Bulletin of Monetary Economics and Banking

Volume 26 | Number 4 Article 3

11-30-2023

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Recommended Citation
Narayan, Paresh K. and Phan, Dinh Hoang Bach (2023) "Do Financial Technology Firms Influence Labour Force Outcomes in Indonesian Banks?," *Bulletin of Monetary Economics and Banking*: Vol. 26: No. 4, Article 3.
DOI: https://doi.org/10.59091/2460-9196.1725
Available at: https://bulletin.bmeb-bi.org/bmeb/vol26/iss4/3

Bulletin of Monetary Economics and Banking, Vol. 26 No. 4, 2023, pp. 587 - 606
p-ISSN: 1410 8046, e-ISSN: 2460 9196

DO FINANCIAL TECHNOLOGY FIRMS INFLUENCE LABOUR FORCE OUTCOMES IN INDONESIAN BANKS?

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ABSTRACT

In this paper, we examined the influence of technology growth on labour outcomes. Using a sample of 37 Indonesian banks and data on Financial Technology (FinTech) firms from 1998 to 2017, we discovered that technology growth negatively influences the number of employees and positively impacts employee compensation. The role of technology in these labour market outcomes are both statistically and economically meaningful. Economically, for instance, with an increase of 1 standard deviation in the number of FinTech establishments, the number of Indonesian bank employees decreases by up to 2.30% of mean employees (equivalent to 58 employees) and employee compensation improves by up to 17.83% of mean compensation (equivalent to US$1,830). Furthermore, we showed that bank characteristics affect technology growth–labour outcomes relation. The effect of technology growth on labour outcomes is stronger for banks that have a bigger market value, are more mature, and are private.

Keywords: Technology growth; Labour outcome; Banks; Indonesia.
JEL Classifications: G00; E20; J21.

Article history:
Received : March 03, 2022
Revised : September 04, 2022
Accepted : February 26, 2023
Available Online : November 30, 2023

https://doi.org/10.59091/2460-9196.1725

I. INTRODUCTION

Digital innovation plays an important role in the evolution of the financial system and economic development. In the financial system and other sectors, the transformation due to digital innovations incorporates challenges for macroeconomic policy and financial stability (Carbó-Valverde, 2017). Given the potential systemic impact of digital innovations, the central banks, supervisors, and regulators need to monitor these innovations carefully, understand the deep-seated changes and new practices that they bring, and identify and assess their benefits and risks to the financial system (Villeroy de Galhau, 2016).

Recently, the emerging player in the finance sector is financial technology or FinTech firms, which refer to start-ups that commercialise technology-based financial innovations. Huang (2015) defines FinTech firms as those that apply innovative technology for banking, payments, financial data analytics, capital markets, and personal financial management. A key feature of FinTech firms is they perform tasks previously reserved for banks, such as lending, payments, or investments (Chishti and Barberis, 2016; Puschmann, 2017). There are four types of FinTech firms, as discussed in Brandl and Hornuf (2017): (i) payments (e.g. cryptocurrencies and alternative payment systems); (ii) financing (e.g. crowdfunding, crowdlending, and crowd investing); (iii) asset management (e.g. robot advice, social trading, and factoring); and (iv) others (e.g. search engines and infrastructure providers).

Indonesia has a fair share of experience in FinTech growth, which has been remarkable. Between 2013 and 2017, Indonesian FinTech start-ups enjoyed US$56 million of funding, according to the Tech in Asia Database. Indonesia's Fintech Association, established in 2015, reveals that there were 135–140 FinTech firms in 2016 which increased to 190 firms in 2017. This marks more than a 35% increase in just 1 year. In addition, the growth in the number of FinTech firms in 2015–2016 was estimated at over 75%.

Despite the emergence of digital innovation and its perceived effect on the financial industry, the effect of digital innovations and FinTech growth on the financial system is less understood. A few exceptions are (i) Cumming and Schwienbacher (2016), who investigated the pattern of venture capital investment in FinTech using a global sample of firms; (ii) Haddad and Hornuf (2018), who examined the economic and technological determinants of the global FinTech market; (iii) Brandl and Hornuf (2017), who traced the transformation of the financial industry after digitalisation; (iv) Li *et al*. (2017), who examined the effect of FinTech start-ups on incumbent retail banks' share prices; and (v) Phan *et al*. (2019) who tested how FinTech growth influences bank performance in Indonesia.

In this paper, we used the number of FinTech firms as the proxy for the technology growth in the banking sector and tested how it affects bank labour outcomes, such as the number of employees and employee compensation. One strand in the literature shows a negative relationship between technology change and employment (Miller, 1964; Standing, 1984; Rotman, 2013; Autor, 2015; Kim *et al*., 2017). Therefore, our first hypothesis is that technology growth, proxied by the number of FinTech firms established, negatively affects the number of employees of Indonesian banks. In addition, adopting new technology can improve the firm's productivity and profitability (Stoneman and Kwon, 1996; Boothby *et al*., 2010;

https://bulletin.bmeb-bi.org/bmeb/vol26/iss4/3
DOI: 10.59091/2460-9196.1725

Chen, 2020). Therefore, our second hypothesis is that technology growth positively affects employee compensation.

