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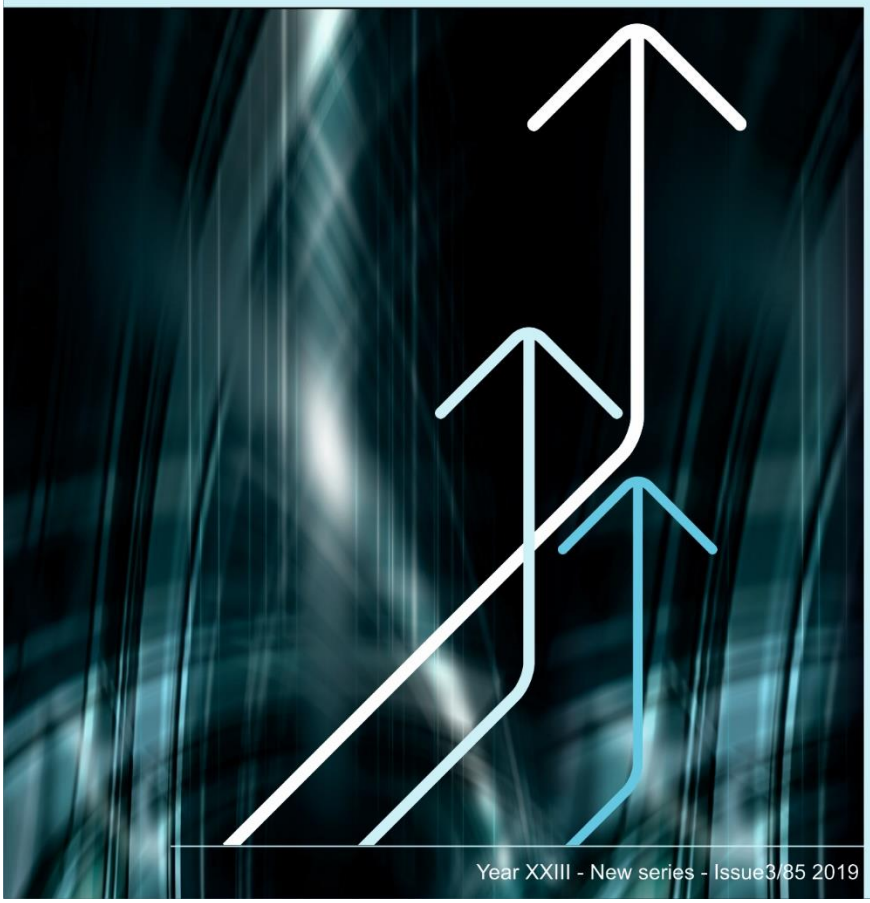

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“VICTOR SLĂVESCU” CENTRE FOR FINANCIAL
AND MONETARY RESEARCH

FINANCIAL STUDIES

ROMANIAN ACADEMY
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CAUSAL RELATIONSHIP BETWEEN BITCOIN PRICE VOLATILITY AND TRADING VOLUME: ROLLING WINDOW APPROACH

Nebiye YAMAK, PhD*
Rahmi YAMAK, PhD**
Serkan SAMUT, PhD Candidate***

Abstract

This study investigates the causal relationship between price volatility and trading volume for bitcoin which is the first cryptocurrency. Data are daily and cover the period starting from December 27, 2013 to March 3, 2019. Price volatility series was produced by using EGARCH model. The Toda-Yamamoto causality test was applied under rolling window approach. According to the Granger causality test, there is a strong causal relationship running from the trading volume to the price volatility. There also exists a causality running from price volatility to volume. But this causality is not statistically strong. At the same time, a positive and significant contemporaneous correlation was found between the two variables. Both findings support the sequential information arrival hypothesis for the bitcoin market.

Keywords: sequential information arrival hypothesis, Toda-Yamamoto causality, cryptocurrency

JEL Classification: C22, G14

1. Introduction

In the finance literature, the causal relationships between the price volatility and trading volume of any asset has long been the subject of discussion. There are two fundamental hypotheses on the dynamic relations between these two variables. One of them is the

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mixture of distribution hypothesis developed by Clark (1973), Epps and Epps (1976), Harris (1986) and Anderson (1996). The mixture of distribution hypothesis indicates the existence of a positive contemporaneous correlation between asset prices and trading volume. The variance of the price change in a single transaction depends on the volume of this transaction. Therefore, the relationship between price volatility and trading volume is based on a fundamental variable called the rate of information flow into the market. Price and trading volume change at the same time. According to this hypothesis, there is no causal relationship between two variables. The other hypothesis on the subject of the relationship between price volatility and trading volume is the sequential information arrival hypothesis. This hypothesis was developed by Copeland (1976) and Jennings et al. (1981), and Smirlock and Starks (1985). The sequential information arrival hypothesis assumes that new information is sequential in terms of the buyers and sellers in the asset market. In the beginning, buyers and sellers are in equilibrium because they have the same set of information. As new information arrives, buyers and sellers may revise their expectations again. However, buyers and sellers cannot receive information signals simultaneously. When all market participants receive new incoming information and according to it they revise their expectations, then the final equilibrium takes place. In this hypothesis, the sequential response to information suggests that there must be a bidirectional causal relationship between price volatility and trading volume.

In the relevant empirical literature, there are numerous studies which test these hypotheses with different econometric approaches. Almost all of the current empirical studies in the literature have investigated the relationship between the two variables for the stock, bond and equity markets. The results are generally that there is a bi-directional causality between two variables. Hiemstra and Jones (1994), Kim et al. (2005), Chen and Wu (2009), Mahajan and Singh (2009), Chiang et al. (2010) and Chan et al. (2018) are some of the studies supporting the sequential information arrival hypothesis. The question to be answered at this stage is whether the findings obtained for the traditional asset markets are also valid to cryptocurriencies with both monetary and asset functions. In other words, does the bidirectional relationship between price volatility and trading volume apply to cryptocurriencies?

As known, bitcoin, the first of the cryptocurrency, was developed in 2009 by a person or group known as Satoshi Nakamoto. Bitcoin, which was circulated as virtual money, was known by very few people in the early days of its emergence, but it has started to be widely traded in the money and financial environment that have put the current international money system in serious danger for the last two years. There is general evidence that the existence, direction and severity of the causal relationships between price and volume in monetary and financial markets depend on the trading volume. For this reason, it is expected that the possible causal relationship between bitcoin price volatility and the trading volume can be strengthened with the increasing trading volume.

In order to answer the above question, the present study examines the dynamic progress of the possible causal relationships between the daily price volatility and the daily trading volume of bitcoin by using the approach of rolling window causality test developed by Hill (2007).

2. Data and econometric method

In the study, daily data were used for the period December 27, 2013 – March 3, 2019. Data on the daily closing price and trading volume of bitcoin are available from coinmarketcap.com. Since the cryptocurrency market is active every day of the week, the data set used in this study covers every day of the year. The natural logarithmic transformations of price and trading volume of bitcoin were taken before the causality test. Then, the volatility series of the bitcoin price was produced by appropriate autoregressive conditional heteroskedasticity (ARCH) model. Finally, the causal relationship between price volatility and trading volume was determined by using the rolling window causality approach.

In traditional econometric models, the variance of the error term is assumed to be constant. However, even though the unconditional variance of the error terms in the time series is constant, the conditional variance may not be constant. It is difficult to provide the assumption that the conditional variance of the error term is constant, especially in the financial time series where daily observations with high frequency are present. In this study, the volatility series of bitcoin price was created by using the ARCH model which was introduced by Engle (1982) considering the conditional variance.

In order to determine the ARCH (p) model for ΔP_t which is the first difference of the natural logarithm of daily bitcoin price, ARMA (p, q) model should be first estimated.

$$\Delta P_t = \delta + \sum_{i=1}^{p} \beta_i \Delta P_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \quad (1)$$

In equation (1) above, p and q are autoregressive (AR) and moving average (MA) degrees, respectively. In this equation, it is assumed that ΔP_t is covariance stationary and μ has a white noise process with variance σ_t^2. The error term μ_t obtained from the ARMA (p, q) model is subjected to the ARCH-LM test. The auxiliary regression model for the ARCH-LM test is as follows.

$$\mu_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \alpha_2 \mu_{t-2}^2 + \ldots + \alpha_p \mu_{t-p}^2 \quad (2)$$

For the ARCH effect in equation (2) above, the null hypothesis $\alpha_1 = \alpha_2 = \ldots = \alpha_p$ must be tested. For this hypothesis, the relevant test statistic is calculated as $T*R^2$. Here T represents the number of observations and R^2 refers to the explanatory power of the auxiliary regression equation. If there is an ARCH effect in the series, this effect can be eliminated by the ARCH (p) produced from ARMA (p, q) model.

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \mu_{t-i}^2 \quad (3)$$

Constraints for ARCH (p) model in equation (3) are $\beta_0 > 0$, $\beta_i > 0$ (I = 1, 2, … p) and $\sum_{i=1}^{p} \beta_i < 1$.

However, in some cases, conditional variance is not only a function of lags of error term, but also its own lags. In this case, GARCH (p, q) model developed by Bollerslev (1986) is used to create volatility series for DLP_t.

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \mu_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \sigma_{t-i}^2 \quad (4)$$

In GARCH (p, q) model (4), in addition to the constraints of ARCH (p) model, the constraints are $\alpha_i > 0$ (I = 1, 2, … q) and $\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i < 1$.

The standard GARCH model fails to capture the asymmetric effect in the variance structure. In financial transactions, investors can react differently to good news and bad news. Nelson (1991) developed the exponential GARCH (EGARCH) model to determine the asymmetric effect. Model EGARCH (1,1) is given in equation (5) below.

$$\ln(\sigma_t^2)=\beta_0+\beta_1\left(\frac{\mu_{t-1}}{\sigma_{t-1}}\right)+\gamma_1\left|\frac{\mu_{t-1}}{\sigma_{t-1}}\right|+\alpha_1\ln(\sigma_{t-1}^2) \quad (5)$$

Since the dependent variable σ_t^2 is the natural logarithm in the EGARCH model, the coefficients in the model can be negative. The EGARCH model also captures leverage effect. If $\frac{\mu_{t-1}}{\sigma_{t-1}}$ is positive, the effect of shocks on conditional variance is equal to $\beta_1+\gamma_1$. Otherwise it will be equal to $-\beta_1+\gamma_1$.

After getting volatility series, the rolling window causality test developed by Hill (2007) was used to examine the causal relationship between bitcoin price volatility and trading volume. The Rolling window causality test is based on traditional causality tests. Toda-Yamamoto (1995) causality test was employed to determine the possible causal relationships between daily price volatility (PV) and daily trading volume (V) of bitcoin. Toda-Yamamoto causality test is as shown in equations (6) and (7).

$$V_t=\lambda_1+\sum_{i=1}^{k}\beta_{1i}V_{t-i}+\sum_{i=k+1}^{k+d_{max}}\beta_{2i}V_{t-i}+\sum_{i=1}^{k}\alpha_{1i}PV_{t-i}+\sum_{i=k+1}^{k+d_{max}}\alpha_{2i}PV_{t-i}+\mu_{1t} \quad (6)$$

$$PV_t=\lambda_2+\sum_{i=1}^{k}\delta_{1i}PV_{t-i}+\sum_{i=k+1}^{k+d_{max}}\delta_{2i}PV_{t-i}+\sum_{i=1}^{k}\theta_{1i}V_{t-i}+\sum_{i=k+1}^{k+d_{max}}\theta_{2i}V_{t-i}+\mu_{2t} \quad (7)$$

In Equations (6) and (7), k represents the lag length for dependent and independent variables. dmax is the maximum integrated degree of the variables. $B_{I,}$,α_I, δ_I, θ_I are coefficients of the variables. Λ_1 and λ_2 represent constant terms.

In equation (6), the null hypothesis that V is not the cause of PV is as follows.

$$H_0 : \alpha_{1i} = 0 \quad (8)$$

Similarly, in equation (7), the null hypothesis that PV is not the cause of V is as follows.

$H_0 : \delta_{1i} = 0$ (9)

Wald test statistics are performed to determine whether the null hypothesis in (8) and (9) are rejected or not. As known, the entire sample set is not used in the rolling window causality test. On the contrary, a sample size smaller than the sample size (window width) is performed to determine the causality analysis. In the first window, a causality analysis is carried out from the first observation until the last observation of the window width. Then the next window is moved, in which the first observation is deleted and the observation after the last observation of the window width is added and the causality analysis is repeated. This process continues until the last observation in the window width is the last observation of the entire sample set.

3. Findings

In the study, ARCH/GARCH approach was employed for producing the price volatility series. Prior to ARC/GARCH estimation, the stationarity characteristics of the relevant series were examined by using Augmented Dickey and Fuller (ADF) unit root test. The related test statistics are presented in Table 1. As a result of the ADF unit root test, it was found that both trading volume and price volatility are stationary in their first differences.

Table 1

Unit root test results

	ADF-t Statistics	
Variable	**Constant**	**Constant and Trend**
P	-0.387	-2.281
V	-0.423	-2.991
ΔP	-12.89***	-12.93***
ΔV	-11.826***	-11.847***

*Note: ***, ** and * indicate that the related statistics is statistically significant at 1%, 5% and 10%, respectively. Δ implies that the related variable is first differenced. P is logarithm of bitcoin price and V is logarithm of trading volume.*

After the ADF unit root test, the ARMA structure of the logarithmic difference of the bitcoin price was determined by information criteria. Based on Akaike information criterion (AIC), ARMA (4,4) model was found to be the most appropriate for 49 ARMA

models. According to the ARCH-LM test in Table 2, which presents the results of the ARMA (4,4) model, there is ARCH effect in the price series at 1% significance level. Due to the ARCH effect in the series, in this study the volatility series was created with ARCH / GARCH models.

