Credit risk cycle indices - properties and macroprudential policy

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Abstract

Current macroprudential policies mostly target credit quantity, managing the cyclicality of credit quantity instead of risk. A new credit cycle index is made possible by leveraging the Credit Research Initiative (CRI) probabilities of default (PDs) that cover virtually all exchange-traded firms globally and are updated daily to provide timely assessments of corporate default risks. Our evidence shows that current policies are effective in containing credit growth, but not necessarily dampening credit risk. The findings also reveal market-initiated credit contraction at the time of heightened credit risk, suggesting that the policy focus should be directed at both quantity and risk.

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1 Introduction

The global financial crisis has led to rejuvenated interest and attention in credit cycle from both academic researchers and policymakers. In contrast to the business cycle, there is no unified definition or measure for the credit cycle. Some popular indices include credit growth rate and credit-to-GDP ratio which measure the total credit quantity accessible in an economy. There have been comprehensive studies on the credit quantity cycle including identifying and characterising the cycle itself; studying the sources of the cycle and explore its nexus with business cycle and other macroeconomic variables.[1]

An important application of quantity measures of credit cycle is to act as the early warning indicator for financial crises. The 2008 global financial crisis led to renewed attention on the credit view argument of Minsky, Kindleberger and others that financial crises can be seen as "credit boom gone wrong." During expansion periods, banks are overly optimistic about borrowers' credit quality and more aggressive in making loans. This sows the seed of heightened credit risk which may in turn trigger systemic risk and result in financial crises once a negative shock hits the economy. There is a growing literature quantifying the relationship between credit growth and occurrence of financial crisis. Aikman et al. (2015) and Schularick and Taylor (2012) show that rapid credit expansion is strongly associated with banking crises with a two-year lag. The "reckless lending" argument combined with empirical evidence have led policymakers to believe that we may be able to prevent crises by containing credit growth. Quantity measures of credit cycle thus are frequently used as the intermediate target variable to assess the effectiveness of regulatory policies guarding against crises.

Macroprudential policy is one such policy that aims at reducing the occurrence and magnitude of financial crises. Ideally, its effectiveness should be assessed in terms of whether it achieves that ultimate goal. However, this remains a challenging task due to the short history of macroprudential policy and the relative infrequency of crises. The alternative proposed in the literature is to look at its impact on some intermediate targets such as the credit-to-GDP ratio. Here we list a few studies while

[1]See Drehmann et al. (2012), Mouatt (2015), Kiyotaki and Moore (1997) among others

leaving a detailed survey of this literature to Lim et al. (2013) and Bruno et al. (2017). Badarau and Popescu (2014) incorporate credit-to-GDP ratio in central bank's objection function/ Taylor rule. Fendoğlu (2017) and Cerutti et al. (2017) compile indices of the macroprudential policy stance for widely-used tools and assess the effectiveness of these tools in containing credit quantity/growth using cross-country panel regressions. They find that macroprudential policy has strong mitigating effects on credit quantity. This is not surprising as most of its policy instruments explicitly target quantity measures. For instance, the credit-to-GDP ratio is adopted by the Basel Committee on Banking Supervision (BCBS) to guide national authorities on the operation of the countercyclical capital buffer regulation. (Committee et al. (2010))

Combining with the previous finding that quantity measures have strong predictive power on crises, people tend to reach the conclusion that macroprudential policy, being effective in controlling credit quantity, is implied to have dampening effects on the credit risk cycle of an economy. However, a few issues exist in this transitivity argument. Firstly, as noted by Barrell et al. (2018), a growing literature supports the view that not all credit-to-GDP amplifications are "credit booms gone wrong", underpinned by "reckless lending" (Schularick and Taylor (2012), Gorton and Ordoñez (2016)). There are cases where financial intermediation disseminates credit towards productivity gains as opposed to risky lending. Taxing via macroprudential tools in such cases may undermine market efficiency and result in even higher risk. Secondly, apart from the quantity channel, there may be other transmission channels through with macroprudential instruments affect credit risk. For instance, under stringent credit controls, banks may be incentivized to seek for more risky investments to maintain profit and competitiveness. These yet-to-be-understood channels may work in the same or opposite direction as the quantity channel leading to reinforced or mitigated policy impacts. Furthermore, not only credit quantity affects future risk, risk outlook could also trigger self-adjustment in credit quantity through market forces. By neglecting the feedback from risk to quantity, we may reach biased estimation for the effect of policy intervention. Therefore it's critical to assess the direct impact of macroprudential policy on credit risk and understand the interplay between credit risk and quantity. Unfortunately, we have not seen much effort in this direction.

This paper sheds light on the above issues by first constructing a novel credit cycle index reflecting credit risk movement. The new index is based on the probabilities of default (PDs) measure generated by the Credit Research Initiative (CRI) of National University of Singapore. CRI PDs measure the credit risk of individual obligors in percent and hence allow sensible aggregation for any subset of the firms under its coverage. Our new credit cycle index is thus a suite of indices constructed in the same spirit as those commonly observed stock market indices for which component firms and weightings are selected with a particular objective in mind. Unique to credit risk, this index can target a specific prediction horizon or a range of horizons of interest.

To illustrate the properties of these new credit cycle indices, we look at the global index, ten sectoral indices based on the Bloomberg Industry Classification and 6 country/region indices at various prediction horizons.[2] We show that these indices are autoregressive and reflective of known events that affect credit risk outlook. More importantly, the risk cycle indeed exhibits different cyclical pattern from the quantity cycle measured by credit-to- GDP ratio.

We use the new credit cycle indices to re-evaluate the effectiveness of macroprudential policy. Our empirical analysis shows that though macroprudential policy has strong mitigating effects on credit growth and the growth is indeed associated with higher risks with a two-year lag, the policy itself has not dampened credit risk. This suggests that there may be other transmission channels that link the use of macroprudential instruments to heightened credit risk that we have overlooked so far. We also find evidence supporting that credit quantity will naturally react to risk perception in the market in the absence of policy intervention. In addition, quantity adjustment in reaction to risk concerns take effect faster than the opposite direction.

