Bulletin of Monetary Economics and Banking, Vol. 21, No. 2 (2018), pp. 177 - 190
p-ISSN: 1410 8046, e-ISSN: 2460 9196

HAS FINTECH INFLUENCED INDONESIA'S EXCHANGE RATE AND INFLATION?

Seema Narayan[1] and Sahminan Sahminan[2]

[1] School of Economics, RMIT University, Melbourne, Australia. Email: swdhar@icloud.com
[2] Departement of Economics and Monetary Policy, Bank Indonesia, Jakarta, Indonesia.
Email: sahminan@bi.go.id

ABSTRACT

The digital financial services industry, or financial technology (FinTech), has emerged in Indonesia in recent years. The FinTech industry, although disruptive, promises among other things to reduce costs of, and improve access to, financial services. This paper investigates the macroeconomic implications of FinTech companies in Indonesia over the period 1998–2017. In particular, we investigate the impact of FinTech on the Indonesian exchange rate (rupiah vis-a-vis the US dollar) and the inflation rate. Our results suggest that FinTech is able to reduce inflation and lead to a real appreciation of the rupiah against the US dollar, although its effect on the exchange rate is delayed. We explain our results and discuss future research directions.

Keywords: FinTech; Real exchange rate; Inflation; Indonesia.
JEL Classification: E31; F31.

Article history:
Received : July 1, 2018
Revised : October 15, 2018
Accepted : October 17, 2018
Available online : October 31, 2018

https://doi.org/10.21098/bemp.v21i2.966

I. INTRODUCTION

Financial technology (FinTech) broadly reflects digitalization of the financial services industry, or financial solutions enabled by information technology (IT) (Puschman, 2017). As a disruptive innovation, FinTech is seen as reshaping the financial services industry by employing entirely new business models for payment, wealth management, crowdfunding, lending, and capital markets; these innovations compete with (or complement) business models of traditional financial services providers (Puschman, 2017; Lee and Sin, 2018; Temelkov, 2018).

FinTech's IT embedded business models reduce financial services costs, improve access and the quality of financial services, and create a more diverse financial landscape (Lee and Shin, 2018). It can access untapped markets, particularly small to medium enterprises (Maier, 2016; Temelkov, 2018). Jagtiani and Lemieux (2018) find that FinTech lenders such as LendingClub are able to provide loans to customers in areas underserved by traditional banks or defined by limited economic activity. Further, the FinTech sector is able to operate with lower costs than traditional financial services providers, for two important reasons: (1) the FinTech sector relies on state-of-the-art technology for the provision of customer-centric financial services; and (2) the FinTech sector faces lower compliance costs compared to banks, which enables them to lower service costs. Particularly since the Global Financial Crisis (GFC), FinTech startups have faced more relaxed regulation than the traditional financial sector, which has meant that FinTech is able to avoid the compliance costs faced by the traditional financial sector, provide services more cheaply, and enter into untapped markets (Lee and Shin, 2018; Temelkov, 2018).

Since it uses business models that differ from the traditional approach to providing financial services, the FinTech sector poses significant challenges for financial regulators, calling for changes in the financial regulatory and supervision systems (Bromberg, Godwin and Ramsay, 2017; Chui, 2017; Temelkov, 2018). Financial innovations, such as digital coins (e.g., Bitcoin), can pose significant challenges for monetary policy as well (Narayan et al., 2018). Further, financial innovation usually leads to higher credit creation, which increases systemic risk. This means that financial innovations, such as FinTech, ultimately make markets and economic systems more susceptible to systemic risk (Chui, 2017). Moreover, FinTech is vulnerable to startups or schemes that are fraudulent (Bromberg, Godwin and Ramsay, 2018).

In light of the disruptive nature of the FinTech sector (as highlighted above), we examine its implications for the macroeconomy, mainly in terms of reducing domestic costs and improving access to financial services. To proxy the macroeconomy, we consider two macroeconomic variables, the real exchange rate (rupiah vis-a-vis the US dollar) and Indonesia's inflation rate. Our first hypothesis, that the FinTech sector aids in reducing the domestic cost of doing business, can be captured using the inflation and exchange rates. Furthermore, since FinTech activities extend beyond national borders, our examination of the real exchange rate will allow us to gauge cross-border activity, which we predict should increase with better access to financial services.