Table 2

ARMA (4.4) Model for Bitcoin price

Dependent Variable: **ΔP**	
Constant	0.001 (0.948)
AR(1)	0.033 (1.259)
AR(2)	1.009*** (41.228)
AR(3)	0.077*** (3.154)
AR(4)	-0.935*** (-36.680)
MA(1)	-0.034* (-1.673)
MA(2)	-1.035*** (-54.015)
MA(3)	-0.053*** (-2.753)
MA(4)	0.959*** (48.637)
AIC	-3.644
F-Statistics	3.503***
Breusch-Godfrey Autocorrelation Statistics	0.121 [0.728]
ARCH-LM Test Statistics	112.544*** [0.000]

*Note: ***, ** and * indicate that the related statistics is statistically significant at 1%, 5% and 10%, respectively. The values in parentheses are t-statistics. Values in square brackets are the probability values.*

After determining the appropriate ARMA model, ARCH, GARCH and EGARCH models were estimated from ARMA (4,4) model, separately. According to both parameter constraints and AIC, ARCH (3), GARCH (2,1) and EGARCH (1,1) models were found to be the most suitable models. The results of these models are given in Table 3. EGARCH (1.1) model among them is the most appropriate model according to the AIC. Therefore, variance series produced from EGARCH(1,1) was used to be price volatility series in the causality test.

Table 3

ARCH Model results for Bitcoin price

	ARCH(3)	**GARCH(2, 1)**	**EGARCH(1, 1)**
Dependent variable	σ_t^2	σ_t^2	$\ln(\sigma_t^2)$
Constant	0.001*** (38.613)	0.001*** (11.678)	-0.512*** (-15.325)
μ_{t-1}^2	0.133*** (8.12)	0.133*** (10.662)	
μ_{t-2}^2	0.044*** (3.1)	0.044** (2.288)	
μ_{t-3}^2	0.044*** (5.419)		
σ_{t-1}^2		0.533*** (14.56)	
$\left\|\frac{\mu_{t-1}}{\sigma_{t-1}}\right\|$			0.256*** (17.823)
$\frac{\mu_{t-1}}{\sigma_{t-1}}$			-0.02** (-2.381)
$\ln(\sigma_{t-1}^2)$			0.949*** (238.025)
AIC	-3.746	-3.772	-3.875
ARCH-LM Test Statistics	2.699 [0.1]	0.986 [0.321]	1.258 [0.262]

*Note: ***, ** and * indicate that the related statistics is statistically significant at 1%, 5% and 10%, respectively. The values in parentheses are t-statistics. Values in square brackets are the probability values.*

The volatility series derived from the EGARCH model above was investigated with the ADF unit root test before causality test. It was found that price volatility series is stationary in its level. Previously, the trading volume of bitcoin has been found to be stationary in its first difference. Therefore, the possible causal relationships between bitcoin price volatility and trading volume was explored by using Toda-Yamamoto (1995) causality approach. The window widths in Toda-Yamamoto causality test are used to be 50, 100 and 200. The optimal lag lengths in the models were identified by AIC. Gauss codes written by Hill (2012) were used to detect the dynamic structure of the possible causal relationships the two variables. The analysis used both Wald and bootstrap statistics resolved 5000 times.

The rate of rejection of the null hypothesis, which states that there is no causal relationship between trading volume and price volatility is shown in Table 4. The null hypothesis that there is no causality running from price volatility to trading volume in the rolling

window analysis is rejected in the 50, 100 and 200 window widths by 33.28%, 43.26% and 41.29% respectively. On the other hand, the null hypothesis that the causality does not run from the trading volume to the price volatility is rejected at the same window widths as 63.95%, 84.68% and 89.02%, respectively.

According to the Bootstrap test statistics, the null hypothesis that implies no causality running from volatility to volume is rejected in the 50, 100 and 200 window widths by 33.71%, 41.76% and 42.04%, respectively. The null hypothesis that there is no causal relationship from volume to volatility is also rejected at the same window widths as 47.63%, 73.39% and 87.98%, respectively. The rate of rejection of the null hypothesis, which states that there is no causal relationship from price volatility to volume, is almost the same in Wald and Bootstrap techniques. This finding is independent of the window widths. However, Wald and Bootstrap techniques differ in terms of the rejection rate of the null hypothesis that there is no causal relationship from volume to price volatility. When the window width is 50 and 100, the rate of rejection of the null hypothesis in the Bootstrap method is less than the Wald method. If the window width is 200, the rejection rate of the null hypothesis is the same in both techniques. According to the test statistics given in Table 4, there is a bidirectional causality relationship between price volatility and trading volume. However, this causal relationship is stronger from trading volume to price volatility.

Table 4

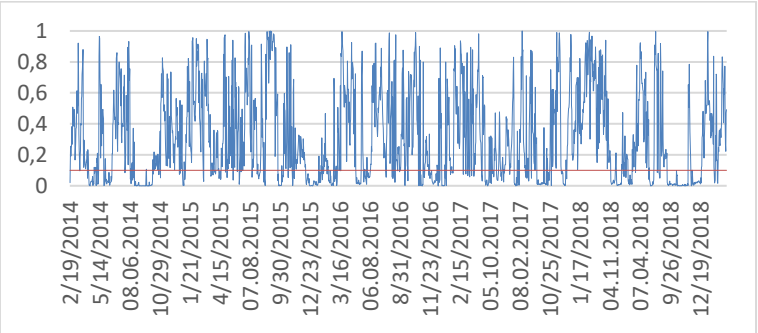
The rate of rejection of null hypothesis at 10% significance level

Window Width	No causality from price volatility to trading volume		No causality from trading volume to price volatility.	
	Wald	**Bootstrap**	**Wald**	**Bootstrap**
50	33.28%	33.71%	63.95%	47.63%
100	43.26%	41.76%	84.68%	73.39%
200	41.29%	42.04%	89.02%	87.98%

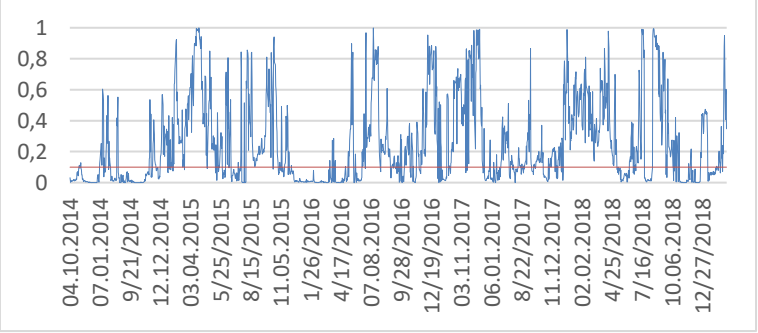
Graph 1

Price volatility does not Granger cause trading volume

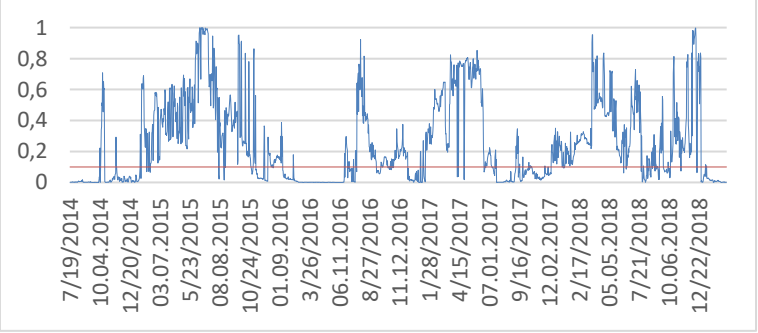
Panel a: Window width of 50



Panel b: Window width of 100



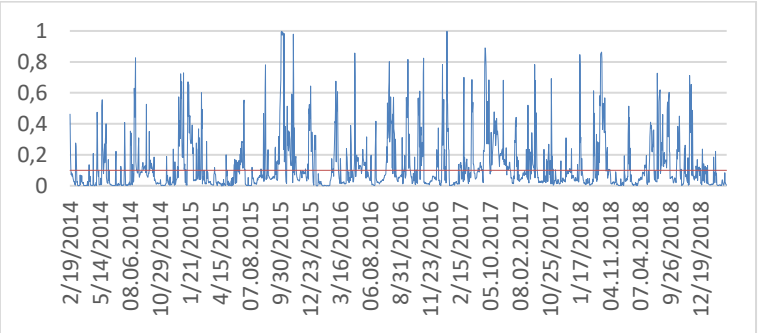
Panel c: Window width of 200



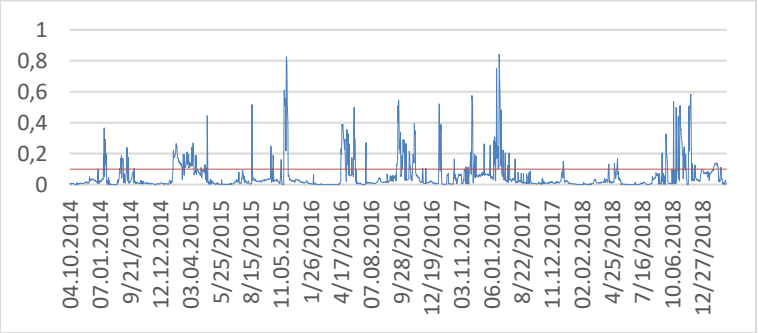
Graph 2

Trading volume does not Granger cause price volatility

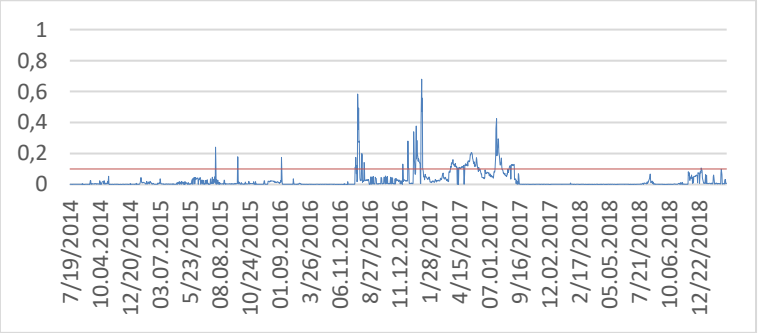
Panel a: Window width of 50



Panel b: Window width of 100



Panel c: Window width of 200



Graph 1 shows the bootstrap p values for the null hypothesis that there is no causal relationship from price volatility to trading volume for 50, 100 and 200 window widths. From the related figure, it is seen

that the causal relationship from price volatility to trading volume in 50 window widths is not continuous. However, in the case of an increase in the width of the window, this causality becomes more continuous. Especially in the analysis using 200 window width, the causality from price volatility to trading volume is continuous between March 2016 and June 2016. In addition, the bootstrap p values for the null hypothesis that the trading volume does not cause price volatility are presented in Graph 2 for window widths 50, 100 and 200. According to this graph, the causal relationship from trading volume to price volatility is not continuous for the window width of 50. However, from the same graph, it can be observed that the causality from volume to volatility is strengthened and becomes more permanent if more window width is used. This continuous causal relationship appears to take place almost over the entire period of the window width of 200. When both graphs are evaluated together, it can be concluded that there is a bidirectional causal relationship between price volatility and trading volume for bitcoin. However, from all panels of both graphs it can be detected that the causal relationship especially from trading volume to the price volatility is stronger and more continuous.

4. Conclusion

The relationship between price volatility and trading volume in any asset market has been a subject of debate in the finance literature for many years. There are two basic hypotheses between the two related variables. The mixture of distribution hypothesis does not predict any causal relationship between the two variables, whereas the sequential information arrival hypothesis states that there is a bidirectional causal relationship between the two variables. The related hypotheses were generally tested on the stock markets in the empirical literature and the findings mostly supported the validity of the sequential information arrival hypothesis.

In the present study, in order to determine whether the findings on stock markets are valid for cryptocurrency market, the possible causal relationships between the price volatility and the trading volume of bitcoin were investigated by using the rolling window causality method. Bitcoin price volatility is produced under EGARCH (1,1) model. According to the findings obtained under three different window widths, there exists a bidirectional causal relationship between two variables. The causal relationship from volume to price volatility is

stronger than the causal relationship from volatility to volume. It means that a new information coming to the bitcoin market is not available at the same moment to all buyers and sellers and hence sometimes price volatility causes trading volume and sometimes volume causes price volatility. In addition, the contemporaneous correlation coefficient between the two variables is positive and statistically significant. Both the causality and correlation analysis results show that the sequential information arrival hypothesis in the bitcoin market is valid. Ultimately, the bitcoin market is not a market within the scope of efficient markets hypothesis.

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IS THERE A RATIONAL BUBBLE IN BIST 100 AND SECTOR INDICES? [1]

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Abstract

Global financial crises, which can stem from the bubbles in asset prices and which have been observed especially in the United States and Europe, have demonstrated once again how important the determination of bubbles is. The bubbles in question in financial markets are referred as excessive increase in asset prices. When considering the close relationship of rational bubbles with financial crises, the analysis and detection of them become even more important for investors, portfolio managers and market regulators. For this purpose, the aim of this study is to examine the existence of rational bubbles in Borsa Istanbul 100 Index (BIST 100) and some sector indices for the period of 1990-2015. For this, right-tailed unit root test, Sup Augmented Dickey-Fuller test and Generalized Sup Augmented Dickey-Fuller test have been used. As a result of the analyses, it has been observed that no rational bubbles existed in BIST 100 and the mentioned sector indices. Our findings may provide policy makers and both domestic and international investors in order to make appropriate decision and thus, to take a position in the markets.