With globalization, corporates and financial systems across countries become increasingly interconnected, which in turn leads to increased synchronization of their credit market. Kurowski and Rogowicz (2018) provides supporting evidence on the existence of one global credit cycle by showing that it accounts for over a half of global credit to non-financial sectors. In other words, observed fluctuations in country-specific

[2] 10 sectors are basic materials, communications, consumer-cyclical, consumer-noncyclical, diversified, energy, financial, industrial, technology and utilities. 6 countries/regions include China, Eurozone, India, Japan, United Kingdom, and the United States.

credit quantity and risks are now determined by both domestic factors as well as their respective global cycles. It is thus important to assure the robustness of our findings with additional control on global trends. Our results show that the ineffectiveness of macroprudential policy on credit risk and the interplay between credit quantity and risk still hold, yet the policy effect on credit quantity is much mitigated.

2 Credit Cycle: Risk Versus Quantity

Notwithstanding its clear goal of smoothing credit risk cycle, most of macroprudential policy instruments have been targeting credit quantity due to lack of good forward-looking risk measures. In this section, we show that credit risk and quantity exhibit different cyclical patterns. Thus targeting quantity measures may lead to inappropriate policy actions. Figure 1 plots the US credit quantity cycle versus its credit risk cycle over the period from January 1991 to April 2008. The quantity cycle is captured by the credit-to-GDP ratio after taking out a linear time trend.[3] The credit risk cycle is reflected by our new cycle index denoted by CCI. We include CCI for both the US banking sector and US as a whole(i.e., all sectors included), both targeting a 1-month prediction horizon. Details on the construction of monthly CCI are discussed in Appendix A.

The risk cycle index captures three episodes of heightened credit risk during the sample period. The first one reflects the early 1990s recession while the second and third episode correspond to the dot-com bubble burst in early 2000s and the 2008 sub-prime crisis. In addition, during the sub-prime crisis, the CCI of the US banking sector is near two times the overall risk level for the country as a whole. This indicates that the new index is well reflective of known credit events and hence a reliable indicator for credit risk movement.

Figure 1 shows clearly that the credit quantity and risk cycle do not coincide with each other. On the one hand, the two trough periods of credit-to-GDP ratio suggest that credit quantity has a cycle with duration of around 13-15 years which is consistent with the identified financial/credit cycle in Drehmann et al. (2012) and Aikman et al. (2015).

[3] Monthly credit data which refers to Bank Credit of All Commercial Banks, and quarterly GDP data are retrieved from FRED, Federal Reserve Bank of St. Louis. To get monthly credit-to-GDP ratio, quarterly GDP are converted to monthly frequency by using the same value for all three months in the reference quarter.

This is much longer than the commonly observed business cycle which has a frequency of some 6-10 years. On the other hand, the three episodes of crises/recessions suggest the credit risk cycle having a frequency of 9-10 years. The different cyclical patterns impose challenges and cast doubt to the use of quantity measures as predictors for credit risk. This is made even clearer by looking at the credit-to-GDP ratio and CCI during the dot-com bubble where the crisis happened when the credit quantity was at the trough. Therefore, using credit quantity as the intermediate target for macroprudential policy may lead to inaccurate judgement of the aggregate risk condition and result in inappropriate policy reactions.

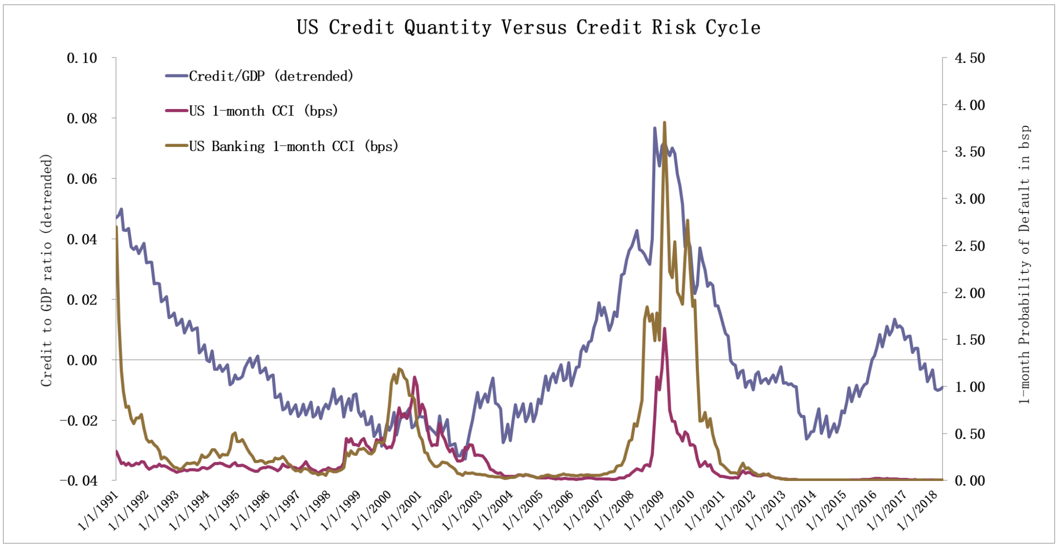


Figure 1: US credit quantity cycle versus credit risk cycle

3 Re-evaluate effectiveness of Macroprudential Policies

Since the 2008 global financial crisis, macroprudential policies are been increasingly used with the objective of strengthening financial stability towards which credit risk is a key contributor. The policy is designed to address two dimensions of credit risk - the cross-section and time dimensions, and the concept of credit cycle is tightly related to the second dimension. That is the dynamic of the aggregate accumulation of risk in the financial system over time. Macroprudential approach to address the procyclicality of the financial system is by, for example, stipulating the accumulation of buffers in "good times" so that these can be drawn down in "bad times". Tools which are already used in this regard include countercyclical capital buffers and dynamic provisioning.