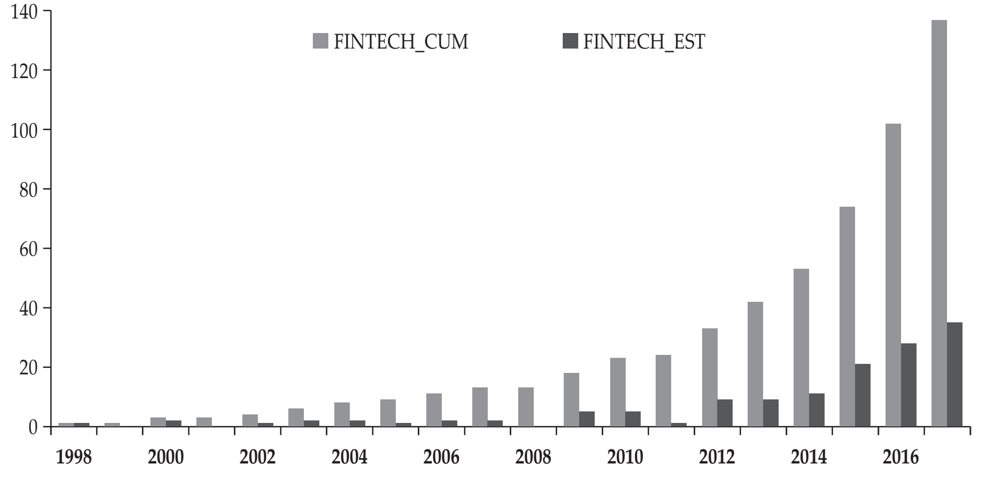
This paper proceeds as follows. Section II explains the FinTech space in Indonesia. Section III outlines our empirical model, theoretical framework and key hypotheses. Section IV outlines the data and preliminary analysis, while empirical results are reported and discussed in Section V. Section VI summarizes our findings and indicates future directions for further research.

II. THE FINTECH SECTOR IN INDONESIA

On the back of rapidly increasing Internet and mobile phone penetration rates, the FinTech sector has also been growing rapidly in Indonesia. According to *FinTechnews Singapore* (2018), the annual growth of the FinTech market in Indonesia in 2017 reached 16.3%.[3] Investment into FinTech companies has continued to be strong, amounting to US$176.75 million in 2017, according to *FinTechnews Singapore* (2018). This is in line with the rapid increase in the number of FinTech companies. In 2014, there were 53 FinTech companies operating in Indonesia (Figure 1). By 2017, FinTech companies increased by 158% to 137 companies (Figure 1). By June 2018, there were 167 FinTech companies operating in Indonesia, and most FinTech companies were established since 2015 (*FinTechnews Singapore*, 2018).

Figure 1. FinTech Start-ups Established (FINTECH_EST) and Cumulative (FINTECH_CUM) Each Year Over the Period 1998-2017

This figure depicts the growth of the FinTech sector in Indonesia over the period 1998-2017. *FINTECH_EST* is the number of new established FinTech firms and *FINTECH_CUM* is the cumulative number of FinTech firms each year.



Based on their activity, FinTech companies in Indonesia are dominated by payments, followed by lending (Figure 2). The rapid increase in the use of FinTech in payments is shown in the growth of SMS and mobile banking, Internet banking, and e-money. The rupiah value of transactions using SMS and mobile banking