Keywords: bubbles, BIST 100, sector indices, SADF, GSADF

JEL Classification: G10, G17

1. Introduction

Rational bubbles in financial markets are referred as excessive increase in asset prices. In other words, rational bubbles can be

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expressed as a deviation between its fundamental value and market value of an asset (Blanchard and Watson, 1982). This kind of deviations from fundamental value of an asset can be monitored the existence of bubble in financial markets. In other respects, bubbles have always been contradictive issue in accordance with the efficient markets. Moreover, if market participants have same information, that is, if there is symmetric information, they will not want to buy the assets with high price which is differ from their fundamental value. Therefore, if there is asymmetric information, there can be bubbles in the markets. Only unexpected news can change asset prices in efficient markets. Nevertheless, striking and rapid price changes in asset prices have been dominant over time. That' why, this issue has examined the market efficiency and has impelled the studies regarding rational bubbles. The main idea of the rational bubble is that asset prices do not reflect the new information effectively and the difference between fundamental prices and market prices may provide investors to make profit. Additionally, because investors are willing to sell the stocks they buy at a higher price tomorrow, they are willing to buy assets today. The case of continues buying stocks can cause rational speculative bubbles in financial markets (Cajueiro and Tabak, 2006).

Some bubbles in asset prices might be closely connected with financial crises in general. It has been said that bubbles have great impact on crises and this kind of bubbles might trigger off crises. Especially financial markets have suffered from bubbles which are observed periodically. Recent examples such as Mississippi Bubble in 1720, Japanese asset price bubbles in 1980s, Great Depression in 1929, the U.S. dot.com bubble in the late 1990s, Mortgage Crisis in 2007, and dot-com bubbles in 2000 are significant and considerable events (Oran, 2011, Friedman and Abraham, 2009). For this reason, it can be said that bubbles come into prominence in global financial markets. In other words, it is expected that determination of the bubbles can be a warning system against the crises appeared in financial markets.

2. Literature review

There are great numbers of research investigating bubbles in stock markets. While some of studies found multiple bubbles in stock markets, others stated absence of the bubble. Chan et al. (1998) investigated bubbles in the U.S. and six Asian stock markets by using

conditional skewness and duration dependence tests of McQueen and Thorley (1994) and explosiveness tests. The conclusions showed that speculative bubbles were existed in especially Malaysia, Hong Kong, and Thailand, whereas bubbles in the U.S. stock market weren't found. Harman and Zuehlke (2004) investigated the existence of bubbles in American Stock Exchange and NYSE by using duration dependence tests.

Likewise, Jirasakuldech et al. (2008) tested speculative bubbles in Thai stock market with duration dependence and cointegration tests and found the presence of speculative bubbles. Zhang (2008) also found the existence of bubbles in Chinese stock market by using duration dependence tests.

In other respects, Jiang et. al. (2010) investigated bubble in Shenzhen stock exchange component exchange and Shanghai stock exchange composite index for the periods of 2005-2007 and 2008-2009. Log-periodic power law model was considered to detect bubbles. The results showed that there were explosive financial bubbles for the periods. Asako and Liu (2013) developed a statistical model including time varying parameters and transition probabilities and estimated by recursive computations to detect bubbles grow and burst in time. They applied this model for the stock markets of China, Japan, and the U.S. and found that the U.S.' stock market had bubbles, whereas Japan and China hadn't. Additionally, their results showed that probability of bubble increased when stock prices decreased or increased too much.

On the other hand, Chang et al. (2014) applied generalized sup Augmented Dickey-Fuller test to analyse the presence of multiple bubbles in the BRICS countries such as South Africa, China, India, Russia, and Brazil by covering monthly data regarding stock price-dividend ratio. They concluded that multiple bubbles existed in the aforementioned stock markets. Phillips et al. (2014) also investigated whether or not there were multiple bubbles in the stock market of S&P 500 by implementing GSADF and SADF tests for the period of 1971-2010. Their findings indicated the existence of bubble in the stock market of S&P 500. Likewise, Chen et. al (2015) applied GSADF test to detect multiple bubbles in sub sector namely health care of some developed markets such as German, the UK, and the U.S. They found that bubbles existed in those all stock markets. Nneji (2015) examined the effects of market liquidity and funding liquidity shocks on stock market bubbles. They stated that both of these shocks raised bubbles

in stock markets. Additionally, the effect of market liquidity had more influence on bubble than the other one.

As far as the research conducted in Turkey are concerned, it has been seen that there have not any bubbles in Istanbul Stock Exchange. Tasci and Okuyan (2009) examined the presence of bubbles by using duration dependence tests for the period of 1987-2008. Öğüt et al. (2009) researched stock manipulation via Artificial Neural Networks and Support Vector Machine. Similarly, Yu and Hasan (2010) also analysed the existence of bubbles in Istanbul Stock Exchange, Middle East and North African stock markets by using duration dependence tests. Parvar and Waters (2010) tested bubbles in Borsa Istanbul through traditional cointegration test and cointegration test including kurtosis and skewness. Yanık and Aytürk (2011) tested the presence of a bubble in Turkish stock market by using duration dependence test for the years between 2002 and 2010. Bozoklu and Zeren (2013) investigated the presence of rational bubbles in Borsa Istanbul by applying hidden and traditional cointegration tests. The findings of the all these studies stated that there weren't any rational expectation bubbles.

As for methodology used in the literature, cointegration and unit root test have implemented to analyse the rational bubbles in general. According to Turkish studies, cointegration, duration dependence and conditional skewness tests have used (such as Öğüt et al., 2009, Tasci and Okuyan, 2009, Parvar and Waters, 2010, Yanık and Aytürk, 2011, Bozoklu and Zeren, 2013). This paper makes contribution to the existing literature especially by using right-tailed unit root test, SADF test and GSADF test developed by Phillips et al. (2011) for BIST 100 and some sector indices in Turkish stock exchange namely Borsa Istanbul.

This study examines the detection of rational bubbles in Borsa Istanbul 100 Index and some sector indices using right-tailed unit root test, SADF test and GSADF test. Section 3 explains methodology used. In section 4, the data used in this research is identified. Section 5 provides empirical findings of the research. Lastly, section 6 presents conclusions.

3. Methodology

We deal with recursive right-tailed unit root tests. The time series which is $\boldsymbol{y_t}, \boldsymbol{t} = \boldsymbol{1}, \ldots, \boldsymbol{T}$ is considered. Null hypothesis test states

whether or not $\boldsymbol{y_t}$ follows AR (1) having unit root through all sample. Alternative hypothesis says that $\boldsymbol{y_t}$ moves as at least AR (1) process for some sub-sample. Philips et al. (2011) proposed PWY test to detect rational bubbles by using recursive Dickey Fuller tests. This test statistic is as follows:

$$PWY = \sup DF_T \tag{1}$$

Here, DF_T is standard Dickey Fuller test, in other words, it is $\widehat{\emptyset}$ t ratio in Ordinary Least Squared Error (OLS) regression estimation.

$$\Delta y_t = \hat{\alpha} + \widehat{\emptyset}_{PWY}\, y_{t-1} + \hat{\varepsilon}_t \tag{2}$$

Sub-sample period is $t = 1, \ldots, [\tau T]$.
Here, $\bar{y}_\tau = ([\tau T] - 1)^{-1} \sum_{t=2}^{[\tau T]} y_{t-1}$
and $\hat{\sigma}^2_{PWY} = ([\tau T] - 3)^{-1} \sum_{t=2}^{[\tau T]} \hat{\varepsilon}_t^2$ (Harvey et al. 2015).

In left-tailed unit root tests, the findings are generally sensitive towards model specification. Formulation of an appropriate hypothesis is difficult especially in the case of the existence of non-stationary series. Because, parameters take different roles under both null hypothesis indicating existence of unit root and under alternative hypothesis in which stationary is provided (Philips et al. 2014).

On the other side, right-tailed unit root tests are quite convenient to determine slightly exploding series or exploding series. For example, Diba and Grossman (1988) implemented right-tailed unit root tests for precisely sampled data to detect financial bubbles. Phillips et al. (2011) suggested applying right-tailed unit root tests to recursive sub-samples. The formulation of regression model specification and null /alternative hypotheses are of importance in both left-tailed and right-tailed unit root tests (Phillips et al. 2014).

One of the right-tailed unit root tests is "Sup Augmented Dickey Fuller Test" denoted by SADF. This test has proposed by Phillips et al. (2011). SADF test is based on recursive estimation of ADF model and it is acquired as sub value of ADF statistic serial in question. Right-tailed unit root tests show asymptotic distribution characteristics based on the regression model and the null hypothesis and it is as follows:

$$x_t = \mu_x + \delta\, x_{t-1} + \sum_{j=1}^{J} \emptyset_j \Delta x_{t-j} + \varepsilon_{x,t}, \qquad \varepsilon_{x,t} \sim NID(0, \sigma_x^2) \tag{3}$$

Here, *NID* is independent and has normal distribution, lag parameter is demonstrated as *J*. Right-tailed alternative hypothesis is $H_0 = \delta > 1$ and null hypothesis is $H_0 = \delta = 1$ in unit root tests. The aforementioned above model is repeatedly estimated increasing one observation at each trial in recursive regressions.

$$ADF_r \rightarrow \frac{\int_0^r \widetilde{W}\, dW}{(\int_0^r \widetilde{W}^2)^{\frac{1}{2}}} \tag{4}$$

$$sup_{r\in[r_0,1]}\, ADF_r \rightarrow sup_{r\in[r_0,1]} \frac{\int_0^r \widetilde{W}\, dW}{(\int_0^r \widetilde{W}^2)^{\frac{1}{2}}} \tag{5}$$

Standard Brownian motion is indicated by W, and $\widetilde{W}(r) = W(r) - \frac{1}{r}\int_0^1 W$ is reduced Browian motion (Phillips et al. 2011: 206-207).

Just like in SADF test, GSADF test depends on a rolling approach but with several different forward expanding sequences begins from the starting point. Sub-samples of GSADF are more extensive value when compared to SADF. Additionally, GSADF test enables starting point *"r_1"* to modify within a possible sequence by considering changing the ending point "r_2" which runs from "r_0" to "1". The largest ADF statistic over all possible sequences of r_1 and r_2 is stated as GSADF. The formulization of GSADF test is as follows (Phillips et al. 2013: 10).

$$GSADF(r_0) = \sup_{\substack{r_2\in \\ r_1\in[0,r_2-r_1]}}^{[r_0,1]} \left\{ADF_{r_1}^{r_2}\right\} \tag{6}$$

4. Data

The research was implemented for Borsa Istanbul stock index (BIST 100) and sector indices including services, financial, industrials, and technology indices in order to analyse the presence of rational bubbles. The monthly data span from 1990 to 2015 except for services

index and technology index which start with the years 1997 and 2000, respectively. The data were taken from Borsa Istanbul official web site.

5. Empirical findings

In this study, right-tailed unit root test, SDAF Test and Generalized SDAF Test were conducted to determine rational bubbles in Turkish financial market.

Table 1 depicts descriptive statistics regarding BIST 100, services, financial, industrials, and technology indices. According to Table 1, all series had excess kurtosis value. Besides, they displayed positive skewness except technology index. As Jargue-Bera statistics were examined, all series had not normal distribution, however they exhibited fat tailed characteristic.

Table 1

Descriptive Statistics

	BIST 100	Financial	Industrials	Services	Technology
Mean	0.02548	0.02784	0.02676	0.01641	0.00559
Median	0.02434	0.01970	0.02394	0.02169	0.01157
Maximum	0.58658	0.61984	0.53305	0.51008	0.35952
Minimum	-0.49485	-0.49077	-0.52417	-0.46965	-0.42628
Std. Dev.	0.13343	0.15095	0.12319	0.11354	0.12351
Skewness	0.26056	0.36219	0.16826	0.05393	-0.34452
Kurtosis	5.20236	4.68217	5.84230	6.67055	4.01657
Jarque-Bera	64.4516	40.6726	99.3273	122.485	11.0602
Probability	0.00000	0.00000	0.00000	0.00000	0.00396
Observations	302	291	291	218	176

The SADF and GSADF tests of the BIST 100, Financial, Industrial, Services and Technology indices are provided in Table 2.

According to this table, the SADF test statistics were -7.308402, -6.720856, -7.635591, -4.963127 and -7.170339, respectively. Besides, GSADF test statistics were -5.168279, -5.799413, -5.391155, 2.472663 and -3.694068, respectively. Both of these tests didn't exceed their respective %1, %5 and %10 right-tail critical values. That's why; the null hypothesis assuming no bubble was not rejected. It cannot be found any evidence regarding to the presence of bubble in BIST 100 and all sub-sector index. The results have parallels with the studies such as Öğüt et al. (2009), Tasci and Okuyan (2009), Yu

and Hasan (2010), Yanık and Aytürk (2011), Bozoklu and Zeren (2013).

Table 2

SADF and GSADF tests of the indices

	SADF	GSADF
BIST 100 Index	**-7.308402**	**-5.168279**
90% critical value	1.016040	1.760996
95% critical value	1.282928	2.053025
99% critical value	1.830091	2.523389
Financial Index	**-6.720856**	**-5.799413**
90% critical value	1.864033	2.612326
95% critical value	1.344502	1.923172
99% critical value	1.106382	1.618296
Industrial Index	**-7.635591**	**-5.391155**
90% critical value	1.864033	2.612326
95% critical value	1.344502	1.923172
99% critical value	1.106382	1.618296
Services Index	**-4.963127**	**2.472663**
90% critical value	1.856858	2.391317
95% critical value	1.296439	1.858786
99% critical value	0.993431	1.647252
Technology Index	**-7.170339**	**-3.694068**
90% critical value	1.903659	2.434469
95% critical value	1.327736	1.888086
99% critical value	0.910942	1.659578

Note: Both tests' critical values are provided from "Monte Carlo simulation" with 1000 replications (sample size 301). The smallest window has 35 observations.