The implementation of these tools requires an indicator to measure the accumulation of vulnerabilities and credit risk before the crisis materializes. Literature suggests the use of quantity measures such as credit growth or the credit-to-GDP ratio as they have been identified as promising indicators for financial crises. In fact, the credit-to-GDP ratio has already been adopted by the Basel Committee on Banking Supervision (BCBS) to guide national authorities on the operation of countercyclical capital buffers. In other words, how much capital a bank is required to hold now depends on the macro credit-cycle position, measured by credit-to-GDP ratio, of the country in which the bank operates. Such instruments by design achieve the goal of protecting the banking sector from periods of excess aggregate credit growth.

The question is whether preventing excessive credit growth imply strengthened financial stability. The answer is likely to be negative as quantity measures miss information about the allocation and riskiness of the credit system, which are essential to financial stability. Recent works on good credit booms and our finding in the previous section show that rapid credit growth itself does not necessarily lead to financial crises and not all crises are associated with excessive growth. Hence, credit quantity cycle is unlikely to display high crisis prediction power. Moreover, it is difficult to make assessments of whether the credit growth is justified by real growth or it is excessive and leading to the build-up of system-wide risk. It is also not straightforward to assess in real time where the economy stands in the cycle, and when it is the right moment to act in order to prevent financial crisis.

It is thus advisable to pay attention to direct credit risk indicators, both for guiding the implementation of macroprudential instruments and for evaluating their effectiveness. Traditional credit risk proxies such as default rate, business failure rate, and non-performing loans suffer from two major drawbacks. Firstly, they are all ex-post outcome measures which cannot serve as early warning indicators to prepare the economy for crisis ahead. Secondly, for random events like corporate defaults, looking at outcome measures may be suboptimal as they can be very noisy when the sample is limited.

In contrast, our CCI index is derived from CRI PD, which predicts individual obligor's probability of default (instead of binary outcomes) based on a theoretical model that incorporates relevant macroeconomic factors and firm-specific attributes. It is a forward-looking measure which has flexible term structures ranging from 1 month up to 5 years that can warn policymakers ahead and allow remedial actions to take effect. More importantly, CRI PD allows aggregation of sectoral credit risk, which helps regulators to identify the trigger of crisis at the early stage and implement targeted interventions. Using the CCI index for policy evaluation is also advantageous as it directly tells us the net policy effect in terms of achieving its ultimate target and avoids any bias arising from omitted transmission channels. In this section, we show how would using different targeting variables leads to contradicting conclusions on the effectiveness of macroprudential policy.

3.1 Model and data

Our model follows the benchmark regression in Cerutti et al. (2017):

$$Y_{i,t} = Y_{i,t-1}\alpha + MPI'_{i,t-1}\beta + GDP'_{i,t-1}\gamma + BankCrisis'_{i,t-1}\delta + Policy'_{i,t-1}\theta + \mu_i + \epsilon_{i,t} \quad (1)$$

The dependent variable $Y_{i,t}$ is either the real credit growth rate in Cerutti et al. (2017), denoted by $CGR_{i,t}$, or $\Delta CCI^h_{i,t}$, which is the change in aggregate credit risk level for country i in year t, targeting a horizon of h months. The real credit growth rate is calculated as the simple year on year percentage change in total credit, deflated by yearly CPI growth. [4,5] Our main interest variable $MPI_{i,t-1}$ stands for 'Macroprudential Policy Index', which indicates the country-specific adoption of macroprudential instruments at a given year. We obtain the index from Cerutti et al. (2017) whose data comes from the Global Macroprudential Policy Instruments (GMPI) survey carried out by the IMF's Monetary and Capital Department during 2013-2014. The survey covers the period 2000-2013 and 18 different policy instruments out of which 12 are included in the construction of MPI.[6] For each instrument, a simple binary measure is assigned

[4]For data source and construction of the real credit growth, see Cerutti et al. (2017).

[5]The construction of monthly CCI^h is detailed in Appendix A. We convert it to annual frequency by taking the average of the 12 monthly CCI in the reference year while requiring for minimum 6 data points. The change is then calculated as the difference between the CCI^h of this year minus that of the previous year.

[6]The 12 instruments are: General Countercyclical Capital Buffer/Requirement (CTC); Leverage Ratio for banks (LEV); Time-Varying/Dynamic Loan-Loss Provisioning (DP); Loan-to-Value Ratio (LTV); Debt-to-Income Ratio (DTI); Limits on Domestic Currency Loans (CG); Limits on Foreign Currency

to indicate whether the instrument was in place and the aggregate MPI is taken as the sum of the 12 binary measures. Since such precautionary policy usually takes a longer time to take effect, we use the first lag of MPI as the explanatory variable. This also mitigates the reverse causality argument that policymakers may decide on the adoption of such instruments after observing the credit growth.

The set of control variables includes: $GDP_{i,t-1}$, lagged GDP growth rate which represents the demand side push; $BankCrisis_{i,t-1}$, a binary indicator capturing the presence of a systemic banking crisis as defined in Laeven and Valencia (2013), and $Policy_{i,t-1}$, the monetary policy rate which is important to control for as macroprudential instruments are normally used in conjunction with monetary tools.[7] μ_i represents country fixed effect which captures any non-time-varying country specifics such as financial development and institutional characteristics. $\epsilon_{i,t}$ is the innovation term which is assumed to be i.i.d..

Cerutti et al. (2017)'s study covers 106 countries which are grouped by income level: 31 advanced, 56 emerging and 19 developing countries; and by financial openness: 47 open and 58 closed countries. Monthly CCI based on CRI PDs are available for 99 countries excluding those in which the total number of firms domiciled is less than 5 throughout the sample period. After converting to annual change and by taking the common set of countries covered by Cerutti et al. (2017) and with CCI data, we reach a sample of 52 countries by further requiring for minimum 5 years of data on all variables. Table 1 list the 52 countries of which 28 are advanced, 24 are emerging, and 32 are open and 20 are closed.

