

## The Business Cycle and the Financial Cycle: Granger Causality for the Peruvian Economy, 2000 – 2019

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### Abstract

*It is relevant to know the relationship between the financial and business cycles to prevent the appearance of financial crises and their negative effects on the macroeconomy. In this sense, a better understanding of the links between financial cycles and the business cycle of Peru can provide valuable information for economic and macroprudential policy decisions. This study examines the causal relationship between Peru's financial and business cycles. The dynamic factors methodology is used to measure the financial cycle, taking four representative indicators of the financial sector: Volume of loans to the private sector (credit market), the Lima Stock Exchange General Index (stock market), Embig Peru (bond market), and the Exchange Rate (currency market) (Ramos, 2019). On the one hand, using the Granger causality test in the frequency domain, it was found that the financial cycle causes the business cycle at frequencies greater than 10 quarters (2.5 years). In contrast, the business cycle does not cause the financial cycle.*

**Keywords:** *Cycles, Financial, Macroeconomic.*

### Introduction

After the financial crisis of 2008 - 2009, it has become clear that a common feature of these recessions is that they are accompanied by several financial disruptions, including sharp contractions in credit and falls in stock prices. The experience of the modern economy shows the importance of financial markets in generating business cycles by acting as a source of new shocks and promoters of volatility in the economy (Akhmetov & Rysaeva, 2015). Therefore, central banks and researchers have focused on the so-called financial cycle (Menden & Proaño, 2017).

The most accepted theoretical definition of the financial cycle is that by (Borio, 2012), which defines the financial cycle as the interaction between perceptions of value and risk, agents' attitudes towards risk, and financial constraints, which reinforce each other, and result in booms and busts in the financial sector. Moreover, these interactions can amplify economic fluctuations and lead to severe economic and financial situations. The most parsimonious way to define the financial cycle is to use the credit/GDP variable. However, given the abstract nature of the financial cycle definition, different methodologies for measuring the financial cycle have emerged (Menden & Proaño, 2017).

The causality study of financial cycles and business cycles is important for economic policymakers because, if they only focus on macroeconomic conditions and do not consider the evolution of the financial system, the occurrence of financial crises and the subsequent negative effects on the macroeconomy could not be prevented. Ramos (2019), in his research, cites studies that point out that the causality between both cycles is bidirectional; other research works point out that the business cycle causes the credit cycle, while other authors evidence that the financial cycle causes the business cycle. Despite the progress in research, there is still an empirical discussion on the direction of causality between both cycles (Duarte, 2014), (Billio & Petronevich, 2017).

In the Peruvian case, research on the financial cycle is scarce and tends to represent the financial cycle as the credit cycle. On the one hand, Lahura et al. (2013) have determined two phases of credit booms

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comprised between late 2008 and early 2009 and between April and June 2019, while Perez & Vilchez (2018) have proposed different methodologies for estimating the financial cycle using quarterly data. On the other hand, Gómez-González et al. (2013) have studied the causal relationship between the credit cycle and the Peruvian business cycle, finding causality from the credit cycle to the business cycle in short and medium frequencies and not the other way around.

In this context, a better understanding of the links between Peru's financial cycles and the business cycle can provide valuable information for economic and macroprudential policy decisions. This paper aims to analyze the causal relationship between Peru's financial and business cycles, using not only the total credit volume of the Peruvian economy as a proxy for the financial cycle but also other representative indicators of the financial sector: the Lima Stock Exchange General Index (stock market), Embig Peru (bond market), and the Exchange Rate (foreign exchange market). The financial cycle is estimated using the dynamic factor method based on these four series. Finally, once the Peruvian financial cycle is obtained, a causality test in the frequency domain is performed to analyze the direction and the type of frequency at which this relationship occurs. In this regard, several research studies suggest the Granger causality test in the frequency domain (Cagliarini & Price, 2017).

The structure of this research paper is as follows: Section 2 presents the empirical literature on both the methods for estimating the financial cycle and the papers that have analyzed the causality relationship between the financial cycle and the business cycle. Section 3 presents the methodology for estimating the Peruvian financial cycle and explains the Granger causality test in the frequency domain. Section 4 explains the results obtained, and Section 5 details the conclusions.

## Literature Review

The estimation of the financial cycle, according to Menden & Proaño (2017), proposes to construct a measure of the financial cycle for the United States from a large dataset of macroeconomic and financial variables using a dynamic factor model from which 03 synthetic components can be extracted. This technique is a state-space representation, where the component that is common to the series is an unobserved AR (1) process. They then investigate whether these financial cycle components have significant predictive power for economic activity, inflation, and short-term interest rates using Granger causality tests in a VAR model. The data set used consists of interest rate spreads, commercial loan and mortgage payoff rates, stock volatility according to the VIX, consumption indicators, aggregate credit variables, money supply, and housing prices. To use the dynamic factor method, the series must be stationary, so the unit root tests are first tested, and the first difference is applied if required. Subsequently, outliers are removed and replaced by the median value of the five values before the outlier. Finally, all series are standardized to have a mean of zero and a variance of one. The authors chose three dynamic factors that account for approximately 45% of the total variation of the variables. The first factor obtained is related to the effect of the business cycle on the structure of short-term interest rates. The second factor is interpreted as the financial accelerator mechanism, and the third factor is more related to expectations and uncertainty regarding aggregate and financial market risk, which is interpreted as the financial cycle.

Granger causality tests based on VAR suggest that the third component of the financial cycle has significant predictive power for GDP growth, inflation, and short-term interest rates.

Rünstler and Vlekke (2017) use multivariate structural time series models (STSM) to estimate trends and cyclical components in real GDP, credit volumes, and house prices. The study was applied to the United States, Italy, France, the United Kingdom, Germany, and Spain with quarterly information from 1973 to 2014. The authors point out that the use of parametric filters, such as Hodrick-Prescott, can lead to spurious cycles. The main findings are as follows: First, the countries were classified into three groups: i) countries with short financial cycles: Germany is in this group with a business and financial cycle similar in length (average of 6.2–7.1 years); ii) countries with moderate financial cycles comprising the United States, France, and Italy, with average lengths varying between 11.8 and 15.3 years; and finally, iii) countries with long financial cycles comprising the United Kingdom and Spain, with average lengths between 15.8 and 18.7

years. The second finding is related to the explanation of the difference in financial cycles. According to the authors, countries with higher mortgage market participation have longer financial cycle lengths. The third finding is that GDP cycles are closely related to financial cycles.