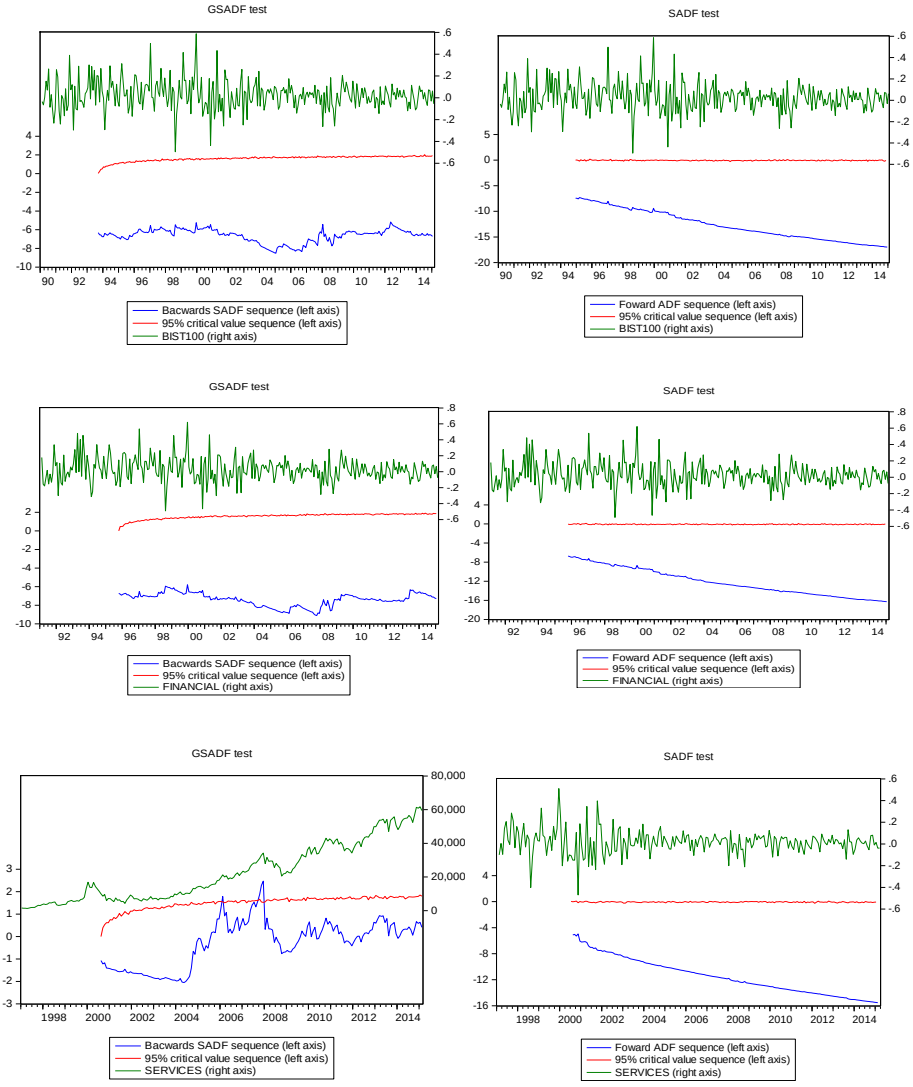
Figure 1 presents findings for the data-stamping bubble periods in the BIST 100, Financial, Industrial, Services, Technology indices for the period of 1990 – 2015.

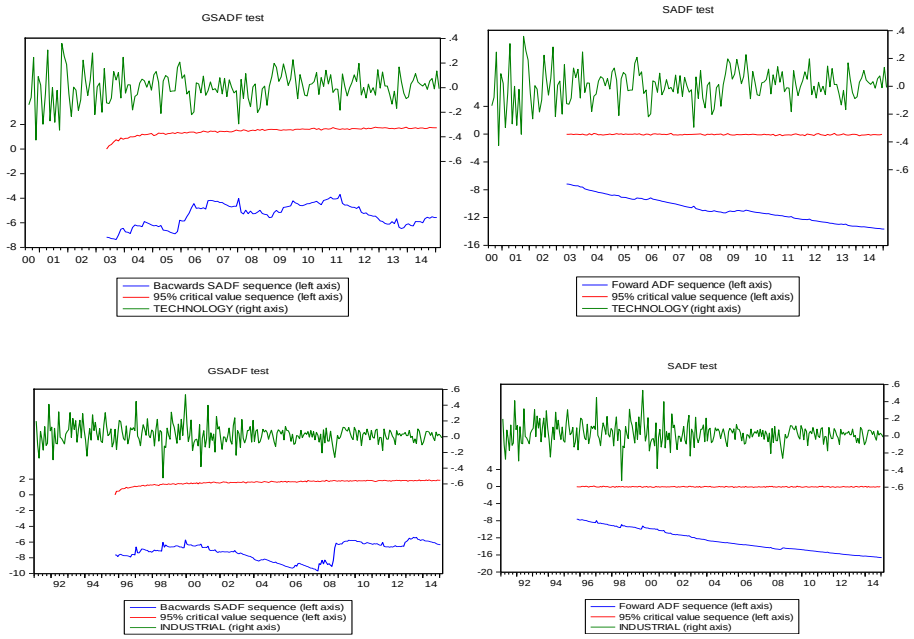
In order to detect bubble periods, we have taken Monte Carlo simulations with to the backward SADF statistic of 95 % critical value sequence and compared it with 1000 replications for each observation. According to Figure 1, it was seen that there was not the presence of bubbles in BIST 100 index and all sub-indices for the so-called period. The findings of this study were similar with the results of Öğüt et al. (2009), Tasci and Okuyan (2009), Yu and Hasan (2010), Yanık and

Aytürk (2011), Bozoklu and Zeren (2013) studies. Consequently, it is claimed that the possible failure appearing in Turkish stock market can stem from the another reasons except bubbles.

Figure 1

Data-stamping bubble periods in the indices: GSADF and SADF test





6. Conclusion

This paper presents whether or not there is a rational bubble in Borsa Istanbul 100 Index namely BIST 100 and some sector indices. In order to understand movements of markets and crises that appear from time to time, it is extremely important issue to identify the bubbles. Furthermore, the presence of rational bubbles in financial markets is an indicator that there are inconveniences in the financial system. That's why, determination of the bubbles can be a warning system against the crises appeared in financial markets. This study differs from the other studies dealing with bubbles in Turkish stock markets in terms of the methodology. For this, we used "right-tailed unit root test" and recent bubble tests which are "Sup Augmented Dickey-Fuller Test" and "Generalized Sup Augmented Dickey-Fuller Test" developed by Phillips et al. (2011) by covering the monthly data between 1990 and 2015. As a result of analyses, it can be stated that there were no rational bubbles in BIST 100, services, financial, industrials, and technology indices in Turkish stock markets. Our findings are consistent with the other studies which are related to determination of

bubbles in Turkish stock markets in the literature. Moreover, the results of this study regarding the absence of rational bubble in BIST 100, services, financial, industrials, and technology indices can state that prices of these indices are consistent with their fundamental values in the period between 1990 and 2015.

When considering the close relationship of rational bubbles with financial crises, the analysis and detection of them become even more important for investors, portfolio managers and market regulators. That's why, our findings may provide policy makers and both domestic and international investors in order to give the right decision and accordingly, to take a position in the markets. In further studies, it can be investigated the bubbles by using price dividend ratios and it can be examined the effects of monetary policy on the bubbles if there are bubbles in the financial markets.

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SYSTEMIC RISK: AN OVERVIEW

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Abstract

In hindsight of the 2008 crisis, the conspicuous underestimation of systemic risk has turned into a strong incentive for authors to develop appropriate measurement techniques. Given the continuously changing nature of the financial system, measurement tools have developed quickly to address diverse and progressively more complex aspects, thereby adding to the issue of establishing a universal framework of measuring systemic risk. In this respect, we tried to devise a brief overview of extant systemic risk approaches, from definition to a selection of measurement instruments. Valuable steps have been made towards producing comprehensive models. However, systemic risk measurement and mitigation remain open issues.

Keywords: systemic risk measurement, systemic crises, prudential measures

JEL Classification: G15, G20, H12

1. Introduction

An extensive amount of literature has been dedicated to studying systemic risk. However, we have yet to reach a commonly, universally accepted definition. Systemic risk is frequently addressed in terms of financial markets, thus being a risk to financial stability so widespread to the point where it entails material effects on economic growth and welfare (European Central Bank, 2010). This risk may take various forms, but it generally occurs in the context of the propagation of economic distress from one economic agent to another (Rochet & Tirole, 1996). Since interdependencies and mutual claims are the very core of financial activities, it is only natural for risks as such to arise in the financial system. Consequently, the nexus between systemic risk and financial contagion is widely acknowledged. There are numerous studies dealing with this issue, of which we mention among many

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others: Allen & Gale (2000), Kaminsky & Reinhert (2000), Claessens & Forbes (2013).

Kaufman (1995) defines systemic risk as "a risk of a chain reaction of falling interconnected dominos". Therefore, risk arises from any disturbance that works itself through the system and is strong enough to threaten the public's confidence in the financial system and its stability as a whole (Sheldon & Maurer, 1998; Billio et al, 2012). Accordingly, market stability may be affected by the impossibility of an institution to fulfil its obligations, because this will impair, in turn, other institutions. According to Martinez-Jaramillo et al. (2010), systemic risk can be conceptualized from two basic principles: the existence of an initial shock that affects one or more financial institutions up to the point of bankruptcy, and the existence of a transmission mechanism of the negative effects of this shock in the system. As these two elements compose the so-called systemic event, systemic risk can also be defined, in a broad sense, as the risk of encountering systemic events (de Bandt & Hartmann, 2000).

There is also a widespread confusion as far as trigger events are concerned. Schwarcz (2008), points out the inconsistency of the existing definitions of systemic risk:

- "the probability that cumulative losses will occur from an event that ignites a series of successive losses along a chain of institutions or markets comprising a system" (Kaufman, 1995);
- "the potential for a modest economic shock to induce substantial volatility in asset prices, significant reductions in corporate liquidity, potential defaults and efficiency losses" (Kupiec & Nickerson, 2004);
- "the risk that a default by one market participant will have repercussions on other participants due to the interlocking nature of financial markets" (Chan et al., 2005)

He states that the singular common factor of these is that one trigger event causing a series of negative economic effects. Otherwise, both the definition of a systemic event and its consequences are inconsistently explained and differ among authors.

As far as the geographical reach is concerned, systemic risk may have regional, national or international character. Strong failures of several institutions, the crash of several markets or, shortly put, events that impact most of the financial system become a source of systemic crises (de Bandt & Hartmann, 2000). Therefore, the

propagation of one bank's failure as a contagion that causes the failure of several banks represents a systemic financial crisis (Acharya, 2009).

A central issue of this debate is that any problem aimed at being solved needs to be clearly defined in the first place. The lack of a clear definition slackens the attempts of addressing and solving multifaceted problems like this.

The subsequent sections build on the following topics: Section 2 addresses several recurring issues debated in literature on systemic risk; in Section 3 we present, in brief, a number of measurement instruments frequently deployed in this field. We conclude in Section 4.

2. Challenges of systemic risk measurement

Systemic risks that are not mitigated properly in a timely manner may materialize, propagate and amplify further up to the point where a systemic crisis becomes impending. Systemic crises imply overwhelming social and economic costs, hence the rising concerns towards ensuring and maintaining the financial stability of the system, and reducing the probability of such events in the future. Ensuring financial stability is particularly dependent on understanding systemic risk. There are some major impediments that derive from the complexity of systemic risk: the actual difficulty of measurement (the multitude of risk measurement instruments) and the relative lack of data needed to perform this task. Brunnermeier & Oehmke (2013) state that systemic risk appears and develops just like an economic cycle, hence data requirements for detecting imbalances will differ depending on the targeted phase:

- the run-up phase, during which disequilibria builds up in the background of the financial system (can be analysed based on low frequency data according to the authors)
- the crisis phase, during which risk materializes and spills over across the financial system (requires more granular, higher frequency data to grasp the system's vulnerabilities).

Beyond the failure of financial institutions, systemic risk has an impact on investors, for it cannot be neutralized through portfolio diversification. That is because risks that are positively correlated with the market cannot be diversified away (Posner, 2003).

Maintaining financial stability can only be done through regulation of the financial system, or else, market participants would most likely not limit their risk-taking behaviour in order to reduce the

contagion hazard for the good of others. This is why regulating systemic risk not only deems appropriate, but is actually necessary (Cifuentes et al., 2005). However, there are also downsides of regulation and safety measures. Such a non-targeted consequence could be fostering moral hazard. The more market participants are being protected from the consequences of risk prone behaviour, the more likely it is for them to engage in this kind of behaviour, as argued by Hallinan (1986). This holds especially for financial institutions that are commonly considered "too big to fail", which means that irrespective of the risk they incur, they will be bailed out for certain.

Some other undesirable consequences would be the institutions performing fewer transactions, thus lowering economic welfare, or regulation acting like a barrier against financial innovation through the implied compliance costs (Gowland, 1990). This is exactly why financial innovation has often coincided with deregulation and new instruments developed the most among non-traditional, less regulated institutions, as stated by Bisias et al. (2012).

The need for systemic risk measurement has been widely discussed. Alexander (2010) highlighted different purposes of systemic risk measures: identifying institutions of systemic importance that pose high risks for the financial system; assessing particularly vulnerable structures of the financial system; identifying shocks that are threatening financial stability; providing early warning signals when financial instability is rising.

