically significant. The fed funds rate increases approximately 25 basis points on impact (bottom right panel), in line with common moves in U.S. monetary policy. The corporate bond spread increases with the raise in the real interest rate, and, as expected, growth in bank core lending capacity initially drops. The inflation response is not statistically significant, and, if anything, inflation initially moves higher together with the real fed funds rate. This is a well-known outcome of this type of VAR models and has received extensive attention in the literature (Ramey, 2016).

We now complement this perspective by pursuing two alternative approaches for identifying monetary policy shocks. First, we follow a high frequency identification strategy, as in Gürkaynak et al. (2005) and Gertler and Karadi (2015). We employ shocks estimated as in Miranda-Agrippino and Ricco (2021) for this first exercise. The second approach estimates monetary policy shocks based on a narrative approach a la Romer and Romer (2004) but using the extended series of shocks constructed by Wieland and Yang (2020).

In both exercises, we estimate impulse response functions for the externally identified shocks with proxy-SVARs, in line with work by Mertens and Ravn (2013) and Stock and

Figure 23: *Orthogonal impulse response functions: Shock to the real federal funds rate*



Notes: The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black). All models are estimated using 2 lags. The sample period is 1996:Q2 to 2019:Q4.

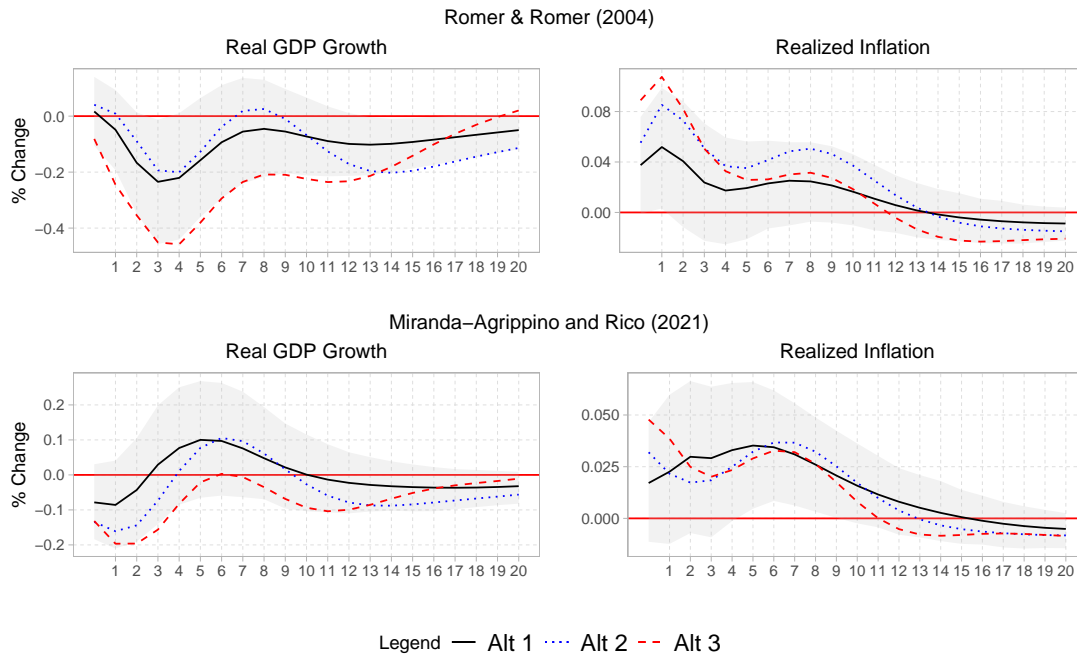
Watson (2018).¹⁶

Figure 24 presents the impulse response of output growth and inflation to a tightening monetary policy shock under the two external identification strategies. As with the orthogonal impulse response functions in Figure 23, we see that a monetary policy shock tends to initially reduce output growth and increase inflation, with both effects very small in economic terms and, in the case of output growth, also statistically insignificant.

Overall, the response of output growth and inflation to interest rate shocks is qualitatively similar to the response of these variables to shocks in overall bank lending standards. While

¹⁶See also Ramey (2016) for a thorough discussion of this methodology.

Figure 24: Externally identified monetary policy shocks: Impulse response functions