To test our hypotheses, we used a sample of 37 Indonesian banks and data on financial technology firms from 1998 to 2017. The results confirmed our hypotheses as we found that technology growth negatively influences the number of employees and positively impacts employee compensation. In terms of the economic significance of the technology growth–labour outcomes relation, with an increase of 1 standard deviation (equivalent to three FinTech firms) in the number of FinTech establishments, the number of Indonesian bank employees falls by up to 2.30% of mean total bank employees (equivalent to 58 employees). On the other hand, a 1 standard deviation increase in FinTech establishments improves bank employee compensation by at most 17.83% of mean employee compensation (equivalent to US$1,830). In addition, bank characteristics such as market value, bank age, and types of ownership affect the technology growth–labour outcomes relation. The stronger effect of technology growth on labour outcomes is found in banks with larger market value, greater maturity, and private ownership.

This paper proceeds as follows. Section II discusses the data and the empirical framework whilst Section III discusses the results. Finally, Section IV presents our concluding remarks.

II. DATA AND EMPIRICAL FRAMEWORK

We collected data of Indonesian banks to test the relation between technology growth and labour outcomes. Our data are from several sources. Our proxy for technology growth in the finance sector is the number of FinTech companies founded in Indonesia. This data set is from FinTech Indonesia Association. Our bank-level data, which include both dependent and control variables, is from the Datastream database. The dependent variable, labour outcomes, is measured by the number of employees (*EN*) and employee compensation (*EC*). We used several bank-level control variables, namely, the book leverage ratio (*LEV*), the bank's profitability (*PRO*), bank size (*SIZE*), and bank's stock returns (*RET*). We also applied Indonesian macro-level control variables such as the unemployment rate (*UN*), GDP growth rate (*GDP*), inflation rate (*INF*), and the stock exchange return (*MKT*). These macro-level data are collected from the World Bank World Development Indicators (except for the *MKT* data which is from Datastream). Based on data availability, our data sample is annual data from 1998 to 2017.[1] We collected all Indonesian banks available in the Datastream database and we ended up with a sample of 37 banks. Overall, we had 498 bank-year observations. Table 1 shows the detailed description of the variables whilst Table 2 reports selected descriptive statistics for the variables.

[1] Our sample starts from 1998, when the first Indonesian FinTech firm was established.

Table 1.
Description of Variables

This table describes the variables and notes their source.

Variable	Description	Source
Dependent variables		
Employee numbers (*EN*)	Log of the employee number	Datastream
Employee compensation (*EC*)	Log of salaries and benefits per employee	Datastream
Explanatory variable		
Technology growth (financial technology [FinTech])	Log of the number of fintech companies established	Fintech Indonesia Association
Firm-specific control variables		
Book leverage (*LEV*)	Long-term debt plus debt in current liabilities divided by assets	Datastream
Profitability (*PRO*)	Ratio of operating income to total assets	Datastream
Firm size (*SIZE*)	Log of total assets	Datastream
Stock return (*RET*)	Annual stock return	Datastream
Macro control variables		
Unemployment (*UN*)	Annual unemployment rate	World Bank
GDP growth rate (*GDP*)	Indonesia annual GDP growth rate	World Bank
Inflation (*INF*)	Indonesian annual inflation rate	World Bank
Market return (*MKT*)	Annual IDX index return	Datastream

Source: Authors

To test the impact of technology growth on labour outcomes, we followed the literature that investigates the determinants of employee turnover and employee compensations (Rayton, 2003; Aldatmaz *et al*., 2018). We incorporated our technology growth variable (*FinTech*) to the conventional model suggested by the literature. Our empirical model takes the following forms:

$$LO_{i,t} = \alpha + \beta_1 FinTech_t + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where, where *LO* is labour outcomes measured by the number of employees (*EN*) and employee compensation (*EC*) measured as the total salaries and benefits; *FinTech* represents technology growth; *i* indexes the firms; *t* denotes the year; *Control* represents two sets of control variables, namely, firm-level control variables (*LEV, PRO, SIZE,* and *RET*), and macro-level control variables (*GDP*, *UN*, *INF*, and *MKT*). We clustered standard errors and controlled for bank and year fixed effects.

Table 2 provides selected descriptive statistics for our variables, including the number of observations, the mean, the median, the standard deviation, and the 25th and 75th percentiles of each variable for a panel of 37 Indonesian banks. On average, nearly six new FinTech firms were established every year in Indonesia during 1998–2017. The mean values of the log of the number of employees (*EN*) and the log of salaries and benefits per employee (*EC*) are 7.826 and 2.331, respectively. These statistics imply that, on average, Indonesian banks have more than 2,500 employees and their yearly compensations are valued at $10,300. The average stock return of Indonesian banks is 6.16% compared to the Indonesian aggregate stock market return of 13.59% over the period 1998–2017. The average

GDP, unemployment rate, and inflation rate during this period were 5.093%, 5.719%, and 7.465%, respectively.

Table 2.
Descriptive Statistics

This table has selected descriptive statistics of the data.