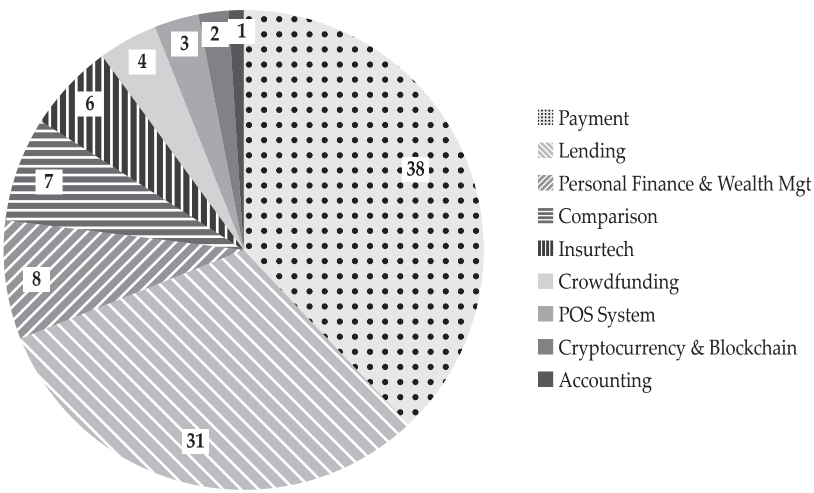
---

[3] The *FinTech Indonesia Report* is found at the FinTechnews Singapore website at: http://FinTechnews.sg/20712/indonesia/FinTech-indonesia-report-2018/

in 2017 increased by 41.3%, while the rupiah value of transactions using Internet banking increased by 16.7%. In the meantime, the number of e-money held by the public in 2017 increased by 75.8% to 90 million with average daily transactions at Rp33.9 billion.

Figure 2. Composition of FinTech in Indonesia in 2017 (%)

This figure shows the composition of FinTech sector in Indonesia in 2017. This is sourced from the FinTech News, Singapore (2018).



The number of lender accounts using FinTech in Indonesia as of May 2018 amounted to 199,539, more than 70% higher compared to January 2018. The growth of borrowers using FinTech expanded even more strongly, from only 330,154 in January 2018 to 1.8 million in May 2018. The rapid increase in the number of FinTech lenders and borrowers has been followed by rapid growth in the amount of loans through FinTech. According to Indonesia's Financial Services Authority (OJK), during the period January–May 2018, outstanding loans through FinTech doubled to Rp6,160 billion.

III. EMPIRICAL MODELS, THEORIES, AND HYPOTHESES

This section outlines our empirical model for hypothesis testing and for motivating the empirical framework with appropriate theories. Our starting point is to build on existing theoretical work related to the determinants of exchange rates and inflation, and to augment them with an exogenous shock, namely FinTech. The following real exchange rate (*RER*) and inflation (*INF*) models are estimated using the robust ordinary least squares estimation method:

$$INF_t = a_0 + \rho FinTech_t + \pi X_t + \varepsilon_t \tag{1}$$

$$RER_t = a_0 + \rho FinTech_t + \pi X_t + \varepsilon_t \tag{2}$$

Here, in addition to *RER* and *INF*, *FinTech* is the volume of *FinTech* firms, measured in terms of new firms established each year (*FINTECH_EST*) or the cumulative of all firms each year (*FINTECH_CUM*).

The inflation model (equation 1) is augmented with FinTech, which is measured as either a count of new FinTech startups or cumulative FinTech startups each year over the period 1998–2017. While FinTech is seen as a disruptive innovation, it also makes for a convenient technology that "… promises to cut costs, improve the quality of financial services and create a more diverse and stable financial landscape" (Lee and Shin, 2018: p.35). As a result, FinTech may be seen as reducing the marginal cost associated with the provision and consumption of financial services. Hence, we hypothesize that *FinTech will reduce inflation*.

Further, since FinTech in Indonesia is predominately focused on the area of lending (45% of total FinTech startups over the period 1998–2017), payments (38% of total FinTech startups over the period 1998–2017), and crowdfunding (2.2% of total FinTech startups over the period 1998–2017), it is reasonable to expect some impact from FinTech on the real exchange rate. Increased activity along the lines of lending, borrowing, or payments between Indonesians and foreigners will have an ambiguous effect on the Indonesian exchange rate. *RER* in this paper is expressed as US dollars in terms of Indonesian rupiah, hence an increase in the exchange rate indicates a depreciation of the rupiah against the US dollar. Thus, we hypothesize that *FinTech will influence RER significantly*. The sign of the effect (that is, whether the effect is an appreciation or depreciation) is an empirical question that we explore.