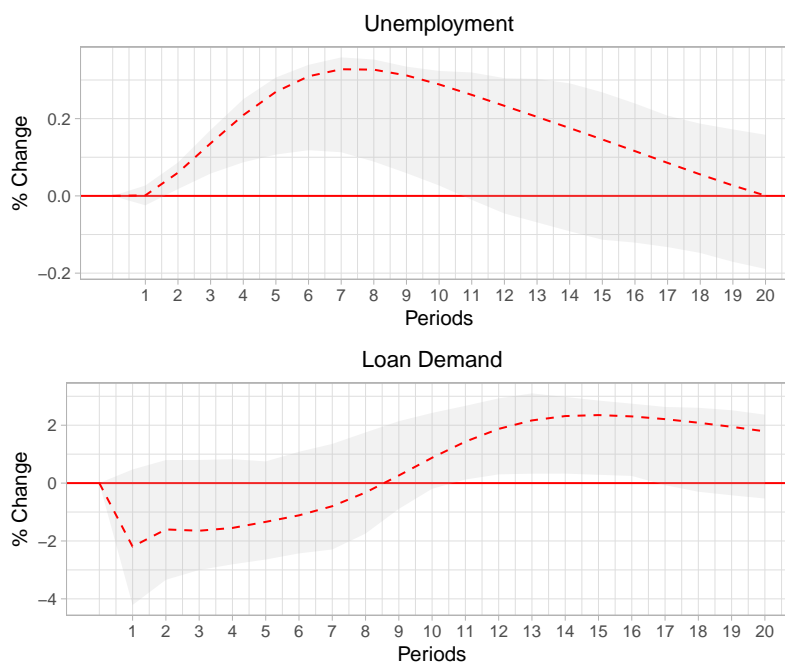


Notes: The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black). All models are estimated using 2 lags. The sample period is 1996:Q2 to 2019:Q4.

lending standards tend to have a more significant impact (economically and statistically) on output growth, their effect on inflation is more subdued. The fact that monetary policy shocks during our sample period did little in terms of changing inflation suggests that the similarly muted response of inflation to lending standard shocks may not be the result of a weak connection between bank credit supply and inflation, but rather the lack of significant variation in inflation (and the concomitant stability of monetary policy) during the period under consideration.

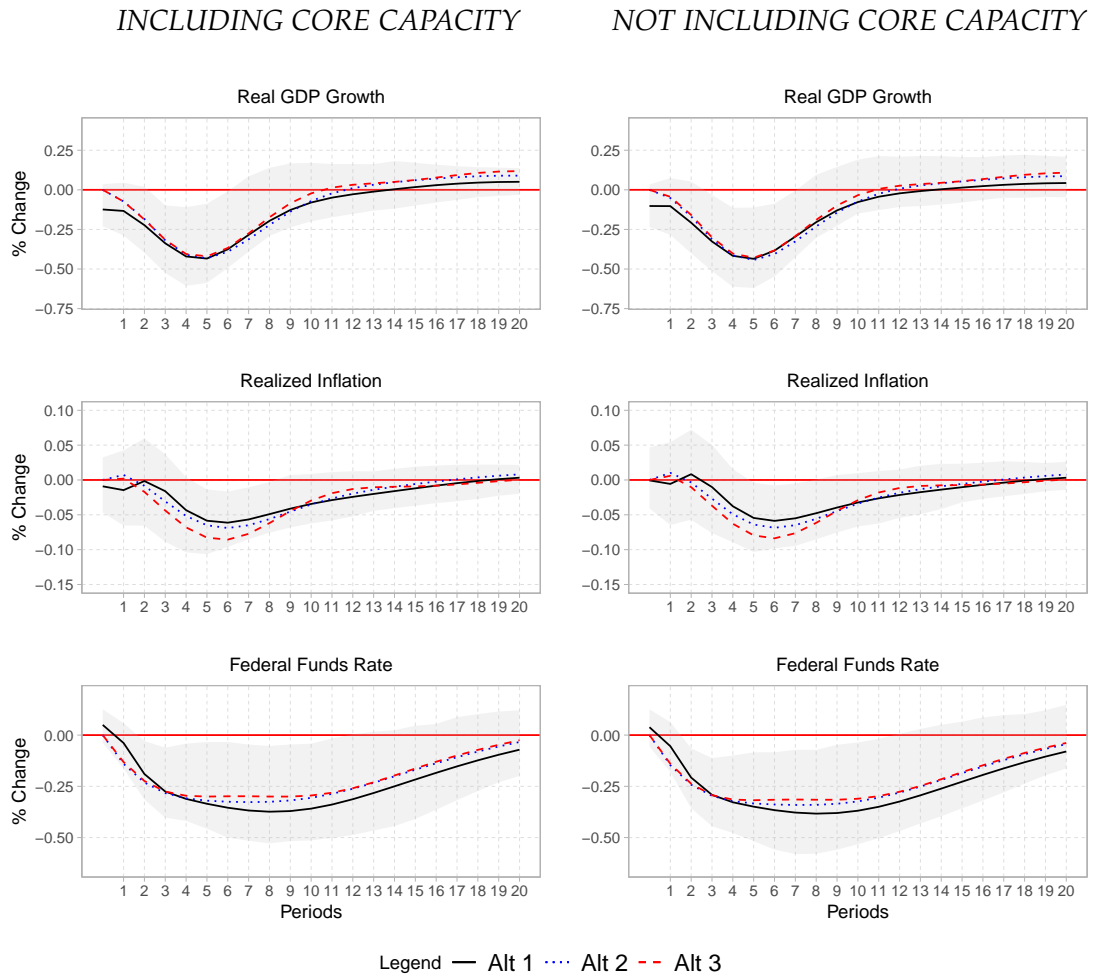
A.2 Other Tables and Figures

Figure 25: OIRFs for unemployment and loan demand from Alternative 3 – Section 3.4.