Variable	Observation	Mean	Median	Std. Dev.	25th	75th
EN	498	7.826	1.689	6.460	7.929	8.998
EC	494	2.331	0.614	1.951	2.337	2.734
FINTECH	498	1.670	1.085	0.693	1.792	2.485
LEV	498	0.077	0.096	0.020	0.057	0.105
PRO	497	0.008	0.045	0.006	0.014	0.023
SIZE	498	14.412	1.857	12.912	14.417	15.880
RET (%)	431	6.106	48.735	-17.726	5.349	32.850
MKT (%)	498	13.589	31.354	-0.990	15.046	37.934
GDP (%)	498	5.093	2.046	4.876	5.067	6.030
UN (%)	498	5.719	1.354	4.336	5.614	6.795
INF (%)	498	7.465	6.115	4.386	6.363	10.227

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

III. EMPIRICAL ANALYSIS

A. Benchmark Model

Our empirical analysis starts with estimating the traditional determinants of labour outcomes using fixed-effect models. This regression model is considered as the benchmark for other analyses in which technology growth variables are included. The results are reported in Table 3. To investigate the robustness of our hypothesis test, we estimated the regression models five times, each time using a different set of control variables. Specifically, we used each firm-level control variable with all macro control variables in models (1) to (4) whilst model (5) comprises all control variables. In all models, we controlled for firm and year fixed effects. Several noteworthy features were observed. Consider macro variables first. We found that *INF* and *GDP* are the strongest determinants for labour outcomes where their coefficients are statistically significant at the 1% level in 8 out of 10 regressions. They are followed by *MKT* and *UN* with statistically significant coefficients in 7 out of 10 cases. For firm control variables, every *LEV* and *SIZE* significantly determine labour outcomes whilst *PRO* and *RET* do not exert any statistical significance. Finally, the adjusted R-squared is at least 76% across all models, which indicates a good fit.

Table 3.
Determinants of Labour Outcomes

This table reports the results for testing the contemporaneous effect of technology growth on labour outcomes. The regression takes the following form: $LO_{i,t} = \alpha + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$, where *LO* is labour outcomes measured by the number of employees (*EN*) and employee compensation (*EC*); *FinTech* represents technology growth; *i* indexes the firms; *t* denotes the year. We report the coefficients and its corresponding t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

Variables	Number of Employees					Employee Compensation				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
LEV	-3.546***				-2.206***	2.131***				2.205***
	(-12.127)				(-9.169)	(9.892)				(8.009)
PRO		-0.767			-1.587**		0.174			0.631
		(-0.630)			(-2.309)		(0.155)			(1.070)
SIZE			0.851***		0.663***			-0.204**		-0.037
			(12.225)		(8.605)			(-2.642)		(-0.438)
RET				-0.001	0.000				0.000	0.000
				(-1.522)	(-0.648)				(0.498)	(0.264)
MKT	0.000	0.004	0.025***	0.007	0.022***	-0.042***	-0.044***	-0.049***	-0.044***	-0.043***
	(0.106)	(0.745)	(6.407)	(1.386)	(6.255)	(-23.888)	(-14.188)	(-20.250)	(-16.474)	(-16.256)
GDP	0.039	0.190*	0.541***	0.209**	0.480***	-0.827***	-0.910***	-0.993***	-0.901***	-0.865***
	(0.572)	(1.893)	(8.301)	(2.742)	(7.429)	(-25.465)	(-12.747)	(-22.550)	(-22.208)	(-13.997)
UN	0.070	0.334	2.007***	0.501	1.672***	-3.080***	-3.229***	-3.628***	-3.200***	-3.150***
	(0.245)	(0.814)	(6.757)	(1.324)	(6.547)	(-24.430)	(-13.911)	(-20.003)	(-16.526)	(-15.869)
INF	0.012	0.034	0.158***	0.041**	0.142***	-0.263***	-0.275***	-0.305***	-0.274***	-0.273***
	(0.702)	(1.420)	(9.223)	(2.214)	(8.387)	(-31.404)	(-17.216)	(-22.785)	(-27.672)	(-16.379)
Constant	7.983***	5.739**	-16.926***	4.978**	-12.030***	21.551***	22.819***	28.247***	22.682***	22.689***
	(4.738)	(2.411)	(-7.586)	(2.348)	(-5.380)	(28.601)	(16.033)	(14.663)	(20.699)	(9.546)
Observations	498	497	498	431	431	494	494	494	430	430
Adjusted *R*-squared	0.939	0.916	0.952	0.915	0.960	0.832	0.770	0.786	0.764	0.840

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DOI: 10.59091/2460-9196.1725

B. Effect of Technology Growth on Labour Outcomes

We now turn to our hypothesis that technology growth influences labour outcomes in Indonesian banks. Table 4 reports the results obtained from equation (1), where we tested the contemporaneous effect of *FinTech* on the number of bank employees and bank employee compensation. Similar to the benchmark model, we also estimated equation (1) five times with different combinations of the control variables. We first considered the results on the number of employees. The coefficients of FinTech are negative and statistically significant at least at the 5% level in four out of five model specifications. The results strongly support our hypothesis that technology growth negatively impacts the number of Indonesian bank employees. The effect of technology growth on the number of employees is also economically meaningful. The magnitudes of the FinTech slope coefficients vary in at 0.104 to 0.166 range. This implies that a 1 standard deviation (equivalent to three FinTech firms) increase in the fintech number will lead to a decrease in the mean value of employees in Indonesian banks (which is 2,500) by 1.39%–2.30%.

