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The credit cycle does exist

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Abstract

Pipień and Tymoczko (2024) make a unique contribution to the literature on the financial cycle, by extracting credit cycle positions at the bank level, rather than focusing on aggregate data. They interpret the results as indicating "a differentiation of credit cycles in individual banks". Also, they suggest the credit cycle is driven mainly by one bank.

In this study I use the same data – for banks operating in Poland – to reinterpret their results and arrive at the following conclusions. First, since – contrary to the dominant stream of the literature – Pipień and Tymoczko (2024) do not focus on medium-term frequencies, their bank-level credit cycle positions are dominated by the business cycle, rather than the financial cycle. Second, even using the same measure of the cycle, the common component for respective banks is substantial. Focusing on medium-term frequencies makes it account for 72% of variability. Third, I find the contributions of respective banks to the cycle to be more balanced.

Keywords: financial cycle, systemic risk, macroprudential policy, banks, micro data

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1. Introduction

The financial cycle has re-emerged as a policy and research issue after the Global Financial Crisis (GFC) of 2007–2009. It could be defined as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts" (Borio 2014). It tends to be measured with the medium-term component of credit and property prices (Drehmann, Borio, Tsatsaronis 2012).

In their unique contribution to the literature on the financial cycle, Pipień and Tymoczko (2024; PT hereafter) extract credit cycle positions at the bank level, rather than focusing on aggregate data. Their research questions concern: (1) the relationship between the bank-level and the aggregate credit cycle, and (2) whether there is a dominant bank driving the credit cycle.

In order to answer these questions, PT use data on lending for a balanced panel of banks operating in Poland and listed on the Warsaw Stock Exchange; the sample starts in 2001 Q4 and ends in 2023 Q2. They apply the Hodrick-Prescott (HP) filter to disentangle the shorter-term frequencies from the longer ones (using 5, 10 or 15 years as the cut-off), and interpret the former as reflecting the financial/credit cycle.[1] Their answers to the research questions are based on correlations between bank-level credit cycle positions and the aggregate. They average over cross correlations, including both leads and lags. Also, PT plot and compare cycle clocks. The latter are not discussed in this study (here considered more as a form of presenting the results than a separate piece of evidence).

PT find "a differentiation of credit cycles in individual banks". Also, they suggest the credit cycle is driven mainly by one bank, due to its size. As policy implications, they prescribe using bank-level credit cycle positions for the purpose of macroprudential policy analysis. They also propose to consider – in the case of the cycle being driven by a single institution or a small number of institutions – partially replacing macroprudential policy with microprudential tools.

In this study, I reinterpret the results of PT. I start with the same set of pre-processed (i.e. merger&acquisition-adjusted; hereafter: M&A-adjusted) data.[2] Then, I replicate their results, but also produce new ones, by using approaches more as in the dominant stream of the literature. First, I compare their HP filter-based credit cycle positions with positions based on a band-pass filter, extracting business-cycle and medium-term frequencies separately, as, for example, Drehmann, Borio and Tsatsaronis (2012). Second, while PT focus on differences between banks, I argue some differences should be expected and instead focus on the common component in bank-level credit cycle positions (in the spirit of the country-level study of Aldasoro et al. 2023) – both using their measure and a measure focused on medium-term frequencies. Third, since correlations between components and the aggregate reflect more than any one-sided causality driven by size, I make use of the additivity of the filters and offer a decomposition of the aggregate credit cycle instead (again, using both their measure of credit cycle position and the measure focused on medium-term frequencies). I also make an attempt to identify spillovers between banks, using the method of Diebold and Yilmaz (2009, 2012).

[1] I interpret the term "credit cycle" as a cycle in credit within the financial cycle, in line with its use in Drehmann, Borio and Tsatsaronis (2012). However, it should be noted that the term is also used in different contexts. For example, Berlin (2009) defines the credit cycle as "a systematic tendency to fund negative NPV [net present value] loans during an expansion and a systematic tendency to reject positive NPV loans during a contraction" – a concept likely to be apparent in business cycle frequencies. In any case, I provide computations for both business cycle frequencies (which could be reconciled with different concepts of the credit cycle) and medium-term frequencies (associated with the financial cycle).

[2] Files for replication, and the online appendix, are available at: https://doi.org/10.6084/m9.figshare.27901146.

The aim of this study is to discuss the results of Pipień and Tymoczko (2024) and to build on them. In principle, I seek answers to the same, above-mentioned questions; for reasons outlined in section 3, I slightly reformulate the research questions of PT as: (1) what is the synchronicity of bank-level credit cycle positions, (2) what is the concentration of contributions of individual banks to the aggregate credit cycle. This study appears to be the first to apply the principal component analysis to bank-level data in the context of the financial cycle and to decompose the credit cycle into the contributions of individual institutions – these are its additions to the literature. Since this is primarily a response article, for detailed data description and literature review the reader is referred to Pipień and Tymoczko (2024). For the clarity of the argument, I also keep the description of research methods to a minimum, referring the reader to respective source articles.

I find the following. First, the bank-level credit cycle positions of PT are dominated by the business cycle, rather than the financial cycle, with the former arguably of less importance for macroprudential policy. Second, even using the same measure of the cycle as PT, the common component for respective banks is substantial. Focusing on medium-term frequencies makes it account for 72% of variability. Third, I find the contributions of respective banks to the cycle to be more balanced. Summing up, I do agree the bank-level credit cycle positions could be a useful reference point for prudential policy. However, in the results I find little support for changing macroprudential policy framework.

In the remaining sections, I separately discuss: the measurement of the credit cycle, bank-level credit cycle synchronicity and the concentration of bank contributions. I start with discussing the approach of PT in each of these areas; then I propose alternative approaches and compare the results of the two. In the last section I conclude.

2. Extracting credit cycle positions

In this section I discuss the measurement of the credit cycle in the study of Pipień and Tymoczko (2024). Since for this purpose the level of aggregation is of secondary importance, I use aggregate data on bank lending for the computations, the results of which are presented in this section. Note, all data are as in PT. For data sources and the description of their pre-processing, see the original study.

PT start with data on the natural logarithm of bank lending. Then they appear to compute seasonal differences (annual growth rate) and further process them by making a 2 × 4 moving average. This can be implied from the reported start of the sample (2001 Q4) and start of the sample for the purpose of credit cycle analysis (2003 Q2). The first four observations are lost by seasonal differencing, and the further two by applying the 2 × 4 moving average. A similar approach is used in one of the referred studies (Lenart, Pipień 2018).

In the next step, PT apply the HP filter. They report to test the cut-off for the length of the cycle of 5, 10 and 15 years. For the purpose of the replication of their results, I used the formula for the lambda parameter from Kufel et al. (2014). It implies the cut-off for the length of the cycle of 5, 10 and 15 years to correspond to the lambda of 104, 1649 and 8,331 respectively. Based on the visual comparison of the resulting filtered data and Figure 1 from Pipień and Tymoczko (2024), I found a satisfactory replication for the 10-year cut-off and the lambda parameter of 1,649.