Adarov (2018) analyzes financial cycles for 34 countries for the period 1960–2014 with quarterly information. The authors, considering that credit, housing, bonds, and stock variables reflect the key characteristics of the financial market, detect the dynamics of boom and bust. To calculate the financial cycles, they use the dynamic factor methodology. Previously, a unit root test was applied to validate whether the series were stationary or not. If the null hypothesis is accepted, the first difference is applied. Then, the series are standardized so that they can be comparable. During the initial estimation stage, financial cycles are evaluated for each country. Then, the countries are grouped by region (Europe, South America, North America, and Asia), and a financial cycle is estimated for each of them, applying the dynamic factor methodology again. Finally, a global financial cycle can be calculated using the same methodology for the three regions previously estimated. The authors find that the estimated average duration of financial cycles is 13 years for credit and housing markets and 10 years for bond and stock markets and that expansions tend to be one year longer on average than contractions. The aggregate financial cycles by country are characterized by high persistence with an autoregressive parameter in the range of [0.82-0.99] and an average duration of 12 years.

Regarding global cycles, the authors demonstrate the existence of a single common cyclical factor behind financial market activity in the world economy and different financial market segments. Moreover, the U.S. financial cycle tends to lead or co-move with the global cycle, suggesting a possible systemic importance of U.S. financial markets: the concordance indicator between the two cycles is 0.76, indicating a highly synchronized co-movement.

El-Baz (2018) investigates financial and business cycles in Saudi Arabia over the period 1970–2016 with quarterly frequency data. They only consider the credit variable as part of the financial cycle. First, using the turning point algorithm, they show that the business cycle lasts 5–26 quarters in expansions and 3–17 quarters in contractions, while the business and financial cycles last 4–49 quarters in expansions and 4–9 quarters in contractions. The index of agreement between cycles equals 0.60, which means that business and financial cycles tend to be in the same phase approximately 60 percent of the time. Likewise, the authors show that economic downturns accompanied by financial recessions tend to be longer and deeper than others. This emphasizes the idea that a greater degree of synchronization between the two cycles amplifies the length of economic contractions. Therefore, any shock to the financial sector is transmitted to the real sector. Subsequently, a VAR (vector autoregressive) model is used to investigate the effects of financial cycles on the real economy of Saudi Arabia. The endogenous variables included in the model are real GDP, consumer prices, the credit gap (extracted with Hodrick-Prescott), the nominal domestic short-term interest rate, and the real effective exchange rate. The exogenous variables are world oil prices, U.S. real GDP, and the U.S. nominal short-term interest rate. The authors show that a positive shock to the domestic credit gap generates a positive effect on real GDP, which means that financial upturns (recessions) have a positive (or negative) effect on the real economy. Likewise, the variance decomposition of real GDP forecast errors confirms the importance of financial conditions for economic stability, where over four years, approximately 9.6% of the variation in real GDP forecast errors is attributable to shocks in the domestic credit gap.

Drehmann, Borio & Tsatsaronis (2012) analyze the properties of the financial cycle using two approaches: turning points and frequency-based filters. The authors apply their study to seven countries (Australia, Germany, Japan, Norway, Sweden, the United Kingdom, and the United States) over the period 1960–2011 with quarterly data. The variables used are: (i) credit to the non-financial private sector; (ii) credit-to-GDP ratio; (iii) stock prices; (iv) residential property prices; and (v) an aggregate asset price index (combining residential property and stocks). The authors suggest that the variables be available for at least 40 years in all countries. For the analysis of turning points, they use the algorithm of Harding and Pagan (2002, 2006), separating the turning points into short- and medium-term cycles. Considering the medium-term cycles, it is found that credit volume is the longest (18 years), and stock prices are the shortest (9 years). On the other hand, using univariate filters, such as the Christiano and Fitzgerald (2003) filter, the authors extract short-

term cycles (5–32 quarters) and medium-term cycles (3–21 quarters). From this second analysis, they show that the medium-term components are more important than the short-term ones since they are more volatile and their amplitude has increased since 1985, when a wave of financial liberalization began. To obtain a financial cycle that is common for the series, the authors average the medium-term cycles (extracted by the Christiano and Fitzgerald filter) of the credit volume, credit-to-GDP ratio, and housing prices series.

#### *The Causal Relationship Between the Financial Cycle and The Business Cycle.*

Juhler, Lassenius, Farver, and Pedersen (2017) consider that there are two types of frequencies: business cycle frequencies (BCF) and financial cycle frequencies (FCF). The former lasts between 2 and 11 years, while the latter lasts between 11 and 30 years. To extract the cycles of different frequencies, the method of Christiano and Fitzgerald (1999) is used. The authors work with the GDP, credit volume, and house price index series in logarithms and also extract the cycle through a linear detrend. In the first part of the paper, the 17 most developed economies are analyzed, separating the cycles into BCF and FCF. The authors find that, in FCF, there is a higher correlation between credit and GDP, which is supported by the theory of Comin and Gertler (2006). In the second part of the paper, the authors focus on Denmark. The cycles of the GDP, credit volume, and house price index variables are estimated using the unobservable component method. Then, using the Granger causality test for medium-term frequencies, they find that the business cycle leads to the credit cycle and, to a lesser extent, to the house price cycle. This relationship may be bidirectional.

Ramírez (2013) aims to analyze the causal relationship between the credit cycle (FC) and the business cycle (BC) in Central American countries. The research uses cross-correlation and causality in the Granger sense for both time and frequency domains. Using the techniques in the time domain, the authors find that the FC lags behind the BC by almost 12 months in Costa Rica and Nicaragua, while, for El Salvador, Honduras, and the Dominican Republic, the lag is between 2 and 6 months. This means that FC leads to BC, or that past values of FC give the current value of BC. These findings are verified with the Granger causality test for the Dominican Republic, Guatemala, and Nicaragua. For Honduras, the relationship is bidirectional, but in Costa Rica and El Salvador, no evidence of causality is found. Using the techniques in the frequency domain, it is analyzed in which type of frequencies a higher correlation is reached between BC and FC. In the business cycle frequencies (between 1.5 and 8 years), the correlation is high for El Salvador, the Dominican Republic, and Costa Rica. In the financial cycle frequencies, the highest correlation occurs in countries such as Guatemala, Honduras, the Dominican Republic, and Costa Rica. Using the Granger causality test in the frequency domain, it is found that, for Costa Rica, El Salvador, Honduras, Guatemala, and the Dominican Republic, FC causes BC at frequencies of more than eight years. Causality from FC to BC is also observed in these countries at business cycle frequencies.