The results from the last three columns of Table 4 confirm our hypothesis on the positive effect of technology growth on employee compensation. The slope coefficients on FinTech are between 0.328 (*t*-statistic = 25.549) to 0.383 (*t*-statistic = 22.706) in models (1) and (5), respectively. In terms of economic significance, a 1 unit standard deviation (equivalent to three fintech firms) increase in the FinTech number leads to an increase in the mean value of employee compensation (equivalent to $10,300) in Indonesian banks by 15.27%– 17.83%.

Table 4.
Contemporaneous Effect of Technology Growth on Labour Outcomes

This table reports the results for testing the contemporaneous effect of technology growth on labour outcomes. The regression takes the following form: $LO_{i,t} = \alpha + \beta_1 FinTech_t + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$ where *LO* is labour outcomes measured by the employee number (*EN*) and employee compensation (*EC*); *FinTech* represents technology growth; *i* indexes the firms; *t* denotes the year. We report the coefficients and its corresponding t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Variables	Number of Employees					Employee Compensation				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
FINTECH	-0.039	-0.115**	-0.166***	-0.104**	-0.140***	0.328***	0.371***	0.383***	0.375***	0.349***
	(-1.255)	(-2.744)	(-5.388)	(-2.607)	(-4.737)	(22.549)	(13.301)	(22.706)	(16.953)	(15.805)
LEV	-3.546***				-2.206***	2.131***				2.205***
	(-12.127)				(-9.169)	(9.892)				(8.009)
PRO		-0.767			-1.587**		0.174			0.631
		(-0.630)			(-2.309)		(0.155)			(1.070)
SIZE			0.851***		0.663***			-0.204**		-0.037
			(12.225)		(8.605)			(-2.642)		(-0.438)
RET				-0.001	0.000				0.000	0.000
				(-1.522)	(-0.648)				(0.498)	(0.264)
MKT	-0.005***	-0.013***	0.001	-0.008***	0.001	0.006***	0.010***	0.007***	0.011***	0.008***
	(-4.548)	(-6.955)	(0.878)	(-5.839)	(0.603)	(7.392)	(6.504)	(6.943)	(11.535)	(7.813)
GDP	-0.086**	-0.175***	0.016	-0.121**	0.035	0.212***	0.264***	0.218***	0.286***	0.241***
	(-2.545)	(-4.767)	(0.420)	(-2.243)	(0.851)	(12.396)	(13.253)	(8.354)	(9.125)	(9.897)
UN	-0.328***	-0.830***	0.335***	-0.551***	0.253**	0.236***	0.515***	0.236***	0.587***	0.378***
	(-4.638)	(-6.708)	(3.887)	(-5.120)	(2.337)	(4.476)	(5.204)	(2.902)	(7.626)	(5.303)
INF	-0.025*	-0.072***	0.005	-0.055**	0.012	0.040***	0.067***	0.049***	0.072***	0.049***
	(-1.861)	(-4.629)	(0.373)	(-2.845)	(0.785)	(6.222)	(6.514)	(4.702)	(6.568)	(5.165)
Constant	10.671***	13.591***	-5.651***	12.071***	-2.463	-0.800**	-2.424***	2.194	-2.844***	-1.095
	(18.509)	(18.583)	(-3.612)	(14.188)	(-1.420)	(-2.233)	(-3.987)	(1.315)	(-5.039)	(-0.697)
Observations	498	497	498	431	431	494	494	494	430	430
Adjusted *R*-squared	0.939	0.916	0.952	0.915	0.960	0.832	0.770	0.786	0.764	0.840

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

We next examined the lagged effect of technology growth on the number of employees and employee compensation in Indonesian banks.

$$LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

The results are reported in Table 5 and mirror those in Table 4. Technology growth negatively affects the number of employees and positively affects employee compensation. The coefficients of the one-lag *FinTech* variable are negative and statistically significant in four out of five models of the number of bank employees. In addition, FinTech slope coefficients are found to be positive and statistically significant at the 1% level in all three models of employee compensations. The economic significance of the effects is also strong. On average, a unit standard deviation (equivalent to three fintech firm) increase of FinTech number leads to (i) a decrease in the number of employees by 1.18%–2.41%, and (ii) an increase in the employee compensations by 12.57%–14.76%.