Since CRI PD has term structure ranging from 1 month to 5 years, in principle, we can have ΔCCI^h for $h = 1, 2, .., 60$. For conciseness, we only present the descriptive statistics and empirical analysis with the 12-month horizon, and drop the superscript $h = 12$ for simplified notations. The regression results are largely the same for ΔCCI of other horizons. Table 2 presents the descriptive statistics for all our variables over the period 2000-2013. The average change in the 12-month CCI is -1.86 basis points

Loans (FC); Reserve Requirement Ratios (RR); and Levy/Tax on Financial Institutions (TAX); Capital Surcharges on SIFIs (SIFI); Limits on Interbank Exposures (INTER); and Concentration Limits (CONC). For further details on the survey questionnaire, readers may see Cerutti et al. (2017).

[7] For detailed variable definition and data source, see Table 1 in Cerutti et al. (2017).

Table 1: Country subgroup classification

Advanced(28)		Emerging(24)		Open(32)		Closed(20)	
Australia	Netherlands	Brazil	Philippines	Australia	Italy	Brazil	South Korea
Austria	New Zealand	Bulgaria	Poland	Austria	Jamaica	China	Sri Lanka
Belgium	Portugal	Chile	Romania	Belgium	Japan	Colombia	Thailand
Canada	Singapore	China	Serbia	Bulgaria	Kuwait	Croatia	Turkey
Cyprus	Slovakia	Colombia	South Africa	Canada	Malaysia	Czech Republic	
Czech Republic	Slovenia	Croatia	Sri Lanka	Chile	Netherlands	India	
Estonia	South Korea	Hungary	Thailand	Cyprus	New Zealand	Kazakhstan	
Finland	Spain	India	Turkey	Estonia	Portugal	Mexico	
France	Sweden	Jamaica		Finland	Singapore	Morocco	
Germany	Switzerland	Kazakhstan		France	Slovakia	Pakistan	
Hong Kong	United Kingdom	Kuwait		Germany	Slovenia	Peru	
Iceland	United States	Malaysia		Hong Kong	Spain	Philippines	
Ireland		Mexico		Hungary	Sweden	Poland	
Israel		Morocco		Iceland	Switzerland	Romania	
Italy		Pakistan		Ireland	United Kingdom	Serbia	
Japan		Peru		Israel	United States	South Africa	

Notes: Income group classification and De Facto financial openness classification follow from Cerutti et al. (2017).

which suggests that overall, the credit risks of the 52 countries have decreased over the sample period. These countries also experienced high real credit growth at the rate of 6.78% per annum with a large variation from -7.85% to 28.71% p.a. The growth rate for real credit is about two times the average rate for GDP growth at 3.38%. The macroprudential policy index also exhibits large variation, which ranges from 0 to 8 with a mean of 1.86 and a standard deviation of 1.75. About 11% of the country-year observations have crisis indicator equal to 1 and the average policy rate is 4.41% with a wide range from 0.1% to 15%.

Table 2: Summary Statistics

VARIABLES	(1) Observations	(2) mean	(3) sd	(4) min	(5) max
Dependent variables					
ΔCCI (bps)	672	-1.86	12.16	-26.15	24.59
CGR (%)	676	6.78	9.46	-7.85	28.71
Independent variables					
MPI (index 0-12)	728	1.86	1.75	0.00	8.00
GDP growth (%)	728	3.38	3.02	-2.81	9.13
Crisis (dummy 0-1)	728	0.11	0.31	0.00	1.00
Policy Rate (%)	686	4.41	4.08	0.10	15.00

Notes: Summary statistics for 52 countries over the period 2000-2013. All variables except the categorical ones are winsorized at the 5% level.

3.2 Effectiveness of MPI on credit quantity and risk

With our data on 52 countries, we first estimate model (1) with credit growth rate being the dependent variable to verify the finding of Cerutti et al. (2017) and others on the mitigating effect of macroprudential policy on credit growth. For such dynamic panel model with fixed effects, demeaning the equation or taking the first difference will unavoidably create endogeneity issue and thus result in biased estimates from commonly used the within or first-difference estimator. To address this issue, the Arellano and Bond (1991) GMM method is a widely adopted solution.[8] It first transforms the model equation by taking the first difference, and then use lagged endogenous variables of order 2 and above as instruments to estimate the transformed equation. Since we have 14 years of data, to avoid instrument proliferation, we restrict our instrumental variable to be the second lag of endogenous variables.[9] Following Cerutti et al. (2017), we treat MPI and all control variables of credit growth, GDP growth, the crisis dummy and the policy rate as endogenous.

The results in Table 3 indicate that macroprudential policy is highly effective in containing real credit growth rate with a one year lag. With one additional macroprudential instruments in place, credit growth rate reduces by some 8.8% on average across the sample. Consistent with Cerutti et al. (2017), GDP growth does not seem to be related to credit expansion in most cases. The occurrence of financial crises leads to credit contraction in the subsequent period. Policy rates which reflect a country's monetary policy stance are also found to be effective in containing credit growth rate. But the magnitude of the mitigating effect is much weaker compared to the macroprudential policy.

We further test the policy effect for different country groups based on both income level and financial openness. The effect of both macroprudential and monetary policy is found to be much stronger in advanced and open economies. This could be due to better regulated policy implementation in these countries. In addition, credit growth rate in emerging and closed economies are less persistent and stable and they are more vulnerable to crisis shocks. Moreover, real economic growth in emerging countries

[8] See Cerutti et al. (2017), Fendoğlu (2017) and Lim et al. (2011) among others.

[9] We repeat all exercises with the second and third lags of endogenous variables being the instrument, the results are largely the same.

have significant stimulation effect on credit expansion. This suggests that the credit market in these countries are more sensitive to the performance of the real economy.