Karfakis and Karfaki (2018) conducted causality tests between the credit cycle (FC) and the business cycle (BC) for the Greek economy. The authors use two types of models: a VAR and a quantile regression. The latter is used to find out the impact that covariates may have on the tails of the distribution of the dependent variable and has the form of an aggregate demand equation (AD), where the interest rate, the trade balance, a lag of the BC and the FC, and the growth rate of the economic sentiment indicator for Greece are incorporated. The FC is measured through the principal components of the credit growth rate and house price growth. Using the VAR model and the Granger causality test, it is evident that the FC causes the BC and not vice versa. The authors then use quantile regression and separate the BC values into three scenarios: 10% percentile (associated with a recession), 50% percentile (associated with average growth), and 90% percentile (associated with an expansion). The causality test indicates that the FC helps explain the BC in any of these scenarios, but is more significant in times of expansion.

Tsiakas and Zhang (2018) analyze the causality of financial cycles (FC) and business cycles (BC) for five industrialized countries: the United States, Canada, the United Kingdom, Germany, and Japan. The BC is determined by the industrial production index (IPI), which has a monthly frequency; the FC is determined by the aggregate credit volume, which is at a quarterly frequency. This leads the authors to use an MF-VAR (mixed frequency vector autoregression) model, where Granger causality is analyzed in mixed frequencies and data aggregation is avoided, thus preserving the dynamics of the variable and avoiding a possible



spurious causality. The FC and BC are represented by the annualized growth rates of credit and output, respectively. Using the Granger causality test in mixed frequencies, it is evident that there is a bidirectional causal relationship for Canada, the USA, and Japan; in the United Kingdom, there is only a unidirectional relationship from FC to BC. In Germany, no causal relationship is found. Additionally, the authors use the BC and FC of the United States as a global leader and find that the BC of the United States causes the BC of the rest of the countries, showing that the United States is a world leader in exporting its (severe) recessions to other countries.

Sala-Rios, Torres-Solé, and Farré-Perdiguer (2016) analyze the properties and causal relationship between the business cycle (BC) and financial cycle (FC) in Spain. To represent the FC, they use the credit cycle based on three different indicators: total credit to the non-financial sector, credit to non-financial corporations, and total credit to households. Quarterly GDP is used to measure the BC. The authors work with the cycles of the series extracted from the Hodrick-Prescott filter. Using cross-correlation tests, it is evident that there is a high correlation of GDP with the lags of the variables Total Credit and Credit to Non-Financial Corporations. On the other hand, there is a forward (leading) correlation of credit to households concerning GDP. Since these previous results do not allow inferences about causality, the authors employ a Granger test in a 2-variable VAR model (BC and FC, where the FC can take three different measures). The results indicate that BC causes FC when measured as total credit or credit to non-financial corporations. But there is also causality from FC to BC when FC is measured as a credit to households.

Duarte (2014) studies the interaction between the business cycle (BC) and the financial cycle (FC) of three countries, namely, Japan, the United Kingdom, and the United States. To measure the FC, three variables were used: the stock index, housing prices, and credit volume. These indicators were grouped into a single index, assuming a weight of 27.4% for the stock index, 39.4% for the house price index, and 33.2% for the credit market. These weights were obtained according to the participation of each sector in each country's economy. On the other hand, they use an OECD Composite Leading Indicator (CLI) to measure the BC. The authors work with the cycles of the series extracted with the Hodrick-Prescott filter. Once the FC and BC for each country have been obtained, an autoregressive distributed lag model (ADL) is proposed to analyze the causal relationship between FC and BC in each country. The lags are introduced into each model based on the results of a Granger causality test. In Japan and the United States, when FC is the dependent variable, it is evident that BC does not help to explain the variability of FC, reaching an R2 value of only 16% (average). However, when the dependent variable is BC, the FC can have a positive impact on BC at time zero, and subsequently, this effect dissipates. Nevertheless, FC is not sufficient to explain variations in BC. In the UK, past BC is not statistically significant in explaining current changes in FC, but when the dependent variable is BC, FC can negatively impact BC at the first lag. Although the explanation percentage of the variability of the cycles is relatively low, the authors conclude that the FCs influence the movements in the BC and vice versa.

Gómez-González, Villamizar-Villegas, Zarate, Sebastian, and Gaitan-Maldonado (2015) study the relationship between financial cycles (FC) and business cycles (BC) for a sample of thirty-three countries, including both developed and emerging economies. The FC is calculated from credit to the non-financial private sector, and the BC from nominal GDP. First, the cross-spectral correlation function, which measures the correlation between two series indexed by frequency, is estimated. The square of the value of this correlation function at each  $\omega$  frequency is defined as the coherence. This statistic is analogous to the square of the correlation coefficient and takes values in the interval  $[0, 1]$ . A coherence value close to one indicates that the two series are highly associated at a given  $\omega$  frequency, while a value close to zero indicates that these series are almost independent at  $\omega$  frequency. From this analysis, the authors find that for 29 of 33 countries, the FC and BC have a higher correlation at medium (32–80 quarters) and long-term (more than 80 quarters) frequencies. The remaining countries (Belgium, India, Mexico, and Peru) present higher coherence values at short-term frequencies (5–32 quarters). Finally, causality is analyzed with the Granger test in the frequency domain of FC and BC, and it is found to be statistically significant in both directions but more strongly in medium- and long-term frequencies, as in Australia, Germany, Japan, Norway, Sweden, the United Kingdom, and the United States.