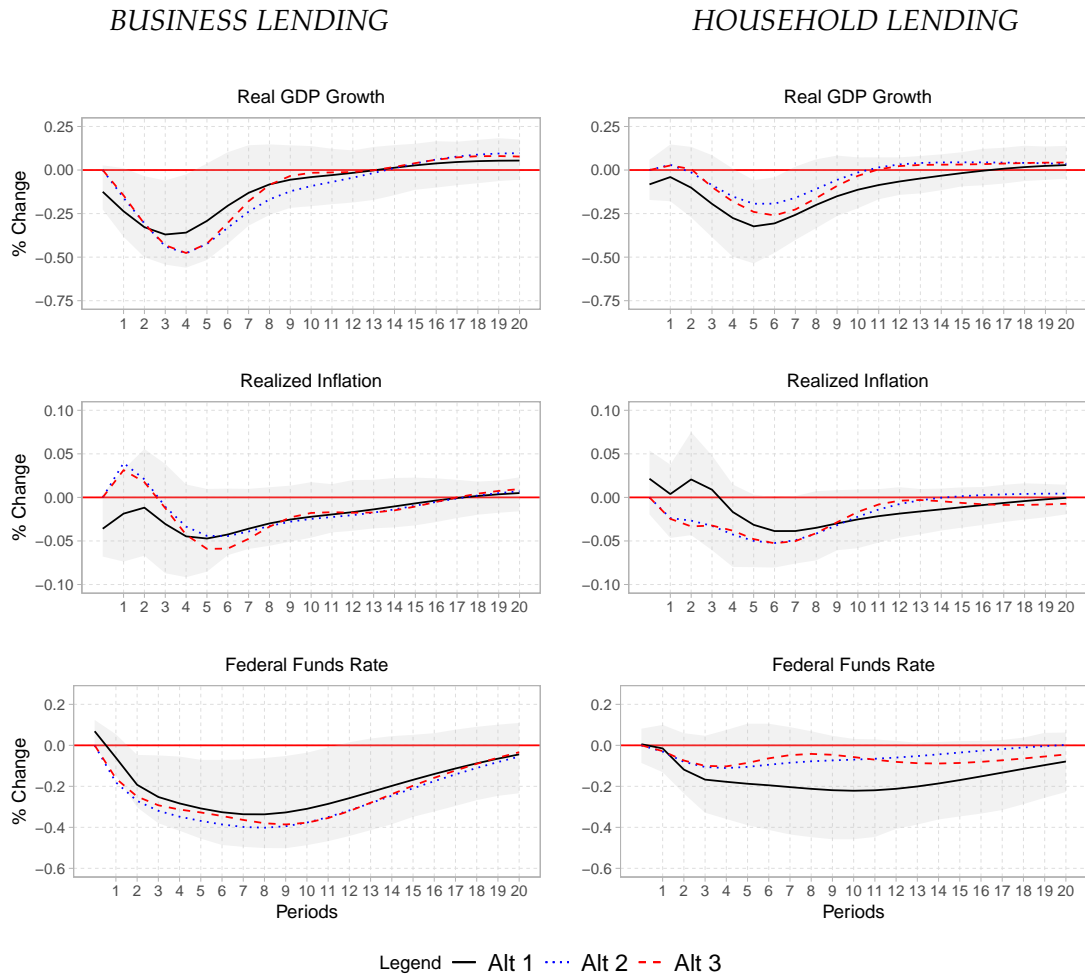
Notes: The impulse response corresponds to the effect of a 1 SD tightening shock to overall lending standards under Alternative 3 (see expression (5) in the text), estimated using 2 lags. The shaded area represents bootstrap 90% confidence intervals from 250 iterations. The sample period is 1996:Q2 to 2019:Q4.

Figure 26: OIRFs for the benchmark model without including core lending capacity



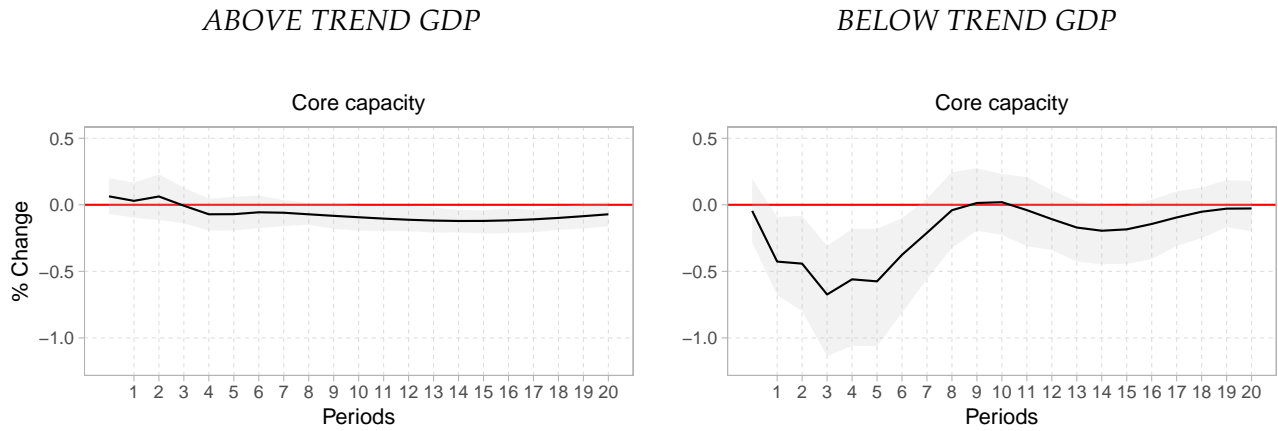
Notes: The left column uses the estimation that includes bank core lending capacity, and the right column uses the one that does not include it. Impulse responses correspond to the effect of a 1 SD shock to overall lending standards. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black); see expression (5). All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