Thus, ex-ante systemic risk measures can help policymakers tighten macroprudential policies and supervisory standards, when and where it is necessary to temper instability-inducing pressures and even provide an incentive for building stress scenarios to test for the system's resilience. Ex-post assessments may be just as important in helping identify ineffective policies, in order to mend what has gone wrong before in the system. Therefore, systemic risk measures are a key element in implementing crisis management systems, as well as safety nets for financial institutions.

The usefulness of early warning signals has also been discussed in the light of the Lucas critique (reiterated by Bisias et al., 2012). Simply put, signals as such presumably become ineffective because individuals adapt their behaviour in response to them. But is that necessarily bad in respect to systemic risk measurement? It clearly isn't, if market participants undertake actions by themselves in order to limit their risk exposures, instead of relying on governmental

intervention and saviours of last resort exclusively. However, from another point of view, financial institutions may react adversely, by manipulating disclosed data and therefore confirming the Lucas critique (Brunnermeier & Oehmke, 2013).

Given the continuously changing nature of the financial system, measurement tools have developed quickly to address diverse and progressively more complex aspects, thereby adding to the issue of establishing a universal framework of measuring systemic risk. It is clear that many risks stemming from different sources will provide for as many approaches and risk measurement tools built to emphasize various aspects.

The global financial crisis of 2008 has spurred even more interest towards measuring systemic risk, as it has revealed that systemic risk must have been underrated. It shifted the attention of policymakers and academia from traditional institutions (banks) to the less supervised ones such as private equity and hedge funds. The crisis reaffirmed the need for heightened prudential supervision[1] and for risk buffers on one hand, as well as for disclosing risk exposure of financial institutions of systemic importance on the other. In hindsight of the 2008 crisis, an impressive amount of studies acknowledged the failure of surveillance as a main contributor to proliferating systemic risk to unbearable levels. We mention Freixas (2010), Hanson et al. (2011), Masciandaro et al. (2011), Akerlof et al. (2014).

As discussed before, extant literature encompasses an extensive number of studies aiming at measuring systemic risk in various contexts. That being the case, surveying the methods has proven to be a correspondingly difficult task. Some issues arose: given the bewildering number of analyses, literature surveys cannot claim to be exhaustive, and secondly, complex methods become difficult to classify into broad categories.

3. Approaches to measuring systemic risk

Lehar (2005) based his systemic risk measurement on a Merton type model of default. He introduced the well-known Expected Shortfall (ES), which is the debt value that cannot be covered by the firm's assets if it defaults. In brief, summing the computed Expected Shortfalls accounts for an aggregated index of systemic risk. Huang,

[1] *Macroprudential and microprudential alike. Distinction between them has been discussed by Brunnermeier et al. (2009).*

Zhou, and Zhu (2012) develop a systemic risk indicator that measures the price of insurance against systemic financial distress. In order to be computed, this cost of insurance requires parameters such as probabilities of default, loss-given defaults, leverage and dynamic conditional correlations between equity returns. According to the authors, this metric is quite similar to expected shortfall (ES), but differs in the aspect that the probabilities in the tail event underlying the cost of insurance are not normalized.

Acharya (2009) models systemic risk as the choice of correlations of banks' returns on assets. He finds that banks are willing to undertake correlated investments in the event of a shock in the system, therefore, prudential measures may actually favour building-up systemic risk. Moreover, regulation is not able to capture risks arising from inter-banking contracts. Allen, Bali & Tang (2012) use both parametric and nonparametric VaR and ES methods to estimate CATFIN as a measure of systemic risk. According to their results, CATFIN is a useful predictive instrument, thus being able to signal economic declines six months in advance.

Kritzman et al. (2011) estimate the fraction of a number of assets' total variance explained by a limited number of factors, by applying a principal component analysis (PCA) and call this the absorption ratio (AR). They find that AR captures very well market fragility. Stock returns drop around spikes in the AR and while most of the global crises corresponded with its increases, the authors state that spikes in AR do not necessarily signal a market crash for certain. That being the case, the AR accounts better for an ex-post measure of systemic risk, rather than an ex-ante one. Billio et al. (2012) also employ principal component analysis (PCA) and Granger causality networks to measure the correlation of monthly returns on hedge funds, brokers and dealers, banks and insurance companies. Among their main conclusions we mention: banks distinguish from other institutions by their very important role in shock transmission; the increase in systemic risk was favoured by the growing interdependencies between the four sectors in the analysed period (1994 to 2008). Lupu et al. (2018) focus on the fragility of the Eastern European capital market through the PCA framework. They assess the contribution of each index to the aggregated systemic risk by subtracting one index AR at a time from the group AR, and further check the validity of this analysis by running a panel regression with

the Economic SentiMent index for each country as exogenous variable on the previously obtained differences.

Brownlees & Engle (2012) introduced a new empirical measurement instrument, the Systemic Risk - SRISK index. Systemic risk is therefore measured as the expected shortage of capital of an institution, determined by an important market decline. They compute SRISK for 94 financial institutions from US (depositories, insurance firms, brokers and dealers, others), between 2000 and 2010. Calculating SRISK requires data regarding equity, debt and the Marginal Expected Shortfall – MES (which in turn depends on the institution's leverage, size and equity loss in the event of a market decline). MES is modelled by means of GARCH-Dynamic Conditional Correlations (Engle et al., 2009) in order to deliver long-run and short-run dynamic volatility, correlations and tails for the returns. Summing up the computed SRISK values accounts for the aggregated systemic risk of the financial system as a whole. Later on, Brownlees & Engle (2016) reiterate the SRISK metric on a panel of US financial institutions with a capitalization greater than 5 billion USD (period 2003-2012), while they settle for the long run MES component (LRMES).

Engle, Jondeau & Rockinger (2015) run the SRISK methodology, this time on a broad selection of large European financial institutions and argue that in some instances government bailout costs become so high, that certain banks may be "too big to be saved".

Acharya et al. (2016) used equity and CDS market data to assess Systemic Expected Shortfall (SES) as a metric for the contribution of a financial institution to systemic risk, defined as "the propensity of that institution to be undercapitalized when the system as a whole is undercapitalized". The Systemic Expected Shortfall proposed by Acharya et al. (2016) is relatively similar to the SRISK, but according to Brownlees & Engle (2016) it may not be as practical, for it requires to observe a systemic crisis in order to measure the systemic risk of a firm. They put forward the argument that SES may overlook the significant aspect of risk building up in the background during low volatility periods and manifesting only when a crisis bursts. SES is calculated as the linear combination of leverage and one step ahead MES[2].

[2] *Computed quite similarly to MES for SRISK, based on a GARCH-DCC approach. The approach of Acharya et al. (2016) differs in that the MES they compute is time invariant.*

Adrian & Brunnermeier (2016) derive CoVaR, a measure of systemic risk, from the very common Value at Risk – VaR used by most financial institutions. CoVaR is the Value at Risk of the financial system conditional on an institution undergoing financial distress. Moreover, ΔCoVaR is the contribution of an institution to systemic risk computed as the difference between CoVaR conditional on the distressed financial institution and CoVaR conditional on the normal state of that institution. The authors compute ΔCoVaR using quantile regressions, but it can also be estimated through GARCH-type models. They compute ΔCoVaR based on weekly data (1971-2013) for US commercial banks, brokers and dealers, real estate companies and insurance companies, all traded on stock exchanges. The main difference between CoVaR and SES is hence the directional approach: Acharya et al. (2016) assess the firm's financial distress conditional on systemic distress, while Adrian & Brunnermeier (2016) measure the systemic distress generated by the individual firm's distress. Girardi & Tolga Ergün (2013) estimate Adrian & Brunnermeier's CoVaR by using both the normal distribution and the skewed-t distribution for the GARCH model. They find that using the skewed-t distribution, and thus taking skewness and kurtosis into consideration, provides for better consistency of the CoVaR obtained. Lopez-Espinosa et al. (2012) apply a generalized version of CoVaR on a sample of international banks and confirm that banks relying exceedingly on short-term debt bear higher risks, hence acting as primary sources of systemic risk. Hautsch, Schaumburg & Schienle (2014) build on the VaR methodology, in order to identify systemically important institutions. If an institution's incremental contribution to the VaR of the system is statistically significant and positive, then the institution is considered systemically relevant.

Authors such as Battiston et al. (2012), or Acemoglu et al. (2015) focused on the architecture of the financial network and how the shape and the nature of financial interlinkages favour shock transmission. Acemoglu et al. (2015) discover that once negative shocks surpass a specific threshold, dense financial linkages are more prone to contagion, whereas the same densely interconnected system is actually more resilient when shocks have a lower magnitude. This is in line with Battiston et al. (2012), who also conclude that moderately integrated systems are the most resilient to shocks. Allen, Babus & Carletti (2010) analyse whether financial institutions' debt maturity is in any way correlated with the shock resilience of the network structure.

They discover that for long-term debt, the network structure is rather irrelevant. Conversely, when banks rely on short-term financing, the network structure becomes of utmost importance, as positive or negative signals determine investors to (or not to) roll-over the debt. Results show that in the event of negative signals, investors are more inclined towards avoiding rolling-over the debt in densely interconnected systems. Cont, Moussa & Santos (2010) contribute to this strand of literature by introducing two measures aimed at localizing sources of systemic risk in an interconnected structure: the counterparty susceptibility (measuring creditors' sentiment towards the default probability of the liable institution), and local network frailty (measuring the upsurge of systemic risk when a network node defaults).

Anginer, Demirguc-Kunt & Zhu (2014) use the credit risk model of Merton (1974) to derive default risk and examine the risk-taking behavior of banks in relation to the network structure. They also approach the issue of financial architecture and systemic risk, but switch their attention to competition rather than financial interlinkages. They find that greater competition fosters stability, because it is an incentive for banks to diversify risk. It follows that the lack of competition makes banking systems less resilient to shocks.

Giglio, Kelly & Pruit (2016) compute several systemic risk measures proposed in the literature in order to examine their consistency in predicting changes in the distribution of macroeconomic shocks in the future. Relying on the hypothesis that these measures do not capture properly the latent systemic risk factor, they compute two estimators – the principal component quantile regression (PCQR) and the partial quantile regression (PQR). By running PCQR and PQR on the cross-section of systemic risk indices, they find that these are more consistent in predicting macroeconomic shocks, but only with the prerequisite of mild conditions. Tarashev, Borio & Tsatsaronis (2010) propose an existing measure that can be computed in conjunction with several systemic risk measures: the Shapley Value of Shapley (1953). They find that the Shapley Value feature of assigning to players their incremental impact on the wider groups makes it appropriate for measuring systemic risk. Intuitively, in terms of financial institutions, individual risk accounts for the difference between systemic risk of the group including the institution and the systemic risk of the group without it. Gauthier, Lehar & Souissi (2012) quantify macroprudential capital requirements by also computing Shapley Values, ΔCoVaR (Adrian &

Brunnermeier, 2012), the MES of Acharya et al. (2016)[3] and VaR (Jorion, 2007). They prove that capital requirements are able to reduce a bank's default probability by 25%, and the probability of simultaneous defaults of several banks by 41%. Rodriguez-Moreno & Peña (2013) compute and compare different systemic risk measures, and results show that methods based on credit default swaps (CDSs) are more consistent than stock or interbank market-based ones.

Providing meaningful systemic risk quantification methods has become an ambition of the academic field and the impressive amount of studies prove the difficulty of this task.

4. Concluding remarks

Systemic risk quantification has been addressed time and again in the academic field, in the attempt to offer valuable inputs for prudential policies. A central issue of this purpose is that any problem aimed at being solved needs to be clearly defined in the first place. The lack of a clear definition slackens the attempts of addressing and solving multifaceted problems like this. Given the continuously changing nature of the financial system, measurement tools have developed quickly to address diverse and progressively more complex aspects, thereby adding to the issue of establishing a universal framework of measuring systemic risk. It is clear that many risks stemming from different sources have provided for as many approaches and risk measurement tools built to emphasize various aspects.

In the aftermath of the 2008 crisis, the conspicuous underestimation of systemic risk has turned into a strong incentive for authors to develop comprehensive measurement techniques. Consequently, surveying the methods has proven to be a correspondingly difficult task. Among the most prominent challenges we emphasize the following: given the bewildering number of analyses, literature surveys cannot claim to be exhaustive, and secondly, complex methods become difficult to classify into broad categories. In

[3] *Time inconsistency in several instances throughout our paper is explained by the numerous earlier versions under working paper form of "Measuring Systemic Risk" by Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. This is also the case for Adrian & Brunnermeier's "CoVaR" and Brownless & Engle's "Volatility, Correlation and Tails for Systemic Risk Measurement". Most of the times, for clarity purposes, we referenced the latest published versions.*

this respect, we tried to devise a brief overview of extant systemic risk approaches, from definition to a selection of measurement tools.

The conclusion that must be drawn is that systemic risk measurement is a worthy challenge for academia and policymakers alike, and a general consensus regarding the framework is neither attainable, nor desirable. Henceforward, although important steps have been made in this direction, systemic risk measurement and mitigation remain open issues.

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THE NEXUS BETWEEN FINANCIAL LITERACY AND THE CREDIT STATUS IN INDONESIA

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Abstract

The ease of access to financial institutions leads to an increase in the number of both consumptive and productive loans. This increase must be balanced with the process of knowledge transfer about financial management so that customers can manage finances well and can pay credit according to a specified schedule. The objectives of this study are to discover factors influencing financial literacy, and test the relationship between literacy and credit status, so that it can become a guideline for banking policies in issuing credit. This research utilized 332 samples of credit clients in rural bank credit (RBC). The testing was done with multinomial logistic regression. The research results reveal that the factor which influences finance literacy is level of education. On the other hand, income, amount of loan, and credit status do not have an influence on finance literacy. The credit status (fluid and stalled) does not have a significant relationship towards finance literacy. Thus, the initial assumption that clients who have a fluid credit status will also have a higher literacy level is not proven. There are no differences in stalled credit clients and fluid credit clients in financial literacy.

