Does the Sectoral Allocation of Credit Matter for Financial Stability Risks?

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Abstract

Do financial stability risks originate in the growth of lending to particular sectors? Should financial regulators target individual sectors, such as mortgages, and should such tools vary over time? In this paper, I discuss what recent research can tell us about these questions and discuss some new evidence based on a dataset on sectoral credit for 120 countries from 1940 to 2014, spanning across almost the entirety of modern banking crises.

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1 Introduction

The Great Financial Crisis 2007-2008 has led to a fundamental rethinking of how the financial sector interacts with the macroeconomy. In an effort to prevent the deep economic downturns associated with severe financial sector disruptions, regulators have been equipped with entirely new toolkits under the grouping of "macroprudential regulations."

A key feature of many of these regulations is that they are aimed at particular sectors of the economy. The underlying rationale is that many boom-bust episodes that end with financial sectors in distress seem to have a sectoral bias. Perhaps most saliently, during the boom of the 2000s, most countries that would experience the worst subsequent downturns saw pronounced increases in mortgage debt (Jones, Midrigan and Philippon, 2018). There is evidence that household debt also played a role in previous banking crises. Other episodes featured a boom and bust in different assets, such as railroads, farm land, or even the proverbial tulip (Kindleberger, 1978).

So what should regulators do when confronted with a boom in a particular sector? At the time of writing, there is an ongoing debate among policy makers in the United States about the potential risks in the leveraged loan market, the market for risky corporate debt. SEC chairman Jay Clayton sees "echos of the 2008 financial crisis" (Wall Street Journal, 2019), while Federal Reserve chairman Jerome Powell stresses that the "financial system appears strong enough to handle potential losses" (Bloomberg, 2019).

A natural move is to turn to the historical record and ask: Has rapid growth in corporate debt preceded banking crises? Or more broadly, is a shift in the allocation of credit to particular sectors of the economy a sign of trouble down the line?

Even more than a decade after the onset of the 2008 crisis, I do not think we can answer these questions with certainty. But a growing body of theoretical and empirical work suggests a number of regularities. In this paper, I discuss what we know and do not know about the "anatomy" of credit booms and present some new insights based on ongoing work. I argue that changes in the *allocation* of credit, not just its quantity, are key to understanding the recurring incidence of crises in the financial sector.

I take a data-driven approach to summarize patterns of credit allocation around financial crises, building on ongoing work in Müller and Verner (2019). In particular, I use a large dataset on sectoral credit from 1940 to 2014 for 120 countries from Müller (2018), crossed with data on systemic banking crises from a variety of sources. Based on the existing literature and the results of my empirical tests, I arrive at two major takeaways.

First, credit booms that end in busts are not created equal. Growth in housing-related debt, both on the household and corporate side, seem to be among the more frequent precursors of financial turmoil. A perhaps even clearer result, both on theoretical and empirical grounds, is that expansions of the nontradable service sector often precede crisis episodes.

I show that an increase in construction and nontradable sector debt appears to precede crises even after controlling for the growth in lending to other sectors. Although there are other explanations, one reading of this evidence is that pronounced sectoral shifts may coincide with a deterioration of lending standards that ultimately ends badly. Particularly striking is that an allocation towards industrial and infrastructure sectors appears to be associated with a considerably *lower* crisis probability going forward.

Sectoral credit growth rates also have a somewhat better ability to classify the data into crises and non-crisis episodes than aggregate credit data. I evaluate classification ability using the Area Under the Curve (AUC) statistic, which essentially asks whether a variable is particularly good at identifying true positives compared to false positives.[1] While I interpret these results purely as in-sample correlations, they suggest that studying the link between the distinctive allocative role of credit markets and financial turmoil may be worth of further study.

Second, I discuss policy implications. An all too obvious conclusion some may want to draw from these findings is that regulators should

[1]More precisely, the AUC is an integral over the Receiver Operating Characteristic (ROC) space given by combinations of the true positive rate (true positives divided by true positives and false negatives) and the false positive rate (false positives divided by false positives and true negatives).

use targeted macroprudential tools to reign in the build-up of sectoral risks. I argue that too much confidence in such regulations may be misguided. One obvious reason is that we know very little about *why exactly* particular types of debt should play a more prominent role in economic fluctuations. The existing empirical evidence is consistent with a number of theories, and disentangling these in the data is important for designing policies. We also do not have a good sense about the elasticity of different types of credit to macroprudential tools on a granular level. Credible estimates of these elasticities, however, are key: if macroprudential policy considerably affects the sectors *least* associated with crises, this might lead to unintended distortions with potential negative welfare consequences. Perhaps even more importantly, time-varying policies are subject to potential political interference. Macroprudential policies targeting specific sectors, for example, are subject to a powerful electoral cycle across countries.

I argue that a better takeaway for policy makers might be to think about transparent *time-invariant* restrictions on particular types of credit for the largest, systematically important financial institutions. While such approaches may have a myriad of downsides, they are perhaps not as easily reversed as time-varying tools when political pressures arise, and do not directly depend on the elasticity lending to different sectors to changes in macroprudential policy.

This paper consists of three parts. In section 2, I discuss existing theory and evidence on the role of credit allocation in periods of financial instability. I also discuss empirical predictions coming out of the existing literature. Section 3 presents some empirical evidence on patterns of sectoral credit growth around banking crises. In section 4, I discuss these findings in light of policy, and further highlight potential challenges to sectoral tools. Section 5 concludes.

2 Credit Allocation and Financial Stability: Theory and Evidence

In this section, I discuss theory and evidence which suggest that the *allocation* of credit, not just its quantity or price, might play a role in understanding the deep recessions associated with financial crises. I begin the discussion with two parts: one that focuses on theories that predict a sectoral bias in booms and busts, and one that focuses on empirical evidence. I then derive a synthesis with a number of empirical predictions.

2.1 Theory

At its very core, finance is about the allocation of resources. As such, the idea that debt booms in some sectors are particularly important for the macroeconomy is as old as the economics discipline itself. However, there is a smaller number of theories with distinct predictions about the allocation of credit.