Figure 27: OIRFs when lending standards for households appears before that for businesses



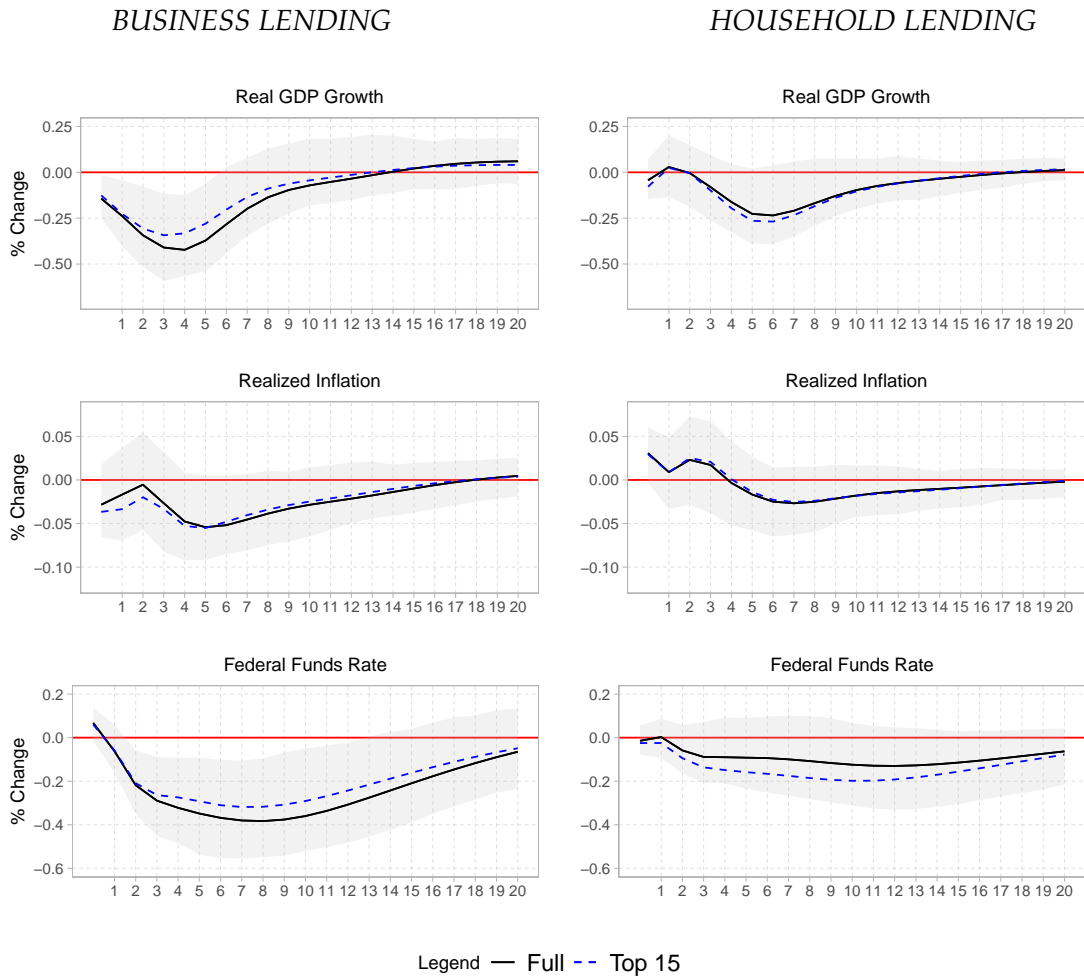
Notes: The left column corresponds to the effect of a 1 SD shock to business lending standards, and the right column a 1 SD shock to household lending standards. The shaded area represents bootstrap 90% confidence intervals from 250 iterations, centered on Alternative 1 (in black); see expression (5). All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.

Figure 28: *Orthogonal impulse response function for core lending capacity: Shock to lending standards*