Finally, X_t represents a vector of control variables. Inflation in the current year (t) depends on two factors: (1) inflation lags proxy for inflation expectations of backward-looking agents, and (2) inflation leads proxy for forward-looking agents. These considerations are motivated by the New Keynesian Phillips Curve (NKPC) framework (see Gali and Gertler, 1999; Chritiano, Eichenbaum, and Evans, 2005; Lanne and Luoto, 2014). There are also other determinants of inflation, such as import prices and oil prices (see Gordon, 1997, 2001; Gali and Monacelli, 2005; Blinder and Rudd, 2008) that influence the marginal cost of production; we factor them in. A key part of the NKPC is the role of unemployment rate in explaining inflation (see Roberts, 1995; Gali and Gertler, 1999; Sbordone, 2002). We model unemployment rate (UNEM) as well.

Equation (2), on the other hand, examines *RER* movements for the US dollar vis-a-vis Indonesian rupiah against control variables that capture the real one-month interbank rate or productivity differential between the US and Indonesia (see, also, Meese and Rogoff, 1988) and oil prices (see, also, Camarero and Tamarit, 2002; Chen and Chen, 2007; Narayan, 2013).

IV. DATA AND PRELIMINARY ANALYSIS

We use annual time-series data comprising a count of FinTech firms and macroeconomic data, namely, the rupiah–US dollar exchange rate, unemployment rate, inflation rate, import price index, and oil price over the period 1990–2017.[4] The data on FinTech companies are sourced from FinTech Indonesia Association. The macroeconomic data are sourced from CEIC data.[5] In Table 1, we describe all series, including those that are further transformed to suit the economic models developed below.

Table 1.
Variable Description

The table provides the definition and calculation of the variables used to investigate the macroeconomic implications of FinTech companies in Indonesia over the period 1998-2017.

Variables	Definition	Author's Calculations/Comments	Source
FINTECH_EST	Number of FinTech start-ups established each year		FinTech Indonesia Association
FINTECH_CUM	Total number of FinTech start-ups each year	Cumulative per year	FinTech Indonesia Association
INF	Inflation rate	Year-on-year percentage change in the Consumer Price Index (CPI, of all items; 2010 base year) Indonesia	CPI – International Financial Statistics; Author's calculations
MPI	Import Price Index	Base year: 2010=100	WB WDI
UNEM	Unemployment rate for Indonesia	(%)	CEIC
WTI	Crude Oil Prices: West Texas Intermediate	US$ per barrel	CEIC

4 FinTech-related data are available from 1998 onwards, hence all empirical models with FinTech cover only the period 1998–2017. However, we also estimate models over an extended period to capture the impact of traditional determinants of inflation or real exchange rate. Hence, the sample period differs between models with FinTech and models without FinTech. In Table 2, we report only descriptive statistics on the largest sample of the data series used.

5 See website: https://www.ceicdata.com

Table 1.
Variable Description (Continued)

Variables	Definition	Author's Calculations/Comments	Source
RER	Real exchange rate, expressed as the US dollar in terms of Rupiah. Increase in the *RER* indicates depreciation of the Rupiah against the US dollar and *vice versa*. (Average of the year)	$RER_t = \frac{USD}{Rupiah} * \frac{CPI_{US}}{CPI_{INDO}}$	Nominal exchange rate is sourced from CEIC; is calculated by the author.
RIR_D	Difference between United States and Indonesian 1-month Interbank Rate (Average of the year)	$RIR_{i,t} = Nominal\ interbank\ rate_{i,t} - inflation\ rate_{\ i,t},$ where *i* is the US or Indonesia; $RIR1_t = RIR_{Indo,t} - RIR_{US,t}$	Nominal interest rate: CEIC; CPI – CEIC; Inflation – author's calculations
DY	Difference of the productivity (Y) between the US and Indonesia	$DY = Y_{Indonesia} - Y_{US},$ where $Y_{Indonesia} = Log(RGDP_{Indonesia}) - Log(Employment_{Indonesia})$ and $Y_{US} = Log(RGDP_{US}) - Log(Employment_{US})$	Indonesia and US RGDP (US$b) and Employment (no. of person) data – CEIC; DY – author's calculations

Inflation over the period 1990–2017 averaged nearly 10% while the unemployment rate averaged 6.5%. Inflation in Indonesia reached as high as 59% in 1998, and the study period saw the lowest inflation (3.5%) in 2016. Such high variability is depicted in the series standard deviation of 37%. This variability may be explained by volatility in general import prices (with a standard deviation of 128) and the *WTI* (crude oil) price ($30). *WTI* averaged $US47 per barrel over the period 1990–2017, reaching a minimum price of $14.4 per barrel in 1998 and a maximum of $100 per barrel in 2008. The import price index averaged 188 over the study period, reaching its highest level (440) in 2012, and it was recorded lowest (118) in 1990.