Gómez-González, Ojeda-Joya, Tenjo-Galarza, and Zarate (2013) analyze the causal relationship between financial cycles (FC) and business cycles (BC) for three Latin American economies (Colombia, Chile, and Peru). The FC is estimated from credit volume and the BC from annualized GDP growth. The authors define short-term frequencies as cycles between 5 and 32 quarters, while medium-term frequencies are between 32 and 80 quarters. The Christiano and Fitzgerald filter was used to extract cycles at different frequencies. This filter was applied to the credit and GDP series and extracted short- and medium-term cycles for both series in each country. The authors find that the short-term frequencies are more important than the medium-term frequencies for each country, except in the FC of Colombia, since the standard deviation of the short-term frequencies is greater than that of the medium-term frequencies. Through the coherence indicator, which measures the degree of correlation at  $\omega$  frequency, the authors find that the FC and the BC are more correlated at medium-term frequencies in Chile. In Peru, there is a greater correlation at short-term frequencies, and in Colombia, there is no evidence of correlation at any frequency. Finally, when analyzing causality in the frequency domain, the results for Chile indicate causality in both directions for frequencies associated with short-, medium-, and long-term cycles. In the case of Colombia and Peru, causality is shown to be stronger from the FC to the BC in the short and medium-term frequencies.

## Methodology

Financial cycle methodologies can be summarized in four parts: i) turning points; ii) univariate decomposition filters; iii) unobservable components; and iv) dynamic factor models. The research works that use turning points identify local minimum and maximum points over a time window (Shen et al., 2019). Harding and Pagan (2002) is the most commonly used identification algorithm to find these points, which is applied to financial series individually. However, Harding and Pagan (2006) propose a methodology to consolidate turning points in an aggregate manner. This method has been applied in different works on financial cycles (Drehmann et al., 2012; Schüller et al., 2017; Shen et al., 2019). The advantage of this method is that it is robust to structural breaks in the time series (Schüller et al., 2017), but the results depend on the censoring rules, i.e., the minimum length that the cycles and phases must have (Cagliarini and Price, 2017). Since a time series is required to analyze causality targets in this research, the turning point method is discarded for the estimation of the financial cycle.

In the case of univariate decomposition filters, different research works usually use the Christiano-Fitzgerald filter because it allows them to extract cycles of different frequencies according to the researcher's interest (Schüller et al., 2017). As the financial cycle is considered a low-frequency cycle (Borio, 2012), many research works have focused on extracting medium-term frequency cycles between 32 and 80 quarters (Gómez-González et al., 2015), others between 44 and 120 quarters (Juhler et al., 2017), but, generally, between 32 and 120 quarters is assumed (Borio, 2012; Drehmann et al., 2012; Stremmel et al., 2015; Cagliarini and Price, 2017). The drawback of this methodology is that the frequencies where the medium-term cycle is found are chosen in advance, and certain arbitrariness is introduced in the results (Cagliarini and Price, 2017; ECB, 2018). Moreover, according to Murray (2003), the Christiano-Fitzgerald filter can generate spurious cycles.

Among the multivariate structural models introduced by Harvey and Koopman (1997), there are unobservable component (UC) models and dynamic factor models (DFM). Both methods have the advantage of reducing the risk of spurious cycles (ECB, 2018). On the one hand, the UC method estimates the cycles of economic and financial variables simultaneously, taking into account the correlation of the cycles of the included series (Juhler et al., 2017). This method assumes that the cyclical component is a bivariate stationary process and estimates the frequencies of each series individually using the Kalman filter. However, the notion of the financial cycle requires the presence of a common cyclical component with a certain degree of co-movement between individual cycles (ECB, 2018). As Adarov (2018) indicates, the financial cycle is a single latent factor driving activity in the financial market and is manifested as correlated cyclical patterns in the observed financial variables. For this purpose, the dynamic factor method is used, considering a set of variables that represent the Peruvian financial market. According to Geweke (1977) and Sargent and Sims (1977), a wide range of observable variables can encompass a smaller number of common unobserved orthogonal factors. As with the unobservable component method, the Kalman filter

is used to estimate the unobservable components, but it has the advantage of estimating the common unobservable cycle of the analyzed series. The estimation is based on the algorithm of Solberger and Spånberg (2019).

*For The Use of The Granger Causality Test.*

To test the causality between the business cycle (BC) and the financial cycle (FC) in the frequency domain, we use the Breitung and Candelon (2006) test, which is based on a VAR model between 2 variables. Being vector  $Z_t = [CF_t, CE_t]$  a two-dimensional vector of the observed series for  $t = 1, 2, \dots, T$ , which represents the total cycle of these two variables. Thus, the VAR model representation can be expressed as:

$$\Theta(L)Z_t = \varepsilon_t \quad (1)$$

The moving average representation of the above system is as follows:

$$\begin{aligned} Z_t &= \phi(L)\varepsilon_t = \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \\ &= \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \end{aligned} \quad (2)$$

Where  $\Phi(L) = \Theta^{-1}(L)$  and  $\Psi(L) = \Phi(L)G^{-1}$ .  $G$  is the lower triangular matrix of the Cholesky decomposition. Using this representation, the spectral density of  $CE_t$ , for example, can be expressed as:

$$f_{CE}(\omega) = 1/2\pi (|\Psi_{11}(e^{-i\omega})|^2 + |\Psi_{12}(e^{-i\omega})|^2) \quad (3)$$

This representation separates the contributions of  $CE_t$  (i.e.,  $\Psi_{11}$ ) and  $CF_t$  (i.e.,  $\Psi_{12}$ ) to the spectrum of  $CE_t$  and, thus, allows testing causality in the Granger sense at any  $\omega$  frequency. The null hypothesis, in this example, is that  $CF_t$  does not cause the Granger to  $CE_t$ , which means that  $\Psi_{12}(e^{-i\omega}) = 0$  and implies that no lagged value of  $CF_t$  influences  $CE_t$ .

The causality measure used in the frequency domain is:

$$M_{CF \rightarrow CE}(\omega) = \ln(2\pi f_{CE}(\omega) / |\Psi_{11}(e^{-i\omega})|^2) \quad (4)$$

This leads to the following expression:

$$M_{CF \rightarrow CE}(\omega) = \ln(1 + |\Psi_{12}(e^{-i\omega})|^2 / |\Psi_{11}(e^{-i\omega})|^2) \quad (5)$$