The approach used by PT deviates from what appears to be the dominant stream of the literature, without motivating it. Drehmann, Borio and Tsatsaronis (2012) identify the financial cycle with the medium-term component in real credit, credit-to-GDP ratio and property prices. In the application of PT it is natural to abstract from credit-to-GDP ratio (it cannot be meaningfully computed by using M&A-adjusted data on bank lending) and property prices (having no meaningful bank-level counterpart). Deflating credit with the price level could also not be optimal, since it would add to the similarity of bank-level credit cycle positions, skewing the answers to the research questions in favour of more similarity between banks. Therefore, using nominal data appears to be natural as well.

However, focusing on the medium-term rather than filtering out the low frequencies only (with PT using the latter approach) appears to be at the very heart of the identification of the financial cycle. While this involves arbitrariness, the guess behind it is educated. As Filardo, Lombardi and Raczko (2018) note, business cycle frequencies in credit are expected to be associated with the financial accelerator mechanism (Bernanke, Gertler, Gilchrist 1999) – a concept distinct from the financial cycle. Even abstracting from this mechanism, credit and GDP (in which the business cycle is reflected) would co-move on higher frequencies simply since some GDP transactions are funded with bank lending (Biggs, Mayer, Pick 2010). This co-movement appears to bear limited relevance from the perspective of systemic risk and macroprudential policy. Drehmann, Borio and Tsatsaronis (2012) "caution against relying on higher-frequency cycles in characterising the financial cycle, at least if one is interested in [financial] crises" specifically for this reason: they are "less important from a systemic point of view". Besides Filardo, Lombardi and Raczko (2018), their approach is followed by, for example, Stremmel (2015), when designing a measure of the financial cycle in Europe. Schüler, Hiebert and Peltonen (2015, 2020) find the co-movement of the relevant financial variables to concentrate at medium-term frequencies empirically in selected European Union countries and the G-7 countries, respectively. Therefore, while emphasising differences in exact financial cycle durations, they also focus on the medium term when designing their measure of the financial cycle. In other words, there are both theoretical and empirical grounds for using medium-term frequencies; see also evidence for a panel of 14 developed economies in Aikman, Haldane and Nelson (2015). Unrestricted look at individual financial variables in the context of the financial cycle appears to be the domain of early contributions to the post-GFC wave of the literature (see, for example, Claessens, Kose and Terrones 2011).

One could argue that credit gaps for macroprudential policy purposes are calculated using the HP filter – a high-pass, rather than band-pass filter – and hence shorter-term frequencies are retained. However, since they are extracted from credit-to-GDP ratios, shorter-term frequencies in credit and GDP at least to some extent cancel out (also, the countercyclical capital buffer is suggested to be introduced only after the gap exceeds some level). Another argument could be that Lenart and Pipień (2018), using monthly data, find cycles in credit of between 3.6 and 7.25 years to be statistically significant in Poland. However, the fact that some frequencies are statistically significant does not mean they should be treated as being a part of the financial cycle.[3]

In Figure 1, I compare the replication of the credit cycle as extracted by PT with measures resulting from filtering the same data (annual growth rate of bank lending, additionally filtered with a moving average), but with the band-pass filter (the asymmetric Christiano-Fitzgerald, or CF, filter, mean-adjusted). I consider business cycle and medium-term frequencies separately. I define them as being between 5 and 32 quarters and between 32 and 120 quarters, respectively, as Drehmann, Borio and Tsatsaronis (2012). I also plot the HP-filtered (and moving average-filtered) annual growth rate of GDP.

[3] Also, with no more than 204 monthly observations in the study (it is not clear whether this takes into account observation loss due to seasonal differencing and moving averaging), corresponding to 17 years, the identification of longer-term frequencies, assuming they are relevant, does not seem very likely.

The comparison reveals the measure of the credit cycle of PT to be driven by business cycle frequencies. The correlation coefficient between the measure based on the HP filter and the one extracted using the CF filter and business cycle frequencies is 0.94. Medium-term frequencies in the annual growth rate of bank lending are of a larger amplitude. The measure of the credit cycle of PT co-moves with HP-filtered GDP in periods other than around the Global Financial Crisis of 2007–2009.

Moving away from the method of filtering and the choice of the frequencies to filter out, while both Drehmann, Borio and Tsatsaronis (2012) and PT filter data in annual growth rates, PT do not transform the filtered series to correspond to the level of bank lending; Drehmann, Borio and Tsatsaronis (2012), do. Therefore, the credit cycle of PT suffers from the phase shift associated with the use of annual growth rates (approximately being a 4-quarter moving average of quarterly growth rates). Since this refers to all the series in the study of PT, this is not relevant for their main results. However, in looking for an alternative approach, this appears to be worth correcting for.

Taking these considerations into account, I offer extracting bank-level credit cycle positions simply from the (log-)level of lending, with the use of the CF filter, drift-adjusted. First, this allows for preserving initial observations, important in the case of short time series (as available for Poland) in particular. Second, Comin and Gertler (2006), on which the approach of Drehmann, Borio and Tsatsaronis (2012) is based, report obtaining "virtually identical results" by filtering adjusted log-levels for series where the growth rate is stationary (which should also be expected in the case of credit).

In Figure 2, I compare the replication of the credit cycle as extracted by PT with a measure obtained by filtering the log-level of bank lending with the CF filter and focusing on medium-term frequencies – an approach equivalent to that of Drehmann, Borio and Tsatsaronis (2012). These two measures offer a very different depiction of the credit cycle in Poland. Henceforth, I refer to the former as the PT credit cycle/approach and the latter as MTF (as: medium-term frequency) credit cycle/approach.

3. Cycle synchronicity

Pipień and Tymoczko (2024) answer both of their research questions (i.e. on the relationship between bank-level credit cycle positions and the aggregate and on the presence of any dominant institution) mainly on the basis of the results of cross-correlation analysis. On the one hand, this approach has the virtue of computational simplicity. On the other hand, it has the following limitations. The correlation between the credit cycle position of a given bank and the aggregate reflects two factors. First, the synchronicity between respective banks. Second, the contribution of the bank to the credit aggregate (as well as any spillovers). A bank perfectly correlated with the aggregate could be so having a very small contribution to the credit aggregate, simply due to the high synchronicity between banks. It does not mean it drives the cycle. The correlation analysis does not allow to disentangle the two factors. In the simplest terms, the answer to the question: "what is the relationship between the credit cycles of individual banks and the credit cycle extracted for aggregate data?" is: the latter is the sum of the former. In this sense, credit cycle positions of respective banks cannot be unrelated to the aggregate, contrary to what PT hypothesise ("If the credit cycles of individual banks are not related to the aggregated credit cycle…").

Furthermore, for sufficiently dense cycles (and since PT do not filter-out higher frequencies, the cycles they extract are dense; see section 2) mean cross-correlation – the summary statistic which

PT rely on – tends to 0 even for barely indistinguishable series. To see this, let us consider two pairs of generated cycle series: one with around 5-year frequency and one with around 10-year frequency (Figure 3).[4] In both cases, the simultaneous correlation is 0.94. However, while for the 10-year cycle the mean cross-correlation is 0.47, for the 5-year cycle it is -0.12 (Figure 4). The combination of very high simultaneous pairwise correlation and autocorrelation of individual series turning negative at sufficiently early lag (6 periods for the 5-year cycle) results in low mean pairwise cross-correlation. Arguably, this makes the statistic unfit for purpose. In any case, I was not able to replicate mean cross-correlations reported by PT for 6 out of 8 banks – not only for lambda corresponding to cut-off at the 10-year cycle, but for any lambda corresponding to cut-offs of between 5 and 15 years. The replicated means were much closer to zero – as would be expected by construction (see the online appendix).