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1. Introduction

Indonesian society's financial understanding, based on a survey conducted by the Financial Service Authority in 2013, is divided into four criteria: 1) well literate at 21.84%, 2) sufficient literate at 75.69%, 3) less literate at 2.06%, and 4) not literate at 0.41%. The financial literacy program that was proclaimed by the Financial Service Authority has been frequently responded to by various spheres, whether national banking, academicians, or various non-government organizations by making finance literacy programs like smart behaviour programs that are carried out by banks through smart behaviour agents divided into various regions in Indonesia.

The development of channelling banking funds in Indonesia every year has experienced an increase, whether in public banks or community credit banks (Otoritas Jasa Keuangan, 2017). The development of fund channelling programs by banks in Indonesia needs to be balanced with a financial knowledge transfer process to clients, so that they have a good understanding about managing finances and are more careful in using finances as well as can pay their obligations as creditors. Financial or individual literacy has substantive differences like education, age, and gender (Rooij et al. 2011). Research conducted by Rooij et al. (2011) also revealed that the majority of households in the Netherlands have limited financial literacy, as well as every privatization program considers that individuals who do not have a financial understanding will not invest in the stock market to prepare for their retirement.

Bahovec et al. (2015) mentioned that excessive debt is a problem that endangers individual and household financial prosperity. The research results found that a low level of financial literacy is one of the factors that can influence debt behaviour and an increase in debt. Research findings discovered that respondents with different levels of financial literacy resulted in varying debt behaviour. Thus, respondents with low finance literacy showed worse debt behaviour, such as more consumer debt than consumers with medium and high levels of financial literacy (Bahovec et al. 2015).

Having a financial understanding is important in making financial decisions. Research carried out by Rooij et al. (2011) found

that a high level of financial literacy results in a high potential for stock market investing and a higher tendency to plan for one's retirement period. In a related article, Christelis et al. (2010) discovered that the tendency to invest in stocks is greatly connected with cognitive ability, whether it is for direct or indirect stock market participation through mutual funds and retirement accounts.

Having a good understanding of financial management is needed by company owners in developing their companies. Research by Kotzè and Smit (2008) found that personal finance education is very important to help individuals in managing their financial matters effectively. Research carried out by Eresia-Eke and Raath (2013) empirically revealed that the majority of small businesses showed signs of growth. This research did not show that there was a statistically significant connection between an owner's finance literacy and the overall business development. However, owners who did not have a good grasp of finances would hire individuals who had studied and understood about finances to help manage the organization's financial matters, so that the business could develop well.

Entrepreneurs who have good finance literacy will not only help the company develop, but they will also easily gain access to finances from financial institutions. Over the years, banking access in Indonesia has experienced changes. Ease of banking access by SMEs that was considered as non-bankable became easier due to government encouragement through various cheap credit programs. This was a blessing for SMEs who already had a good understanding of financial management, so that they could pay their obligations. Increasing the flow of funds for SMEs also had an effect on the increase of stalled credit according to the banking data that was issued by the 2017 Financial Protection Authority. This increase in stalled credit must be managed, in order that banks can remain in a safe condition. This needs related research on credit that is given to bank clients.

2. Literature review

2.1. Measuring financial literacy

Understanding financial literacy is very useful in making consumer financial decisions, whether it is collectively or individually, and also in facing market competition (Hastings et al. 2012). Measuring financial literacy basically combines conceptual and operational aspects, including the awareness, knowledge, and ability of an

individual or society that are the subjects in accessing a financial institution to do a budgeting activity, manage savings, take out a loan, or make investments according to the level of financial understanding one possesses (Atkinson and Messy 2011).

Lusardi and Mitchell (2011) stated that it is important to evaluate how people understand about finances, but in practice it is difficult to explore how individuals process economic information and make decisions about household finances. Lusardi and Mitchell (2011) designed steps in measuring the United States society's financial literacy by using the four main principles of simplicity, relevance, brief, and ability in differentiation.

According to the Australian Securities and Investments Commission - ASIC (2011), in understanding in-depth and knowing the level of an individual's financial literacy, a benchmark used includes one's knowledge of the value of a good and the priority scale in one's life; budgeting, savings, and how to manage money; credit management, the importance of insurance and protection against risks; investment basics; retirement; retirement planning; taking advantage of purchasing and comparing products; knowing where to go to look for advice and acquiring additional guidance and support; as well as how to recognize the potential for conflict in usage (priority). Meanwhile, according to the Financial Service Authority (2014), Indonesian society's financial literacy is divided into four parts, which are well literate, sufficient literate, less literate, and not literate.

2.2. Relation between financial literacy and bank credit clients

The level of financial literacy that a person has will influence the amount of credit taken from a bank/ financial institution. Financial literacy indicates an individual's level of understanding towards a financial concept and it can be seen from one's ability to interpret financial data accurately (Gathergood, 2012). An SME entrepreneur is faced with very complex decision making to achieve success in one's business. For instance, an entrepreneur must be able to decide saving and investing to develop one's business. Understanding finance literacy becomes crucial in making decisions related to financial matters. As Lusardi and Mitchell (2006) stated that those who have a high financial literacy and basic understanding of financial concepts can support their business expansions well.

Financial literacy improves an individual's ability to independently arrange one's personal finances, whether it is in helping

with one's personal spending or in arranging household items, including in managing loans. Bahovec et al. (2015a) detected individual financial literacy users and analysed the relationship between different levels of financial literacy and socio-demographic characteristics. Financial literacy reveals how an individual understands financial concepts and shows the ability to interpret financial data accurately.

Having extensive knowledge about finances will affect the success in overcoming problems to access and manage loans. For example, financial literacy can assist in decision making such as making payments on time. Good debt management can improve one's credit value for potential loans to support the business performance (Adomako and Danso 2014).

Bosma and Harding (2006) explained that several companies have failed due to a lack of financial literacy, inefficient business acquisitions, and negligence of entrepreneurial activities. Various research supports the viewpoint that entrepreneurs who do not consider age will not be able to consistently do decision making activities by considering resource income, allocation, and utilization. In general, these activities have financial consequences. Therefore, to be effective, an entrepreneur must have a sufficient level of financial literacy.

Financial literacy is a form of education in improving one's potential financial decisions in the household. Eventually, it will increase savings and prosperity as credit clients from a financial institution. From an explanation by Cole et.al. (2009), with data obtained through the World Bank's Access to a Finance Survey with a sample of 3,360 households, Indonesia received a score of 52% for understanding the questions put forth based on the methodology of Lusardi and Mitchell (2006). This enables financial literacy or an understanding of financial knowledge in Indonesia to be better.

2.3. Interrelatedness of financial literacy and loan accessibility

Having financial literacy for a business owner or business manager is crucial to make company capital structure decisions. The importance for small and medium sized businesses is that it reflects the low agency costs that are used for loan source diversification to improve the business asset value. Nkundabanyanga et.al. (2014) discovered that many SME owners have limited information about bank products, low personal financial management, weak knowledge, a lack of abilities, and less expertise in finances, which makes the budgeting,

record keeping, and financial planning become weak. This research used small and medium entrepreneurs in Uganda. The financial literacy and management ability were also very low, so that requests for financial products were also small.

Access to loans for small and medium business owners is determined by financial literacy. Receiving access to loans for businesses by having opportunities and entrepreneurs who are full of creative ideas will help improve revenue distribution and business growth (Nkundabanyanga et al., 2014). Loan access is one of the ways to improve the SME business capital structure. Possessing a capital structure is an important condition for a company's growth and development, such as SMEs that can be supported by manager/ owner characteristics. In the condition where it is difficult to gain access to financial resources, financial literacy is beneficial for business growth and competition, so that it facilitates SMEs in accessing funds from financial institutions (Delić et.al., 2016).

The condition which facilitates a finance source in a business environment is by developing a long-term relationship with a bank and being supported by good knowledge to evaluate the benefits and drawbacks of the financial resources. Loans are a financing source in adding an asset and as a revenue source for a financial institution or bank. Loans that are issued by a bank depend on society's savings. A low level of financial literacy will be related with low savings in the household. This is reported by households as being the main factor in engaging borrowing (Ombongi, 2015).

An individual with a low literacy level can borrow without considering the size of the loan, so that the burden of debt and interest rate that will be paid can experience outstanding payments, so that it makes the financial institution have low performance. Financial education teaches about how knowledge, abilities, and ethics are needed to adopt a good money management practice by channelling, receiving, saving, borrowing, and investing money appropriately. This can assist in adding loans from clients and reducing the form of debt and outstanding balance, so that the financial institution performance can also be improved (Ombongi, 2015).

Regarding the level of financial knowledge, especially about loans towards financial institutions or banks, entrepreneurs need to know the interest rate level that is offered by the bank. Besides knowing the interest rate level, they also need to know how to make debt payments, in order that the bank does not channel more funds than is

needed which stalls the credit (Bengi and Njenje, 2016). Several banks allocate resources to support training for business clients to improve their financial record keeping and credit management ability. Financial literacy is an initial source of knowledge to measure loans that originate from initial funds that are used to build a business (Mutegi et.al., 2015).

This study focuses on the effect of the level of customer literacy on credit status. Credit status of bank customers shows the ability of customers to pay credit instalments. The study wants to examine the effect of the level of financial literacy on the credit status, where no previous research had found the effect of financial literacy on the credit status of customers.

3. Data and methodology

Research design: The research design used in this study is quantitative analysis. The researcher collected information through questionnaires and direct interviews with clients of rural bank credit (RBC) in Central Java, Indonesia. There were 332 RBC client samples taken. The study aims to analyse the influence of the level of financial literacy on education, the influence of the level financial status on income, the influence of the level financial status on amount of loan, and the influence of the level financial status on credit status on RBC in Central Java. The analysis in this research used a Logistic Regression Analysis model, so that the predictor variables (level of education, income, amount of loan, and credit status) were known, and a real influence on the level of finance literacy as a response variable was seen. Besides that, a further analysis in the form of a correlation analysis was done to find out the tendency or strong relationships between variables (financial literacy, education, income, and size of loan) with the level of credit return fluidity. This correlation analysis was done to support the previous logistic regression analysis results.

Research model: The financial literacy of rural bank credit clients used indicators that were issued by the Financial Service Authority and research by Chen and Volpe (1998), by looking at the averages of the correct answers that were then grouped into four categories, including not literate (< 30%), less literate (30% < 60%), sufficient literate (60% < 80%), and well literate (>80%) to facilitate the observations. The loan amounts were used as a predictor variable because an individual's ability in financial literacy will influence

budgeting, managing loans, or doing investments (Atkinson and Messy, 2011).

The research variables used were financial literacy (FL) as the dependent variable and education (Edu), income, Amount of loans (AoL), and credit status (CS) as independent variables. The model that was used is:

$$\mathrm{FL} = \ln\left[\frac{\mathrm{p}}{1-\mathrm{p}}\right] = \beta_0 + \beta_1 \mathrm{Edu} + \beta_2 \mathrm{Income} + \beta_3 \mathrm{AoL} + \beta_4 \mathrm{CS} + \varepsilon_\mathrm{i} \quad ...(1)$$

Explanation:

Li = Response variable, here Financial Literacy (1= *Not Literate*, 2 = *Less Literate,* 3 = *Sufficient Literate*, 4 = *Well Literate*); β_0 = Constant; β_1 = 1st predictor variable coefficient; β_2 = 2nd predictor variable coefficient; β_3 = 3rd predictor variable coefficient; β_4 = 4th predictor variable coefficient; Edu = 1st predictor variable, here the level of education; Income = 2nd predictor variable, here income; AoL = 3rd predictor variable, here amount of loan; CS = 4th predictor variable, here credit status.

4. Results

This research used a credit client financial literacy indicator by asking about their understanding of general finance, insurance, banking, capital model, simple calculating, and client financial attitude. The general finance literacy asked about investments, inflation, and client financial management. The results in Table 1 reveal that the education, income, and credit status variables have a relationship with the level of financial literacy.

The education variable in Table 1 reveals that a college or university degree education level is considered the highest well literate compared with other education levels at 37 percent. The highest less literate literacy level is at the elementary school level. This shows that the higher the level of clients' education level, the better their financial literacy level will be. The client income variable indicates that a client income level of more than 25 million has a well literate financial literacy level of 60 percent. This reveals that clients who have a good financial understanding will find it easier to produce high incomes.

The client loan amount variable for rural bank credit in Table 1 displays that the majority of them have a sufficient literate level of 59 percent. The loan amounts with the highest well literate individuals are clients who have loans of more than 50 million. The level of financial

literacy from each of the loan amount levels is almost the same so that clients who borrow 1-5 million are distributed with about the same finance literacy level as the larger loan amounts. This means that there is no connection between clients with small or large amounts of loans and the level of financial literacy.

The credit status variable reveals that the majority of the clients have a sufficient literate at 59 percent. Credit clients with a stalled status mostly have a sufficient literate level of 79 percent, and 4 percent of credit clients have a well literate level. The condition above is the same as credit clients with a fluid status, as the majority of them have a financial literacy level of sufficient literate at 57 percent, and 19 percent of credit clients with a fluid status have a well literate level. There is relatively no difference in the fluid or stalled credit status. The distribution of financial literacy levels in fluid clients and stalled clients are similar so that there is no relationship between the financial literacy level and the client credit status.

