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Abstract

In this paper, we develop the hypothesis that the growth of financial technology (*FinTech*) will negatively influence bank performance. We study the Indonesia market, where *FinTech* growth has been impressive. Using a sample of 41 banks and data on *FinTech* firms, we show that the growth of *FinTech* firms negatively influences bank performance. We test our main conclusion through multiple additional and robustness tests, such as the sensitivity to bank characteristics, effects of the global financial crisis, and use of alternative estimators. Our main conclusion is that *FinTech* negatively predicts bank performance holds.

Keywords: financial technology; bank performance; predictability; estimator.

1. **Introduction**

The past decade has witnessed a strong growth of digital innovations, especially in financial technology (*FinTech*) start-up formations as well as their market volume. However, the traditional players, i.e., financial institutions in the industry, in the financial sector have only slowly participated in new technological innovations (Brandl and Hornuf, 2017). Although recent years have seen some acquisitions of *FinTech* firms by banks, most *FinTech* start-ups are independent of banks and are open to investment interests. Because many banks, apart from the well renowned big banks, still offer old-fashioned, costly, and cumbersome financial services (Brandl and Hornuf, 2017), the emergence of *FinTech* firms will see them take over some key functions of traditional banks (Li, Spigt, and Swinkels, 2017). In other words, with *FinTech* firms there is likely to be a substitution effect, whereby banks are likely to lose out some part of their business activity. How much and to what extent banks will be affected or *FinTech* firms will substitute the activities held by banks is an empirical issue, which is the subject of our investigation.

Against this background, our hypothesis is that the growth of the *FinTech* firms will have a negative effect on the performance of banks. 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: (a) Cumming and Schwienbacher (2016), who investigate the pattern of venture capital investment in *FinTech* using a global sample of firms; (b) Haddad and Hornuf (2016), who examine the economic and technological determinants of the global *FinTech* market; (c) Brandl and Hornuf (2017), who trace the transformation of the financial industry after digitalization; and (d) Li, Spigt, and Swinkels (2017), who examine the effect of *FinTech* start-ups on incumbent retail banks' share prices.

In this paper, we test our hypothesis using bank level data from Indonesia. We consider Indonesia because amongst emerging markets the growth in *FinTech* has been phenomenal. Figure 1 demonstrates this. This trend in the growth of *FinTech* firms makes Indonesia an interesting case study for understanding the impact of *FinTech* on bank performance at least in the emerging market context where absolutely nothing is known about the role of *FinTech* in influencing the banking sector. Using data from 41 banks, our panel models of the determinants of banking sector performance suggest that *FinTech* firms have had a negative effect on Indonesia bank performance. *FinTech*, we show, also negatively predicts bank performance.

Specifically, our key findings can be summarized as follows. First, we find that *FinTech* reduces net interest income to total assets (*NIM*), net income to total equities (*ROE*), net income to total assets (*ROA*) and yield on earning assets (*YEA*) by 0.38%, 7.30%, 1.73%, and 0.38% (of their sample mean values, which are reported in Table 1), respectively.

Second, *FinTech* also predicts bank performance. With every new *FinTech* firm introduced in the market, we find that Fintech negatively predicts *NIM*, *ROE*, *ROA*, and *YEA* by 0.53%, 9.32%, 2.07%, and 0.48% (of their sample means), respectively. Third, we test whether bank characteristics, such as market value (*MV*) and firm age (*FA)* influence the way *FinTech* influences bank performance. We find they do: specifically, the effect of *FinTech* is stronger on (a) large banks compared to small banks, and (b) matured banks compared to younger (new) banks. We conclude our analysis by testing whether *FinTech* affects bank performance differently for state-owned versus private-owned banks. We show that *FinTech* has a bigger effect on state-owned banks.

We confirm the results through multiple robustness tests. At the beginning, we ensure by using four measures of bank performance, that our results of the effect of *FinTech* on bank performance are not dependent on our measure of performance. We explore the effects of *FinTech* on bank performance by asking whether the way *FinTech* affects performance is dependent on specific bank characteristics. By and large, we find that *Fintech* negatively influences performance regardless of bank size and age, and while we do discover some positive effect of *FinTech* for younger banks, there is no evidence that *FinTech* predicts bank performance of the younger banks. We explain the positive effect as follows Giunta and Trivieri (2007) and Haller and Siedschlag (2011), which find younger firms are more successful in adopting and using technology innovation. In addition, in testing the effects of *FinTech*, we utilized a wide range of control variables consistent with the banking performance determinants literature. The role of *FinTech* in influencing performance survives. We also checked for the sensitivity of our results by (a) controlling for the 2017 global financial crisis (GFC) effects and (b) using a different panel data estimator. We conclude that the negative effect of *FinTech* on bank performance holds across all the additional tests.