Table 2.
Descriptive Statistics: 1990-2017

This table presents common statistics for the variables covered in the paper over the sample period specified for each variable. *FINTECH_EST* is the number of new established FinTech firms and *FINTECH* is the cumulative number of FinTech firms each year. The other variables are inflation rate (*INF*, %), unemployment rate (*UNEM*,%), *WTI* oil price, real exchange rate (*RER*), log difference in productivity between Indonesia and the US (*DY*) and difference in real interest rate between Indonesia and the US (*RIR_DIF*).

	FINTECH_ EST	*FINTECH_ CUM*	*INF*	*MPI*	*UNEM*	*WTI*	*RER*	*DY*	*RIR_ DIF*
Mean	6.9	28.9	9.8	188.1	6.5	46.8	11028.9	-1.6	1.7
Median	2	13	6.8	117.7	6.2	36.3	10507.6	-1.8	2.1
Maximum	35	137	58.5	439.7	11.2	99.7	21065.7	-1.2	11.9
Minimum	0	1	3.5	65.2	2.6	14.4	7998.7	-1.9	-7.2
Std. Dev.	9.9	36.8	10.4	127.7	2.4	29.4	3009.1	0.3	4.1
Sample period	1998-2017	1998-2017	1991-2017	1991-2017	1990-2017	1990-2017	1990-2017	1990-2017	1997-2016
Observations	20	20	27	27	28	28	28	28	20

RER averaged Rp11,029 over the period 1990–2017, with the rupiah seeing its lowest level (to Rp21,066) in 1998. The rupiah was strongest against the US dollar in 1996. Nonetheless, *RER* has lower variability than the inflation rate or unemployment rate. The productivity differential between Indonesia and the US is negative on average, suggesting that productivity in Indonesia lags the US. The difference in the one-month real interbank rate between Indonesia and the US is the most volatile series examined here. The one-month real interbank rate is, on average, higher in Indonesia by 1.7%. The difference in the interbank rate between the two countries reached a maximum in 1997 (nearly 12%), which is when this series begins for the present study. Sometimes, such as in 1998–99, 2005–2006, and 2008, the interbank rate in Indonesia was lower than that of the US.

Table 3.
Unit Root Tests

This table presents for all the variables belonging to the inflation (*INF*) and real exchange rate (*RER*) models, the unit root results derived from the conventional *ADF* test (with intercept) that tests the null hypothesis of a unit root. The associated lag length (Lags), test statistics (*T*-stat), and probabilities (Prob.) are reported for the variables in the first column in either levels, I(0) or in first difference, I(1) forms. Variables, namely import price index (*lMPI*), new FinTech start-ups each year (*FINTECH_NEW*), cumulative FinTech start-ups (*FINTECH_CUM*), WTI oil price (*lWTI*), and *lRER*, are not measured in percentage terms, hence represented in logarithmic (l) terms.

	I(0)			**I(1)**		
	Lags	***T*-stat**	**Prob.**	**Lags**	***T*-stat**	**Prob.**
INF	0	-4.139	0.004			
LMPI	0	-0.908	0.77	0	-5.104	0
UNEM	0	-1.794	0.375	0	-4.506	0.002
LFINTECH_NEW	0	-0.92	0.747	1	-5.389	0.003
LFINTECH_CUM	4	2.189	1	0	-6.474	0
LWTI	0	-1.061	0.716	0	-4.71	0.001
LRER	0	-1.413	0.561	0	-4.979	0.001
DY	0	-1.596	0.471	0	-5.071	0
RIR_DIF	0	-5.751	0			

Unit root test results, reported in Table 3, suggest that all, except *INF* and *RIR_dif*, are nonstationary or I(1) and become stationary only after first differencing. This means that *INF* and *RIR_dif* appear in our empirical models in level form, while the other variables appear in first differenced form.