Table 1

Cross tabulation in the finance literacy level

	Less Literate		Sufficient Literate		Well Literate		Total	Chi-Square
	Freq	%	Freq	%	Freq	%		
Gender	76	23	196	59	60	18	332	
- Male	40	20	120	61	38	19	198	
- Female	36	27	76	57	22	16	134	
Education	76	23	195	59	61	18	332	30.45*
- Elementary school	32	40	42	52	7	9	81	
- Middle school	34	19	113	64	30	17	177	
- High school	3	9	22	65	9	26	34	
- College or University	7	18	17	45	14	37	38	
- Master to up	0	0	1	50	1	50	2	
Income	76	23	196	59	60	18	332	20.534**
- 1-5 million	62	25	147	59	42	17	251	
- 6-10 million	8	17	32	68	7	15	47	
- 11-15 million	3	25	5	42	4	33	12	

	Less Literate		Sufficient Literate		Well Literate		Total	Chi-Square
	Freq	%	Freq	%	Freq	%		
- 16-20 million	0	0	5	83	1	17	6	
- 21-25 million	1	17	5	83	0	0	6	
- >25 million	2	20	2	20	6	60	10	
Amount of loan	76	23	196	59	60	18	332	6.629
- <=10 million	47	24	118	59	35	18	200	
- 11-20 million	15	27	31	56	9	16	55	
- 21-30 million	5	19	18	69	3	12	26	
- 31-40 million	3	19	9	56	4	25	16	
- 41-50 million	1	11	7	78	1	11	9	
- >50 million	5	19	13	50	8	31	26	
Credit status	76	23	196	59	60	18	332	4.982***
- Stalled	4	17	19	79	1	4	24	
- Fluid	72	23	177	57	59	19	308	

*P-Value: *p<0.001, **p<0.05, ***p<0.10*

Table 2 conveys that the -2 log likelihood experienced a reduction in the *chi-square* of 52.169 and the p-value of 0.000 when the independent variable was added. This reveals that the model with the independent variable provides better accuracy to predict the financial literacy level.

Table 2

Model fitting information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	330.546			
Final	278.377	52.169	10	.000

Table 3 shows that the overall model prediction ability is 62.3 percent.

Table 3

Classification

Observed	Predicted			
	Less Literate	Sufficient Literate	Well Literate	Percent Correct
Less Literate	10	66	0	13.2%
Sufficient Literate	2	193	1	98.5%
Well Literate	1	55	4	6.7%
Overall Percentage	3.9%	94.6%	1.5%	62.3%

Table 4 displays the contributions of every independent variable towards the model. The variables which contribute towards the model is education, while the other variables do not contribute to the model. These research results convey that the variables which have a relationship towards finance literacy is the education level variables. Meanwhile, client income, amount of loan, and credit status are not connected with financial literacy.

Table 4

Likelihood ratio tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of the Reduced Model	Chi-Square	df	Sig.
Intercept	305.144	26.767	2	.000
Education	298.992	20.615	2	.000
Income	281.862	3.485	2	.175
Amount of loan	278.826	.449	2	.799
Credit status	283.559	5.182	2	.075

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

5. Discussion

The research findings show that the education level is one of the factors that have a relationship with financial literacy. The education level of the society shows a level of understanding of various life issues, including financial management. These results are in line with Agarwal et al., (2015); Alsemgeest, (2015); and Dwiastanti, (2015) that the high level of one's education is positively and significantly related to the cognitive aspects of financial literacy.

In this study, 18 percent of respondents were well-literate. It means that in general customers with elementary to postgraduate education understand investment as well as their benefits and risks to be accepted, able to manage personal finances, and understand the use of credit cards. All customers with elementary school to postgraduate education are at a sufficient-literate level. In addition, lower levels of education are also dominated by sufficient-literate customers. However, there are also many less-literate customers, that is, almost a quarter of them. They only know financial institutions and their products and services without the skill to use them. The results of this study also show that none of the customers included in the category of not-literate. Moreover, the results also document the level of financial literacy of Rural Bank customers, which is mostly at the sufficient-literate level and this is owned by almost all levels of education. Thus, customers with low education tend to have poor financial literacy, even though it will harm them.

Different results can be seen in income, loan amount, and credit status, where the three do not have an influence on the level of customers' financial literacy. This is supported by the results of statistics from the calculation of Likelihood Ratio Tests which show 0.175 that income levels have no relation to the financial literacy level. Each individual may have a condition that contradicts the benefits of financial literacy, by managing finances or looking for additional sources of funds to improve personal well-being either personally or family. Customers with high income reaching 25 million tend to be between the less-literate and sufficient-literate levels. Indonesia is ranked fourth in the world with the highest level of consumer optimism. This consumer optimism is about the prospect of local employment, personal financial conditions and the desire to shop. This consumptive index shows that the Indonesian people in general, including the Central Java community, tend to need additional funds for their daily needs. With the existence of consumer loans provided by the Rural Credit Banks, this further increases their consumption and this contrasts with the benefits of financial literacy. Therefore, the amount of one's income does not affect the level of financial literacy. This study is in line with Agarwal et al., (2015) that the amount of income does not depend on the financial literacy level.

Financial literacy can be a key to success in making financial decisions and in taking credit (Gathergood, 2012 and Hastings et al., 2012). However, this study shows different results that there is no

relationship between the amount of credit and understanding of financial literacy. It might happen because respondents chose to trust financial advisors or someone who had better financial experience as expressed by (Disney, Gathergood, and Weber, 2015). The results of this study support researches of (Villa and Diagne, 2012) and Agarwal et al., (2015).. Various life factors may cause respondents to take large amounts of loans even though their financial literacy is bad. Life factors include daily needs, divorce, and layoffs. Therefore, they need additional funds by borrowing money from banks to support their daily lives.

The average number of loans taken by respondents in this study is less than ten million (<10 million). Regarding the number of loans, one important thing is the type of collateral. Therefore, this study proves that the high or low credit loans by respondents do not affect the level of financial literacy as long as the respondent has collateral which can be used to take large amounts of loans. Large levels of debt that are not based on financial management knowledge can be caused by household needs or even marital status, and lifestyle that cannot be linked to the level of education or the amount of income. This is commonly called the symptoms of financial depression as described in the study of (Berger, Collins, and Cuesta, 2015). Loans in the amount of 41-50 million are included in the Sufficient Literate category with a score of 77.8%. With a sufficient literate condition, respondents are brave enough to take a large amount of credit. This might occur because the collateral factor owned is one of the successes of the respondents in getting a large amount of credit beyond the ability to manage credit and the success of credit payments.

This study found that credit status has a relationship with financial literacy. The findings of this study can be taken into consideration by banks in providing credit to customers. Credit and debt management are interrelated activities. Bad debt management will result in the LDR (Loan to Deposit Ratio) of financial institutions, in this case the Rural Banks (BPR), exceeding the safe limit of the LDR value determined by Bank Indonesia (BI). Respondents who answered questions related to banking literacy scored high; 75 percent of customers are in the Well-Literate category but they have credit status as stalled credit customers. Barua dan Sane (2014) shows that literacy rates cause a reduction in the number of days and months in late credit payments. Therefore, it is necessary in increasing financial education to improve the ability of customers who have low literacy levels. The

results of this study document that 59 percent of Indonesian bank credit customers are at sufficient literate level and 79.2 percent of them are customers with bad credit. This figure is quite high because more than three quarters of customers are stalled credit even though they have good financial literacy. Thus, whatever the customer's credit status, fluid or stalled, is not affected by the customer's financial literacy level.

6. Conclusions

Bank lending to small and medium-sized communities has become a trend of banking business today. Therefore, there must be a real effort by banks to provide an understanding of financial management to their customers so there is no increase in stalled credit. Low financial understanding can lead to errors in financial management. The findings of this study indicate that credit status (fluid and stalled) does not have a significant relationship to financial literacy. Therefore, there is no difference between stalled credit customers and fluid credit customers in financial literacy. The average level of financial understanding of credit customers is at the level of sufficient literate. This is in accordance with the customer's financial attitude where the average respondent has a good attitude in financial management. Other findings show that education and religiosity have significant relationships towards financial literacy. Thus, respondents who have a higher level of education show a better level of literacy. The results of this study support previous researches where the higher education has a significant positive relationship to the cognitive aspects of financial literacy.

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ASSESSING THE DETERMINANTS FOR THE ADOPTION OF E-BANKING SERVICES: THE CASE OF DASHEN BANK

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Abstract

The study deals with assessing the determinants for the adoption of e-banking at Dashen Bank selected branches in Addis Ababa, Ethiopia. To meet the objectives of the study, primary data was gathered from selected employees and customers of selected branches of Dashen bank east district in Addis Ababa. These districts include: Bole Medihanialem Branch, Kotebe Branch, Yerer Branch, CMC Branch and Ayat Branch. Hence, Simple random sampling method was employed to draw the sample respondents. Hence out of 388 respondents, 356 responded the questionnaire. The collected data was analyzed using descriptive statistics, correlation and regression analysis. Accordingly, the findings reveal that except perceived risk, which had a negative relationship, perceived ease of use and perceived usefulness had significant and positive relationship with adoption of e-banking. Hence, the study recommended that to enhance e-banking adoption, banks should combine the concepts of perceived ease of use, perceived usefulness, and perceived risk dimensions into e-banking services to increase the level of e-banking adoption and adopt a clear strategy in order to reduce e-banking risk and to improve adoption rate.

Keywords: perceived usefulness, perceived ease of use, perceived risk, e-banking adoption

JEL Classification: G21, G29

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1. Introduction

The introduction of e-banking makes the bank services to be accessed more than the usual banking services. Even in the rural destinations, where branches are rarely accessible, e – banking plays paramount role to access banking services by clients. Despite this, the utilization and adoption of e–banking is contingent with poor level of connectivity, level of awareness of clients, costs associated with it and client's attitude towards the technological advancement. Now days financial institutions and specially banks are transforming themselves from time to time in order to make their services more accessible to their customers. That is, the introduction of e- banking made the sector to be more competitive. Promoting service quality typically in line with banking services is a function of having a sound internet services which is rendered by providers and the cost associated with it. As a matter of fact, customers get interested whenever the newly endorsed technological advancement is cheaper than the existing service providing tools (Vijay, 2014). Also, clients' adoption of e – banking is a function of perceived risk, ease of use, usefulness and having a background in internet utilization (Yoseph, 2017). As per Katuri, et al., (2003) it is the introduction of internet banking that made its perceived usefulness at the highest degree. Besides, internet banking made the customers to easily access the products of banks everywhere where there is an access of internet connection. Hence, the aim of this study is to assess the determinants for the adoption of e-banking services: special emphasis is given to Dashen bank on selected branches in Addis Ababa, Ethiopia.

2. Statement of the problem

The past couples of decades made the banking sector to transform and adopt changes in its day-to-day operations. The reason for such changes includes: the keen competition held with in banks, the introduction of internet and other state of art technologies, the ever-increased customer requirements etc. Therefore, coping such dynamicity calls for the banking industry to get rid of the traditional banking services and adopting new way of rendering services. Keeping other things constant, the introduction of internet banking made the availability of banking services everywhere and any time. That means, customers can undergo any transactions at whatever situation they are and in whatever geographical locations they exist. Simply, it is worth to

say that life becomes simple due to the technological advancement (Katuri, et al., 2003)

Adoption of e-banking in Ethiopia is challenged with lack of skilled man power, failure to set an appropriate regulatory modalities, poor internet band width that is supplied to the bank, cost of adopting the technology, low level of telecom infrastructure and low level of customers or clients awareness. That means, Ethiopian banks suffer from institutional and structural problems to adopt e- banking. Despite these, most banks have been introducing the e- banking services to their customers. But the service is not reliable due to the aforementioned factors. Here it is possible to add that perceived ease of utilization is the leading advantage of electronic banking as it made the operations of bank services more efficient and also perceived usefulness is the other advantage that made banks to adopt electronic banks which in turn leads to maintain good reputation as it is a means to enhance public confidence in a wider fashion (Mahlet, 2016). Therefore, this study aims at revealing out the factors that determine the adoption of e-banking services: at Dashen bank on selected branches in Addis Ababa, Ethiopia.

The general objective of the study is to investigate the major determinants for the adoption of e-banking in Dashen Bank, Ethiopia.

3. Literature review

It is a general truth that electronic commerce is making a paradigm shift in the world of business. Because it connects different stakeholders through technology in order to make the transactions simple. It makes the usual way of transactions or trading to business unusual fashion. That is simply the world of internet makes the operations of business to more advanced state of art technology by connecting major actors of business such as: producers, customers, suppliers, and sellers etc. on one ring to facilitate the transactions to be held among themselves. Generally speaking, transformations of businesses from oldest form of operations to modern or emerging approaches is came into being due to the introductions of internet services throughout the globe. This makes the world a small village and operations of businesses smooth sailing. Furthermore, the marketing activities can take place in an efficient and effective manner by meeting the requirements of the customers. Hence, changes in the world of business is due to the advancements of technology

(Scarborough and Scott,2012). Generally speaking, e- banking can be defined as: rendering banking services to clients or customers by a bank through internet connection undergo and monitor financial transactions. Hence, customers can make of such service provisions whenever the cost associated with it is minimal, having prior knowledge in making use of internet and degree of complexity. Also, it is possible to deduce that e- banking helps in building non-cash society by making transactions more convenient to customers and at the same time benefits the bankers in maintaining efficiency in handling transactions (Saviour and Bornwell, 2018)

The banking industry is transforming itself in making use of technologies to render its services to customers. This marks an end of traditional way of banking services. Also, the core banking approach came in to being to make the industry operate in state of art technology. Such advancements change the conditions of transactions in other sectors too. Because when the e – banking is highly customized by clients, no doubt that the selling and buying of goods and services is also changed. Furthermore, the e- banking and e – commerce made business firms to operate in a smooth and fascinating style in order to meet the requirements of their customers. It is also a sound idea to notice that the e – banking service is constrained by factors such as: perceived risk, experiences in making use of technologies, and level of qualifications (Maitlo et al., 2015). It is worth functioning to understand that e- banking services should be regulated and monitored in a strictest way. Unless it is given due consideration in controlling the system, it would be subject to vulnerability. Always banks are expected to build the confidence of their customers by updating the system regularly. In case if the customer is in a position to attempt any fraud tactics, the bank should warn such acts by informing the customers through text messages and even directly calling and take corrective actions. This will minimize cyber-crime associated with advancement of technologies. In additions, the bank should pay attention to suggestions of customers and possible common fraud or cheating tactics and then assessing the case to in order to take corrective actions. Here it is mandatory to the bank to inform its customers pertaining to e- banking services on a regular basis if need arise to boast the morale of its customers. Whenever banks maintain the psychological relief of their customers or clients, they would have more reputation and able to overcome the challenge of competitors (Do and Nguyen, 2017).