As a starting point, a sizeable literature studies how inefficient private borrowing can generate financial instability (e.g. Lorenzoni, 2008; Bianchi, 2011; Guerrieri and Lorenzoni, 2017; Jeanne and Korinek, 2018). Of the many potential sources that may exacerbate deep downturns following crises, downward nominal rigidities (e.g. Farhi and Werning, 2016; Schmitt-Grohé and Uribe, 2016) and liquidity traps (e.g. Eggertsson and Krugman, 2012; Korinek and Simsek, 2016) have received special attention. The empirical predictions from these models stand somewhat in contrast to models where the permanent income hypothesis holds. If households smooth permanent income over the cycle, an anticipation of higher income in the future generates a positive link between borrowing today and output tomorrow (e.g. Aguiar and Gopinath, 2007).

A first link to sectoral heterogeneity comes from early work on borrowing constraints. In models that follow Kiyotaki and Moore (1997), debt is determined by asset prices and collateral requirements. Changes to collateral requirements, in turn, drive credit cycles (e.g. Eggertsson and Krugman, 2012; Guerrieri and Lorenzoni, 2017; Jones, Midrigan and Philippon, 2018); also see Bernanke, Gertler and Gilchrist (1999). This body of work serves as the theoretical backdrop for empirical studies on collateral values, which may differ across sectors (e.g. Chaney, Sraer and Thesmar, 2012). In models with borrowing constraints, higher credit demand puts upward pressure on interest rates. That is, booms coincide with higher borrowing costs, resembling a credit demand shock. Justiniano, Primiceri and Tambalotti (2015) build a model where a loosening of *lending* constraints (combined with loosened *borrowing* constraints) leads to a largely supply-driven boom-bust pattern in credit and house prices.

In models that follow Mendoza (2002), (household) borrowing depends on income from the tradable and nontradable sectors (e.g. Bianchi, 2011). This closely ties credit growth to sectoral output and prices. Mian, Sufi and Verner (2017*b*), for example, use a stylized framework to derive sectoral predictions about credit booms. In their model, shocks to household credit increase non-tradable output and prices, while shocks to non-tradable (tradable) sector credit decreases (increases) prices. Schneider and Tornell (2004) study a setting with bailout guarantees for lenders and asymmetries between borrowing firms in the tradable and nontradable sectors. In particular, tradable sector firms have access to perfect financial markets while the nontradable sector cannot commit to repay debt. This setup gives rise to endogenous borrowing constraints, a currency mismatch, and a boom-bust cycle. Rognlie, Shleifer and Simsek (2018) explicitly model how a relaxation of borrowing constraints (due to low interest rates) can lead to a reallocation of resources towards sectors with durable capital, such as housing.

Sectoral booms and busts do not, however, require the existence of collateral constraints. Schmitt-Grohé and Uribe (2016), for example, study an open-economy model where booms drive up the demand for non-tradables in a full liability dollarization setup. The key inputs here are downward nominal wage rigidity and currency pegs. These create a negative externality in the bust because real wages cannot adjust downward, which causes unemployment.

A finance-driven key insight comes from recent work by Khorrami (2019). He shows that a shock to the ability of financiers to diversify risks in one sector of the economy can lead to a reallocation of investment towards it. Because better diversification reduces risk premia (such as during the 2000s US housing boom), financiers borrow more, which leads to an increase in leverage. This ultimately leads to a bust because financiers do not internalize their impact on aggregate risk premia. In Gorton and Ordoñez (2016), boom-bust cycles can arise after positive productivity shocks because lenders do not sufficiently examine the quality of collateral. Because less collateral screening reduces the quality of projects that are financed, an increase in screening can prompt a recession.

2.2 Existing Empirical Studies

An increasing body of work suggests that debt in some sectors of the economy might be more consequential for macroeconomic downturns than others. Jappelli and Pagano (1994) were perhaps the first to single out a role for household credit. They use an overlapping generations model and cross-country regressions to argue that household debt can decrease aggregate saving rates and economic growth. Radelet et al. (1998) show that, between 1990 and 1996, many countries that were later affected by the East Asian Crisis experienced a pronounced shift in lending from agriculture and manufacturing towards household credit and the construction sector. In an early account of the Great Financial Crisis 2007-2008, Hume and Sentance (2009) argue that the use of credit for the purchase of existing assets was at the heart of the "growth puzzle" of the early 2000s. In what is perhaps the first paper linking sectoral debt to banking crises more systematically, Büyükkarabacak and Valev (2010) study the period 1990 to 2005 in a sample of 45 mostly developing countries. They find that growth in household debt is associated with the onset of banking crises, and more so than growth in firm debt. Jordà, Schularick and Taylor (2015*a*,*b*) find similar evidence for mortgage vs. total credit for advanced economies. They show that banking crises are more likely and followed by deeper recessions when preceded by a boom in mortgage credit.

Mian, Sufi and Verner (2017*a*) find that this boom-bust pattern of increases in household debt also holds without conditioning on a banking crisis. Growth in credit to households is accompanied by a predictable short-term boom in consumption, imports, and current account deficits that is followed by a severe bust in output. The same pattern does not hold true for credit expansions to firms. Using state-level banking deregulation in the US as a quasi-experiment, Mian, Sufi and Verner (2017*b*) extend these findings. More precisely, deregulation led to a short-term boom in household debt, house prices, and a shift of employment towards the non-tradable sector. This boom was followed by a severe bust. Because consumer prices in the non-tradable sector increased markedly, they conclude that these patterns are most consistent with credit supply boosting household demand, rather than firm productivity.

Di Maggio and Kermani (2017) exploit the federal exemption from local predatory lending laws as a credit supply shock in the 2000s and find similar evidence along many dimensions. The finding that credit boosts house prices also holds in other settings. Favara and Imbs (2015) use interstate branching deregulation as an exogenous shock and show that it increased mortgage credit and house prices; Adelino, Schoar and Severino (2012) construct an identification strategy based on non-conforming loan limits. Rajan and Ramcharan (2015) document that credit availability boosted farm land prices during the 1920s boom, i.e. an agricultural boom. These studies are important because they suggest that, during booms, credit and real resources are being reallocated towards sectors with a higher dependence on real estate or land. Indeed, there is some direct evidence that rising house prices benefit firms and industries with larger real estate holdings (Chaney, Sraer and Thesmar, 2012; Doerr, 2018) and reallocate credit from firms to households (Chakraborty, Goldstein and MacKinlay, 2018).