Table 3: Effectiveness of macroprudential policy on credit growth rate

Dependent Variable: CGR (real credit growth rate)

Groups	All	Advanced	Emerging	Open	Closed
L.CGR,	0.3338***	0.5069***	0.0756	0.4544***	0.2025*
	(0.0853)	(0.0994)	(0.0962)	(0.0844)	(0.1206)
L.MPI,	-8.8279***	-10.6562***	-6.4428***	-11.5479***	-6.0654***
	(1.9605)	(3.6716)	(1.8050)	(3.5441)	(1.9626)
L.GDP,	0.1331	0.0414	0.8158**	0.1882	0.4919
	(0.2250)	(0.2719)	(0.3212)	(0.2276)	(0.3831)
L.Crisis ,	-10.8453***	-5.1414*	-17.8353***	-8.4762**	-11.0433
	(3.9735)	(2.9899)	(6.4645)	(3.5654)	(7.2053)
L.INT,	-1.5797***	-1.5630***	-1.2313***	-1.8071***	-1.5016***
	(0.4033)	(0.4156)	(0.3782)	(0.6252)	(0.4724)
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	545	313	232	348	197
Number of Countries	52	28	24	32	20

Standard errors are clustered at the country level
*** p<0.01, ** p<0.05, * p<0.1

In Table 4, we replace the dependent variable by the change in the 12-month CCI to shed light on the effectiveness of macroprudential policy on credit risk. Surprisingly, the coefficients in front of our main interest variable $MPI_{i,t-1}$ are consistently positive and in some cases highly significant. This implies that increased use of macroprudential policy instruments has not reduced credit risk. It may even lead to increased credit risk possibly due to tightened credit accessibility.

Similarly, monetary policy does not exhibit dampening effect on credit risk neither notwithstanding its strong effect on credit growth rate. GDP growth rate is positively related to changes in credit risk and the result is highly significant across all country groups. This is consistent with the reckless lending argument which says during "good times" when real economic experience strong growth, firms and financial institutions tend to be over-optimistic and make more risky investment which later leads to higher credit risk. This phenomenon is found to be more likely to happen in emerging and closed economies.

Table 4: Effectiveness of macroprudential policy on credit risk

Dependent Variable: ΔCCI (change in credit risk index)

Groups	All	Advanced	Emerging	Open	Closed
L.ΔCCI,	-0.0760	-0.0916**	-0.0657	-0.0603	-0.0956
	(0.0562)	(0.0414)	(0.0808)	(0.0545)	(0.0867)
L.MPI,	8.6747***	13.6550**	1.5053	13.4060***	3.9228*
	(2.5990)	(6.0448)	(1.5967)	(4.5587)	(2.3051)
L.GDP,	2.2451***	1.8456***	2.1828***	2.0873***	2.3522***
	(0.3499)	(0.4013)	(0.4637)	(0.4175)	(0.4426)
L.Crisis,	1.6552	-1.0013	7.9591	2.6007	4.7714
	(6.0649)	(3.3428)	(14.3985)	(4.4539)	(12.9425)
L.INT,	2.5038***	2.2669	1.5761	2.0101**	2.4537*
	(0.8348)	(1.4503)	(1.0269)	(0.9377)	(1.2640)
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	544	331	213	361	183
Number of Countries	52	28	24	32	20

Standard errors are clustered at the country level

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4 The lag structure of macroprudential policy and the interplay between credit quantity and risk

In general macroprudential policy takes effect with longer lag than monetary policy.[10] For instance, based on existing findings that macroprudential policy reduces credit growth in the subsequent year which is in turn associated with reduced credit risk with a two-year lag, the policy should have dampening effect on credit risk with a three-year lag through the quantity channel. In this section, we investigate the lag structure of macroprudential policy's effect on its intermediate target - credit growth rate, and on its ultimate goal - credit risk. Since the lags of the policy are highly correlated, we include only one lag series at a time. Existing studies focus on how excessive credit expansion leads to heightened credit risk. However, the opposite direction of how credit risk outlook could drive natural quantity adjustment through market force is usually overlooked. Without taking into account the interplay between credit risk and quantity, we may reach biased estimation for the effectiveness of macroprudential

[10]https://www.brookings.edu/on-the-record/implementing-macroprudential-and-monetary-policies-the-case-for-two-committees/

policy. Thus in our analysis in this section, we incorporate such interplay by adding the lag terms of credit risk into regressions where credit quantity is the dependent variable and vise versa.

On the one hand, the results in column (1), (3) and (5) of Table 5 lend further support to the effectiveness of macroprudential policy in containing credit growth rate. This effect is robust for all lags from lag 1 to lag 3, even after controlling for credit risk. However, the magnitudes of the policy effect are much smaller than those estimated without the lag terms of credit risk. Thus previous models leaving out of the credit risk tend to overestimate the effect of macroprudential policy. Similarly, the mitigating effect of monetary policy on credit growth rate is also reduced by half after taking into account the credit risk. In other words, we may mistakenly attribute part of the credit contraction which is driven by natural market adjustment due to risk concerns, to policy interventions. Using such results to guide policy design hence may not achieve the desired macroeconomic outcomes.

On the other hand, column (2), (4) and (6) confirm that the policy has not dampened credit risk. In fact, the use of macroprudential policy instruments is even positively correlated with credit risk at all three lags. This indicates that the quantity channel may not be the dominant channel through which macroprudential policy affects risk. Thus using effectiveness on credit quantity growth to imply effectiveness in containing credit risk may not be appropriate. Other unknown side-effects or transmission channels may exist and are overlooked in current studies. This is not surprising because given the substantial delay in the process of "credit boom gone wrong", many factors may play a part and lead to unpredictable outcomes.

Results in Table 5 also confirm the finding of Schularick and Taylor (2012) and Aikman et al. (2015) that credit expansion leads to heightened credit risk with a two-year lag. In our data, real credit growth rate is measured in percent and the change in credit risk in basis points. The coefficient estimates thus indicate that a one-standard-deviation increase in the credit growth rate will lead to around 3 basis points increase in the change of aggregate credit risk two years later. A one-standard-deviation increase in the change of risk will cause about 1% reduction in the quantity growth rate. In contrast to the substantial lagged effect of credit growth rate on risk, quantity adjustments in reaction to risk perceptions take effects much faster. By controlling for macroprudential and monetary policy measures, we show that market forces naturally drive credit contraction when facing heightened credit risk. That means investors and financial institutions take precautionary actions due to risk concerns and not purely regulatory interventions.