Our paper's main contribution is to show how *FinTech* influences bank performance. There are no studies on this subject to-date. Our paper, therefore, represents the first empirical study exploring the hypothesis that *FinTech* negatively influences bank performance using bank-level data from Indonesia. We show a robust negative effect of *FinTech* on bank performance.

The balance of the paper proceeds as follows. We discuss the data and the empirical framework in the next section. This is followed by a discussion of the results. The final section provides concluding remarks.

2. **Data and empirical framework**

This section has two objectives. In the first part, we discuss the data. In the second part, we present the empirical framework for testing our hypothesis that *FinTech* has a negative effect on bank performance.

2.1 Data

We collect data from multiple sources. The data on *FinTech* firms are obtained from the FinTech Indonesia Association. The bank-level data—*NIM*, *ROA*, *ROE*, *YEA*, total assets (*SIZE*), ratio of equity to total assets (*CAP*), cost to income ratio (*CTI*), loan loss provision (*LLP*), annual growth of deposits (*DG*), interest income share (*IIS*), and funding cost (*FC*) are obtained from DataStream. Of the data, *NIM*, *ROA*, *ROE*, and *YEA* are proxies for bank performance—our dependent variable in the regression model (1). Variables *SIZE*, *CAP*, *CTI*, *LLP*, *DG*, *IIS* and *FC* are firm-specific control variables. The last set of control variables—i.e.,, gross domestic product (*GDP*) growth rate and inflation (*INF*) rate—are macroeconomic indicators, used as additional controls, and are obtained from the *Global Financial Database*. All data are annual and cover the period 1988 to 2017. Specific details including variable definitions are provided in Table 1.

A description of our dataset appears in Table 2. Selected basic statistics are reported to get insights about the data. The statistics are for the entire sample of banks as well as for banks at the 25th and 75th percentile. The number of new *FinTech* firms was around seven per annum over the 1988 to 2017 period. The sample of 41 bank performance statistics reveals the following message. The average *NIM* has been 4.94% per annum while the *ROE* has been 7.99% per annum. By comparison, *ROA* stands at 0.40% per annum. Moreover, the *YEA* is valued at over 10% per annum. The annual average *CAP*, a measure of market capitalization, is around 12%. The performance statistics, as expected, are higher at the 75th percentile compared to the 25th percentile. Amongst the control variables, interest income is 91.2% of total income, with a *CTI* of around 56% per annum. The growth of deposits is valued at 16.32% per annum.

2.2 Empirical framework

Our empirical specification follows the literature that estimates the determinants of bank performance (Trujillo-Ponce, 2013; Dietrich and Wanzenried, 2011, 2014; Köster and Pelster, 2017; Shaban and James, 2018). We augment this conventional model of performance determinants with the *FinTech* variable. The regression model we have has the following form:

$$PER_{i,t} = \alpha + \beta_1 FinTech_t + \beta_2 PER_{i,t-1} + \beta_3 CAP_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 CTI_{i,t} + \beta_6 LLP_{i,t} + \beta_7 DG_{i,t} + \beta_8 IIS_{i,t} + \beta_9 FC_{i,t} + \beta_{10} GDP_t + \beta_{11} INF_t + \varepsilon_{i,t}$$

We collected the data for all Indonesian banks from DataStream and we ended up with a sample of 41 banks. Our data sample starts from 1998, when the first *FinTech* firm was established, to 2017. A two-step GMM system dynamic panel estimator is employed to test the null hypothesis that *FinTech* negatively influences bank performance in Indonesia.