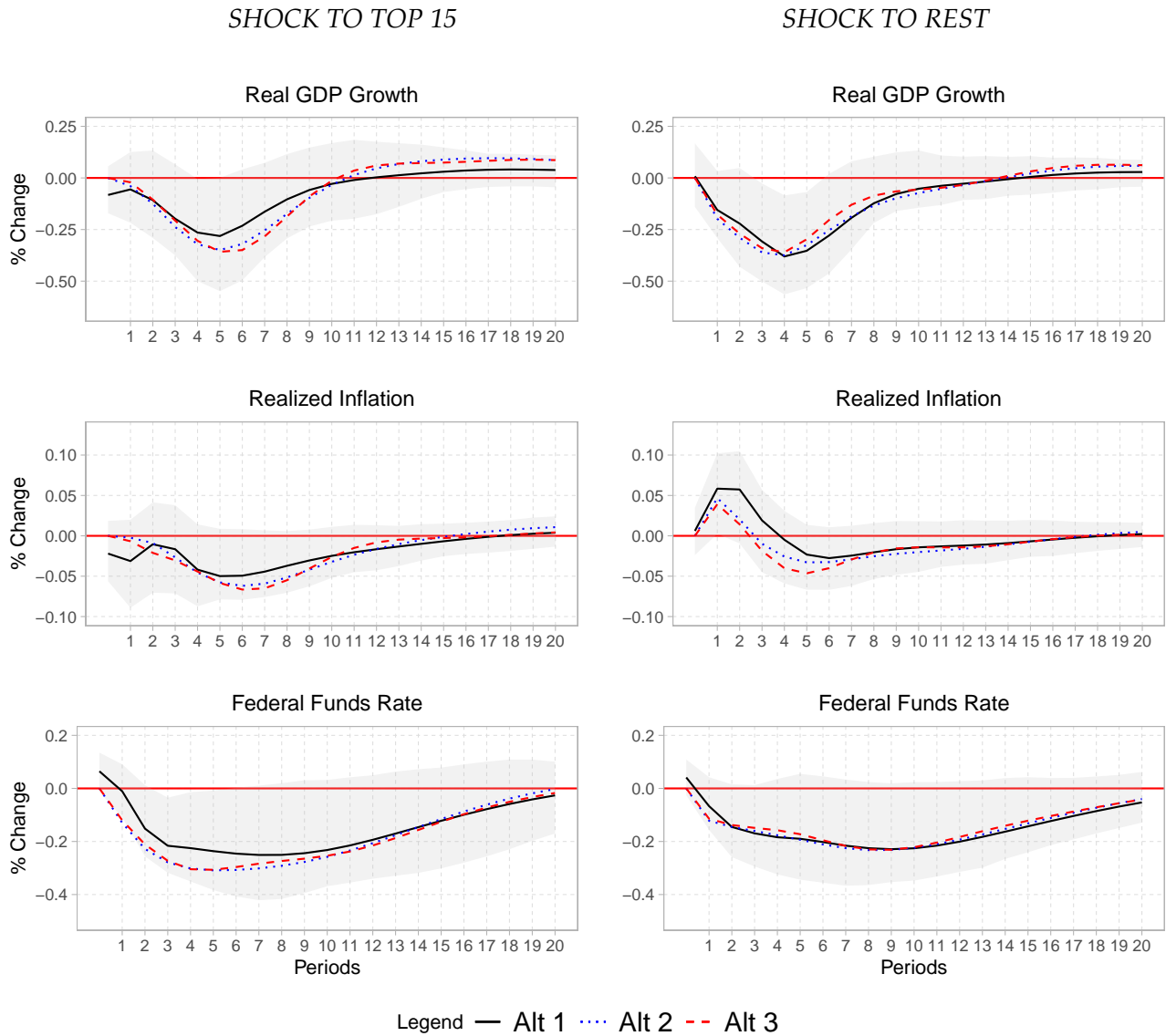
Notes: *Based on the estimation of Alternative 1, the plots correspond to the effect on core lending capacity of a 1 SD shock to overall lending standards that happens when real GDP is above trend (left column) and below trend (right column). The shaded area represents bootstrap 90% confidence intervals from 250 iterations. All models use 2 lags. The sample period is 1996:Q2 to 2019:Q4.*

Figure 29: Comparison of OIRFs when using all SLOOS banks or only the top 15 largest



Notes: OIRFs for a VAR model with adjusted lending standards for both businesses and households, with business lending standards appearing in the order of variables before household lending standards, as in Section 4. The impulse functions are for a 1 standard deviation shock to business lending standards in the left column and a one standard deviation shock to household lending standards in the right. The black line corresponds to the lending standards for all the SLOOS banks, and the red line is for the top 15 largest. The shaded area represents bootstrap 90 % confidence intervals from 250 iterations, centered around the impulse response functions for the full sample of SLOOS banks. All models use 2 lags. The sample period is 1996 Q2 to 2019 Q4.

Figure 30: Orthogonal impulse response functions to shock in lending standards of top 15 and others