Also, it should be noted that PT average over both leads and lags in cross-correlation analysis. While both being contemporaneously correlated with the aggregate and leading it would be under some conditions consistent with driving the cycle (with the caveats above), it is unclear why lagging behind the cycle is taken into account in the same way (this concerns the answer to the question: "is there a dominant institution in the Polish banking sector influencing fluctuations in the aggregated credit cycle").

Taking these considerations into account, I propose separating the question of synchronicity between banks from the question of their contribution to the aggregate (as well as spillovers). In this section, I focus on the former one; in the next section – on the latter question.

In the results of the cross-correlation analysis, PT focus on the differences between banks. However, neither does it appear easy to image banks having perfectly synchronised credit cycle positions, nor is it necessary for the purpose of macroprudential policy. The perspective of macroprudential policy is systemic risk. Even assuming the build-up of risk being driven by a limited number of institutions, it appears that the remaining ones should also withstand its materialisation. Taking this into account, it is difficult to imagine how macroprudential policy not tailored to each bank could "harm the stability of the financial system", as argued by PT. In any case, in fact, macroprudential policy allows for both system-wide and bank-specific components (for example, capital buffers for systemically important institutions).

With this in mind, I offer to focus on the degree of similarity between bank credit cycle positions instead. In the spirit of Aldasoro et al. (2023), who – among other things – extract the common component from several financial cycle positions at the country level, I do the same at the bank level. To this end, I use the principal component analysis.[5]

Figures 5 and 6 present bank-level credit cycle positions and their common components, computed based on the PT credit cycle (data in annual growth rates, HP filter) and the MTF credit cycle (data in levels, CF filter), respectively. In the former case, the common component is responsible for 58% of variability in the data – arguably a substantial degree of co-movement. In the latter case it increases to 72%. Also interestingly, the common components are highly correlated with the aggregate credit cycle (with the correlation coefficients of 0.95 and 0.98, respectively). Indeed, one could consider interpreting the common component as another measure of the aggregate credit cycle; similarly as Rey (2015) identifies the global financial cycle as the common component in risky asset prices.

[4] For each t, the series were generated as: $\sin\left(2 \cdot \pi \cdot \frac{t}{\frac{T}{4}}\right) + \varepsilon$ for the 5-year (precisely, 4.9375-year) frequency and $\sin\left(2 \cdot \pi \cdot \frac{t}{\frac{T}{2}}\right) + \eta$ for the 10-year (precisely, 9.875-year) frequency, with $T = 79$, as in the data used in the study and ε and η drawn from the normal distribution with mean 0 and standard deviation as that of the deterministic component scaled by 1/4.

[5] Another standard approach would be to use cross-spectral measures, as coherence. See, for example, Krupa and Skrzypczyński (2012) for its use in the context of the business cycle.

Of course, whether such shares of variability are large or small is partially subject to subjective interpretation.[6] However, in the light of the complementary evidence above, support for the argument that "banks in Poland have their own distinct credit cycle, often independent of each other" appears to be somewhat weaker.

4. Concentration of bank contributions

In this section I offer an alternative approach to the determination of the contributions of bank-level credit cycle positions to the aggregate credit cycle. As described in the previous section, Pipień and Tymoczko (2024) rely on cross-correlations between respective banks and the aggregate. A simple alternative would be to use the additivity of bank lending (plus a measure of spillovers; see below).

Aggregate credit is the sum of lending of respective banks. One should also expect (after a proper M&A adjustment – indeed used in this case) the aggregate credit cycle to be a weighted average of bank-level credit cycle positions.

While the additivity of the data is unquestionable, the characteristics of the filters used to extract the credit cycle – whether they allow for a simple decomposition – are another matter. The filters used in the study are additive – in principle, the cycle series of the sum equal the sum of the cycle series extracted from the components of the sum. However, here the cycle series are obtained either based on the annual growth rate or from the log-level of a variable. Such cycle series extracted from the components of the sum do not add up to the cycle series of the sum – a weighted average does approximate it. Below I provide evidence on the size of the approximation error for the HP and CF filters in the case of the data at hand.

While after M&A adjustment, data at the bank level have no meaningful units, they can be normalised so that the orders of magnitude are retained – by making them have the same mean as unadjusted series. After such a normalisation, I compute a sum of the normalised series and extract the credit cycle from it – both using the PT approach and the MTF approach. Finally, I compare such measures of the aggregate credit cycle with a weighted average of bank-level credit cycle positions.

The results of such exercise are in Figures 7 and 8. While again, this is to some degree up to subjective interpretation, the aggregate and the sum of the components appear very similar. This is more the case in the PT approach.

I consider these results as encouraging. Therefore, in Figures 9 and 10 I present the results of an actual decomposition, i.e. using unadjusted weights in the aggregate (as opposed to adjusted weights in the sum of the sample of banks). I also compute a residual between the aggregate credit cycle and the sum of components – in the light of the evidence above likely to be driven by the fact that not the whole banking sector is covered by the study, rather than any approximation error of the filters.

In this case there is also no universal way of deciding whether the contributions of respective banks are large or small. Without data for all banks, concentration measures as the Herfindahl-Hirschman Index could not be used. Here, I offer a visual inspection of the contributions of the respective banks as compared to the aggregate credit cycle. Perhaps paradoxically, no bank stands out when using the

[6] One approach to answer this question would be to test for the number factors. Using the Bai and Ng (2002) method, the result turned out to strongly depend on the maximum number of factors. The minimum average partial method (Velicer 1976) pointed to two factors. The second factor adds 19–23 percentage points to the variability in the data.

PT approach to the identification of the cycle. In the MTF approach, the largest bank (and indeed the bank indicated by PT as dominant), made the largest contributions at the peaks and the troughs of the cycle. But the contributions of the remaining banks are not far behind. Indeed, while PT argue "the leading role of [the] bank (…) in creating cyclical fluctuations at the aggregated level for the whole system" can "be attributed to the share of [the] bank (…) in the total credit portfolio of the entire Polish banking system", its average share in lending in the sample is a mere 17%, followed by 12% and 8% of the second and the third bank used in the analysis, accordingly (with the shares of the remaining banks being: 8%, 7%, 5%, 2% and 1%). According to the ECB dataset on structural financial indicators for 2023, the share of the five largest credit institutions in total assets in Poland was relatively low – around the first quartile for the European Union (58%).

4.1. Spillovers

Not only could a bank contribute to the credit cycle directly, through its share in the credit aggregate, but also, for example, by making competitive pressure on the others. For the reasons listed in section 3, correlations between lagged bank credit cycle positions and the current aggregate credit cycle are ill-suited for the identification of such a channel as well. However, similarly as the principal component analysis summarises contemporaneous correlations between banks, a measure summarising dynamic relationships between banks could be used.