Table 5.
Lagged Effect of Technology Growth on Labour Outcomes

This table reports the results for testing the lagged effect of technology growth on labour outcomes. The regression takes the following form: $LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$ where *LO* is labour outcomes measured by the employee number (*EN*) and employee compensation (*EC*); *FinTech* represents technology growth; *i* indexes the firms; *t* denotes the year. We report the coefficients and its corresponding t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Variables	Number of Employees					Employee Compensation				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
FINTECH	-0.037	-0.085*	-0.174***	-0.091**	-0.154***	0.270***	0.299***	0.317***	0.293***	0.276***
	(-1.325)	(-2.001)	(-6.285)	(-2.521)	(-6.038)	(21.953)	(10.203)	(20.006)	(16.104)	(14.427)
LEV	-3.764***				-2.326***	2.261***				2.358***
	(-18.156)				(-10.387)	(12.079)				(9.049)
PRO		-0.929			-1.763*		0.430			0.550
		(-0.559)			(-2.033)		(0.272)			(0.757)
SIZE			0.853***		0.663***			-0.203**		-0.028
			(12.021)		(8.219)			(-2.589)		(-0.311)
RET				-0.001	0.000				0.000	0.000
				(-1.572)	(-0.489)				(0.527)	(0.245)
MKT	-0.005***	-0.007***	0.002***	-0.005***	0.001	-0.005***	-0.004***	-0.006***	-0.004***	-0.005***
	(-10.256)	(-6.223)	(3.692)	(-12.081)	(1.183)	(-19.813)	(-4.023)	(-8.980)	(-15.322)	(-8.582)
GDP	-0.056***	-0.083***	0.133***	-0.043	0.135***	-0.040***	-0.024*	-0.074***	-0.005	-0.026
	(-4.297)	(-4.733)	(6.396)	(-1.718)	(4.968)	(-4.473)	(-1.921)	(-3.441)	(-0.331)	(-1.088)
UN	-0.307***	-0.533***	0.299***	-0.405***	0.159**	-0.338***	-0.207***	-0.415***	-0.211***	-0.304***
	(-12.629)	(-6.273)	(5.180)	(-14.208)	(2.514)	(-18.770)	(-2.914)	(-6.624)	(-11.592)	(-6.113)
INF	-0.022**	-0.044***	0.004	-0.041***	0.006	-0.016***	-0.003	-0.015	-0.004	-0.017**
	(-2.343)	(-3.125)	(0.379)	(-2.891)	(0.628)	(-4.016)	(-0.333)	(-1.732)	(-0.575)	(-2.561)
Constant	10.387***	11.526***	-6.140***	10.870***	-2.536	3.556***	2.903***	7.158***	2.888***	3.777**
	(48.774)	(28.316)	(-4.320)	(42.081)	(-1.602)	(28.581)	(7.944)	(4.504)	(20.516)	(2.266)
Observations	493	492	493	426	426	489	489	489	425	425
Adjusted R-squared	0.940	0.916	0.952	0.915	0.961	0.829	0.763	0.779	0.754	0.837

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

C. Additional Tests

Although both contemporaneous and lagged effects of technology growth on the number of bank employees and employee compensation are consistently confirmed in previous analyses, how that relation is shaped is worth investigating. We focus on identifying any role that firm characteristics, such as market value, firm age, and ownership, might have in the technology–labour outcomes relation.

To test the impact of a firm's market value, we created a dummy variable *LARGE* (*SMALL*), which is set to a value of 1 if a firm's market value is above (below) the average market value of all banks over the sample period, and a value of 0 otherwise. We incorporated the market value depicting the dummy variables into our regression models in the following manner:

$$LO_{i,t} = \alpha + \beta_1 FinTech_t * LARGE_i + \beta_2 FinTech_t * SMALL_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

$$LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} * LARGE_i + \beta_2 FinTech_t * SMALL_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

The results of this analysis are reported in Table 6, where panel A contains results of the contemporaneous effect whilst the lagged effect results occupy panel B. The previous findings are confirmed in this analysis, too. For instance, we found that, statistically, technology growth significantly and negatively affects the number of bank employees whilst its effect on employee compensation is positive and statistically significant. The new feature of the results we observed relates to the effect of the market value of banks on this relation. The absolute value of β_1 is higher than the absolute value of β_2, indicating that the effect of technology on firms with large market value is stronger than on firms with small market value. A 1 standard deviation (equivalent to three FinTech firms) increase in technology growth leads to a decrease of up to 2.19% of the mean value of the number of employees of large banks (equivalent to 67 employees), whilst the corresponding decrease for small banks is equivalent to 45 employees. Consider the effect on employee compensation. The increase in employee compensation due to a standard deviation increase of technology growth is at least 15.81% (equivalent to $1,640) of the mean value of employee compensations for large banks and at least 15.32% (equivalent to $1,550) for smaller banks. In the case of the lagged effect, the stronger effect of technology growth on labour outcomes on large banks can be evidenced by two points: (i) the slope coefficients of the *FinTech* variable for the large banks, β_1, are statistically significant in all cases whilst it is (β_2) only significant in four out of six cases for the smaller banks; and (ii) the magnitude of β_1 is bigger than the magnitude of β_2 in five out of six cases. Therefore, the conclusion, taking all evidence together, is that technology growth has a stronger effect on labour outcomes for banks with a larger market value compared to those with smaller market value.