The definition and expected signs on each of the variables are stated in the last column of Table 1. We briefly discuss the relations here. The first control variable is *CAP*, which is equity scaled by total assets. Previous studies that examine the effect of capital on bank performance fail to find conclusive evidence on the role of bank capital. Some studies document a positive relationship between capital and bank performance (Berger 1995; Jacques and Nigro, 1997; Holmstrom and Tirole, 1997; Rime, 2001; Iannotta, Nocera, & Sironi, 2007; Naceur and Omran, 2011; and Mehran and Thakor, 2011; Berger and Bouwman, 2013), while others discover the opposite (Altunbas, Carbo, Gardener, and Molyneux, 2007; Lee and Hsieh, 2013) or mixed results (Dietrich and Wanzenried, 2014). Berger (1995) explains the positive relationship between capital and profitability using the bankruptcy cost hypothesis. This hypothesis suggests that banks with a higher capital ratio increase their expected profits by lowering interest expenses on uninsured debt. Berger (1995) also provides an alternative explanation through the signaling hypothesis, which describes an increasing capital as a positive signal for the bank’s future prospects. Banks with higher equity-to-asset ratios may not require external funding, which can positively influence profitability. On the other hand, Osborne, Fuertes, and Milne (2012) suggest a possible negative relation between *CAP* and performance resulting from the fact that higher capital is costly for banks because of capital market imperfections and tax advantages of debt. The authors also provide an alternative view, suggesting a possible positive relation by claiming that higher capital reduces risk and hence lowers the premium demanded to compensate investors for the costs of bankruptcy. This claim is consistent with the popular “trade-off” view, which implies a positive relationship between capital and bank performance. As a result, we expect *CAP* to have either a negative or a positive effect on bank performance.

On the effect of bank size (*SIZE*), which we proxy using bank total assets, the effect is again a *priori* unknown. Large banks are likely characterized by economies of scale (increased operational efficiency) and economies of scope (higher degree of product and loan diversification) compared to small banks. We therefore expect a positive effect of size on bank profitability, consistent with studies such as Pasiouras and Kosmidou (2007) and Smirlock (1985). Short (1979) argues that large banks have access to cheaper capital, which is reflected in a healthy profitability status. Djalilova and Piesse (2016) argue that large banks reduce their level of risk by diversifying their products and services, which contributes to higher operational efficiency and profitability. Furthermore, Flamini, McDonald, &Schumacher (2009) argue that in a non-competitive environment large banks can obtain higher profits compared to small banks. This is because large banks, since they occupy a greater market share, can offer lower deposit rates and maintain high lending rates. On the other hand, Stiroh and Rumble (2006), Berger, Hanweck, and Humphrey (1987), and Pasiouras and Kosmidou (2007) show that bank size is negatively related to profits due to bureaucracy. On the other hand, Shaban and James (2018) and Chen, Liao, Lin, and Ye (2018) find mixed results on the effects of size on bank performance.

The *CTI* variable is defined as the operating costs (staff salaries, property costs, administrative costs, excluding losses due to bad and non-performing loans) over total generated revenues. Our measure is consistent with studies by Pasiouras & Kosmidou (2007) and Dietrich and Wanzenried (2014). As *CTI* increases, implying lower bank efficiency, it should negatively impact bank performance. This negative relationship is documented in previous empirical studies; see, *inter alia*, Hess & Francis (2004), Athanasoglou, Brissimis, and Delis (2018), Pasiouras and Kosmidou (2007), and Dietrich and Wanzenried (2014).

To proxy credit risk, we use the *LLP*. The *LLP* variable is considered as a reserve to cover for any potential loan default, which protects banks' positions in terms of profitability and capital (Beatty and Lioa, 2009). The level of *LLP* is an indication of a bank's asset quality and signals changes in future performance (Thakor, 1987). Miller and Noulas (1997) argue that an increase in bank exposure to high-risk loans will lead to higher accumulation of unpaid loans and a lower profitability. Athanasoglou et al., (2008), Sufian (2009), and Dietrich and Wanzenried (2014) suggest that increased exposure to credit risk is associated with decreased bank profitability as bad loans are expected to reduce profitability. We, therefore, expect a negative effect of *LLP* on bank performance.

To measure a bank's growth, we use *DG*. One might expect a faster growing bank to be able to expand its business, thus generating greater profits. However, an increasing amount of deposits does not necessarily improve bank profits. Banks need to be able to convert deposits into additional income earning assets. Furthermore, growth is often achieved by allocating loans to borrowers with lower credit quality. In addition, high growth rate in deposits might also attract additional competitors. This can potentially reduce profits for all market participants. Therefore, the overall effect of *DG* is indeterminate from a theoretical point of view. The existing empirical evidence is mixed. Naceur and Goiaed (2001), for instance, find a positive relation; Demirguc-Kunt and Huzinga (1998) find a negative relation, while Dietrich and Wanzenried (2014) discovered an insignificant relation.