An example of such a measure is a part of the return spillovers analysis of Diebold and Yilmaz (2009, 2012). Their approach was originally used for financial asset returns, but since then applied to other concepts as well; see Hałka, Szafranek (2016), for an example of the use of the method for inflation spillovers and for a literature review on uses other than financial asset returns.

The method of Diebold and Yilmaz (2009) is based on forecast error variance decompositions, themselves based on vector autoregressive (VAR) models. Here I apply the extended approach of Diebold and Yilmaz (2012), where a generalised framework (as opposed to a framework based on orthogonalised impulse response analysis) is used and the results are invariant to the ordering of variables. I focus on the contributions of respective variables to forecast errors of other variables, which can be added.

I start with three variants of a VAR model. Each contains eight variables, each corresponding to a bank. In the first two variants, I use PT and MTF credit cycle positions, respectively. However, as Kilian and Lütkepohl (2017) note, "there is increased recognition in the literature that statistical filters that can be represented as a symmetric, two-sided moving average of the raw data inevitably distort the estimates of impulse responses (…). Thus, the use of band-pass filters in the VAR analysis should be avoided." This matters because forecast error variance decompositions are related to impulse responses. Also, this is relevant for the HP filter (not being a band-pass filter), which has a moving average representation too. Therefore, for comparison, in the third variant I estimate a VAR on the quarterly growth rate of lending.

Having a relatively large number of variables (eight) compared to the number of observations (87 or less), I start with the number of lags in VARs according to the rule-of-thumb of Ouliaris, Pagan and Restrepo (2016), so that the number of parameters is below the number of periods divided by 3. Such a rule suggests using two lags. However, due to the multicollinearity, for the variant with MTF credit cycle positions the lag length had to be lowered to one period.

The last parameter to set is the horizon for which forecast error variance decompositions are considered. I present results for 4, 8, 12, 16 and 20 quarters (or, between 1 and 5 years).

Figures 11–13 present the sums of contributions of respective banks to forecast errors of other banks (in percentage points). To facilitate an easy interpretation, the banks are ordered according to their size. The results differ depending on whether PT or MTF bank-level credit cycle positions are used, or simple lending growth. For the PT approach, on average, the contributions of the fourth largest in the sample come first, followed by the smallest one and then by the largest bank. As far as the MTF approach is concerned, the third largest bank dominates, followed by the sixth one and then by the second one. When using simple lending growth, the largest bank indeed dominates, but closely followed by the sixth largest bank, and then by the second one.

The results do not offer a clear picture of the banks being the source of spillovers in terms of lending; in any case, there is little evidence of a clear-cut relationship between bank size and its role as a source of spillovers.

5. Conclusion

In this study I agree with Pipień and Tymoczko (2024) that the bank-level credit cycle positions they propose could make a useful reference point for prudential policy. For their remaining conclusions, I interpret what I find in the same data as evidence to the contrary.

First, since – in contrast to the dominant stream of the literature – PT do not focus on medium-term frequencies, their bank-level credit cycle positions are dominated by the business cycle, rather than the financial cycle. Second, even using the same measure of the cycle, the common component for respective banks is substantial. Focusing on medium-term frequencies makes it account for 72% of variability (answer to research question 1). Third, I find the contributions of respective banks to the cycle to be more balanced (answer to research question 2). I consider these results are offering little support for changing the current conduct of macroprudential policy.

For future research, I believe resolving the following issues would be useful. First, how to make use of the unbalanced part of the banking sector in the analysis. Second, how to deal with any approximation errors of the filters. Third, how (if at all) to complement the analysis with data on credit-to-GDP ratios and property prices. Last but not least, how to include measures of credit broader than loans and institutions other than banks in the analysis.

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Appendix

Figure 1

Aggregate credit cycle – PT replication based on the HP filter, compared to business cycle and medium-term frequencies based on the CF filter, and cycle in GDP based on the HP filter (all based on data in growth rates)

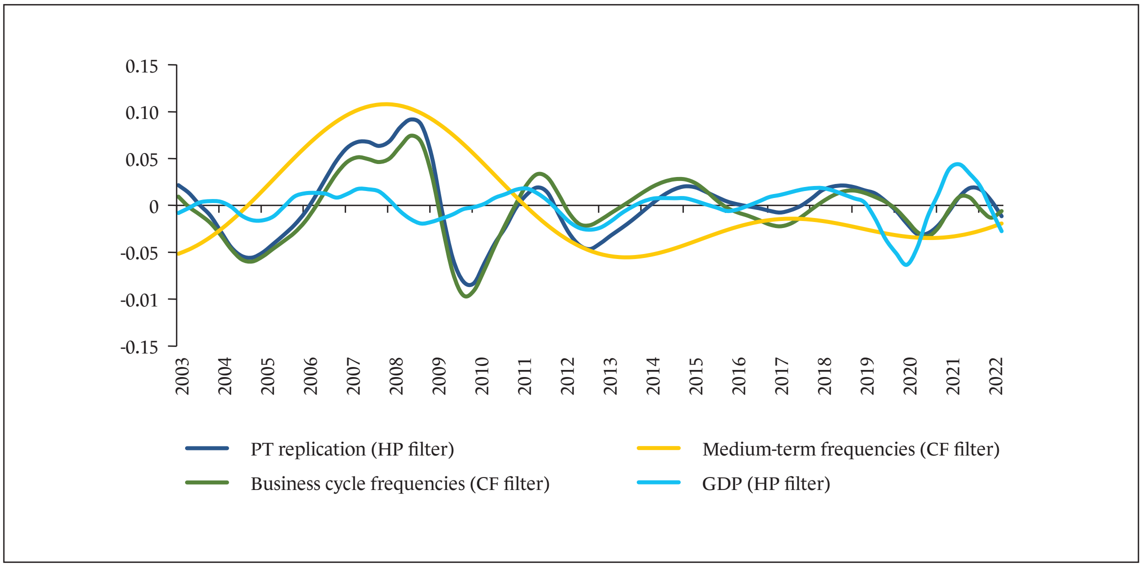


Figure 2

Aggregate credit cycle – PT replication based on the HP filter and data in growth rates, compared to medium--term frequencies based on the CF filter and data in levels