Table 6.
Effect of Market Value on Technology Growth–Labour Outcomes Relation

This table reports the results for testing the effect of the market value of firms on technology growth-labour outcomes relation. The regressions take the following form: $LO_{i,t} = \alpha + \beta_1 FinTech_t * LARGE_i + +\beta_2 FinTech_t * SMALL_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$ and $LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} * LARGE_i + +\beta_2 FinTech_{t-1} * SMALL_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$. Where *LO* is labour outcomes measured by employee number (*EN*) and employee compensation (*EC*); *FinTech* represents technology growth; *LARGE* is a dummy variable, which equals 1 if the firm market value in a firm is higher than the average of all firms in the sample or equals zero otherwise; *SMALL* is a dummy variable, which equals 1 if the firm market value in a firm is lower than the average of all firms in the sample or equals zero otherwise; *i* indexes the firms; *t* denotes the year. We report the coefficients and its corresponding t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Contemporaneous Effect										
Variables	**Number of Employees**					**Employee Compensation**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FINTECH*LARGE	-0.099**	-0.155***	-0.170***	-0.159***	-0.177***	0.329***	0.381***	0.400***	0.376***	0.356***
	(-2.793)	(-3.242)	(-4.337)	(-3.273)	(-4.525)	(17.391)	(13.616)	(23.242)	(16.262)	(13.948)
FINTECH*SMALL	0.008	-0.083*	-0.162***	-0.050	-0.098***	0.327***	0.357***	0.361***	0.373***	0.341***
	(0.208)	(-1.851)	(-5.165)	(-1.215)	(-3.112)	(20.691)	(12.243)	(18.666)	(15.065)	(14.016)
Observations	498	497	498	431	431	494	494	494	430	430
Adjusted R-squared	0.940	0.916	0.952	0.916	0.961	0.831	0.770	0.787	0.763	0.840

Panel B: Lagged Effect										
Variables	**Number of Employees**					**Employee Compensation**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FINTECH*LARGE	-0.102***	-0.129**	-0.177***	-0.145***	-0.192***	0.270***	0.311***	0.339***	0.302***	0.279***
	(-3.032)	(-2.688)	(-4.830)	(-3.314)	(-5.317)	(14.847)	(10.242)	(18.177)	(14.101)	(11.818)
FINTECH*SMALL	0.021	-0.047	-0.172***	-0.032	-0.106***	0.270***	0.285***	0.294***	0.285***	0.273***
	(0.629)	(-1.057)	(-5.616)	(-0.826)	(-3.561)	(14.401)	(8.947)	(15.041)	(14.327)	(12.329)
Observations	493	492	493	426	426	489	489	489	425	425
Adjusted R-squared	0.941	0.916	0.952	0.916	0.961	0.829	0.763	0.780	0.754	0.837

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

The second firm characteristic that we examined is firm age. As suggested by previous studies (Giunta and Trivieri, 2007; Haller and Siedschlag, 2011), younger firms tend to be more active and successful in implementing new technology compared to mature firms. Therefore, we believe that firm age matters to how technology growth affects labour outcomes. To test this hypothesis, we created a dummy variable *MATURE* (*YOUNG*) that takes a value of 1 if firm age is above (below) the average firm age of all banks over the sample period, and a value of 0 otherwise. Our regression models are:

$$LO_{i,t} = \alpha + \beta_1 FinTech_t * MATURE_i + \beta_2 FinTech_{i,t} * YOUNG_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

$$LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} * MATURE_i + \beta_2 FinTech_{i,t} * YOUNG_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (6)$$

We reported the results for equations (5) and (6) in Table 7's panels A and B, respectively. Our main finding – that technology growth negatively affects the number of employees and positively affects employee compensation – remains intact. In addition, results presented in Table 7 reveal that the relation between technology and labour outcomes is stronger for the younger banks than the more mature banks. This can be evidenced from interpreting β_2, which is higher in absolute value compared to β_1 in all regression models. With a unit standard deviation increase in the number of FinTech firms (equivalent to three FinTech firms), the number of employees in the younger banks drops by 1.37%–2.65% whilst the corresponding drop in mature firms is recorded at 0.85%–1.79%. Similarly, the employee compensation of younger banks increases by 17.41%– 20.91% compared to 13.24%–15.26% of more mature firms after a 1 standard deviation increase in technology growth. We obtained similar results when examining the lagged effect of technology on labour outcomes.