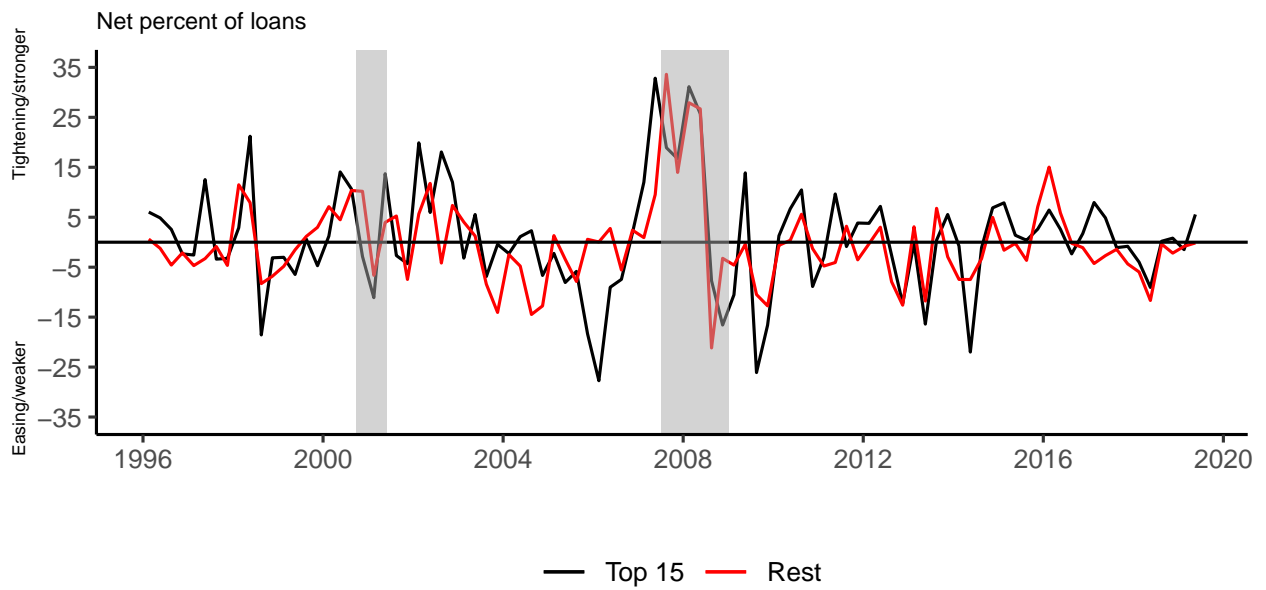
Notes: OIRFs for a VAR model that includes two lending standard series, one for the top 15 banks and another for all the rest. The impulse responses on the left are for a shock to the lending standards of ONLY the top 15 SLOOS banks by assets. The plots on the right show a shock to lending standards to all SLOOS banks that are not in the top 15 group. The shaded area represents bootstrap 90 % CIs from 250 iterations, centered around the impulse response for Alternative 1, the black line. All models use 2 lags. The sample period is 1996 Q2 to 2019 Q4.

Table 7: Forecast error variance decomposition for Alternative 3 of the VAR

Forecast error in	Forecast horizon h	Proportions of forecast error variance h periods ahead accounted for by innovations in									
		RGDP	Unemp	BUS _d	HOU _d	CC	INF	CBS	FFR	BUS _s	HOU _s
RGDP	1	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2	89.5	1.2	1.8	1.5	0.8	1.1	0.5	0.2	2.9	0.5
	3	70.0	0.9	2.1	2.5	2.0	6.5	3.8	0.2	11.1	0.9
	4	53.0	0.8	2.4	4.4	1.4	10.5	5.9	0.1	21.0	0.6
	8	29.7	4.9	1.4	11.2	3.7	8.6	5.2	1.0	31.0	3.4
	12	29.1	5.3	1.3	11.7	3.6	9.4	4.9	1.2	29.5	4.0
	20	28.2	5.1	1.4	12.8	3.5	10.0	4.8	1.2	29.0	3.9
INF	1	0.6	1.6	0.0	0.0	0.4	97.3	0.0	0.0	0.0	0.0
	2	0.3	1.9	0.3	3.3	7.7	83.3	0.4	0.0	1.1	1.7
	3	0.7	3.0	0.2	10.7	11.9	68.5	0.9	0.5	0.9	2.7
	4	1.1	3.3	0.3	16.2	12.8	60.1	1.4	0.8	1.0	3.0
	8	2.1	3.2	0.3	17.0	10.1	47.6	1.9	0.9	11.2	5.5
	12	3.9	3.4	0.4	16.5	9.4	44.9	1.8	1.0	12.5	6.3
	20	4.2	3.3	0.5	16.7	9.3	43.5	2.0	1.6	12.7	6.2
FFR	1	6.0	1.1	4.5	2.7	1.5	38.4	1.0	44.8	0.0	0.0
	2	10.5	2.1	2.1	1.5	0.6	26.6	1.0	45.0	10.7	0.0
	3	12.5	5.0	1.1	0.8	0.4	17.3	0.6	42.6	19.5	0.1
	4	14.6	7.0	0.7	0.5	0.4	11.8	0.5	40.0	24.2	0.2
	8	24.6	7.7	1.3	0.2	0.4	5.1	1.0	28.6	31.0	0.2
	12	26.4	6.8	1.9	0.8	1.2	4.2	2.7	20.1	35.7	0.2
	20	25.5	6.5	1.9	2.6	2.2	4.4	3.8	16.1	36.5	0.4