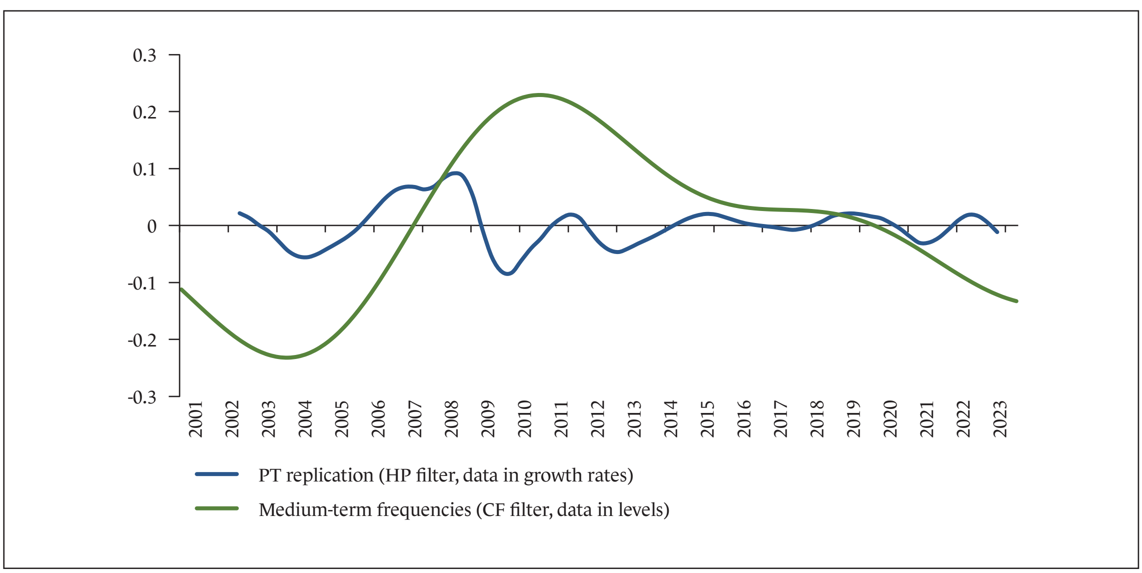


Figure 3
Cycles – an example

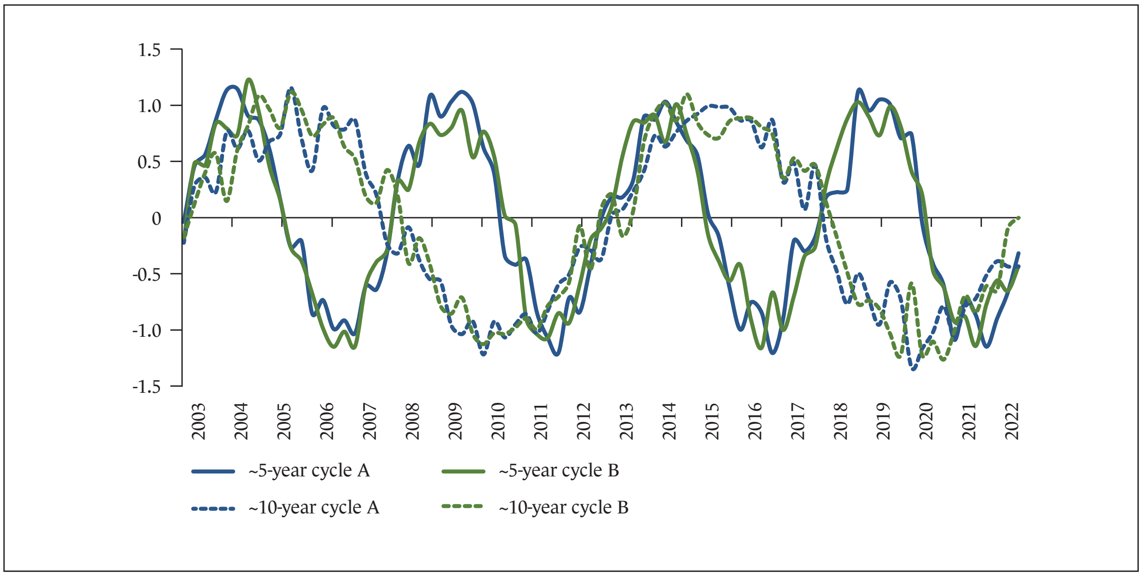


Figure 4
Cycles – an example, cross correlations

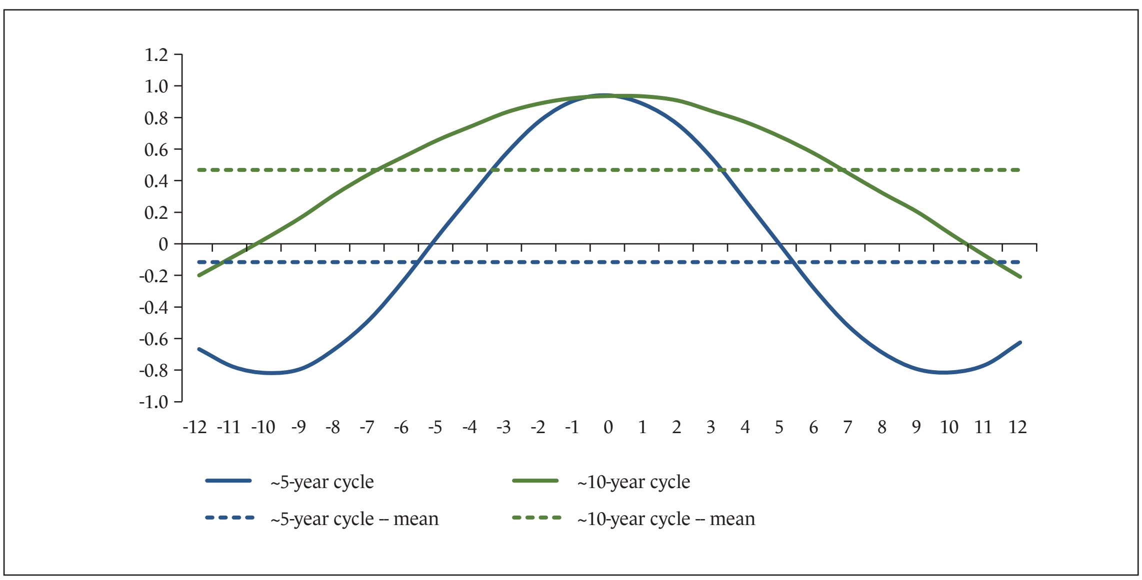
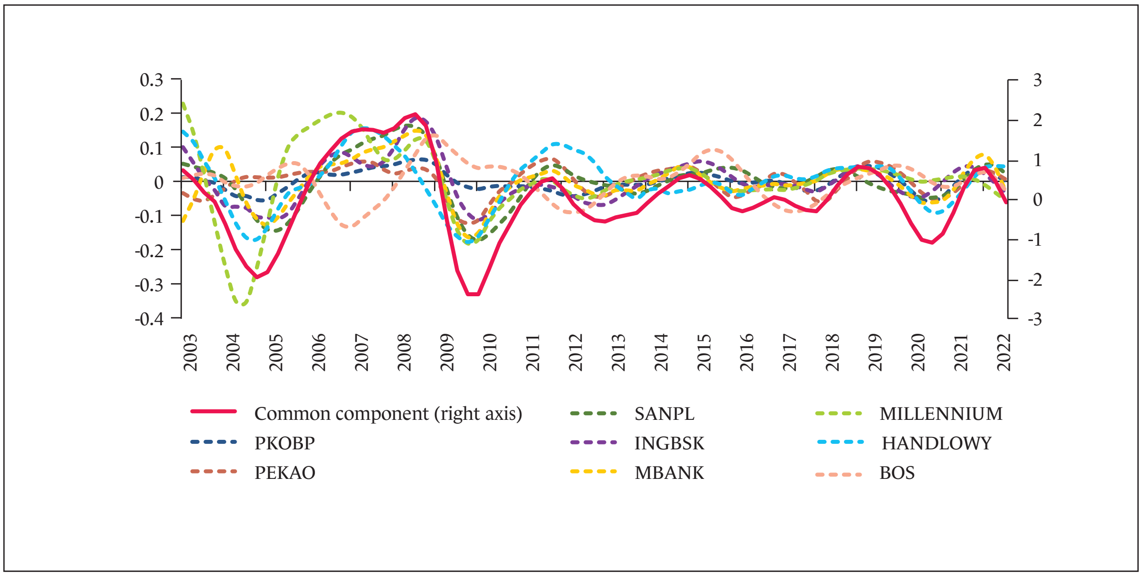


Figure 5

Disaggregated credit cycle – PT replication and the common component (HP filter, data in growth rates)



Note: bank IDs in the legend are as on the Warsaw Stock Exchange; the same concerns the remaining figures.