The pattern that credit booms are accompanied by an expansion of the nontradable sector and real exchange appreciations also create a natural bridge with a large literature on imbalances in international economics (e.g. Calvo, Leiderman and Reinhart, 1996). Bahadir and Gumus (2016) show that, in a sample of emerging markets, household debt is more correlated with macroeconomic variables than firm debt. Household debt booms predict real exchange appreciations and an expansion of the nontradable sector. In an important paper, Gopinath et al. (2017) show that capital inflows into Southern Europe since the early 2000s were accompanied by a reallocation towards firms with high net worth but low productivity. Relatedly, Reis (2013) argues that capital misallocation helps explain the Portuguese crisis experience. More support comes from cross-country panel evidence in Borio et al. (2016), who show that credit booms tend to coincide with a reallocation of employment towards low productivity sectors. Because firms in the nontradable sector are generally less productive, this also meshes well with the cross-country pattern in Kalantzis (2015), who shows that capital inflow episodes are associated with nontradable sector expansions (also see Tornell and Westermann, 2005; Giovanni et al., 2017). It is also consistent with the pattern documented in Gorton and Ordoñez (2016) that "bad" credit booms coincide with low productivity growth. Credit allocation during the boom may also have long-term consequences by affecting educational choices across sectors (Charles, Hurst and Notowidigdo, 2018).

Much of the literature on finance and economic growth also makes explicit reference to sectoral heterogeneity. A classic paper by Rajan and Zingales (1998) shows that manufacturing industries with a higher dependence on external financing grow fast in countries with more developed financial sectors. Braun and Larrain (2005) show that these industries are hit harder during recessions; Kroszner, Laeven and Klingebiel (2007) report that the same holds true for banking crises. Hsu, Tian and Xu (2014) show that high-tech industries patent more in countries with *smaller* credit markets (but larger equity markets).

2.3 Empirical Predictions

Taken together, the existing theoretical and empirical literature is broadly consistent with the following interpretation. Private debt booms ending in crises are often driven by credit supply, and can be fueled by capital flows. These booms follow a predictable pattern. As financing conditions loosen, marginal loans are increasingly extended to ex-post riskier households and firms with high net worth or particularly collateralizable assets. This is reinforced by debt-fueled household demand for non-tradable goods and rising house prices. If a shock brings the boom to a halt, large-scale financial turmoil ensues. But reversing inefficient investments during the boom is costly, particularly in the presence of frictions such as nominal rigidities. This leads to prolonged downturns.

This synthesis has a clear empirical prediction for sectoral credit growth in the run-up to banking crises: lending should expand particularly in nontradable industries and housing-related sectors. It might even be that the *share* of credit to these sectors increases prior to crises, while that of other industries might decline.

There is a clear contrast between this synthesis and the idea that many assets or sectors might be prone to experience "bubbles". Rajan and Ramcharan (2015), for example, write that "[t]he usual difficulty in drawing general lessons from episodes of booms and busts in different countries is that each crisis is *sui generis*, driven by differences in a broad range of hard-to-control-for factors." Broadly speaking, this view holds that booms are inherently sparked by some novel element that makes their outcomes unpredictable. In the data, Barberis et al. (2016) document a pattern of extrapolation during bubble episodes in different asset classes. In his classic history of financial crises, Kindleberger (1978) revisits episodes resulting from overinvestment in assets as diverse as Tulips, railroads, and government bonds. The empirical prediction of the "sui generis" hypothesis is that credit to particular sectors should *not* be special. Booms and busts could essentially occur in any sector of the economy. In a close to comprehensive sample of banking crises, we should thus not find that lending growth differs systematically across sectors before they hit.

3 Some Evidence on Sectoral Credit and Crises

3.1 Data

In this section, I discuss some systematic empirical evidence on credit allocation around crises based on work in (Müller and Verner, 2019). This work extends the previous literature in a few ways. For one, the systematic evidence on banking crises and sectoral debt are based on a limited number of observations. Jordà, Schularick and Taylor (2015*a*,*b*) use a long-run narrow panel of 17 advanced economies; Büyükkarabacak and Valev (2010) use a broader but short panel of 16 years. Mian, Sufi and Verner (2017*a*) use a somewhat larger dataset but test for the role of firm vs. household credit in *business cycles* more broadly, not banking crises (also see Bahadir and Gumus, 2016).

A second extension overcomes the limited availability of sectoral data. Existing work has treated corporations as homogeneous. They also do not consistently differentiate between mortgage and household credit. These differences, however, might be important: in related work (Müller, 2018), I show that non-mortgage credit is important for understanding the expansion of household debt in emerging economies. Within corporate credit, there has been a secular shift towards real estate and service industries.

Third, existing network has largely focused on the *quantity* of credit and not explicitly addressed its *allocation*. There are, however, good reasons to expect allocation to matter over and above quantities empirically: in an important paper, Greenwood and Hanson (2013) show that the risk of corporate debt issues is higher during credit booms, and this increased risk-taking is not appropriately priced in bond returns. Krishnamurthy and Muir (2017) show that credit spreads are unusually low prior to banking crises.

I extend existing work using the historical sectoral credit data from Müller (2018). These data cover 120 countries for the period 1940-2014, which notably include many small open economies that often experience crises (Laeven and Valencia, 2018). As a starting point, Figure 1 plots how corporate and household credit have evolved relative to GDP since 1960 in an unbalanced panel of 66 emerging and 54 advanced economies (as classified by the World Bank in 2018). Household credit has grown almost uniformly around the world. The ratio of corporate credit to GDP has been essentially flat since the mid-1980s but shows a pronounced upward shift during the 2000s, particularly in advanced economies.

For crisis dates, I use multiple sources to maximize data availability. The starting point is the crisis indicator based on bank equity crashes from Baron, Verner and Xiong (2019). This measure has the advantage that it is motivated by theory and has a consistent definition, in contrast to many existing narrative crisis indicators (Bordo and Meissner, 2016). Taken together with the crisis dates in Laeven and Valencia (2018), Reinhart and Rogoff (2009), Bordo et al. (2001), I can construct a panel of credit and systemic banking crises for 108 countries and up to 5,275 country-year observations. There are 107 crises in the sample. Figure 2 plots the countries experiencing banking crises in the sample by year; there were no recorded crises between 1940 and 1972.

3.2 Patterns of Credit Growth Around Crises

As a starting point, I plot how different types of credit developed relative to GDP around systemic banking crises (conditional on country fixed effects). To aid the interpretation, I standardize the change in credit/GDP for each variable to have a mean of 0 and a standard deviation of 1. That means all numbers can be interpreted as changes in standard deviations relative to the country mean.