The *IIS*, which equals total interest income over total income, is also used as a control variable. In general, commercial banks obtain higher margins from asset management activities, such as "fee and commission income" and "trading operations" compared to interest operations. We expect banks with a higher share of interest income relative to their total income to be less profitable (Dietrich and Wanzenried, 2011, 2014). In other words, the expected effect of *IIS* on bank performance is negative.

The final firm specific control variable is *FC*, which equals interest expenses over average total deposits. As *FC* increases, bank profits are expected to be lower. Dietrich and Wanzenried (2011 and 2014), for instance, find a negative and statistically significant effect of *FC* on bank performance.

To conclude the motivation for our empirical framework, we discuss the use of macroeconomic indicators, *INF* and *GDP*, as control variables. The effect of *INF* on bank profitability depends on whether wages and other operating expenses increase at a faster rate compared to the inflation rate. Most studies (e.g., Bourke, 1989; Molyneux & Thornton, 1992; Athanasoglou et al., 2008; Claeys and Vander Vennet, 2008; García-Herrero, Gavilá, and Santabárbara, 2009; Kasman, Tunc, Vardar, & Okan, 2010; Pasiouras and Kosmidou, 2007, Trujillo-Ponce, 2013) have found a positive relationship between inflation and profits. However, if inflation is not anticipated and banks do not adjust their interest rates accurately, there is a possibility that costs may increase faster than revenues thus adversely affecting bank profitability. Accordingly, the overall effect is *a priori* unknown.

Finally, the role of *GDP* influences bank performance through the business cycle. When the economy is not doing well (recession), the quality of the loan portfolio worsens, generating credit losses, which eventually reduce bank profits. Furthermore, banks' profits might be procyclical because *GDP* growth also influences net interest income via the lending activity as demand for lending is increasing (decreasing) in cyclical upswings (downswings). Additionally, there is a vast literature that shows that economic growth stimulates the financial system (e.g., Albertazzi & Gambacorta, 2009; Athanasoglou et al., 2008; Bikker & Hu, 2002; Demirguc-Kunt & Huizinga, 1999). We, therefore, expect that *GDP* growth rate will have a positive effect on bank performance.

3. **Results**

3.1 Benchmark model

We begin a discussion of results based on Table 3, where we estimate the traditional determinants of banking sector performance. The panel data model is estimated using the two-step generalized method of moments (GMM) system dynamic panel estimator. The results are provided column-wise representing each of the four dependent variables—which are measures of banking sector performance. This regression sets the benchmark for the rest of the analysis because it is estimated without the *FinTech* variable. There are several messages that appear from Table 3. The first is to ask which of the four proxies for banking sector performance perform best from a statistical point of view. The weakest model is when the dependent variable is *ROE*: four of the 10 determinants are statistically significant. When the dependent variable is *NIM*, *ROA*, and *YEA*, 60% of the determinants are statistically different from zero. The variables that are statistically significant regardless of the dependent variable are *CTI* and *GDP*, followed by *CAP* and *INF*. Variables *LLP*, *DG* and *IIS* are statistically significant in two of the four models. Finally, *FC* is the only variable which has no explanatory power.

3.2 Effect of FinTech on bank performance

We now examine how, if at all, *FinTech* affects bank performance. We start with Table 4, where we present results from a test of the contemporaneous effect of *FinTech* on each of the four measures of bank performance. In all four models, the slope coefficient on *FinTech* is statistically different from zero. *FinTech* negatively effects *NIM* (-0.019, *t-stat*.=-2.67), *ROA* (-0.029, *t-stat*.=-3.04), *ROE* (-0.138, *t-stat*.=-2.72) and *YEA* (-0.038, *t-stat*.=-3.51). The slope coefficients imply that with one extra *FinTech* firm that enters the financial services industry, *NIM*, *ROA*, *ROE*, and *YEA* decline by 0.38%, 7.30%, 1.73%, and 0.38% of the mean value, respectively. (The mean values of *NIM*, *ROA*, *ROE*, and *YEA* are 4.94%, 0.40%, 7.99% and 10.11%, respectively, as noted in Table 1).

In our next set of results, we test whether *FinTech* can predict bank performance. Like with the contemporaneous results, we find from results presented in Table 5 that *FinTech* negatively predicts *NIM* (-0.026, *t*-stat. = -2.86), *ROA* (-0.037, *t*-stat. = -3.74), *ROE* (-0.165, *t*-stat. = -1.83), and *YEA* (-0.049, *t*-stat. = -4.47). Economic significance-wise, the slope coefficients imply that with every new *FinTech* firm introduced into the market *NIM*, *ROA*, *ROE* and *YEA* decline by 0.53%, 9.32%, 2.07% and 0.48% (of their sample mean), respectively (see Table 9).