After taking into account the interplay between credit quantity and risk, GDP growth rate remain to be unrelated to credit growth rate and positively correlated with credit risk. Financial crises in the preceding year leads to on average more than 5% reduction in real credit growth rate. But it has no prediction power on the subsequent risk movements. Similarly, monetary policy has strong mitigating effects on credit growth rate but has not helped in containing risk.

Table 5: The lag structure of MPI and the interplay between credit quantity and risk

Dependent Variables	(1) CGR	(2) ΔCCI	(3) CGR	(4) ΔCCI	(5) CGR	(6) ΔCCI
L1.CGR,	0.3768***	0.1388	0.4307***	0.0440	0.4594***	0.1090
	(0.0787)	(0.1317)	(0.0806)	(0.1179)	(0.0804)	(0.1082)
L2.CGR,	0.0196	0.3435***	0.0200	0.3268***	0.0327	0.3332***
	(0.0756)	(0.0982)	(0.0721)	(0.1025)	(0.0750)	(0.1024)
L1.ΔCCI,	-0.0878**	-0.1729***	-0.0739**	-0.1880***	-0.0759*	-0.1916***
	(0.0344)	(0.0580)	(0.0359)	(0.0596)	(0.0400)	(0.0508)
L2.ΔCCI,	0.0211	-0.1464***	0.0438	-0.1756***	0.0643*	-0.1965***
	(0.0314)	(0.0513)	(0.0306)	(0.0528)	(0.0334)	(0.0539)
L1.MPI,	-5.9565***	8.6904**				
	(1.8176)	(3.6646)				
L2.MPI,			-4.3706***	6.1785**		
			(1.4656)	(2.4827)		
L3.MPI,					-6.2554***	11.0461***
					(2.1632)	(2.4755)
L.GDP,	0.1115	1.6794***	0.0907	1.7696***	0.0685	1.8489***
	(0.2215)	(0.3992)	(0.2276)	(0.3977)	(0.2371)	(0.4661)
L.Crisis,	-6.2155**	4.6724	-5.3760**	3.4547	-5.2851*	5.2408
	(2.8146)	(4.0597)	(2.6461)	(4.0950)	(2.9208)	(5.3289)
L.INT,	-1.1751***	1.7815**	-1.1596***	1.7258*	-1.2001***	1.6534*
	(0.4280)	(0.8862)	(0.4368)	(0.8921)	(0.4278)	(0.8887)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	470	470	470	470	440	440
Number of Countries	52	52	52	52	52	

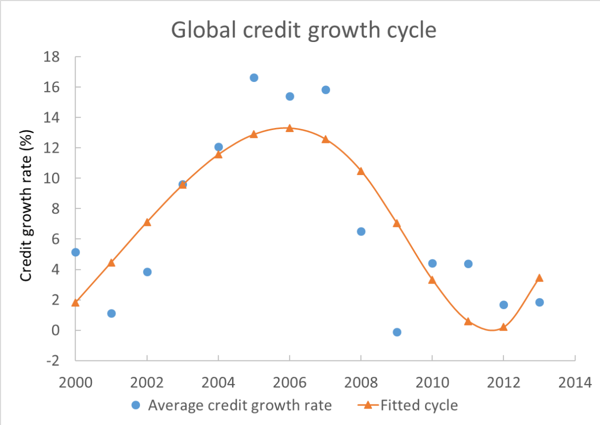
Standard errors are clustered at the country level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5 The impact of global cycles

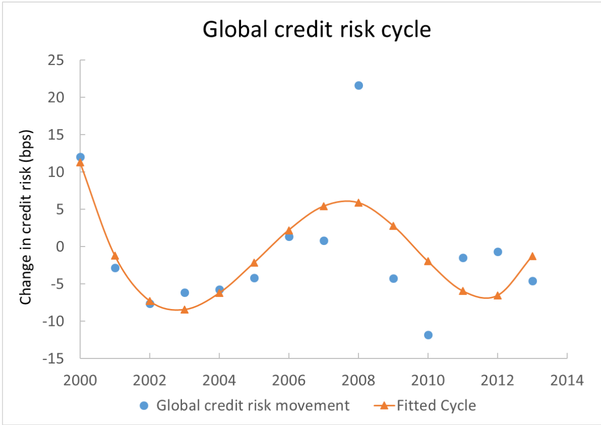
Financial globalization and increased capital mobility have led to synchronization of credit markets across countries. Thus fluctuations in country-specific credit quantity and risk are now jointly determined by both domestic development and policies, and some global factors. In cross-country panel studies like what we have, a typical way to account for such global environment is via the inclusion of time-fixed effect. It is however not optimal in our setting because our policy variables, MPI and interest rate, also exhibit some synchronized movement due to enhanced policy coordination in the past decade. Thus simply adding time dummies would allow them too much freedom in picking up global trends which could be partly due to worldwide increased adoption of macroprudential policy.

A better alternative is to estimate the natural global cycle on credit quantity/risk and examine the policy effectiveness by looking at how it affects fluctuations of the target variable in deviation from the global cycle. More specifically, we re-estimate all the regressions for which real credit growth rate is the dependent variable with an additional control variable denoted by CGR_global_t. This country-independent variable captures the global credit growth cycle and it is obtained by first taking the average credit growth rate for each sample year and then fit it with two cubic spline curves with the year 2008 being a break point. Figure 2a plots the average credit growth rate and the fitted global quantity growth cycle. Similarly, we estimate a global cycle for credit risk movement by applying the same curve fitting procedure to the annual change in the 12-month global CCI (See Figure 2b). We denote the fitted risk cycle by ΔCCI_global_t and add it to all regressions with credit risk being the dependent variable. Both CGR_global_t and ΔCCI_global_t are treated as strictly exogenous and are not instrumented with their lagged values.