Figure 6

Disaggregated credit cycle – medium-term frequencies and the common component (CF filter, data in levels)

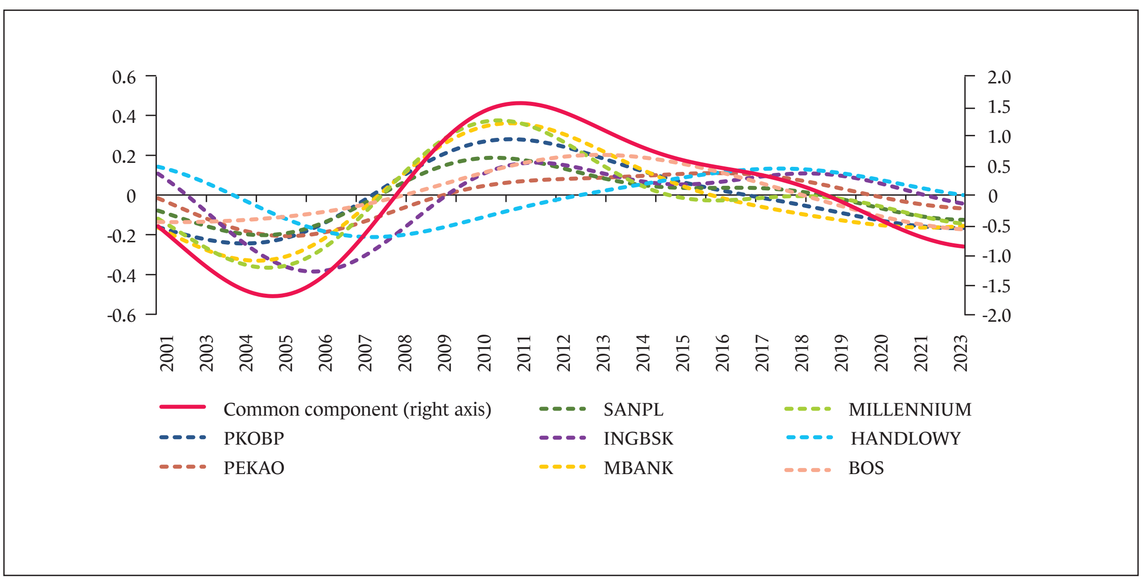


Figure 7
The approximation error of the HP filter – an example

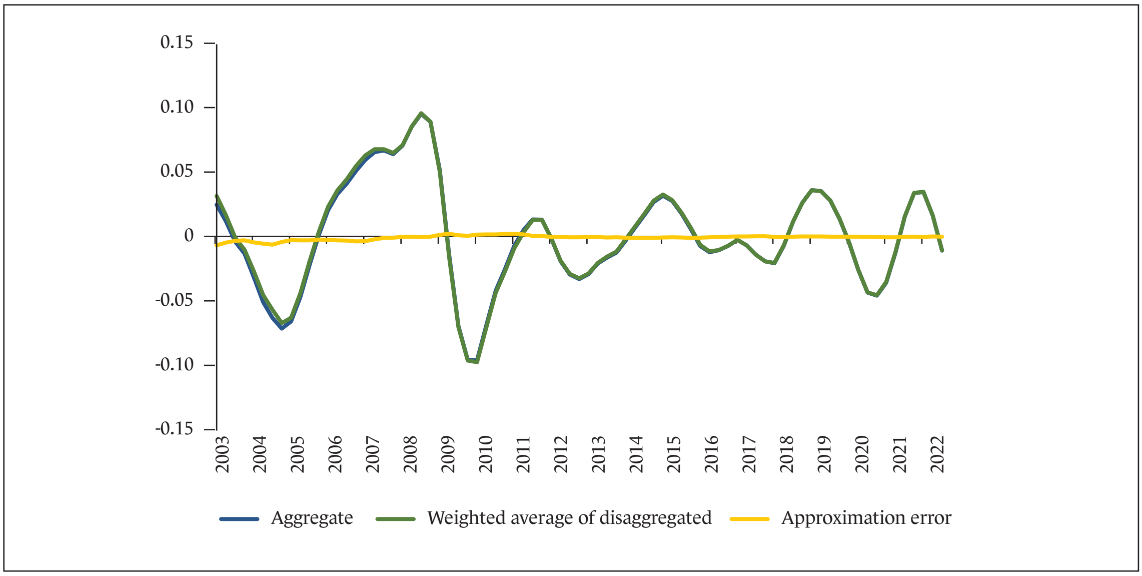


Figure 8
The approximation error of the CF filter – an example

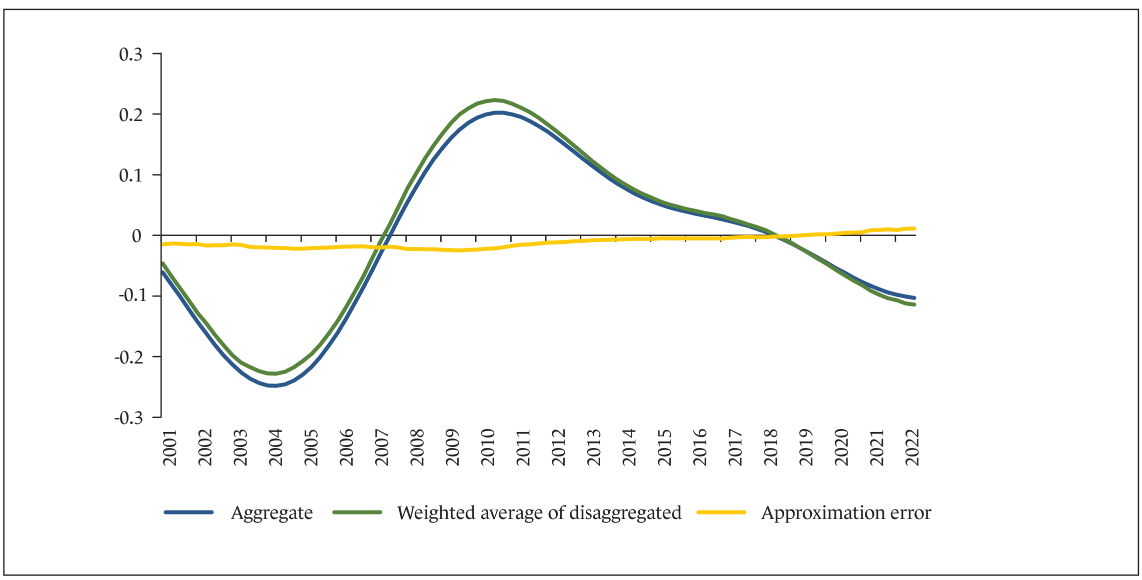


Figure 9
Contributions of respective banks to the credit cycle – based on PT replication (HP filter, data in growth rates)