We ask whether banks characteristics have something to do with the effect *FinTech* has on their performance. The motivation for paying attention to characteristics in shaping this relation has roots in the work of Iannotta et al (2007), Dietrich and Wanzenried (2011, 2014), Matousek, Rughoo, Sarantis, & Assaf (2015), Köster and Pelster (2017), and Talavera, Yin, and Zhang (2018). The studies show that bank characteristics are instrumental in shaping bank performance. We consider two aspects of bank characteristics, i.e., market value (*MV*) and firm age (*FA*). High *MV* firms, because they have greater visibility and are expected to be more liquid, are those that are more competitive and efficient. We, therefore, expect that how *FinTech* impacts high *MV* (MV2) banks will be different compared to low *MV* (MV1) banks. In addition, with age (maturity), we expect the effects of *FinTech* to be heterogeneous as well.

Our results are reported in Table 6. We see clear patterns in the *FinTech* effect conditional on firm characteristics. Based on *MV*, the effect of *FinTech* is negative for both large and small banks but it is stronger for the large banks. A possible explanation for this is that the smaller firms are able to adapt the technology innovation faster than the larger firms (Dos Santon and Peffers, 1995; Giunta and Trivieri, 2007; Haller and Siedschlag, 2011; and Scott, Reenen, and Zachariadis, 2017). The literature argues that larger firms must bear a lot more costs in re-organizing because of their legacy proprietary systems compared to smaller firms. Smaller enterprises can adapt faster to internal and external changes in their operating environment when there is a technological transformation. On the other hand, larger firms may respond slowly due to legacy systems that demand substantial modifications.

FinTech negatively affects matured banks with a slope of -0.018 (*t*-stat. = - 1.69), -0.028 (*t*-stat. = -2.43), and -0.037 (*t*-stat. = -2.87) when *NIM* and *YEA* are dependent variables, respectively. However, younger banks are positively affected with a slope coefficient of 0.052 (*t*-stat. = 1.87) and 0.020 (*t*-stat. = 2.42) when *NIM* and *YEA* are dependent variables, respectively. Previous studies find younger firms to be more successful in adopting and using technology innovation as they are ready to embrace innovative developments and carry out the company reorganization that goes along with technological innovation (Giunta and Trivieri, 2007; Haller and Siedschlag, 2011).

Predictability is also dependent on bank characteristics. Both small and large sized banks have performances that are predictable by *FinTech*; however, *FinTech* matters more to small size banks than to large size banks. With age, on the other hand, *FinTech* predicts performance only of matured banks and not of the relatively young banks.

In our sample, we have both private- and state-owned banks. The results can be summarized as follows. In additional results reported in Table 7 we focus on controlling for bank ownership. The first thing to note is with respect to the effect of *FinTech* on the performance of state-owned banks. We find that *NIM* is unaffected by *FinTech* firms while *FinTech* negatively and statistically significantly influences *ROA* (-0.043, *t*-stat. = -2.20), *ROE* (-0.276, *t*-stat. = -1.79), and *YEA* (-0.036, *t*-stat. = -2.65). However, when it comes to FinTech's ability to predict performance, we see that it predicts *NIM* (-0.027, *t*-stat. = -3.15), *ROA* (-0.034, *t*-stat. -3.29) and *YEA* (-0.050, *t*-stat. -3.06). *FinTech*, however, does not predict *ROE* of state-owned banks. With respect to private-owned banks, we see that *FinTech* contemporaneously affects all four performance measures but predicts only *ROA* (-0.052, *t*-stat. = -2.10) and *YEA* (-0.051, *t*-stat. = -2.93). Overall, the results suggest that the negative effect of *FinTech* is stronger for the state-owned banks compared to private banks. The reason is the following. The state owned (public) banks are likely to be slow in adopting and using technological innovations compared to private firms. While private banks generally adopt innovations proactively, state owned firms tend to introduce innovations reactively due to a bureaucratic culture.[1] Additionally, the state-owned firms are slow in adopting technology innovation due to budget timing restrictions (Caudle, Gorr, and Newcomer, 1991). They are subject to constraints of budgeting cycles dictated by political influences or periodic changes in political priorities.