Figure 3 begins by plotting changes in total credit, household credit, and corporate credit. This reveals a distinctive pattern. Relative to the country mean, lending systematically expands in the years prior to banking crises. In the more distant years, household credit expands considerably faster than corporate credit. However, in the immediate run-up to the crisis, corporate credit growth in fact outpaces household lending. This could be read in at least two ways. On one hand, perhaps firms are relatively slower when it comes to "participating" in credit booms. On the other hand, it could be that the spike prior to crises is because firms draw down their credit lines during the early signs of a crisis, which increases total debt. This latter phenomenon was seen, for example, in the most recent crisis episode in the US.

Figure 4 divides household credit into its mortgage and non-mortgage components, where the latter largely reflects consumer lending. Here we can see that, while both mortgages and consumer lending expand prior to crises, increases in household debt mainly reflect mortgage credit.

Figure 5 looks at heterogeneity in corporate credit. Based on their patterns around crises, I divide industries into those with a clear "boom-bust" pattern (in Panel A) and those without (in Panel B). As it turns out, increases in corporate credit prior to crises are mainly driven by construction and real estate, nontradables, and other services. The patterns are considerably more muted for lending to industry (manufacturing and mining), agriculture, and transport and communication.

3.3 Does Sectoral Credit Help "Predict" Crises?

To formally investigate which types of credit growth systematically tend to precede crises, I turn to a simple logit prediction framework. These regressions broadly take the following specification:

$$P_{it} = \alpha + \beta \Delta_3 Credit/GDP^j_{it} + \varepsilon_{it}, \quad (1)$$

where P_{it} is a dummy for the onset of a systemic banking crisis and $\Delta_3 Credit/GDP^j_{it}$ is the 3-year change in the ratio of credit to GDP for sector j from $t-4$ to $t-1$ (see e.g. Mian, Sufi and Verner, 2017*a*). I also consider specifications with country fixed effects, where I run a "horse race" between different types of credit.[2] These fixed effects soak up unobserved heterogeneity across countries; however, they also mean I can only estimate these models for countries with at least one crisis. Again, I standardize all credit variables to have a mean of 0 and a standard deviation of 1 in the regression sample; I report marginal effects multiplied by 100 for readability. The error term is assumed to be well-behaved.

Table 1 presents the results for a few variants of these logit models. In model 1, I begin with total credit growth. This serves to replicate existing evidence using a larger sample. The results confirm a tight statistical link between credit expansions and future periods of financial turmoil. But how does this relationship vary depending on the type of credit? Models 2 through 4 start by differentiating between corporate, household, and mortgage loans. Note that mortgages here refer to *total* mortgage credit, as in Jordà, Schularick and Taylor (2015*a*,*b*), not only those for residential purposes.

Interestingly, I find that the estimated marginal effect of lending to corporations is very close to that of household loans. This is also reflected in terms of classification ability (AUC), which are in both cases comparable to that of total credit. This implies that, over the broad sweep of recent banking history around the world, crises have been preceded both by increases in household and corporate debt. The coefficient and

[2] Note that, because the sub-sectors add up to total credit growth, including all credit shares in the same regression is similar to using the *shares* of different credit types.

AUC for mortgage loans is somewhat smaller.

Models 5 and 6 then differentiate between household loans: *residential* mortgages and consumer credit. I find that the coefficient for residential mortgages is almost equivalent to that of total household loans in column 3. For consumer loans, the coefficient is somewhat smaller. The AUC of consumer loans is only 0.59 and I cannot reject that it is equal to 0.5, which would mean a coin toss. The AUC for residential mortgages is close to the total household credit estimate in column 3.

Models 7 through 12 in the bottom row investigate heterogeneity in corporate credit. This paints a striking picture. On average, since 1940, lending growth to agriculture and industrial sectors is not a systematic precursor of banking crises. This can most clearly seen when looking at the AUC, which include a coin toss (0.5) in the 95% confidence interval. Instead, the results for total corporate credit seem to be driven by loans to the construction and services sectors in columns 9, 10, and 12. Importantly, the AUC values for these three sectors – ranging from 0.62 to 0.71 – are close to or above those for total credit in the full sample in column 1. Credit to transport and communication is not statistically significant and has an AUC close to a coin toss.

A challenge in interpreting these results is that, during booms, credit growth across different sectors is likely highly correlated. Another issue is that credit growth rates and crisis probabilities may depend on unobserved differences across countries. I thus turn a "horse race" of different types of credit growth using fixed effects regressions in Table 2. Here, I focus on a more parsimonious number of sectors to preserve statistical power.[3] The bottom row plots the AUC of a model that only includes the change in total credit/GDP in the estimation sample (as in column 1 of Table 1).

The results in columns 1 to 7 confirm the main patterns in Table 1. On average, lending to the agriculture, industry, and transport/communication sectors does not reliably classify periods into crisis and non-crisis episodes, for which the 95% confidence interval for the AUC always includes

[3] Note that the inclusion of country fixed effects means that countries without banking crises drop out of the sample. The results here are almost equivalent without fixed effects.

0.5. Credit to the non-tradable service sector, other services, construction, and households yield the highest AUC. Most importantly, the horse race in column 8 suggests that banking crises are preceded by predictable shifts in the allocation of credit. The coefficients for agriculture, industry, and transport and communication now turn negative. This suggests that, prior to crises, lending systematically shifts away from these sectors and towards households, construction, and the nontradable sector.

Overall, these preliminary empirical results are a first indication of a systematic pattern of credit allocation around banking crises. However, I urge readers to interpret these with caution. For one, financial crises are notoriously hard to date, and it is unlikely that the same types of debt matter to the same degree across countries. We discuss these sources of heterogeneity in more detail in Müller and Verner (2019). Most importantly, the results here do not imply that credit growth or changes in credit allocation to particular sectors are necessarily good *forecasting* variables for banking crises. Instead, the findings should be read as in-sample correlations that describe broad patterns in credit allocation around crises.

4 Lessons for Policy Makers

Interpreted jointly with the existing literature, the empirical evidence discussed above seems to suggest a relatively clear pattern: financial crises are often "credit booms gone bust", and there is a predictable shift in credit growth towards particular sectors preceding them. In particular, it seems tempting to conclude that leverage in the non-tradable and also real estate sectors might play a special role.

It is all too easy to infer from these patterns that macroprudential tools aimed at sectors such as housing should be well-suited to contain financial stability risks. I want to caution that this conclusion may be premature for three reasons.