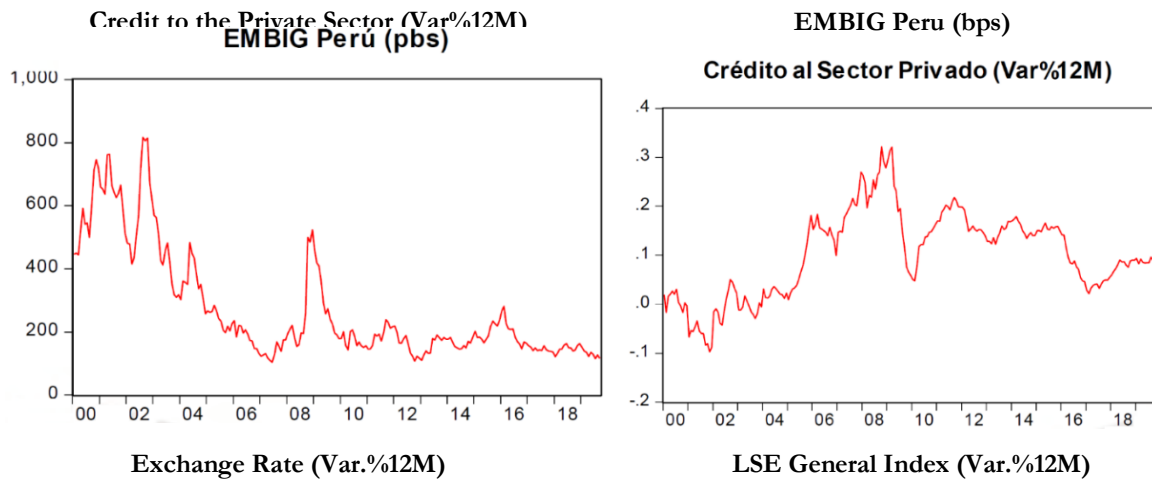
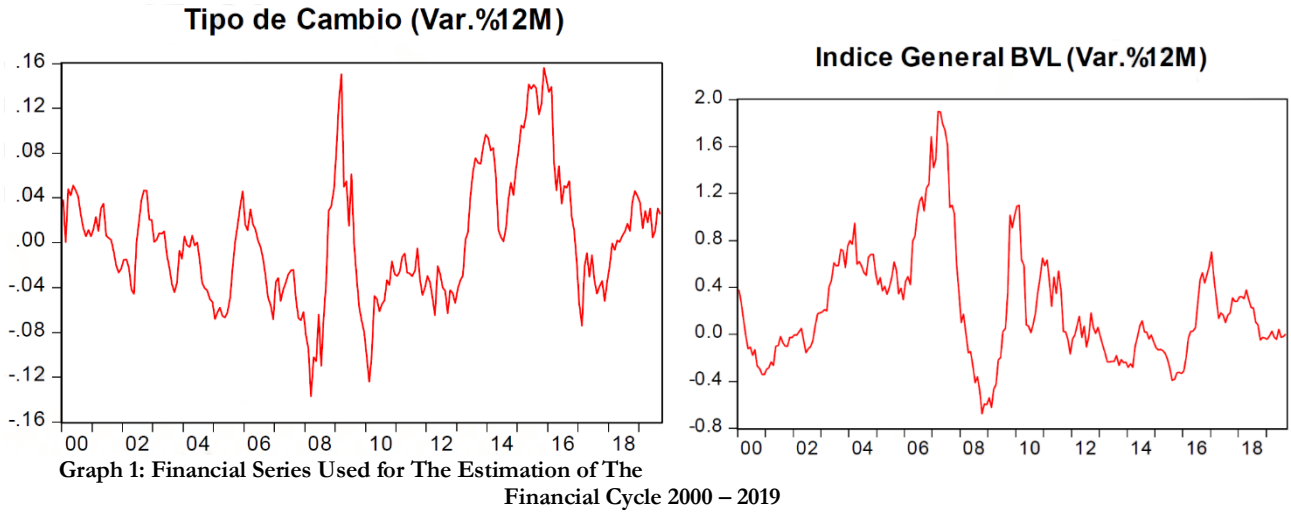
$M_{CF \rightarrow CE}(\omega) = 0$  if  $|\Psi_{12}(e^{-i\omega})|^2 = 0$ , i.e.,  $FC$  does not cause in the sense of Granger BC.

## Results

For the Peruvian financial cycle (FC), monthly information from January 2000 to September 2019 was used. Unlike other research that has focused on analyzing credit or equity properties separately instead of the entire financial cycle (Claessens and Kose, 2017), four variables were chosen to represent the Peruvian financial system: credit market, stock market, bond market, and foreign exchange market. As for the credit market, the credit of the financial system to the non-financial private sector was used (Var% 12M); for the stock market, the Lima Stock Exchange General Index was used (Var% 12M); in the case of the bond market, the Peruvian EMBIG was used; and for the foreign exchange market, the interbank exchange rate US\$ per S/ month-end was chosen (Var% 12M). Graph N°1 shows the series used for the estimation of the financial cycle. A description of the variables and the sources used can be found in Annex A.

The result of estimating the dynamic factor model generated two components in common with the financial variables (Graph No. 2). It is observed that both component 1 and component 2 reached their maximum

value in April and November 2001, respectively, a period when a bubble of companies related to technological services was going through, which was later known as the Dot.com Bubble. On the other hand, the minimum value of component 1 occurred in April 2007, a period before the 2008 financial crisis, while component 2 reached its minimum value in February 2009.



Graph

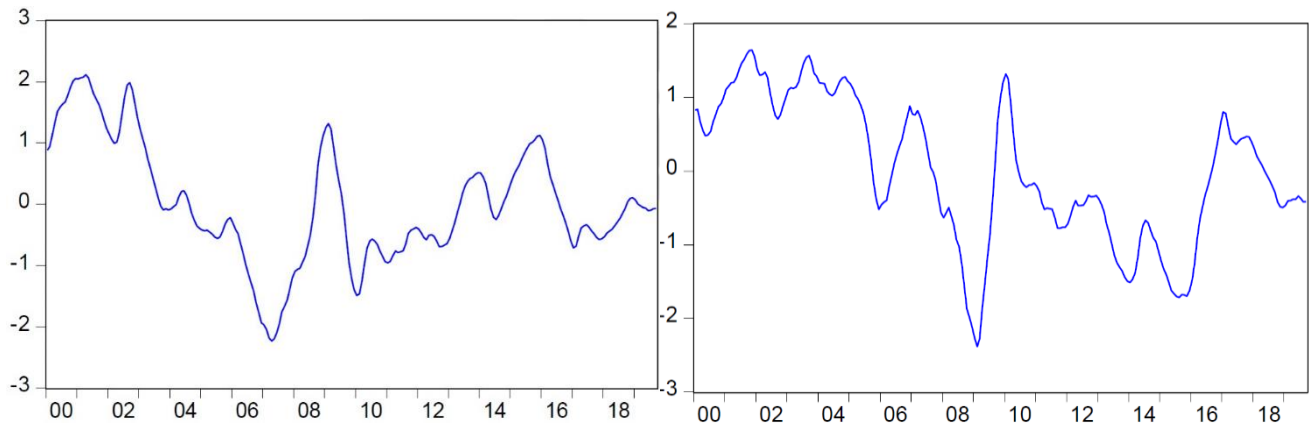
2:

Components of the Peruvian Financial Cycle 2000-2019

### Component 1



**Component 2**



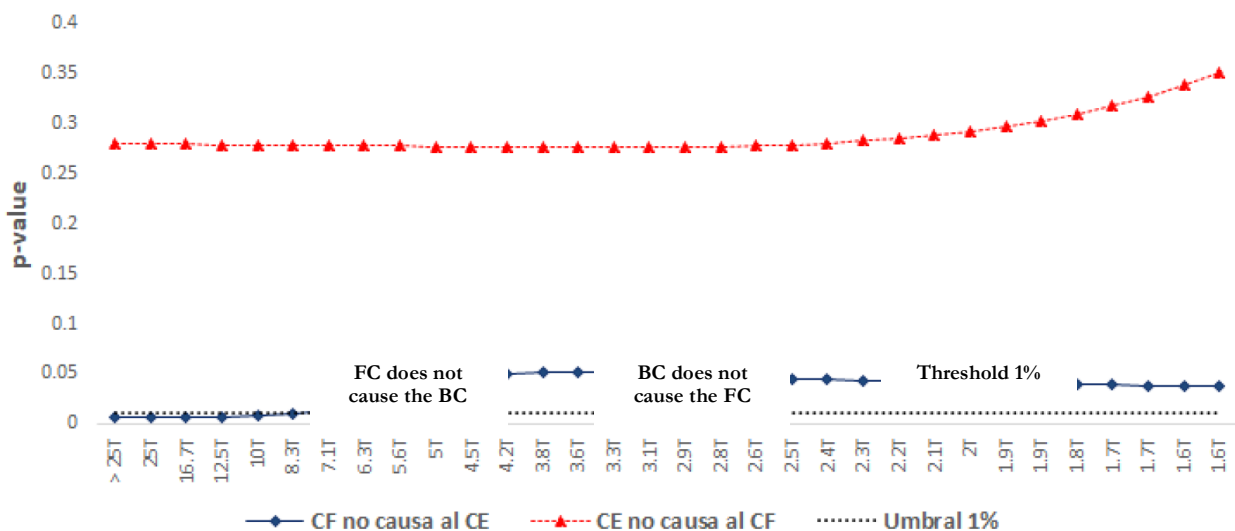
*Granger Causality Test in The Frequency Domain*

In this section, the Breitung and Candelon (2006) test was performed to analyze the causality relationship between the financial cycle (FC) and the business cycle (BC). The null hypothesis of the test is that there is no causality in the Granger sense at the  $\omega$  (omega) frequency. On the other hand, the BC was estimated from the monthly production index: first, the series was log-transformed; then, it was deseasonalized; and, finally, the Hodrick-Prescott filter was applied to extract the business cycle.

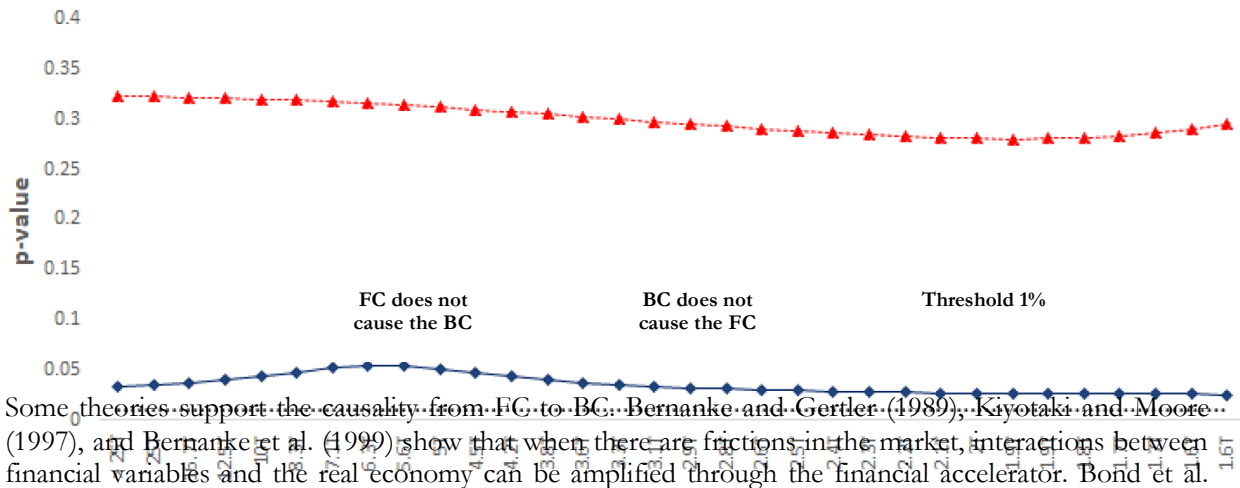
The test results show that there is a causal relationship between the financial cycle and the business cycle in component 1 only, with a significance level of 1%. However, there is no evidence that the BC causes the FC in either of its two components. In the case of the first component, causality to the BC occurs at frequencies greater than 10 quarters (2.5 years). These frequencies are within the range of the business cycle between 2 and 11 years (Juhler et al., 2017). On the other hand, like Gómez-González et al. (2013), evidence was found that FC causes BC, but extending the use of variables other than the credit ones. Although the frequencies at which causality has been demonstrated do not necessarily coincide with the traditional ranges (32-120 quarters), what has been shown is that financial variables are relevant in explaining the business cycle and not the other way around.

An important application of the causality from FC to BC is that a business cycle adjusted by financial variables can be estimated. Grintzalis et al. (2017), using the Hodrick-Prescott filter in a state-space representation, have estimated a business cycle for 15 emerging countries, considering credit cycles and showing that recessionary phases are better identified. Juselius et al. (2017) suggest that the extraction of a long-term trend in output and the estimation of a natural interest rate must go beyond the standard full employment paradigm so that the financial cycle must be considered. Likewise, the financial cycle can be used to identify inflationary and disinflationary pressures through a structural New Keynesian model (Chafik, 2018).