3.3 Robustness test

This section is devoted to robustness tests. We mount two lines of inquiry to confirm robustness, which we believe could compromise our main conclusion. The first is the effect of the 2017 GFC. Several studies (See Berger and Bouwman, 2013; Vazquez and Federico, 2015; Matousek et al., 2015; Olson and Zoubi, 2017) have shown that the GFC impacted the banking sector. One limitation of our work, therefore, is that we have not specifically controlled for the GFC effect. We do so now by including a dummy variable in the regression model, which takes a value of one in years 2007 and 2008, and a value of zero for the rest of the years. The results reported in Table 8 suggest that the effect of *FinTech* on bank performance is insensitive to the inclusion of the GFC control. *FinTech* still impacts all four measures of bank performance negatively and statistically significantly.

Our second inquiry relates to the use of an alternative estimator. We use what is popular in this literature—a fixed effects (firm and year) panel estimator. The results, also reported in Table 8, reveal that the effects of *FinTech* on bank performance are insensitive to the use of an alternative estimator.

From the robustness tests, we conclude that the effects of *FinTech* we document are insensitive to the 2007 GFC and the use of a different (popular) estimator.

4. **Concluding Remarks**

This paper is inspired by the phenomenal growth of *FinTech* firms in Indonesia and indeed globally. Yet, nothing is known on whether they impact the banking sector. We develop our hypothesis—that *FinTech* growth hinders bank performance—out of this gap in the literature. We collect a unique sample of data on banks and *Fintech* firms in Indonesia. Using a panel of 41 banks (over 1997 to 2017), we estimate both a banking performance determinants and predictability model. In this traditional banking performance model, we augment the model with our *FinTech* measure. Given the lack of understanding of how, if at all, *FinTech* affects banking sector performance, we use four measures of performance—i.e.,, ratio of net interest income to total assets (NIM), ratio of net income to total assets (ROA), ratio of net income to total equities (ROE), yield on earning assets (YEA). We show from a range of different models that *FinTech* negatively and significantly impacts all four performance measures. A subset of our results suggests that high value, mature, and FinTech compared to lower valued, younger and private-owned banks relatively more negatively impacts state-owned banks. Our results are robust in the sense that they hold across most proxies of bank performance, multiple control variables, controls for GFC, different composition of firm panels, and a different estimator.

1This point is made with respect to firms by Troshani, Jerram, & Hill (2011)

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This figure plots the number and accumulated number of **FinTech** firms established each year in Indonesia in 1998-2017. Data was obtained from the Fintech Indonesia Association.