First, we do not have a good sense of why exactly credit booms in some sectors systematically precede crises and others do not. We have a few candidate theories but no strong sense of which ones best describe the empirical patterns. Maybe some sectors are more prone to booms because their assets are easier to collateralize when financing conditions are loose (e.g. Braun and Larrain, 2005; Braun, 2005). Maybe some sectors are simply more procyclical than others and move closer in tandem with the ups and downs of the business cycle. Maybe some sectors are less likely to have access to alternatives sources of financing and are thus particularly reliant on the health of financial institutions. Maybe lending to some sectors is systematically more profitable than others. Without knowing which factors are key, it is difficult to know whether and how to regulate lending to these sectors.

Second, we do not have reliable causal estimates of the elasticity of different types of credit to changes in macroprudential policy on a granular level. This elasticity, however, is a key statistic for policy prescriptions. If the sectors that most clearly expand prior to crises are also the most responsive to policy tools, regulations targeting aggregate credit may be desirable. But if sectors whose lending growth moves little around crises are the most responsive, aggregate tools could lead to serious distortions, which may provide a rationale for targeted sectoral tools.

Third, there is evidence that time-varying financial regulation is subject to powerful political constraints. For the case of macroprudential regulation, I provide evidence elsewhere that these constraints are most binding for tools aimed at household and real estate credit (Müller, 2019). More precisely, I show that *sectoral* macroprudential tools are subject to a predictable electoral cycle across countries, particularly during booms. Figure 6 illustrates this point. Of course, these regulations are aimed at exactly the sectors we may be most worried about from a financial stability perspective, particularly housing. This should make us wary of the idea that even the most enlightened policy makers are, in practice, able to enforce countercyclical regulations.

So what, then, should policy makers do? Clearly, more research is needed before giving clear guidance. But maybe it is worthwhile considering simpler alternatives, particularly in light of evidence that even the most complicated regulations often seem to be systematically circumvented by financial institutions (see e.g. Behn, Haselmann and Vig, 2016).[4] Simple and transparent guidelines may not only be cheaper but also easier to enforce.

If one were to be convinced that regulation should address sectoral risks, one simple approach could be lending restrictions that vary by sector but not by time. Because the health of large institutions is especially important from a macroeconomic perspective, perhaps one would want to target these institutions. While such regulations are surely also subject to political economy concerns, their time-invariant nature might insulate them at least somewhat from the most short-lived political pressures. It is also worth noting that such restrictions were common place in much of the advanced world until the 1980s. In the US, FDIC regulations limit the maximum exposure of institutions to individual borrowers, which can be thought of as somewhat similar.

Obviously, such regulations introduce inefficiencies that have to be weighed against the benefits from potentially limiting boom-bust patterns. Indeed, we have sound theoretical reasons to think that time-invariant regulations may not be optimal from a welfare perspective (e.g. Bianchi and Mendoza, 2018). But I would argue that the conclusions from these models are unlikely to be as clear-cut if we allow for realistic real-time uncertainty in crisis probabilities and political constraints. From a policy perspective, the idea that time-varying sectoral tools will prevent the next systemic banking crisis may be overly optimistic.

5 Conclusion and Future Research

The main message of this article can be summarized as follows. Yes, the sectoral allocation of credit appears to play a role for understanding periods of financial instability. The policy implications, however, are far from clear. This is due to the combination of three factors: a limited understanding of why sectoral debt grows differently prior to crises; a lack of estimates on the elasticity of different credit types to policy tools; and the political economy factors inherent in restricting growth in credit

[4] In most places, financial regulation is extremely complex. As one indication, the Basel Committee on Banking Supervision has issued a total of more than 16,000 pages of supervisory guidance (Penikas, 2015); Basel III alone has more than 600 pages.

to particular sectors.

I particularly want to highlight the gaps I see in our understanding. Perhaps most importantly, we do not have a good sense of *why exactly* credit allocation matters. While we have a number of candidate theories, disentangling these in the data is tricky. This makes it difficult for policy makers to draw lessons from the historical record.

We also have surprisingly little direct insight about what actually happens in *credit markets* during booms on the micro level. The reason for this appears to be that we do not have sufficiently long time series that would allow for detailed insights, so the usual approach is to infer credit outcomes from "real" macroeconomic data. As such, it is hard to disentangle sectoral allocation from other potentially correlated factors.

Finally, we know very little about what drives fluctuations in credit allocation. While we have a good idea about what predicts the *size* of credit markets, we do not know much about what drives its *structure*. Müller (2018) provides some evidence that measures of wealth, financial deregulation, and information sharing institutions correlate with the share of household lending both across and within countries. However, the starting point for studying credit allocation clearly has to be more empirical groundwork.