Table 7.
Effect of Firm Age on Technology Growth–Labour Outcomes Relations

This table reports the results for testing the effect of the market value of firms on technology growth-labour outcomes relation. The regressions take the following form: $LO_{i,t} = \alpha + \beta_1 FinTech_t * OLD_i + +\beta_2 FinTech_t * YOUNG_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$ and $LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} * OLD_i + +\beta_2 FinTech_{t-1} * YOUNG_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$. Where *LO* is labour outcomes measured by employee number (*EN*) and employee compensation (*EC*); *FinTech* represents technology growth; *OLD* is a dummy variable, which equals 1 if the firm age in a firm is higher than the average of all firms in the sample or equals zero otherwise; *YOUNG* is a dummy variable, which equals 1 if the firm market value in a firm is lower than the average of all firms in the sample or equals zero otherwise; *i* indexes the firms; *t* denotes the year. We report the coefficients and its corresponding t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Contemporaneous Effect										
Variables	**Number of Employees**					**Employee Compensation**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
*FINTECH*OLD*	-0.062*	-0.100*	-0.128***	-0.100*	-0.134***	0.282***	0.303***	0.309***	0.325***	0.320***
	(-1.773)	(-1.987)	(-3.207)	(-1.923)	(-3.741)	(14.941)	(9.027)	(12.725)	(13.116)	(14.417)
*FINTECH*YOUNG*	-0.023	-0.127***	-0.193***	-0.109**	-0.149***	0.363***	0.420***	0.436***	0.424***	0.386***
	(-0.652)	(-3.120)	(-7.569)	(-2.782)	(-4.806)	(31.164)	(18.599)	(39.916)	(16.561)	(14.237)
Observations	498	497	498	431	431	494	494	494	430	430
Adjusted *R*-squared	0.939	0.916	0.953	0.915	0.960	0.837	0.78	0.798	0.771	0.843

Panel B: Lagged Effect										
Variables	**Number of Employees**					**Employee Compensation**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
*FINTECH*OLD*	-0.061*	-0.073	-0.137***	-0.089*	-0.153***	0.231***	0.238***	0.252***	0.245***	0.249***
	(-2.079)	(-1.468)	(-3.929)	(-1.766)	(-5.373)	(14.854)	(6.755)	(11.781)	(9.450)	(11.238)
*FINTECH*YOUNG*	-0.017	-0.094*	-0.206***	-0.093**	-0.155***	0.302***	0.345***	0.372***	0.344***	0.309***
	(-0.494)	(-2.060)	(-7.550)	(-2.579)	(-5.387)	(19.075)	(12.182)	(19.204)	(16.267)	(13.723)
Observations	493	492	493	426	426	489	489	489	425	425
Adjusted *R*-squared	0.940	0.916	0.953	0.915	0.961	0.832	0.770	0.788	0.760	0.839

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

Finally, we tested whether the types of ownership influence the relationship between technology growth and labour outcomes. Previous studies suggested that, compared to private banks, public banks are likely to be slower in applying new technology in their operations. The reason is that whilst private banks proactively adopt technological innovations, public banks, in contrast, tend to be reactive due to a bureaucratic culture (Troshani *et al*., 2011) or budget-timing constrains (Caudle *et al*., 1991). To test this hypothesis, we created a dummy variable *PRIVATE* (*PUBLIC*) that takes a value of 1 when a bank is a private (public), and a value of 0 otherwise. The following models capture this proposed relation:

$$LO_{i,t} = \alpha + \beta_1 FinTech_t * PRIVATE_i + \beta_2 FinTech_{i,t} * PUBLIC_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (7)$$

$$LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} * PRIVATE_i + \beta_2 FinTech_{i,t} * PUBLIC_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (8)$$

The results of this analysis are reported in Table 8. Our main finding from this analysis is that the effect of technology growth is stronger for private banks compared to public banks, just as we expected. Consider both contemporaneous and lagged effects analyses for the number of employees and employee compensation. The coefficients on FinTech for private banks are larger than those of public banks. This is true in 10 out of 12 cases. On average, a 1 standard deviation increase in the FinTech number (equivalent to three FinTech firms) leads to a drop of up to 2.39% (2.25%) in the number of bank employees and an increase of at most 21.38% (16.14%) of employee compensation for the private (public) banks.

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Table 8.
Effect of Firm Age on Technology Growth–Labour Outcomes Relation

This table reports the results for testing the effect of the market value of firms on technology growth-labour outcomes relation. The regressions take the following form: $LO_{i,t} = \alpha + \beta_1 FinTech_t * PRIVATE_i + +\beta_2 FinTech_t * PUBLIC_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$ and $LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} * PRIVATE_i + +\beta_2 FinTech_{t-1} * PUBLIC_i + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}$. Where *LO* is labour outcomes measured by employee number (*EN*) and employee compensation (*EC*); *FinTech* represents technology growth; *PRIVATE* is a dummy variable, which equals 1 if the firm is a private firm or equals zero otherwise; *PUBLIC* is a dummy variable, which equals 1 if the firm is public firm or equals zero otherwise; *i* indexes the firms; *t* denotes the year. We report the coefficients and its corresponding t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Contemporaneous Effect

Variables	Number of Employees					Employee Compensation				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
*FINTECH*PRIVATE*	-0.052	-0.134**	-0.172***	-0.167***	-0.155***	0.390***	0.432***	0.443***	0.444***	0.405***
	(-1.278)	(-2.659)	(-3.950)	(-3.031)	(-3.507)	(17.235)	(12.820)	(16.333)	(13.159)	(15.133)
*FINTECH*PUBLIC*	-0.037	-0.111**	-0.164***	-0.092**	-0.137***	0.317***	0.358***	0.371***	0.362***	0.337***
	(-1.157)	(-2.575)	(-5.440)	(-2.341)	(-4.812)	(20.324)	(12.211)	(21.349)	(17.121)	(15.015)
Observations	498	497	498	431	431	494	494	494	430	430
Adjusted R-squared	0.939	0.916	0.952	0.915	0.96	0.834	0.772	0.788	0.766	0.842