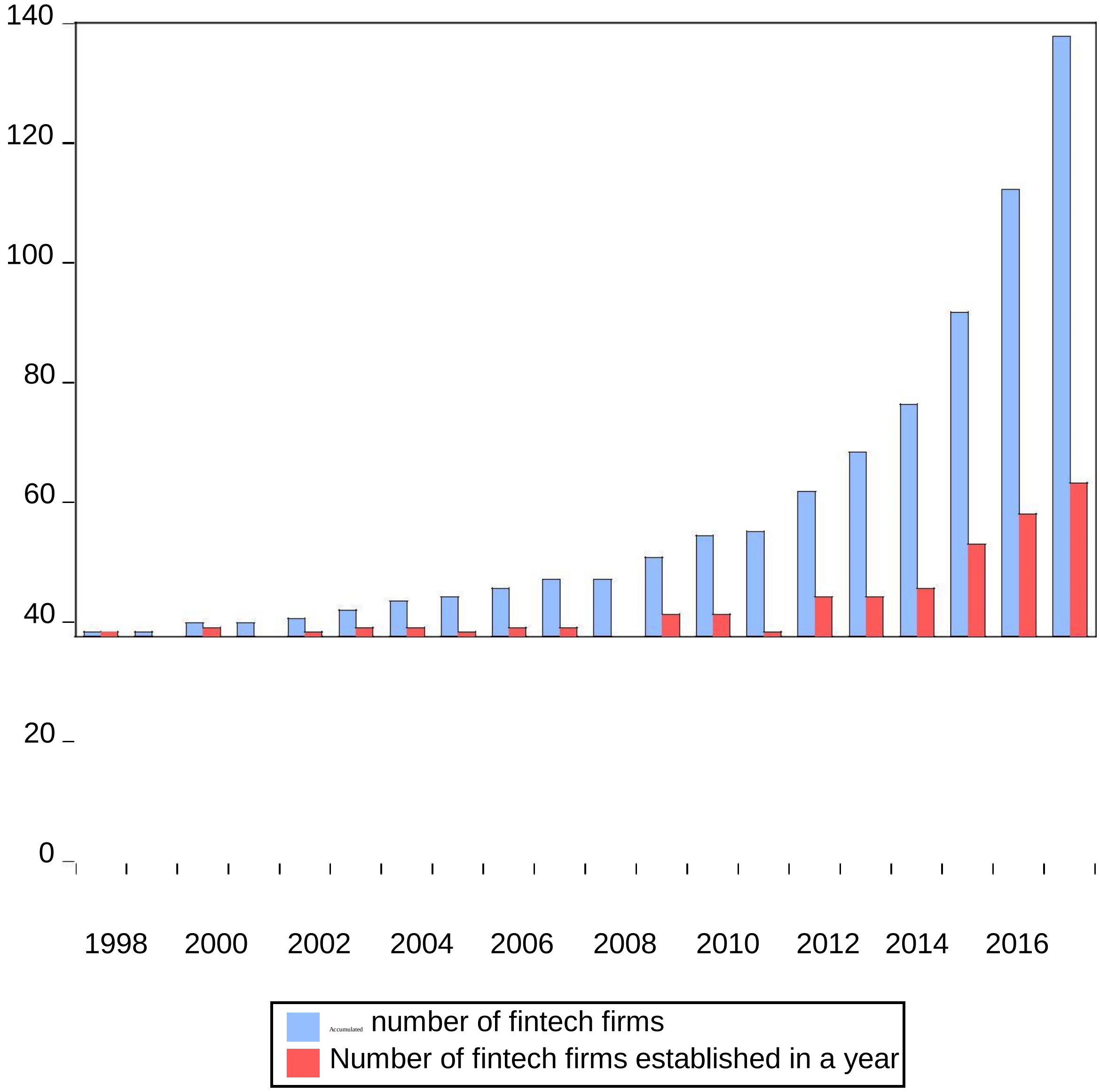

Figure 1. FinTech firms in Indonesia in 1998-2017

Table 1. Variable description

This table contains descriptions and sources of variables.

Variable	Definition	Source	Expected sign
FinTech	Number of financial technology (FinTech) companies founded	Fintech Indonesia Association	
NIM	Ratio of net interest income to total assets	DataStream	
ROA	Ratio of net income to total assets	DataStream	
ROE	Ratio of net income to total equities	DataStream	
YEA	Yield on earning assets	DataStream	
SIZE	Log of total asset ($US million)	DataStream	+/-
CAP	Capital ratio equals equity over total assets	DataStream	+/-
CTI	Cost-to-income ratio equals total expenses over total generated revenues	DataStream	-
LLP	Loan loss provisions equals loan loss provisions over total loans	DataStream	-
DG	Annual growth of deposits	DataStream	+/-
IIS	Interest income share equals total interest income over total income	DataStream	-
FC	Funding cost equals interest expenses over average total deposits	DataStream	-
GDP	Indonesia annual GDP growth rate	Global Financial Database	+
INF	Indonesia annual inflation rate	Global Financial Database	+/-

Table 2. Descriptive statistics

Table 2 shows selected descriptive statistics for the variables. The statistics include the mean, median, standard deviation (SD), 25% percentile, 75% percentile, skewness, kurtosis, the Jarque-Bera (JB) test of non-normality of returns, and a panel stationarity (Levin–Lin–Chu) test examining the null hypothesis of a unit root (*t*-statistic is reported. The null hypothesis of normality is based on the p value from the JB test.

	Mean	Median	SD	25%	75%	Skewness	Kurtosis
FinTech	6.850	2.000	9.672	1.000	9.000	1.791	5.055
NIM (%)	4.943	4.903	3.292	3.951	6.113	-1.969	13.123
ROA (%)	0.397	1.000	4.237	0.455	1.617	-5.964	41.270
ROE (%)	7.988	7.023	15.221	2.922	12.136	1.589	18.369
YEA (%)	10.112	9.444	2.923	8.200	11.272	1.558	6.186
SIZE	7.267	7.129	1.902	5.695	8.769	0.143	2.003
CAP (%)	11.968	10.960	6.931	8.585	14.834	-0.083	10.710
CTI (%)	55.976	54.446	19.185	44.909	64.596	1.657	8.333
LLP (%)	1.714	0.629	4.718	0.170	1.509	5.523	35.919
DG (%)	16.322	13.700	20.123	5.510	23.524	1.238	7.191
IIS (%)	91.175	92.680	6.355	87.913	95.779	-0.991	3.461
FC (%)	8.929	6.728	11.304	5.158	8.225	5.699	38.278
GDP (%)	7.515	7.665	0.651	6.907	8.175	-0.420	1.808
INF (%)	7.669	5.939	13.343	3.359	9.400	2.103	10.793