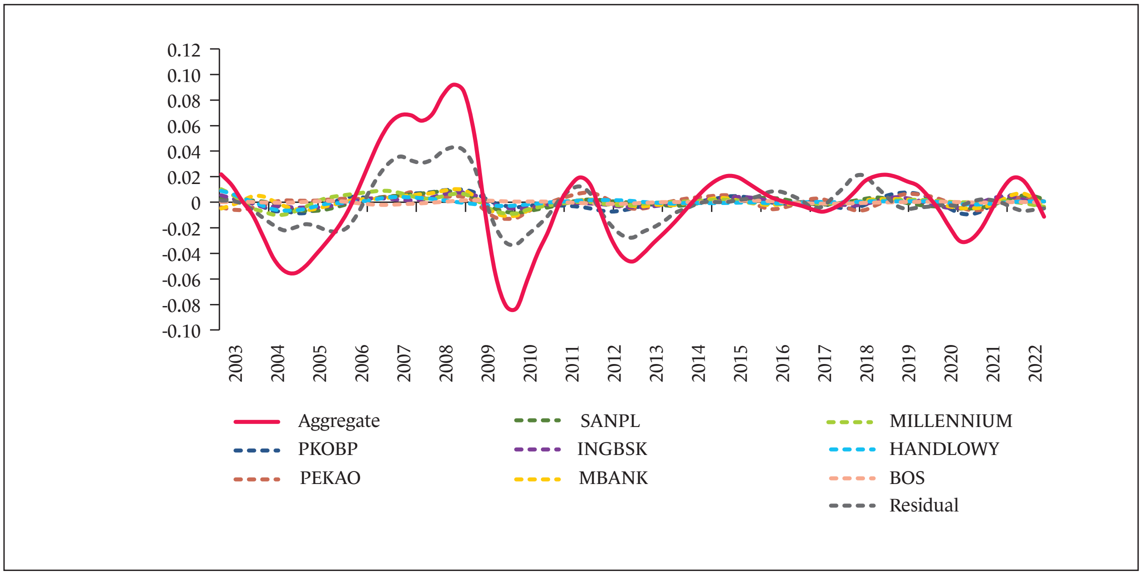


Figure 10
Contributions of respective banks to the credit cycle – medium-term frequencies (CF filter, data in levels)

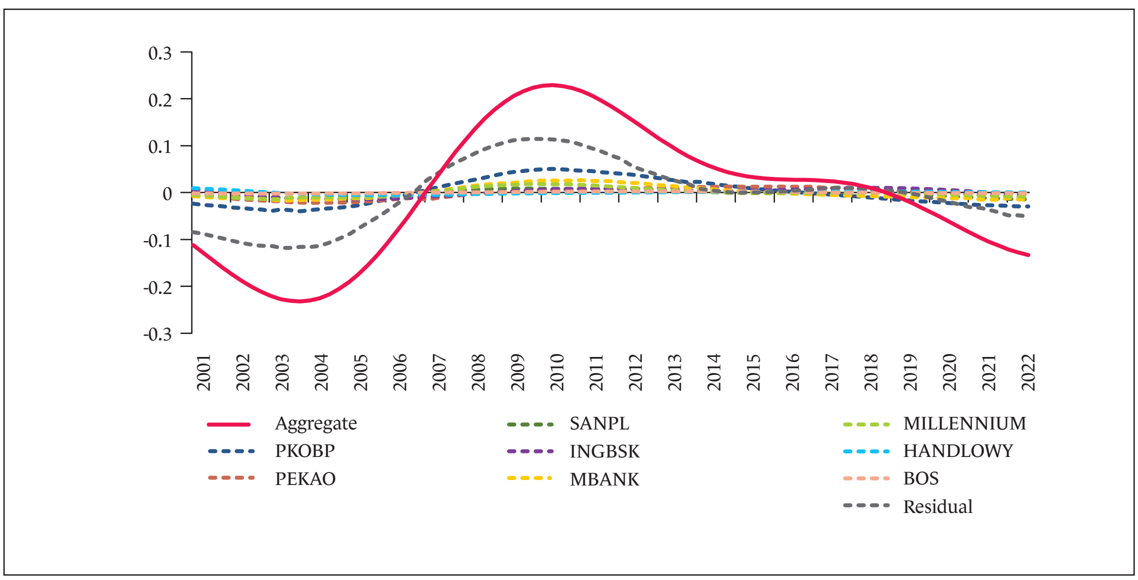


Figure 11
Contributions of respective banks to forecast errors of the remaining banks for respective forecast horizons – PT credit cycle positions

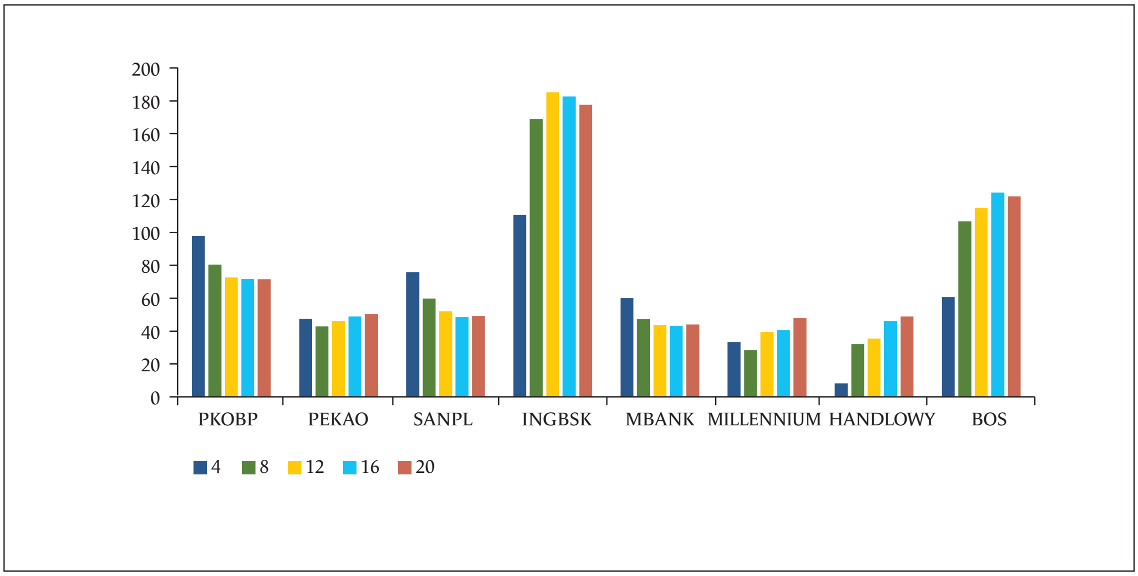


Figure 12
Contributions of respective banks to forecast errors of the remaining banks for respective forecast horizons – MTF credit cycle positions