Panel B: Lagged Effect

Variables	Number of Employees					Employee Compensation				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
*FINTECH*PRIVATE*	-0.027	-0.093	-0.150***	-0.129***	-0.147***	0.313***	0.345***	0.358***	0.338***	0.311***
	(-0.713)	(-1.731)	(-3.640)	(-3.004)	(-4.154)	(10.417)	(7.896)	(9.740)	(11.970)	(14.846)
*FINTECH*PUBLIC*	-0.038	-0.084*	-0.178***	-0.083**	-0.155***	0.263***	0.291***	0.310***	0.284***	0.268***
	(-1.296)	(-1.869)	(-6.138)	(-2.235)	(-6.257)	(20.469)	(9.675)	(19.230)	(15.348)	(12.890)
Observations	493	492	493	426	426	489	489	489	425	425
Adjusted R-squared	0.940	0.940	0.916	0.952	0.915	0.961	0.830	0.764	0.779	0.754

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

https://bulletin.bmeb-bi.org/bmeb/vol26/iss4/3
DOI: 10.59091/2460-9196.1725

D. Robustness Test

In addition to using different regression model specifications based on control variables to test the consistency of our results, we now control for potential endogeneity in our model regression due to reverse causality and/or omitted variable(s). We apply the two-step Generalized Method of Moments system dynamic panel estimator to the following regressions:

$$LO_{i,t} = \alpha + \beta_1 FinTech_t + \beta_2 LO_{i,t-1} + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (9)$$

$$LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} + \beta_2 LO_{i,t-1} + \gamma Control_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \quad (10)$$

The results of this analysis are reported in Table 10. In brief, our results remain unchanged after controlling for endogeneity, suggesting that endogeneity is not a concern in our hypothesis test.

Table 9.
Robustness Test: Generalized Method of Moments

This table reports the results for testing the effect of technology growth on labour outcomes relation with controlling for potential endogeneity. The regressions take the following form: $LO_{i,t} = \alpha + \beta_1 FinTech_t + +\beta_2 LO_{i,t-1} + \gamma Control_{i,t} + \varepsilon_{i,t}$ and $LO_{i,t} = \alpha + \beta_1 FinTech_{t-1} + +\beta_2 LO_{i,t-1} + \gamma Control_{i,t} + \varepsilon_{i,t}$. Where *LO* is labour outcomes measured by employee number (*EN*) and employee compensation (*EC*); *FinTech* represents technology growth; *i* indexes the firms; *t* denotes the year. The estimation method is the two-step GMM system dynamic panel estimator. The Arellano-Bond (AB) test for serial correlation is based on the null hypothesis of second-order autocorrelation in the first differenced residuals. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Contemporaneous Effect										
Variables	**Number of Employees**					**Employee Compensation**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FINTECH	-0.035*	-0.033*	-0.208***	-0.028*	-0.227**	0.307***	0.250***	-0.016	0.092***	0.213***
	(-1.702)	(-1.783)	(-4.796)	(-1.920)	(-2.384)	(5.789)	(3.191)	(-0.114)	(2.808)	(3.090)
AR(2)	0.265	0.305	0.540	0.436	0.743	0.465	0.982	0.859	0.253	0.344
Hansen	0.193	0.240	0.980	0.382	0.750	0.427	0.207	0.381	0.266	0.985
Panel B: Lagged Effect										
Variables	**Number of Employees**					**Employee Compensation**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FINTECH	-0.012	-0.013	-0.099***	-0.030**	-0.187***	0.233***	0.142***	-0.007	0.098***	0.202*
	(-0.722)	(-0.787)	(-5.748)	(-2.011)	(-3.681)	(6.346)	(3.060)	(-0.092)	(4.782)	(1.664)
AR(2)	0.290	0.369	0.548	0.410	0.742	0.390	0.881	0.856	0.300	0.688
Hansen	0.257	0.401	0.974	0.359	0.760	0.341	0.123	0.379	0.298	0.655

Source: Authors, based on data from World Bank, Datastream, and Fintech Indonesia Association

IV. CONCLUSION

In this paper, we investigated how technology growth, measured by the number of established FinTech firms, influences labour outcomes. We measured labour outcomes by the number of employees and employee compensation in Indonesian banks over the period 1998–2017. We hypothesised that technology growth negatively impacts the number of bank employees and positively affects employee compensation. The results from our regression analyses confirm our hypotheses. We found both contemporaneous and lagged effects of technology on labour outcomes. This relation is both statistically significant and economically meaningful. Economically, we showed that a unit standard deviation (equivalent to three FinTech firms) increase in the number of FinTech establishments reduces the number of bank employees by at most 2.30% (of mean total bank employees, which is valued at 2,500 employees). On the other hand, a 1 standard deviation increase in FinTech establishments improves employee compensation by up to 17.83% (of mean employee compensation which is valued at US$10,300). An additional insight obtained from our analysis is that the effects of technology growth on labour outcomes are stronger for banks that have a larger market value, are more mature, and are privately owned.

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