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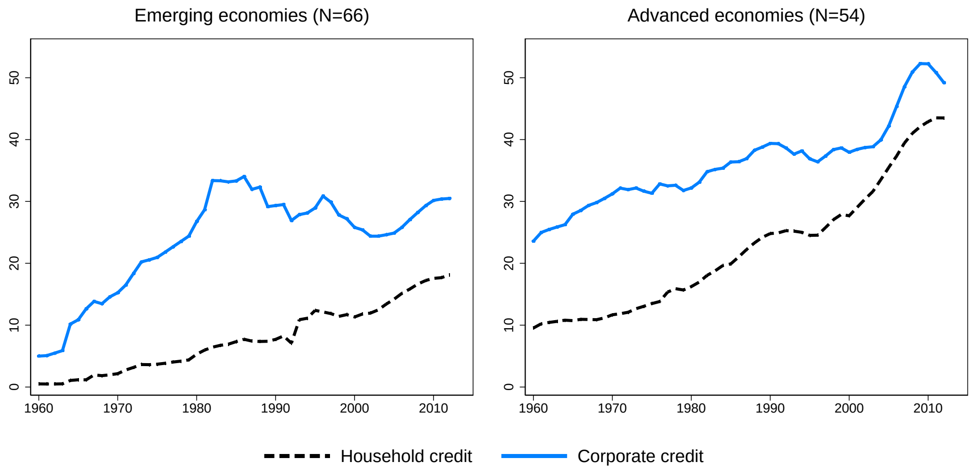
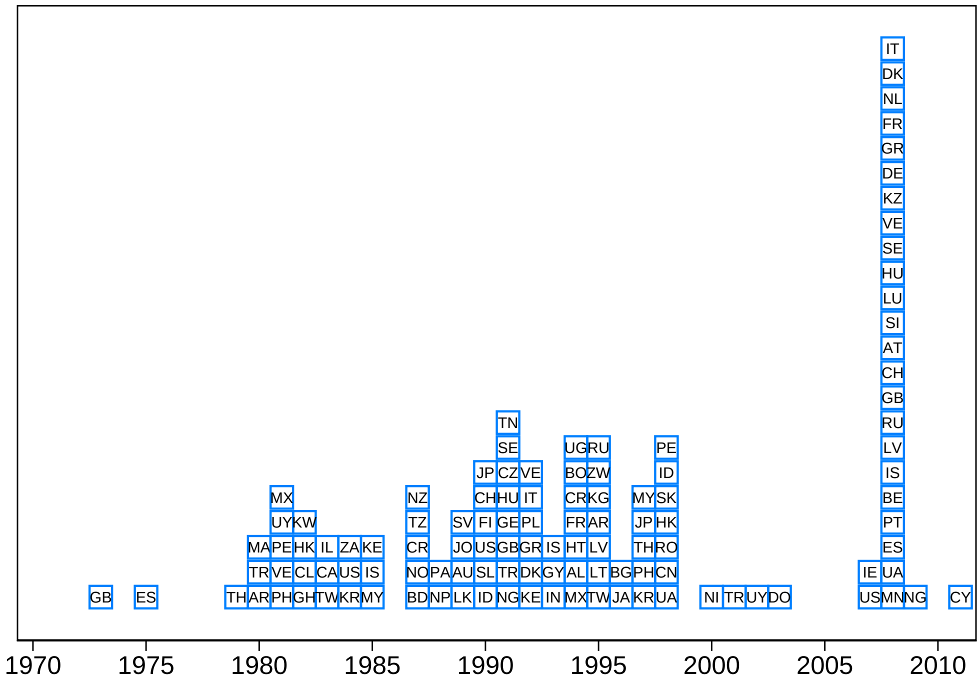
Figure 1: Ratio of corporate and household credit to GDP, 1960-2014



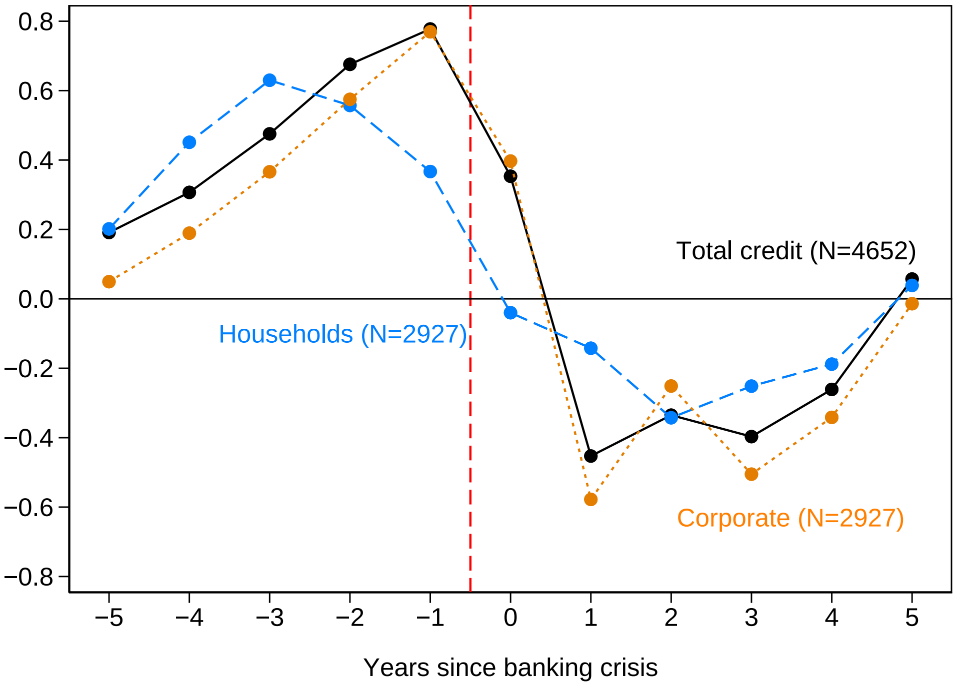
Notes: This figure plots the average ratio of corporate and household credit to GDP for an unbalanced panel of 66 emerging and 54 advanced economies, as classified by the World Bank in 2018. The data are from Müller (2018).

Figure 2: Number of banking crises per year, 1970-2014



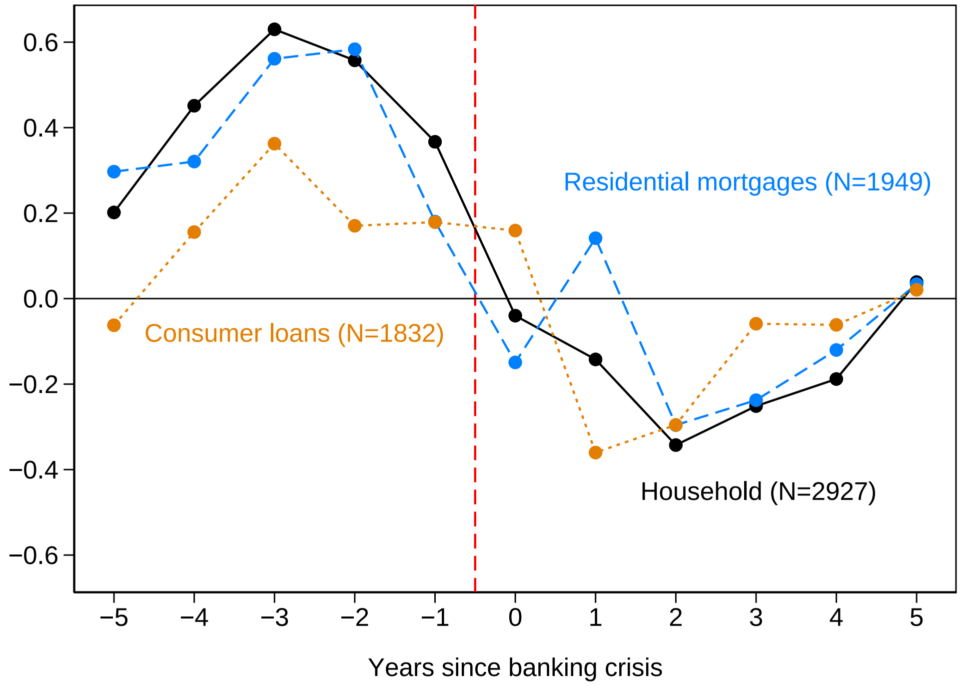
Notes: This figure plots the number of systemic banking crises per year used in the sample. I create a "consensus" measure of crises based on the data in Baron, Verner and Xiong (2019), Laeven and Valencia (2018), Reinhart and Rogoff (2009), and Bordo et al. (2001). See Müller and Verner (2019) for details.