V. EMPIRICAL RESULTS

Of key interest is the impact of the FinTech sector since 1998 on Indonesia's inflation and *RER*. Nonetheless, we carefully work with the control variables, particularly in the case of the inflation model, to arrive at a robust set of models. As a result, we estimate several models of inflation and *RER*. Tables 4 and 5, respectively, report the robust models of inflation and *RER*.

Beginning with the inflation models, we use the Schwarz and Hannan–Quinn information criteria to choose the appropriate number of lags and leads of inflation. We begin with a model with four lags and leads and successively reduce the number of lags and leads by one until we come to models with only one lag or one lead. We repeat this for five sets of models, each with either the traditional variables (*DY*, and *RIR_dif*); *FINTECH_EST* and traditional variables; *FINTECH_EST*, lags of *FINTECH_EST*, and traditional variables; *FINTECH_CUM* and traditional variables; and *FINTECH_CUM*, lags of *FINTECH_CUM*, and traditional variables.

Table 4.
Inflation Models

This table displays the estimated output for selected inflation models. Model 1 depicts the traditional inflation model with determinants, backward inflation (*INF*(-1)), unemployment rate (Δ*UNEM*), oil price (*WTI*), and import prices (*MPI*). We augment model 1 with the number of new FinTech companies established each year (*FINTECH_EST*) or FinTech companies cumulative each year (*FIN_CUM*) (models 2 and 3). Models 4 and 5 comprise of variables from all models including one- and/or two-period lags of *FINTECH_CUM*. *, **, *** denote level of significance at the 10. 5. And 1 per cent levels.

Models	**1**		**2**		**3**		**4**		**5**	
Variable	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**
C	12.884***	0.001	4.771	0.149	8.335	0	8.283	0.005	8.234	0.068
INF(-1)	-0.083	0.724	0.335	0.362	0.162**	0.027	0.403	0.113	0.336	0.239
ΔUNEM	1.089	0.555	0.95	0.499	1.320*	0.084	1.891**	0.045	1.435	0.269
ΔLWTI	22.278	0.185	4.597	0.562	5.926	0.296	5.953	0.307	5.722	0.364
ΔLMPI	-49.763**	0.028	-4.915	0.681	-6.032	0.441	-6.481	0.417	-7.135	0.415
ΔLFINTECH_CUM					-8.270***	0.004	-12.545***	0.006	-14.146*	0.067
ΔLFINTECH_CUM(-1)							-2.566	0.453	-1.247	0.819
ΔLFINTECH_CUM(-2)									2.192	0.572
ΔLFINTECH_EST			-0.329	0.786						
Adjusted R-squared	0.182		-0.325		0.713		0.457		0.358	

From this exercise, we first note that the one-year lagged inflation structure is the most robust in all the sets of models considered. Second, we find that *FINTECH_EST*, which is simply a count of new FinTech startups, is never robust in any of the sets estimated (model (2) is one example). Third, the instantaneous effects of *FINTECH_CUM* are significant in most cases. We report the most robust results under model 3. Fourth, lags of *FINTECH_CUM* are insignificant, as reported in model 4. Overall, *FINTECH_CUM* is found to have a negative effect, and this effect is instantaneous (models 3–5). This means that our hypothesis, that FinTech reduces inflation, is accepted. It seems that FinTech collectively assists in reducing the cost of conducting business as well as transaction costs for customers.

Table 5.
RER Models

This table reports estimated output for the *RER* models. The dependent variable, *lRER* is real exchange rate, expressed as US dollar in terms of the Rupiah, where an increase in real exchange rate indicates a depreciation of the Rupiah against the US dollar. The traditional determinants of the *RER* are the Difference in Productivity (*DY*) and real interest rate (*RIR_DIF*) between Indonesia and the US. Model 1 captures these traditional variables only. Several authors also find oil price to significantly determine the *RER*, hence we use *WTI* (Model 2). We augment Model 2 with the number of new FinTech companies established each year (*FINTECH_EST*) or cumulative each year (*FIN_CUM*) (models 3 and 4). Models 5 and 6 comprise of the one- and/or two-period lagged effects of *FINTECH_CUM*. *, **, *** denote level of significance at the 10, 5, and 1 per cent levels.