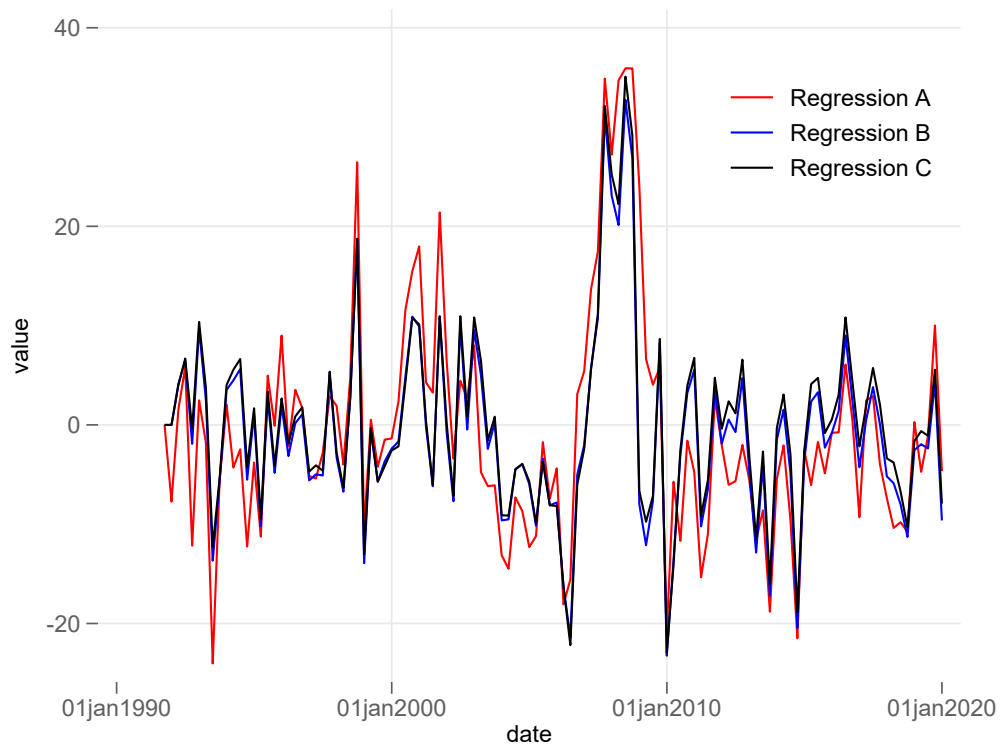
Notes: Forecast error variance decomposition for real GDP, realized inflation, and the federal funds rate. The variance decomposition is constructed via Cholesky decomposition, using quarterly data from 1996:Q2 to 2019:Q4. All variances are reported as percent of the total error variance at horizon h attributed to the given shock.

Figure 31: Adjusted lending standards for top 15 SLOOS banks by assets and the rest



Note: Sample period is from 1996:Q1 to 2019:Q4.

Figure 32: *Micro approach: Alternative regressions — residuals*



Note: *Sample period is from 1996:Q1 to 2019:Q4.*

A.3 On the Comparison of the Micro and Macro Approaches

Denote by S_{it} the lending standards and D_{it} the loan demand index of bank $i \in I$ at time t . Let the standards for bank i have an endogenous and an exogenous component with the endogenous component being a response to the demand side of the market. Then, we can write:

$$S_{it} = \alpha_i D_{it} + u_{it},$$

where u_{it} is the exogenous component. Furthermore, assume that u_{it} has an aggregate and an idiosyncratic portion, so that $u_{it} = u_t + \epsilon_{it}$.

The demand for loans of bank i could in principle depend on many micro and macro factors, but for simplicity, we consider a simple specification where demand is the combination of two components, an aggregate component (that could be endogenous to other aggregate variables) and an exogenous idiosyncratic component. That is:

$$D_{it} = D_t + e_{it}.$$

Here, both ϵ_{it} and e_{it} are assumed to be mean-zero random variables.

Under these conditions, it is easy to see that when α_i is the same for all banks, controlling for endogeneity at the micro or macro level gives equivalent results. For simplicity, assume all banks are of the same size so when we compute aggregate variables, we use simple averages (when banks differ in size, as they do in our sample, using weighted averages is a better option).

For the micro approach, we first project S_{it} onto D_{it} and then compute the average exogenous component of S_{it} . That is, we estimate:

$$S_{it} = \hat{\alpha} D_{it} + \hat{u}_{it},$$

and then average \hat{u}_{it} to get the aggregate exogenous component of lending standards. For large I , the average \hat{u}_{it} converges to u_t .

Alternatively, with the macro approach, we first aggregate lending standards and demand, and then project standards on demand. That is, we estimate:

$$\bar{S}_t = \hat{\alpha}\bar{D}_t + \hat{u}_t,$$

where $\bar{S}_t = \sum_i S_{it}$ and $\bar{D}_t = \sum_i D_{it}$ and, using that $S_{it} = \alpha D_{it} + u_t + \epsilon_{it}$, we get that:

$$\hat{u}_t = \bar{S}_t - \hat{\alpha}\bar{D}_t = \alpha\bar{D}_t + u_t + \bar{\epsilon}_t - \hat{\alpha}\bar{D}_t,$$

where $\bar{\epsilon}_t = \sum_i \epsilon_{it}$. Hence, we have that \hat{u}_t converges to u_t as the sample size becomes large. In summary, both the micro and the macro approach identify u_t as the exogenous component of lending standards relevant for macro analysis.