Figure 3: Changes in credit/GDP around crises – By broad sector



Notes: This figure plots changes in credit/GDP relative to the country mean around up to 107 banking crises in 108 countries. Changes are standardized to have a mean of 0 and standard deviation of 1. See Müller and Verner (2019) for more details.

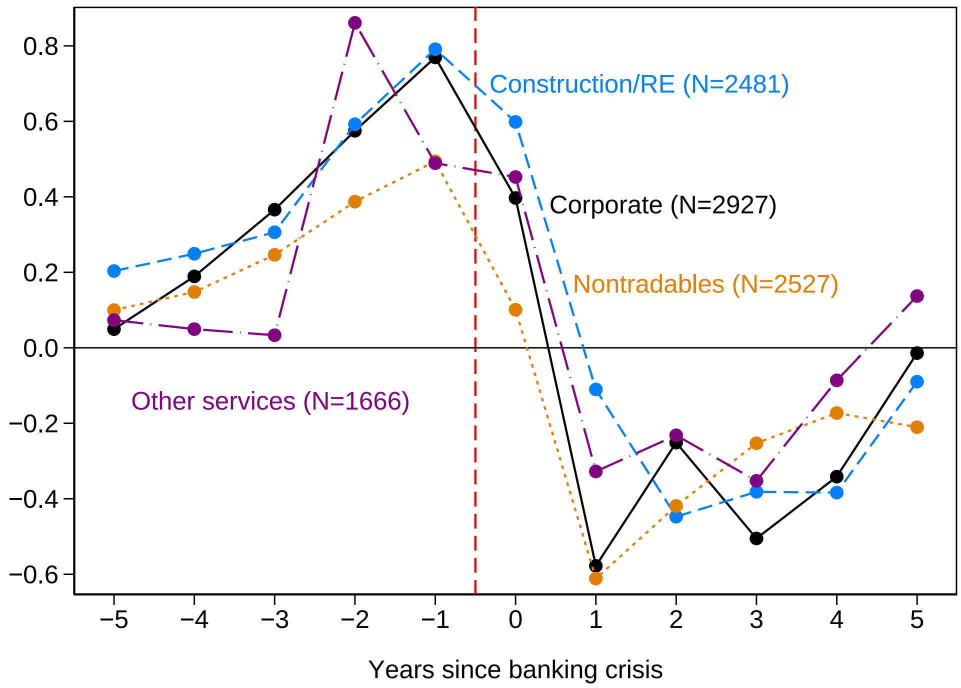
Figure 4: Changes in credit/GDP around crises – By household credit type



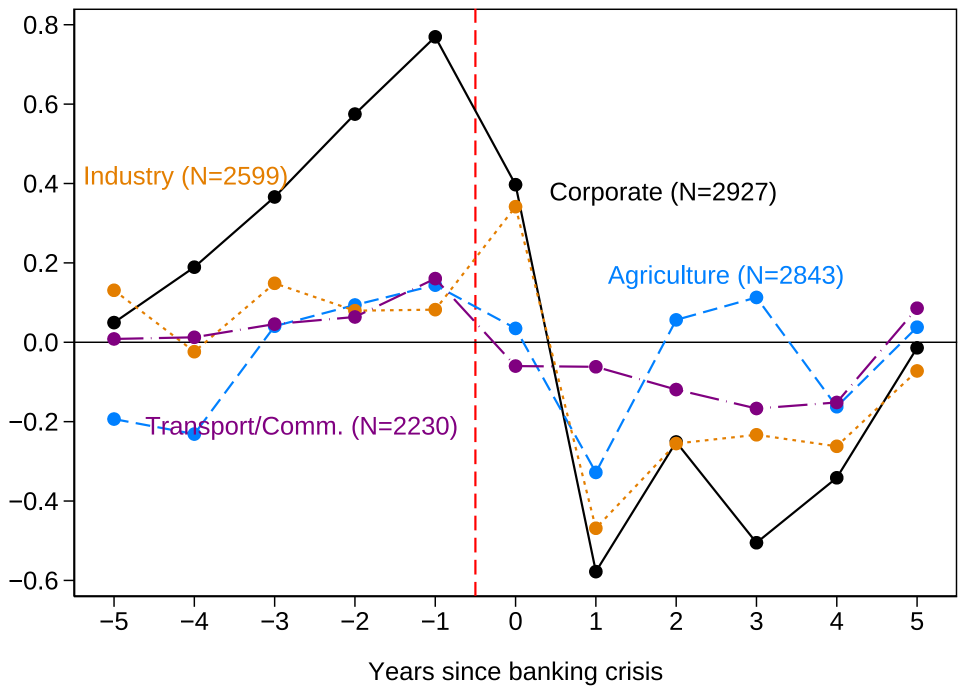
Notes: This figure plots changes in credit/GDP relative to the country mean around up to 107 banking crises in 108 countries. Consumer credit refers to household credit other than residential mortgages. Changes are standardized to have a mean of 0 and standard deviation of 1. See Müller and Verner (2019) for more details.