4. Methodology

The study deals with assessing the determinants for the adoption of e-banking at Dashen Bank selected branches in Addis Ababa, Ethiopia. To meet the objectives of the study, primary data was gathered from selected employees and customers of selected branches of Dashen bank east district in Addis Ababa. These districts include: Bole Medihanialem Branch, Kotebe Branch, Yerer Branch, CMC Branch and Ayat Branch. Hence, Simple random sampling method was employed to draw the sample respondents. Since the total number of target respondents (customers and employees) is 12,869, the researchers used Taro Yamane's (1967) simplified formula and table to calculate sample size.

$$n = \frac{N}{1 + N(e)^2}$$

Where:

n= sample size, N = Population size, e= the margin of error (0.05).

Therefore, $n = \frac{12869}{1+12869(0.05)^2}$, n = 388

Hence out of three hundred and eighty- eight (388) respondents, three hundred and fifty- six (356) respondents responded the questionnaire. Here it is possible to infer that more than 90% responses rate was made. Therefore, it is based on this response rate that the analysis was made. The collected data was analyzed using descriptive statistics, correlation and regression analysis.

Therefore, the study specifically deals with:

1. To determine the extent to which Perceived Usefulness (PU) affect e-banking adoption
2. To reveal out the extent to which Perceived ease of Use (PEOU) affect e-banking adoption
3. To examine the effect of perceived risk (PR) on adoption of e-banking.

Hypothesis: The study tests the following hypothesis

1. There is a significant relationship between perceived Usefulness (PU) and adoption of e-banking in Addis Ababa.
2. There is a significant relationship between perceived ease of use (PEOU) and adoption of e-banking in Addis Ababa.
3. There is no significant relationship between perceived risk (PR) and adoption of e-banking in Addis Ababa.

5. Results and discussions

The study deals with the assessing the factors that determine the adoption of e- banking. To meet the objectives of the study, independent variables such as: perceived usefulness (PU), perceived ease of use (PEOU) and perceived risk (PR) were computed with the dependent variable (adoption of e- banking). Hence, the result is illustrated as follows.

- **Perceived usefulness**

This study evaluated the impact of perceived usefulness in the adoption of e-banking using six dimensions/items. Results obtained from survey respondents regarding their perception towards the usefulness of the existing e-banking service, using percentage distribution statistics are depicted in Table- 1 below. Most of the respondents responded positively that perceived usefulness has an effect in terms of enhancing adoption of e-banking. Respondents indicates that e-banking has substantially contribute in providing information and saving costs of customers at 80.9% and 75.8% positive responses respectively. Adoption of electronic banking contributed in facilitating flexible transaction, providing alternative to manage financial transactions, and allows managing financial activities efficiently with percentages 87.9%, 85.5% and 85.2 of respondents in agreement, respectively. Minimize the risk of theft and save cost of users were the highest among other items of perceived usefulness factor in which respondents disagreed on, 63 (17.7%) and 31 (8.7%) respectively.

Table 1

Perceived usefulness dimension

Items	Strongly Disagree	Neutral	Strongly agree
Provides up to date information	28(7.9)	40(11.2)	288(80.9)
Save cost of users	31(8.7)	55(15.4)	270(75.8)
Minimize the risk of theft	63(17.7)	67(18.8)	226(63.4)
Offer alternatives to manage financial transaction	5(1.4)	42(11.8)	309(85.5)
Facilitates flexible transaction	11(3.7)	30(8.4)	313(87.9)
Allows to manage financial activities efficiently	7(2.0)	42(11.8)	307(85.2)

Source: Survey 2018

- **Perceived ease of use**

Table 2 below presented percentage distribution statistics of perceived ease of use. It is indicated that 82.6% of the respondents believed that electronic banking helps to perform banking tasks in a simpler way. Transaction mistakes are less likely to occur compared to manual system is the lowest response at 63.2%. On the other hand, e-banking service helps to perform banking tasks in a simple way was the least response among others 13 (3.7%) and transaction mistakes are less likely to occur was the highest response on which the respondents responded negatively with 64 (18.0%). Hence, it is possible to infer that majority respondents responded positively for the perceived ease of use dimensions has an effect in terms of enhancing adoption of e-banking.

Table 2

Perceived ease of use dimension

Items	Disagree	Neutral	Agree
Bank provides easy and clear instruction	52(14.6)	57(16.0)	247(69.4)
E-banking is simple enough to handle or operate	36(10.2)	62(17.4)	258(72.5)
E-banking service helps to perform banking tasks in a simple way	13(3.7)	49(13.8)	294(82.6)
Transaction mistakes are less likely to occur	64(18.0)	67(18.8)	225(63.2)

Source: Survey, 2018

- **Perceived risk**

Respondents were asked about their agreement or disagreement regarding the perceived risks associated with adoption of e-banking. As shown in Table 3, the majority of respondents responded positively for all items related to perceived risk. Specifically, high risk perception was expressed for fear of financial risk (72.9%), fear of security risk (62.9%), fear of losing privacy (65.5%), fear of the possibility of failure (73.5%) and service limitation (77.9%).

Table 3

Perceived risk dimension

Items	Disagree	Neutral	Agree
Fear of financial risk	43(12.1)	72(20.2)	241(72.9)
Fear of possibility of defect	35(9.8)	59(16.6)	252(73.5)
Fear of security risk	78(21.9)	54(15.2)	224(62.9)
Fear of losing privacy	51(14.4)	72(20.2)	233(65.5)
E-banking limits services	30(8.5)	49(13.8)	277(77.9)
E-banking cause high risk perception	46(12.9)	55(15.4)	255(67.7)

Source: Survey 2018

- **Inferential analysis**

The inferential analysis is used to examine the level and magnitude of relationship in between independent variables and dependent variable. Hence, Pearson's Correlations and Regression Analysis were employed. To carryout regression analysis, diagnosis tests such as: Normality, Linearity, Multicollinearity and Heteroscedasticity were tested.

Table 4

Correlations

		Adoption of e-banking	Perceived Usefulness	Perceived Ease of Use	Perceived Risk
Adoption of e-banking	Pearson Correlation	1	.748**	.704**	-.564**
	Sig. (2-tailed)		.000	.000	.000
	N	356	356	356	356
Perceived Usefulness	Pearson Correlation	.748**	1	.563**	-.434**
	Sig. (2-tailed)	.000		.000	.000
	N	356	356	356	356
Perceived Ease of Use	Pearson Correlation	.704**	.563**	1	-.411**
	Sig. (2-tailed)	.000	.000		.000
	N	356	356	356	356
Perceived Risk	Pearson Correlation	-.564**	-.434**	-.411**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	356	356	356	356

*** Correlation is significant at the 0.01 level (2-tailed).*

Source: Survey 2018

The correlation analysis result shown in the Table 4. above reveals that there is strong positive relationship between PU and PEOU while PR has a strong negative relationship with e-banking adoption. Perceived usefulness has the highest association (correlation coefficient of 0.748), followed by perceived ease of use (correlation coefficient of .704). Perceived risk has the lowest association with adoption of e-banking (correlation coefficient of -.564)

- **Multiple regression analysis from customers' perspective**

Table 5 below presents the model summary for regression analysis for the adoption of e-banking. The model summary table helps to measure appropriateness of the regression model employed. The model summary shows that, the independent variables (perceived usefulness, perceived ease of use and perceived risk) explained adoption of e-banking with the adjusted R-square (70.6%). This implied that there is a significant relationship with the adoption of e-banking. Furthermore, the value of R=0.841 which is greater than 0.50 indicates that there is a strong correlation between the dependent variable and the independent variables (PU, PEOU and PR) together with the effect on the dependent variable of 70.8% (R-Square=0.708). The remaining 29.2% is explained by other variables out of this model.

Table 5

Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	. 841[a]	.708	.706	.463

a. Dependent Variable: Adoption e-banking; b. Predictors: (Constant), Perceived Risk, Perceived Ease of Use, Perceived Usefulness
Source: Survey 2018

Table 6

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	183.401	3	61.134	284.604	.000[b]
	Residual	75.610	352	.215		
	Total	259.011	355			

a. Dependent Variable: Adoption of e-banking; b. Predictors: (Constant), Perceived Risk, Perceived Ease of Use, Perceived Usefulness
Source: Survey 2018

Table 7

Result of multiple regressions - coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.792	.169		10.600	.000
	Perceived Usefulness	.348	.029	.439	12.105	.000
	Perceived Ease of Use	.305	.030	.363	10.109	.000
	Perceived Risk	-.158	.023	-.226	-6.895	.000

a. Dependent Variable: Adoption of e-banking
Source: Survey 2018

The ANOVA Table 7 above shows the overall acceptability of the model from a statistics point of view. The test statistics (284.60) is larger than the critical value ($F_{3,\ 352,0.05}$=2.60). As P is less than 0.05, the model is significant, and the variation explained by the model is not due to chance. Thus, the combination of the independent variables (PR, PEOU and PU) significantly predicted the dependent variable (F=284.604; p <0.05).

The Beta (B) values were used as coefficients to complete the previously formulated regression model.

$$\boldsymbol{E - banking\ adoption = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon} \qquad (1)$$

Table 8

Summary of hypothesis test

Hypothesis	Variables	Findings	Hypothesis Status
H_1	**PU** → adoption of EB	Positive and statistically significant (β=**0.348**;p<0. 01)	Supported
H_2	**PEOU** → adoption of EB	Positive and statistically significant (β=**0.305**;p<0. 01)	Supported
H_3	**PR** → adoption of EB	Negative and statistically significant (β= **-0.158**;p<0. 01)	Supported

The outcomes of regression analysis from customers' perspective shows that intention to adopt e-banking is individually and jointly predicted by PU (β=0.348; P<0.01), PEOU (β=0.305; P<0.01) and PR (β=-0.158; P<0.01). These variables together explain 70.6% of the variance on intention to adopt e-banking technology. Thus, hypothesis 1, 2 and 3 are supported. The result also shows that the

adoption of e-banking is primarily and positively affected by perceived usefulness (β = 0.348), and less affected by perceived ease of use (β = 0.305) and perceived risk (β = -0.158). This implied that perceived usefulness is the most important predictor for the adoption of e-banking. Perceived ease of use also has a significant impact and appears to be the second determinant of a customer's perception to adopt e-banking services.

The Regression analysis result from customers' perception (Table-7) shows that one unit increase in perceived usefulness dimension would lead to 0.348 unit (or 34.8%) increase in adoption of e-banking provided that other variables being held constant. Similarly, one unit increase in perceived ease of use dimension would lead to 0.305 (30.5%) increase in adoption of e-banking provided that other variables remain constant. Lastly, one unit increase in perceived risk dimension would lead to -0.158 (15.8) decrease in adoption of e-banking provided that other variables remain constant. To sum-up the results of the regression analysis conducted on the factors indicated that PU, PEOU, PR, were found to be influential factors explaining e-banking adoption.

The established regression equation for adoption of e-banking is written as follows:

$$\text{Overall e} - \text{banking adoption} = 1.792 + 0.348(\text{PU}) + 0.305(\text{PEOU}) - 0.158(\text{PR}) + \varepsilon \quad (2)$$

7. Conclusions and recommendations

As per the above result, the adoption of e-banking is primarily affected by perceived usefulness (β = 0.348), and less affected by perceived ease of use (β = 0.305) and perceived risk (β = -0.158). This implied that perceived usefulness is the most important predictor for the adoption of e-banking. Perceived ease of use also has a significant impact and appears to be the second determinant of a customer's perception to adopt e-banking services. The findings of the study is consistent with other researches. Accordingly, the utilizations of technological advancement in the banking industry could save the cost and time of clients. However, clients' adoption of e – banking is a function of perceived risk, ease of use, usefulness and having a background in internet utilization (Yoseph, 2017). As per Katuri, et al. (2003) it is the introduction of internet banking that made its perceived usefulness at the highest degree. Also, internet banking made the

customers to easily access the products of banks everywhere where there is an internet connection. Also, according to Poon (2008) the adoption of electronic banking is a function introducing reliable security systems, building responsive management system, the costs associated with the technology, suitability of the system to users or whether the system or services are user friendly, the types of product available to use are some of the critical factors in meeting the requirements of customers. Of course, to make the adoption of e-banking, banks are expected to raise the level of awareness of their customers and maintain the level of security of e- banking. This is justified by Hussein & Abdelhalim (2016) who reveal that the level of feedback given by Jordan commercial banks affects customer's adoption of internet banking. Hence, it is advantageous for the banks to focus on security related matters as it is a fact that internet is susceptible to unauthorized accesses and hackings. Also, the authors added that banks are expected improve the service quality in all facets of their operations. Last but not least, banks should segment their clients by making use of demographic factors of internet banking in order to enhance their efficiencies and marketing mix endeavours.

Hence, the study recommends that to enhance e-banking adoption, banks should combine the concepts of perceived ease of use, perceived usefulness, and perceived risk dimensions into e-banking services to increase the level of e-banking adoption and adopt a clear strategy in order to reduce e-banking risk and to improve adoption rate.

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