Table 6 reproduces the analysis in the previous section while accounting for global cycles. Both CGR_global_t and CCI_global_t appear to be highly significant, suggesting strong global cycle effects. Macroprudential policy remains ineffective in dampening credit risk. In addition, its mitigating effect on credit quantity is significantly reduced. This is in contrary to the generally positive finding in the literature but is supporting another stream of argument. It says new macroprudential instruments are usually



(a) Global credit growth cycle



(b) Global credit risk cycle

Figure 2: Global credit cycles

adopted near the peak of global credit boom as regulators start to worry about the cumulated risk. Credit growth rate in the subsequent year slows down due to the natural cycle movements. Yet it is mistaken as the effect of macroprudential policy in existing studies that fail to consider global cycles. As to the interaction between credit growth and risk, the positive correlation between current quantity growth and credit risk two years later and the self-correction adjustment of quantity growth in response to risk concerns remain to hold.

6 Conclusion

Unlike business cycle, there is no unified definition or measure for credit cycle. Quantity measures such as credit growth rate and credit-to-GDP ratio are commonly used while indices reflecting risk movement of the credit system have been scarce. An important use of quantity measures is to act as the target variable in assessing the effectiveness of macroprudential policy based on the empirical finding that they are good early warning indicators for banking crises. In particular, the credit-to-GDP ratio are even adopted as the official indicator by BIS to guide macroprudential instruments. However, more recent research shows that not all credit boom end up in financial crises. Thus policy actions guided by quantity measures may not achieve the desired results. In this context, a credit cycle index reflecting credit risk movement become necessary and practically important.

Table 6: The effectiveness of MPI and the interplay between credit growth and risk while considering global cycles

Dependent Variables	CGR	ΔCCI	CGR	ΔCCI	CGR	ΔCCI
L1.CGR,	0.2992***	0.0263	0.3205***	-0.0673	0.3705***	-0.0270
	(0.0769)	(0.1321)	(0.0803)	(0.1216)	(0.0829)	(0.1119)
L2.CGR,	-0.0518	0.2522**	-0.0569	0.2347**	-0.0357	0.2208*
	(0.0626)	(0.1087)	(0.0591)	(0.1149)	(0.0630)	(0.1127)
L1.ΔCCI,	-0.0946***	-0.2016***	-0.0911**	-0.2083***	-0.0950**	-0.2372***
	(0.0353)	(0.0599)	(0.0370)	(0.0603)	(0.0386)	(0.0537)
L2.ΔCCI,	0.0134	-0.1806***	0.0236	-0.2107***	0.0346	-0.2374***
	(0.0287)	(0.0491)	(0.0286)	(0.0490)	(0.0266)	(0.0524)
L1.MPI,	-3.2115***	7.5837**				
	(1.1571)	(3.5279)				
L2.MPI,			-1.8585	4.3939*		
			(1.2790)	(2.3067)		
L3.MPI,					-2.6558	9.0151***
					(1.7743)	(2.1317)
L.GDP,	-0.0543	1.5575***	-0.0822	1.6032***	-0.0700	1.6626***
	(0.2175)	(0.3741)	(0.2233)	(0.3567)	(0.2135)	(0.4362)
L.Crisis,	-3.8165	3.1509	-3.0753	2.0769	-2.5610	3.5878
	(2.3342)	(3.8657)	(2.2167)	(3.9968)	(2.3019)	(5.0444)
L.INT,	-1.4272***	1.5619*	-1.4140***	1.4186*	-1.4360***	1.2534
	(0.3597)	(0.8681)	(0.3679)	(0.8534)	(0.3861)	(0.8294)
CGR_global	0.6466***		0.7043***		0.6408***	
	(0.1480)		(0.1429)		(0.1550)	
ΔCCI_global		0.4188***		0.4128***		0.5517***
		(0.1216)		(0.1151)		(0.1387)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	470	470	470	470	440	440
Number of Countries	52	52	52	52	52	52

Standard errors are clustered at the country level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In this paper, we construct such indices for a large number of countries based on the probability of default measures (PDs) generated by the Credit Research Initiative (CRI) of National University of Singapore. We document the autoregressive properties of these indices and show that they exhibit different cyclical pattern from the credit cycle measured by credit-to-GDP ratio. With the novel credit risk cycle indices, we re-evaluate the effectiveness of macroprudential policy. Our empirical analysis shows that notwithstanding its strong effectiveness in containing quantity growth, it has not dampened credit risk. Furthermore, we confirm that credit expansion is indeed linked to higher credit risk with a two-year lag. We also find evidence supporting the other direction that credit quantity will naturally react to changes in risk outlook in the absence of policy interventions. When the respective global cycle is controlled, all our results stay but the policy effectiveness on credit quantity is weakened.

These findings have important implications on the macroprudential policy design. This policy aims to strengthen financial stability to which credit risk is a key contributor. Unfortunately, current instruments targeting credit quantity instead of quality have not been effective. Given the validity of the quantity channel, the results suggest that there may be alternative transmission mechanism through which quantity-oriented instruments affect credit risk, which results in undetermined overall policy effectiveness. These side products that come along with credit control add complexity and uncertainty to the implementation of macroprudential policy. Nevertheless, understanding potential mechanism and smoothing the transition to a better-regulated and stable financial market worth more attention from both academic researchers and practitioners.

A Construction of Credit Risk Indices

Our new credit cycle index reflecting movements of aggregate credit risk is built based on the probability of default measure (PDs) generated by the Credit Research Initiative (CRI) of National University of Singapore. The CRI PDs cover essentially all exchange-traded firms around the world and assess their individual default risks over prediction horizons ranging from 1 month to 5 years. (For details on the modelling, estimation, and performance of CRI PDs, please refer to RMI-CRI Technical Report Version 2017 Update 1)[11]. Different from commonly used letter grade credit ratings, CRI PD has finer granularity and measure individual credit risk in percent. This allows for sensible aggregation for any subset of firms under its coverage.

Our credit cycle index, denoted by $CCI^h_{i,t}$, reflects the aggregate credit risk of an entity i for a horizon of h months at time t. The entity could by a country, a region, an industrial sector or a set of those. In other words, this new credit cycle index is actually a suite of indices constructed in the same spirit as those commonly observed stock market indices for which component firms and weightings are selected with a particular objective in mind. Unique to credit risk, this index can target a specific prediction horizon or a range of horizons of interest. As an illustration, country i's CCI is calculated as the median PD of all firms that domiciled in country i. That is,

$$CCI^h_{i,t} := \underset{1 \leq j \leq n, j \in domiciled\ in\ i}{median} (P^h_{j,t})$$

where $P^h_{j,t}$ is the h-month probability of default for firm j at time t.