Figure 5: Changes in credit/GDP around crises – By industry

Panel A: Industries with clear "boom-bust" pattern

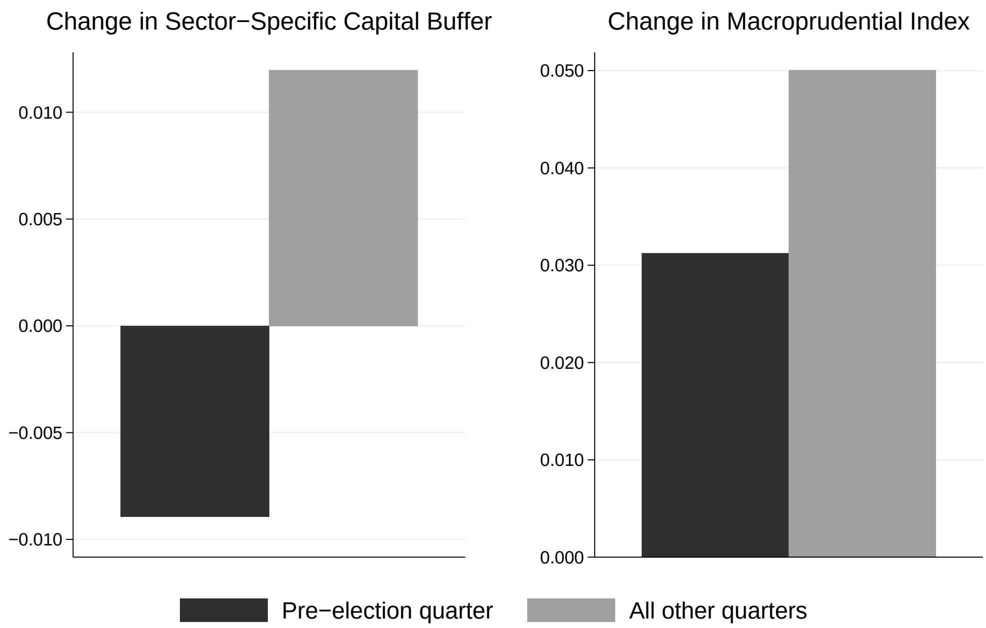


Panel B: Industries without clear "boom-bust" pattern



Notes: This figure plots changes in credit/GDP relative to the country mean around up to 107 banking crises in 108 countries. Industry refers to manufacturing and may also include mining. Nontradables refers to wholesale and retail trade, restaurants, and may include accommodation services. Changes are standardized to have a mean of 0 and standard deviation of 1. See Müller and Verner (2019) for more details.

Figure 6: Macroprudential Policy Is Looser Before Elections



Notes: This figure plots the average change in macroprudential policy (measured by sector-specific capital buffers or an aggregate index). I differentiate between quarters prior to 212 elections, and all other quarters, across 58 countries between 2000 and 2014. See Müller (2019) for more details.

Table 1: Sectoral Credit Growth and Banking Crises

Notes: This table presents the results of logit regressions predicting systemic banking crises. Δ_3Credit/GDP is the 3-year change in the credit-to-GDP ratio from $t-4$ to $t-1$ for the sector in the column header. This credit growth measure is standardized to have a mean of 0 and standard deviation of 1 in each regression sample. The reported coefficients are marginal effects multiplied by 100 for readability. *AUC (Total cr., est. sample)* is the AUC statistic for models with the change in total credit to GDP (as in column 1) in the estimation sample. Standard errors in parentheses are clustered by country. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Broad sectors			Household sectors	
	Total credit	Corporate credit	Household credit	Mortgage credit	Residential mortgages	Consumer credit
Δ_3Credit/GDP	0.887***	1.115***	1.115***	0.916***	1.187***	0.757**
	(0.172)	(0.291)	(0.155)	(0.298)	(0.203)	(0.347)
N	5,275	3,279	3,279	1,094	2,182	2,038
Number of countries	108	104	104	36	88	88
Pseudo R^2	0.04	0.04	0.04	0.03	0.04	0.01
AUC	0.63	0.67	0.65	0.62	0.66	0.59
AUC (95% CI)	[0.57; 0.70]	[0.61; 0.74]	[0.58; 0.71]	[0.49; 0.76]	[0.57; 0.74]	[0.49; 0.68]
AUC (Total cr., est. sample)	–	0.67	0.67	0.69	0.73	0.72
	(7)	(8)	(9)	(10)	(11)	(12)
	Corporate sectors					
	Agriculture credit	Manufacturing/ mining	Construction loans	Services (nontradable)	Transport/ Communication	Services (other)
Δ_3Credit/GDP	0.412**	0.229	0.820***	1.113***	0.323	0.755***
	(0.184)	(0.333)	(0.174)	(0.289)	(0.320)	(0.213)
N	3,155	2,888	2,779	2,813	2,493	1,852
Number of countries	104	102	101	100	97	86
Pseudo R^2	0.00	0.00	0.03	0.03	0.00	0.02
AUC	0.56	0.54	0.62	0.71	0.53	0.70
AUC (95% CI)	[0.49; 0.63]	[0.46; 0.62]	[0.55; 0.70]	[0.64; 0.77]	[0.45; 0.61]	[0.62; 0.78]
AUC (Total cr., est. sample)	0.70	0.70	0.70	0.71	0.70	0.73

Table 2: Fixed Effects Horse Race: Credit Allocation and Banking Crises

Notes: This table presents the results of fixed effects logit regressions predicting systemic banking crises. Δ_3Credit/GDP are different sectoral measures of the 3-year change in the credit-to-GDP ratio from $t-4$ to $t-1$. These credit growth measures are standardized to have a mean of 0 and a standard deviation of 1 in each regression sample. The reported coefficients are marginal effects multiplied by 100 for readability. *AUC (Total cr., est. sample)* is the AUC statistic for a model that only includes the change in total credit to GDP (as in column 1 of Table 1) in the estimation sample. Country dummies are not reported. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_3Household credit/GDP	1.115***							9.976***
	(0.155)							(3.536)
Δ_3Agriculture credit/GDP		0.412**						-1.242
		(0.184)						(3.546)
Δ_3Industry credit/GDP			0.229					-11.191***
			(0.333)					(3.799)
Δ_3Construction credit/GDP				0.820***				10.168**
				(0.174)				(4.209)
Δ_3Nontradable services credit/GDP					1.113***			15.514***
					(0.289)			(4.467)
Δ_3Transport and comm. credit/GDP						0.323		-6.137**
						(0.320)		(2.900)
Δ_3Other services credit/GDP							0.755***	2.890
							(0.213)	(2.542)
N	3,279	3,155	2,888	2,779	2,813	2,493	1,852	1,014
Number of countries	58	51	44	47	49	41	34	34
Pseudo R^2	0.04	0.00	0.00	0.03	0.03	0.00	0.02	0.16
AUC	0.64	0.56	0.55	0.62	0.71	0.52	0.69	0.76
AUC (95% CI)	[0.57; 0.70]	[0.48; 0.63]	[0.48; 0.63]	[0.54; 0.70]	[0.65; 0.78]	[0.44; 0.59]	[0.60; 0.77]	[0.69; 0.82]
AUC (Total cr., est. sample)	0.66	0.69	0.69	0.70	0.70	0.68	0.71	0.72