**Graph 3. Causality Test Between FC1 And BC**



Graph 4. Causality test between FC2 and BC



Some theories support the causality from FC to BC. Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke et al. (1999) show that when there are frictions in the market, interactions between financial variables and the real economy can be amplified through the financial accelerator. Bond et al. (2012) indicate three reasons why the stock market causes the business cycle: i) Real firms learn new information from secondary market prices and use this information to guide their actual decisions, which in turn affects the firm's cash flow and value; ii) Managers may care about the firm's stock price because their compensation is often tied to the stock price, which in turn affects their incentives to take real actions; iii) Managers may even irrationally follow the stock price and use it as an anchor simply because of their general belief that prices are informative. On the other hand, Shen et al. (2019) point out that the causality problem can be analyzed using a standard production function where financial variables interact: in this function, for example, housing prices, as well as credit, are inputs to the production of goods and services in an economy.

## Conclusions

The study of the financial sector and financial crises gave rise to the notion of the financial cycle (a concept that represents the aggregate link between the real and financial sectors). The most accepted theoretical definition of the financial cycle is that by Borio (2012), who describes it as the interaction between perceptions of value and risk, agents' attitudes towards risk, and financial constraints, which reinforce each other, and result in booms and busts in the financial sector. Moreover, these interactions can amplify economic fluctuations, and lead to severe economic and financial situations. There are different methodologies for calculating the financial cycle, and much of the research has focused on describing its cyclical properties, such as the longer length of the business cycle, predictor of financial crises, and high level of synchronization with the business cycle. However, the causal relationship with the business cycle has not been studied in depth.

Since it is essential to know the causality between the financial cycle and the business cycle, this research has proposed a new calculation methodology for estimating the financial cycle. Unlike previous research that has focused on analyzing the properties of credit or stocks separately instead of the complete financial cycle (Claessens and Kose, 2017), this research uses a set of variables representing the four most relevant financial markets in Peru: i) credit market, ii) stock market, iii) bond market, and iv) foreign exchange market. On the credit market, the total volume of credit to the non-financial private sector series (Var. % 12M) was chosen; on the stock market, the Lima Stock Exchange General Index (Var. %12M) was chosen; in the case of the bond market, the Peruvian EMBIG was used; and, concerning the foreign exchange market, the exchange rate (Var. %12M) was used. As the objective is to obtain a time series to analyze the

causal relationship and also that the cycle reflects a component that is common to the set of financial variables, the following estimation methods were discarded: turning points, univariate filters, and unobservable component models. Like Menden and Proaño (2017), we used the dynamic factor model, where we extracted the components that are common to the observed financial series using the Kalman filter. These components comprise the financial cycle.

The results indicate that two components are common to the financial series. The first one reached its minimum value in April 2007, before the 2008 financial crisis; the second one did it in February 2009. Once the components of the cycle were estimated, the causality relationship was analyzed with the Granger causality test in the frequency domain of Breitung and Candelon (2006). This test not only allows knowing the direction of causality between two variables but also analyzing the frequencies of this relationship. In the Peruvian case, it has been shown that only the first component of the FC causes the business cycle at frequencies greater than 10 quarters (2.5 years), while the second does not cause the BC at any frequency. The relationship of the first component can be associated with business cycle frequencies between 2 and 11 years (Juhler et al., 2017). In addition, it has been shown that the BC does not cause any component of the financial cycle. This finding is different from what has been found in previous literature, where it has been shown that this causal relationship between the two tends to occur at medium-term frequencies of 8-30 years (Gómez-Gonzalez et al., 2015). However, it is worth highlighting that financial variables play a significant role in explaining Peru's business cycle. Like Gómez-Gonzalez et al. (2013), we found evidence that the FC causes the BC but extends the use of variables other than the credit ones.

On the other hand, unlike Lahura et al. (2013) and Pérez and Vilchez (2018), who studied the Peruvian financial cycle, other variables were used to represent the rest of the financial markets, namely, foreign exchange, equity, and bonds. Other research works can be extended from this first part, such as the identification of inflationary and disinflationary pressures through a structural New Keynesian model, including the financial cycle, and the estimation of the potential output and a natural rate of interest that differs from the standard full-employment paradigm (Juselius et al., 2017).

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## Annex

## Annexes

## Variables used

The following variables were used to estimate the financial cycle in section 3.1:

| Variable  | Abbreviation | Description   | Source |
|---|--------------|---|--------|
| Annualized growth of credit to the private sector | credit       | Credit from depository corporations to the private sector (end of period) - Total at Constant Exchange Rate (millions S/ million) | BCRP   |
| Annualized growth of the average exchange rate    | Exchange     | Exchange rate - average for the period (S/ per US\$) - Interbank - Average  | BCRP   |
| EMBIG Peru  | EMBIG        | Emerging Market Bond Index Yield Spread (EMBIG) - Peru  | BCRP   |
| Annualized growth of LSEGI                        | Equity       | Lima Stock Exchange - Stock Market Indexes - LSE General Index (base 12/31/91 = 100)  | BCRP   |
| Gross Domestic Product Index                      | GDP          | Gross domestic product and domestic demand (index 2007=100) - GDP   | BCRP   |

For the calculation of the business cycle ( $yt$ ), the following steps were performed:

The logarithm was applied to the GDP series. New series:  $\log\_gdp$

To deseasonalize the  $\log\_gdp$  series with the Census  $x12$  method. New series:

$$\log\_gdp\_sa$$

To apply Hodrick-Prescott filter with parameter  $\lambda = 14,400$  to the series

$$\log\_gdp\_sa. \text{ New series: } \log\_gdp\_sa\_trend$$

To calculate the business cycle ( $yt$ ) as the difference between the deseasonalized series and the trend estimated in step iii):

$$y = \log\_gdp\_sa - \log\_gdp\_sa\_trend$$

## Results of the Granger causality test

The  $p$ -values for the null hypothesis that FC (BC) does not cause BC (FC) are shown below:

| Quarters | Months | Angular Frequency<br>( $\omega$ ) | Component 1                 |                             | Component 2                 |                             |
|----------|--------|-----------------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
|          |        |                                   | FC does not<br>cause the BC | BC does not<br>cause the FC | FC does not<br>cause the BC | BC does not<br>cause the FC |
| > 25T    | 200    | 0.0314                            | 0.0057                      | 0.2796                      | 0.0341                      | 0.3223                      |
| 25T      | 100    | 0.0628                            | 0.0058                      | 0.2795                      | 0.0352                      | 0.3220                      |
| 16.7T    | 67     | 0.0942                            | 0.0061                      | 0.2793                      | 0.0372                      | 0.3214                      |
| 12.5T    | 50     | 0.1257                            | 0.0067                      | 0.2791                      | 0.0401                      | 0.3207                      |
| 10T      | 40     | 0.1571                            | 0.0079                      | 0.2788                      | 0.0439                      | 0.3197                      |
| 8.3T     | 33     | 0.1885                            | 0.0101                      | 0.2785                      | 0.0483                      | 0.3185                      |
| 7.1T     | 29     | 0.2199                            | 0.0140                      | 0.2782                      | 0.0521                      | 0.3171                      |
| 6.3T     | 25     | 0.2513                            | 0.0203                      | 0.2778                      | 0.0541                      | 0.3155                      |
| 5.6T     | 22     | 0.2827                            | 0.0287                      | 0.2774                      | 0.0536                      | 0.3137                      |
| 5.0T     | 20     | 0.3142                            | 0.0375                      | 0.2770                      | 0.0510                      | 0.3118                      |
| 4.5T     | 18     | 0.3456                            | 0.0447                      | 0.2767                      | 0.0474                      | 0.3097                      |
| 4.2T     | 17     | 0.377                             | 0.0492                      | 0.2763                      | 0.0437                      | 0.3075                      |
| 3.8T     | 15     | 0.4084                            | 0.0513                      | 0.2761                      | 0.0404                      | 0.3051                      |
| 3.6T     | 14     | 0.4398                            | 0.0516                      | 0.2759                      | 0.0377                      | 0.3027                      |
| 3.3T     | 13     | 0.4712                            | 0.0510                      | 0.2759                      | 0.0355                      | 0.3002                      |
| 3.1T     | 12     | 0.5027                            | 0.0499                      | 0.2760                      | 0.0338                      | 0.2977                      |
| 2.9T     | 12     | 0.5341                            | 0.0487                      | 0.2763                      | 0.0323                      | 0.2951                      |
| 2.8T     | 11     | 0.5655                            | 0.0474                      | 0.2769                      | 0.0312                      | 0.2927                      |
| 2.6T     | 11     | 0.5969                            | 0.0461                      | 0.2777                      | 0.0303                      | 0.2902                      |
| 2.5T     | 10     | 0.6283                            | 0.0450                      | 0.2789                      | 0.0295                      | 0.2880                      |
| 2.4T     | 10     | 0.6597                            | 0.0439                      | 0.2806                      | 0.0289                      | 0.2859                      |
| 2.3T     | 9      | 0.6912                            | 0.0430                      | 0.2827                      | 0.0284                      | 0.2840                      |
| 2.2T     | 9      | 0.722                             | 0.0422                      | 0.2853                      | 0.0279                      | 0.2824                      |
| 2.1T     | 8      | 0.754                             | 0.0414                      | 0.2886                      | 0.0275                      | 0.2812                      |
| 2.0T     | 8      | 0.7854                            | 0.0407                      | 0.2926                      | 0.0272                      | 0.2805                      |
| 1.9T     | 8      | 0.8168                            | 0.0401                      | 0.2975                      | 0.0269                      | 0.2803                      |
| 1.9T     | 7      | 0.8482                            | 0.0396                      | 0.3033                      | 0.0267                      | 0.2806                      |
| 1.8T     | 7      | 0.8796                            | 0.0391                      | 0.3102                      | 0.0265                      | 0.2817                      |
| 1.7T     | 7      | 0.9111                            | 0.0387                      | 0.3182                      | 0.0263                      | 0.2835                      |
| 1.7T     | 7      | 0.9425                            | 0.0383                      | 0.3275                      | 0.0261                      | 0.2862                      |
| 1.6T     | 6      | 0.9739                            | 0.0380                      | 0.3382                      | 0.0259                      | 0.2899                      |
| 1.6T     | 6      | 1.0053                            | 0.0376                      | 0.3504                      | 0.0258                      | 0.2946                      |
| 1.5T     | 6      | 1.0367                            | 0.0373                      | 0.3642                      | 0.0257                      | 0.3004                      |
| 1.5T     | 6      | 1.0681                            | 0.0371                      | 0.3797                      | 0.0256                      | 0.3074                      |
| 1.4T     | 6      | 1.0996                            | 0.0368                      | 0.3970                      | 0.0255                      | 0.3157                      |
| 1.4T     | 6      | 1.131                             | 0.0366                      | 0.4160                      | 0.0254                      | 0.3253                      |
| 1.4T     | 5      | 1.1624                            | 0.0364                      | 0.4368                      | 0.0253                      | 0.3362                      |
| 1.3T     | 5      | 1.1938                            | 0.0362                      | 0.4594                      | 0.0252                      | 0.3485                      |
| 1.3T     | 5      | 1.2252                            | 0.0360                      | 0.4835                      | 0.0252                      | 0.3620                      |
| 1.3T     | 5      | 1.2566                            | 0.0359                      | 0.5091                      | 0.0251                      | 0.3769                      |
| 1.2T     | 5      | 1.2881                            | 0.0357                      | 0.5359                      | 0.0250                      | 0.3929                      |



|      |   |        |  |        |        |  |        |        |
|------|---|--------|--|--------|--------|--|--------|--------|
| 1.2T | 5 | 1.3195 |  | 0.0356 | 0.5637 |  | 0.0250 | 0.4101 |
| 1.2T | 5 | 1.3509 |  | 0.0355 | 0.5922 |  | 0.0249 | 0.4282 |
| 1.1T | 5 | 1.3823 |  | 0.0354 | 0.6211 |  | 0.0249 | 0.4471 |
| 1.1T | 4 | 1.4137 |  | 0.0352 | 0.6501 |  | 0.0249 | 0.4667 |
| 1.1T | 4 | 1.4451 |  | 0.0351 | 0.6788 |  | 0.0248 | 0.4868 |
| 1.1T | 4 | 1.4765 |  | 0.0350 | 0.7070 |  | 0.0248 | 0.5071 |