Caveats. Here, we assume that the idiosyncratic components of loan demand and supply average to zero every period if the sample of banks is large. However, the size distribution of banks is very skewed, and it is likely that idiosyncratic shocks to individual large banks result in aggregate effects. These derivations, however, still hold since the driving force behind u_t is left unspecified (and could be a shock to a large bank).

A.4 Data Appendix

We present a glossary and summary statistics of the variables used in the construction of adjusted lending standards based on bank-level changes in lending standards and demand. Since we deal with traded and non-traded banks in our analysis, we do not use Tobin's Q and stock returns as controls, and we instead use returns on assets available in call reports.

Table 8: *Glossary of variables in the cross-section regressions*

Variable	Symbol	Source
Change in Standards	ΔS_{cit}	SLOOS
Change in Loan Demand	ΔD_{cit}	SLOOS
Economic Outlook: Real GDP	$E_{t-1}[y_{t+4} - y_t]$	SPF
Economic Outlook: Unemployment	$E_{t-1}[u_{t+4} - u_t]$	SPF
Economic Outlook: Treasury Bill	$E_{t-1}[r_{3mt+4} - r_{3mt}]$	SPF
Economic Outlook: Treasury Bond	$E_{t-1}[r_{10yt+4} - r_{10yt}]$	SPF
Change in Real GDP	$[y_t - y_{t-4}]$	FRED
Change in Unemployment	$[u_t - u_{t-4}]$	FRED
Change in Real FF Rate	Δrff_t	FRED (authors' calc.)
Change in EBP	ΔEBP_t	Favara et al. (2016)
Change in CBOE Volatility Index	ΔVIX_t	FRED
Change in Net Interest Margin	$\Delta NIM_{i,t-1}$	Call Reports
Change in Loan Loss Provisions	$\Delta LLP_{i,t-1}$	Call Reports
Bank Size (Log of Assets)	$\ln A_{i,t-1}$	Call Reports
Return on Assets	$ROA_{i,t-1}$	Call Reports
Core Deposits over Tot. Assets	$CoreDep_{i,t-1}$	Call Reports
C&I Loan Share of Tot. Assets	$C\&ILns_{i,t-1}$	Call Reports
CRE Loan Share of Tot. Assets	$CRELns_{i,t-1}$	Call Reports
RRE Loan Share of Tot. Assets	$RRELns_{i,t-1}$	Call Reports
Consumer Loan Share of Tot. Assets	$CONSLns_{i,t-1}$	Call Reports

Notes: The first set of variables, from row 2 to row 7 in the table, are the macroeconomic variables denoted by m_t in expression (3). The next two variables characterize general risk attitudes in the economy, denoted by f_t in expression (3). Finally, the bottom nine variables are the components of the vector Z_{it} of bank-specific controls. SPF is the Survey of Professional Forecasters.

Table 9: Summary statistics for regressor variables in Table 1

Variable Name	Variable Units	Mean	Standard Deviation	1st Percentile	Median	99th Percentile
One-Year GDP Outlook	Percent	2.677	0.504	0.839	2.713	3.880
One-Year Unemployment Outlook	Percentage Points	-0.132	0.316	-0.647	-0.188	1.003
One-Year Treasury Bill Rate Outlook	Percentage Points	0.441	0.394	-0.222	0.447	1.374
One-Year Treasury Bond Rate Outlook	Percentage Points	0.393	0.266	-0.189	0.464	0.805
One-Year Yearly Change in Real GDP	Percent	2.491	1.569	-3.344	2.558	4.764
Yearly Change in Unemployment	Percentage Points	-0.127	0.937	-1.333	-0.367	3.633
Quarterly Change in Excess Bond Premium	Percentage Points	-0.006	0.348	-1.351	-0.003	0.945
Yearly Change in Real Federal Funds Rate	Percentage Points	-0.015	0.415	-1.403	0.055	0.664
Quarterly Change in Net Interest Margin (Lagged)	Annualized Percentage Points	3.534	0.972	0.918	3.537	6.129
Quarterly Change in Loan Loss Provisions (Lagged)	Annualized Percentage Points	0.382	0.653	-0.229	0.205	3.228
Quarterly Change in CBOE Volatility Index	Index Units	-0.061	5.020	-11.984	-0.428	13.425
Bank Size (Lagged)	Thousands of US Dollars	110000	284000	1647	25000	1680000
Return on Assets (Lagged)	Percent	0.262	0.273	-0.510	0.282	0.640
Share of Core Deposits (Lagged)	Percent	9.318	6.784	0.000	7.884	28.151
Commercial and Industrial Loan Share (Lagged)	Percent	15.244	7.934	0.856	14.400	39.077
Commercial Real Estate Loan Share (Lagged)	Percent	15.199	10.509	0.368	13.189	44.721
Residential Real Estate Loan Share (Lagged)	Percent	11.413	6.990	0.018	10.569	33.615
Consumer Loan Share (Lagged)	Percent	6.597	5.948	0.040	5.180	28.563

Notes: All data series begin 1991:Q3 and end 2019:Q4, with the exception of One-Year Treasury Bond Rate Outlook which begins in 1992:Q1. Series are not seasonally adjusted.