CRI PDs are updated on a daily bases, therefore in theory, we can construct daily CCI measures. However, monthly CCI serves the purpose of documenting the properties of these series adequately. Therefore we work with monthly PD which is taken as the PD of the last trading date of the month. The median is then taken across the monthly individual PDs to form monthly CCIs.

[11] Available at http://d.rmicri.org/static/pdf/2017update1.pdf

B Characterizing Credit Risk Cycle

In addition to the CCIs of individual countries, we construction a global CCI which is the median PD of all firms under the CRI coverage, and 10 sectoral CCIs based on Bloomberg classification, reflecting industrial specific credit risk movement. In Table 7, we present the properties of these 11 series plus the CCIs of 6 representative major economies/regions: Japan, United States, United Kingdom, China, India, and Eurozone over the period from January 1991 to October 2018.[12]

We examine the autoregressive property and stationarity of the global CCI by regressing it on its own 12 lags, and of the rest 16 CCI series by regressing on both the global CCI and their respective 12 lags. More specifically, we fit the global CCI series to a potential AR(12) model and the other sectoral and country CCIs to a potential AR(12) model with the global CCI added as an exogenous variable. They are potential AR(12) because we use a web-based variable selection tool named "DeepSelect" to determine the correct orders of lags to include and meanwhile obtain the estimation results.[13] This tool allows us to specify a set of always-included regressors and a set of selective regressors. For our study, we set the tool to always include the lag 1 terms for all regressions and the global CCI for sectoral and country CCI regressions. Higher order lags are selective where model selection is based on 5-fold cross-validation.

Table 7 presents the results of the above-described autoregressive analysis for 1-month, 1-year and 5-year CCI. Sample months indicate the number of months with valid aggregate PD for a specific CCI group over the sample period from January 1991 to October 2018.[14] There are four entries in each cell of CCI of a particular group and horizons. The two entries on the left correspond to the coefficients of their respective lag 1 term and standard deviation. The top right element indicates whether any higher order lags are selected and estimated to be significant. Lastly, the bottom right element indicates whether the CCI series is stationary based on the spectral radius of the

[12]The calculation of Eurozone CCI is based on current membership.

[13]The author(s) acknowledge CriAT, a FinTech company specializing in deep credit analytics, for making available its proprietary software - DeepSelect, a variable selection tool based on a density-tempered Sequential Monte Carlo zero-norm penalty algorithm developed by Prof Jin-Chuan Duan of National University of Singapore.

[14]The aggregate PD, i.e. the median is calculated only when there are more than 5 firms exist in the CCI group

autoregressive matrix of the VAR(1) representation of the estimated AR model. The result shows that most of these CCI series are highly persistent. Most of them have lag structure beyond one period even after taken out the effect of global CCI, with a few exceptions including the United States, communication sector and the 1-month and 5-year CCI for the consumer-noncyclical sector. All the CCI series are stationary.

Table 7: Global and country CCI

CCI groups	Sample months	$CCI_{i,t}^{1}$		$CCI_{i,t}^{12}$		$CCI_{i,t}^{60}$	
Global	346	1.34	Yes	1.36	Yes	1.05	Yes
		(0.05)	Yes	(0.05)	Yes	(0.02)	Yes
China	311	1.03	Yes	1.02	No	1.07	Yes
		(0.04)	Yes	(0.04)	Yes	(0.04)	Yes
Eurozone	346	0.83	Yes	1.01	Yes	0.96	Yes
		(0.03)	Yes	(0.06)	Yes	(0.03)	Yes
India	295	1.05	Yes	1.11	Yes	1.10	Yes
		(0.04)	Yes	(0.06)	Yes	(0.06)	Yes
Japan	280	1.05	Yes	0.85	Yes	0.69	No
		(0.06)	Yes	(0.04)	Yes	(0.04)	Yes
United Kingdom	346	1.09	Yes	1.26	Yes	1.34	Yes
		0.05	Yes	0.05	Yes	0.05	Yes
United States	335	0.74	No	0.83	No	0.91	No
		(0.02)	Yes	(0.02)	Yes	(0.04)	Yes
Basic Materials	346	0.99	Yes	1.11	Yes	1.06	Yes
		(0.05)	Yes	(0.05)	Yes	(0.05)	Yes
Communications	346	0.77	No	0.84	No	0.92	No
		(0.03)	Yes	(0.02)	Yes	(0.02)	Yes
Consumer-Cyclical	346	0.45	Yes	0.53	Yes	0.69	Yes
		(0.05)	Yes	(0.03)	Yes	(0.03)	Yes
Consumer-NonCyclical	346	0.24	No	0.77	Yes	0.77	No
		(0.02)	Yes	(0.05)	Yes	(0.03)	Yes
Diversified	342	0.85	Yes	0.86	Yes	0.85	Yes
		(0.06)	Yes	(0.06)	Yes	(0.03)	Yes
Energy	342	1.23	Yes	1.21	Yes	1.05	Yes
		(0.05)	Yes	(0.05)	Yes	(0.03)	Yes
Financial	346	0.96	Yes	1.13	Yes	1.03	Yes
		(0.05)	Yes	(0.05)	Yes	(0.03)	Yes
Industrial	346	0.04	No	0.33	Yes	0.68	Yes
		(0.02)	Yes	(0.04)	Yes	(0.03)	Yes
Technology	342	0.77	Yes	0.94	Yes	0.94	No
		(0.05)	Yes	(0.06)	Yes	(0.01)	Yes
Utilities	342	1.06	Yes	1.19	Yes	1.03	Yes
		(0.06)	Yes	(0.05)	Yes	(0.02)	Yes

* 10 sectors based on Bloomberg classification

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