Models	1		2		3		4		5		6	
Variable	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**
C	-0.054***	0.008	-0.052**	0.017	-0.025**	0.054	-0.058***	0.005	0.008	0.808	0.011	0.725
ΔDY	-1.575***	0	-1.553***	0	-2.269***	0	-2.647***	0	-2.397***	0	-2.263***	0
RIR_DIF	0.009***	0.049	0.008*	0.074	0.004	0.265	0.004	0.474	0.004	0.313	0.003	0.398
ΔLWTI			-0.02	0.759	-0.003	0.945	0.014	0.779	0.028	0.488		
ΔLFINTECH_CUM							0.065	0.296	-0.014	0.885	-0.029	0.756
ΔLFINTECH$_{CUM}$ (-1)									-0.083	0.139	-0.072	0.16
ΔLFINTECH$_{CUM}$ (-2)									-0.074*	0.053	-0.073**	0.048
ΔLFINTECH_EST					0.002	0.854						
Adjusted R-squared	0.909		0.904		0.897		0.853		0.945		0.912	

The traditional determinants of inflation are significant in Narayan et al. (2018), which uses monthly data. Here, with annual data, the traditional determinants of inflation are mainly insignificant (model 1). Taken together, this means that the effects of the traditional factors do not seem to persist up to one year. Nonetheless, when we model only the instantaneous effects of *FINTECH_CUM*, we note that backward expectations and unemployment rate become significant. Unemployment is found to have a positive effect on inflation—suggesting that the Phillips curve is not to be found with annual data. This result is not uncommon. With monthly data, Narayan et al. (2018) suggest the presence of a Phillips curve.

Backward expectations of the economic agents are associated with higher inflation in the current year (model 3). This means that economic agents who draw on the previous year to build their expectations of inflation in the current year usually expect inflation to be higher, which forms a basis for pricing on future financial contracts. However, when we use a model that accounts for the instantaneous and lagged effects of the FinTech sector, the effects of such expectations become insignificant. This finding is evidence that the presence of FinTech helps to stabilize inflation expectations.

Let us now turn to the *RER* models and discuss the impact of traditional factors. We find that FinTech is not able to disturb the effects of the traditional factors on *RER*. These remain prominent even with FinTech. *FINTECH_EST*, as in inflation models, is not an important variable, but *FINTECH_CUM* is. However, *FINTECH_CUM* has only a negative but delayed effect. The negative effect of *RER* indicates that increases in cross-border FinTech activity strengthens the rupiah against the US dollar. Plus, the delayed effect probably reflects that economic agents begin to use FinTech services more often only as they become more experienced using services offered by FinTech companies and begin to trust FinTech firms. Venkatesh and Bala (2008) make a point that once individuals get accustomed to the IT system (offered by the FinTech) and gain hands-on experience with the IT system, the effect of perceived ease of use on behavioural intentions will recede into the background and allow these customers to continue using the system. Maier (2016) finds that apart from greater convenience (speed, flexibility, and simplicity), the switching of small to medium enterprise borrowers from traditional bank financing to crowdlending (Fintech) is also driven by process transparency.

VI. CONCLUSION

FinTech innovation is disruptive and is not free of risk. It uses technology-integrated business models that deliver financial services to customers in a more cost effective and convenient manner than traditional financial service providers. This paper examines whether the FinTech sector in Indonesia impacts its macroeconomy, mainly via inflation and the real exchange rate.

Overall, we propose and test two hypotheses: (1) that FinTech (measured as *FINTECH_CUM*) reduces costs, which should be reflected in the inflation rate; and (2) that FinTech (measured as *FINTECH_CUM*) leads to greater cross-border financial activity, which may see the rupiah–US dollar exchange rate become responsive to FinTech activity. Our empirical analyses provide evidence in favor of both hypotheses. The *RER* models are specifically for foreign transactions, and we see delayed effects of FinTech only on *RER*.