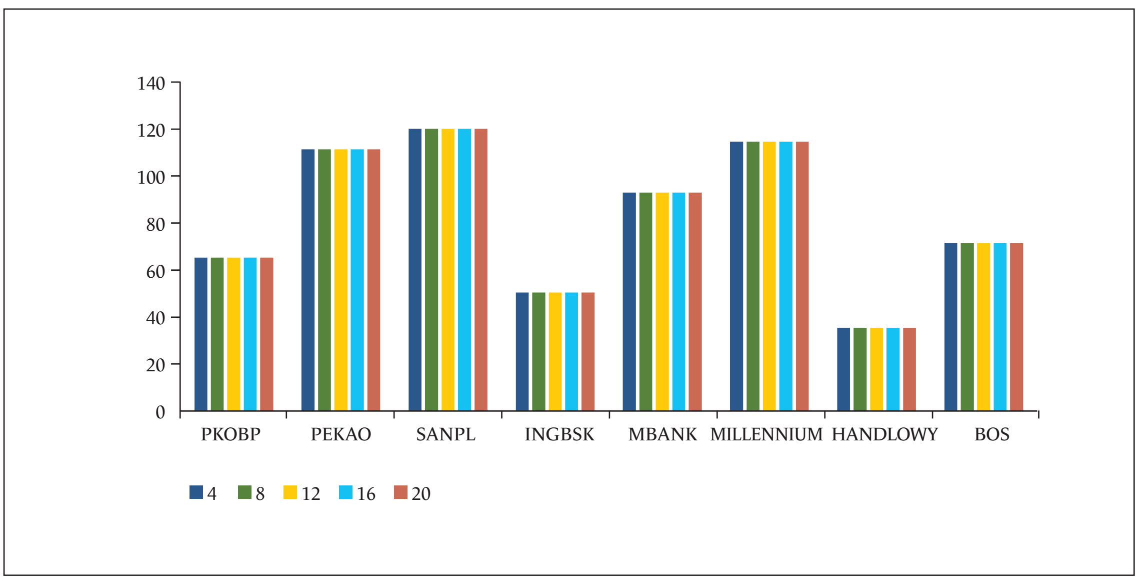
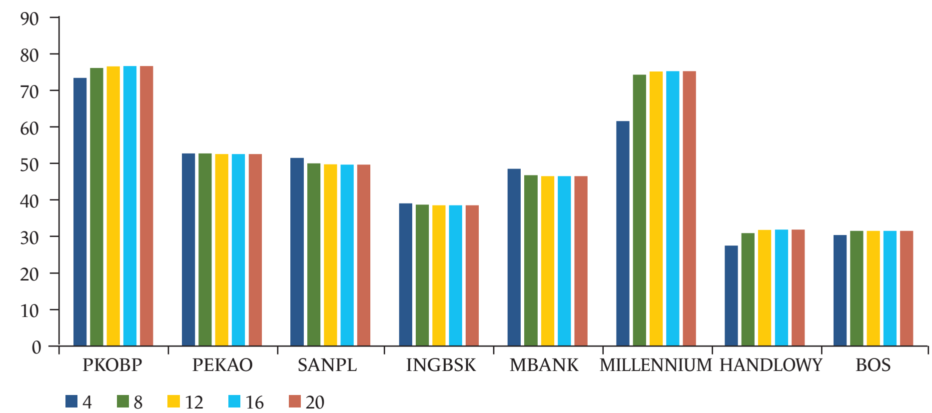


Figure 13
Contributions of respective banks to forecast errors of the remaining banks for respective forecast horizons – lending growth



Cykl kredytowy istnieje

Streszczenie

Po globalnym kryzysie finansowym lat 2007–2009 cykl finansowy ponownie stał się przedmiotem zainteresowania polityki gospodarczej oraz obszarem badań. Można go zdefiniować jako „wzajemnie wzmacniające się interakcje pomiędzy postrzeganymi wartościami [aktywów] a ryzykiem, podejściem do ryzyka oraz ograniczeniami w dostępie do finansowania, przekładające się na boomy, po których następuje kryzys” (Borio 2014). Zgodnie z aktualną tendencją w literaturze jest on wyznaczany jako średniookresowy komponent kredytu i cen nieruchomości (Drehmann, Borio, Tsatsaronis 2012).

Pipień i Tymoczko (2024) zaproponowali unikalny wkład do literatury dotyczącej cyklu finansowego, wyznaczając pozycje w cyklu kredytowym poszczególnych banków, zamiast ograniczać się do wykorzystania danych zagregowanych. Ich pytania badawcze są następujące: (1) „jaka jest zależność pomiędzy cyklami kredytowymi poszczególnych banków a cyklem kredytowym wyznaczonym na danych zagregowanych”, (2) „czy występuje instytucja dominująca w polskim sektorze bankowym, która wpływa na zagregowany cykl kredytowy”. Wykazują, że występuje „zróżnicowanie w cyklach kredytowych na poziomie poszczególnych banków”. Ponadto sugerują, że cykl kredytowy jest determinowany głównie przez jeden bank, w związku z jego wielkością. Jako implikacje proponują wykorzystanie pozycji w cyklu kredytowym na poziomie banków na potrzeby analiz polityki makroostrożnościowej. Proponują również rozważenie – gdyby cykl kredytowy był determinowany przez jedną instytucję lub ich ograniczoną liczbę – częściowego zastąpienia polityki makroostrożnościowej narzędziami polityki mikroostrożnościowej.

Celem tego badania jest dyskusja wyników Pipienia i Tymoczki (2024) oraz uzupełnienie ich. Co do zasady poszukuję odpowiedzi na te same pytania, które zostały wymienione powyżej. Wykorzystuję te same dane co Pipień i Tymoczko (2024) – dla banków działających w Polsce, replikuję ich wyniki oraz dostarczam nowych, wykorzystując rozwiązania metodyczne, które wydają się bardziej zgodne z podejściem dominującym w literaturze. Zamiast wykorzystywać filtr Hodricka-Prescotta i analizę korelacji krzyżowych, proponuję zastosować filtr Christiano-Fitzgeralda, analizę głównych składowych, dekompozycję zagregowanego cyklu kredytowego na wkłady poszczególnych banków oraz analizę zarażania (*spillover analysis*) Diebolda i Yilmaza (2009, 2012).

Po pierwsze, argumentuję, że pozycje banków w cyklu kredytowym wyznaczone przez Pipienia i Tymoczkę (2024) są zdominowane przez cykl koniunkturalny, a nie przez cykl finansowy; ten pierwszy wydaje się mieć mniejsze znaczenie dla polityki makroostrożnościowej. Po drugie, nawet wykorzystując tę samą miarę cyklu co Pipień i Tymoczko (2024), znajduję znaczący wspólny komponent w pozycjach banków. Po wydzieleniu i skupieniu się na średnim okresie wahań wspólny komponent odpowiada za jeszcze więcej zmienności (72%). Po trzecie, wskazuję, że wkład poszczególnych banków do cyklu kredytowego jest bardziej zbilansowany.

Podsumowując, trudno się nie zgodzić, że pozycje w cyklu kredytowym na poziomie banków mogłyby być użytecznym punktem odniesienia dla polityki ostrożnościowej. Jednak w swojej interpretacji wyników nie znajduję wsparcia dla zmian w polityce makroostrożnościowej postulowanych przez Pipienia i Tymoczkę (2024).

Słowa kluczowe: cykl finansowy, ryzyko systemowe, polityka makroostrożnościowa, banki, dane mikro