While the results in this study give some indications that FinTech has implications for inflation and exchange rate, it is too early to draw a policy implication. It is true that FinTech is growing rapidly and could bring down costs and improve the quality of financial services. However, its share in the economy and financial markets remains small. Moreover, there are potential risks to financial stability emanating from FinTech. Taking into account financial stability, which is beyond the scope of this research, would allow a more comprehensive understanding of the impacts of FinTech on the economy, and its policy implications. We leave these issues for future research. The important conclusion here is that the macroeconomy is influenced by FinTech—a finding that future studies will be able to use as motivation to develop new research ideas.

REFERENCES

Bromberg, L., Godwin, A., and Ramsay, I. (2018). Cross-border cooperation in financial regulation: crossing the FinTech bridge. *Capital Markets Law Journal*, 13, 59-84.

Camarero, M., and Tamarit, C. (2002). Oil prices and Spanish competitiveness: a cointegrated panel analysis. *Journal of Policy Modeling*, 24, 591–605.

Chui, I. H-Y. (2017). Fintech and Disruptive Business Models in Financial Products, Intermediation and Markets - Policy Implications for Financial Regulators. *Journal of Technology Law and Policy*, 21, 55-112.

Chen, S. S. and Chen, H. C. (2007). Oil prices and real exchange rates. *Energy Economics*, 29, 390–404.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (2005). Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy*, 113: 1-45.

FinTech Singapore News. (2018). *The FinTech Indonesia Report*. Downloaded from: http://FinTechnews.sg/20712/indonesia/FinTech-indonesia-report-2018/

Gali, J., and Monacelli, T. (2005). Monetary policy and exchange rate volatility in a small open economy. *Review of Economic Studies*, 72, 707–734.

Gali, J., and Gertler, M. (1999). Inflation dynamics: A structural econometric analysis. *Journal of Monetary Economics*, 44, 195-222.

Gordon, R. J. (1997). The time-varying nairu and its implications for economic policy. *Journal of Economic Perspectives*, 11, 11–32.

Gordon, R. J. (2011). The history of the Phillips curve: consensus and bifurcation. *Economica*, 78, 10–50.

Jagtiani, J., and Lemieux, C. (2018). Do FinTech lenders penetrate areas that are underserved by traditional banks?. *Journal of Economics and Business*, Forthcoming.

Lannet, M., and Luoto, J. (2014). Does Output Gap, Labour's Share or Unemployment rate drive inflation?. *Oxford Bulletin of Economics and Statistics*, 76, 715-726.

Lee, I., and Shin, Y. J. (2018). FinTech: Ecosystem, business models, investment decisions and challenges. *Business Horizons*, 61, 35-46.

Meese, R., and Rogoff, K. (1988). Was it real? The exchange rate-interest rate differential relation over the modern floating-rate period. *Journal of Finance*, 43, 933-948.

Maier, E. (2016). Supply and demand on crowdlending platforms: connecting small and medium sized enterprise borrowers and consumer investors. *Journal of Retailing and consumer Services*, 33, 143-153.

Narayan, P., Narayan, S., Rahman, R. E., and Setiawan, I. (2018). Bitcoin Price Growth and Indonesia's Monetary System. *Emerging Markets Review*, Forthcoming.

Narayan, S. (2013). Foreign exchange markets and oil price in Asia. *Journal of Asian Economics*, 28, 41–50.

Puschmann, T. (2017). FinTech, Business & Information Systems Engineering. *The International Journal of WIRTSCHAFTSINFORMATIK*, 59, 69-76.

Roberts, J. M. (1995). New Keynesian economics and the Phillips curve. *Journal of Money, Credit and Bankin*g, 27, 975–984.
Sbordone, A. M. (2002). Prices and unit labor costs: a new test of price stickiness. *Journal of Monetary Economics*, 49, 265–292.
Temelkov, Z. (2018). Fintech firms opportunity or threat for banks?. *International Journal of Information, Business and Management,* 10, 137-143.
Venkatesh, V., and Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences*, 39, http://dx.doi.org/10.1111/j.1540-5915.2008.00192.x.

This page is intentionally left blank