Table 3. Determinants of bank performance

Table 3 indicates regression results from the bank performance determinants model. The model has the following form:

$$PER_{i,\,t} = \alpha + \beta_1 PER_{i,\,t-1} + \beta_2 CAP_{i,\,t} + \beta_3 SIZE_{i,\,t} + \beta_4 CTI_{i,\,t} + \beta_5 LLP_{i,\,t} + \beta_6 DG_{i,\,t} + \beta_7 IIS_{i,\,t} + \beta_8 FC_{i,\,t} + \beta_9 GDPC_t + \beta_{10} INF_t + \varepsilon_{i,\,t}$$

In this regression, it is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table 1. 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. The *p*-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	NIM	*ROA*	*ROE*	*YEA*
PER(-1)	0.183	0.069	0.181*	0.416***
	(1.41)	(1.41)	(1.76)	(5.38)
CAP	-0.005	0.056**	-0.896***	-0.084**
	(-0.18)	(2.12)	(-3.04)	(-2.21)
SIZE	-0.115	0.242***	-0.230	-0.155
	(-0.85)	(3.84)	(-0.37)	(-1.30)
CTI	-0.107***	-0.028***	-0.337***	-0.046***
	(-5.53)	(-3.32)	(-4.19)	(-3.13)
LLP	-0.075**	-0.550***	-0.338	0.070
	(-2.27)	(-8.57)	(-0.58)	(0.92)
DG	-0.019***	-0.004	0.037	-0.022***
	(-4.50)	(-1.07)	(0.95)	(-3.99)
IIS	0.060**	-0.025	-0.056	0.105***
	(2.10)	(-1.49)	(-0.30)	(4.49)
FC	-0.010	0.003	0.062	-0.004
	(-1.04)	(0.30)	(1.32)	(-0.33)
GDP	-0.102***	-0.096***	-0.483***	-0.240***
	(-4.23)	(-3.34)	(-2.59)	(-7.39)
INF	0.026***	0.015***	-0.017	0.029***
	(2.90)	(3.85)	(-0.31)	(4.62)
Constant	6.472*	3.236	43.696***	2.110
	(1.77)	(1.61)	(2.62)	(0.63)
AR(2)	0.382	0.268	0.441	0.759
Hansen	0.722	0.588	0.527	0.346
Observation	374	494	492	494

Table 4. Contemporaneous effect of FinTech firms on bank performance

Table 4 presents regression results from the bank performance determinants model augmented with the *FinTech* variable. The regression model has the following form:

$$PER_{i,t} = \alpha + \beta_1 FinTech_t + \beta_2 PER_{i,t-1} + \beta_3 CAP_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 CTI_{i,t} + \beta_6 LLP_{i,t} + \beta_7 DG_{i,t} + \beta_8 IIS_{i,t} + \beta_9 FC_{i,t} + \beta_{10} GDPC_t + \beta_{11} INF_t + \varepsilon_{i,t}$$

In this regression, it is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table 1. 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. The *p*-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	NIM	*ROA*	*ROE*	*YEA*
FinTech	-0.019***	-0.029***	-0.138***	-0.038***
	(-2.67)	(-3.04)	(-2.72)	(-3.51)
PER(-1)	0.168	0.060	0.149	0.367***
	(1.43)	(1.28)	(1.38)	(4.80)
CAP	0.006	0.086***	-0.761**	-0.049
	(0.17)	(2.99)	(-2.57)	(-1.19)
SIZE	-0.091	0.300***	-0.177	-0.096
	(-0.69)	(5.45)	(-0.24)	(-0.71)
CTI	-0.110***	-0.026***	-0.318***	-0.044**
	(-6.15)	(-2.61)	(-3.92)	(-2.48)
LLP	-0.065*	-0.542***	-0.290	0.109
	(-1.74)	(-8.94)	(-0.52)	(1.32)
DG	-0.021***	-0.007*	0.022	-0.026***
	(-4.10)	(-1.83)	(0.64)	(-4.58)
IIS	0.064**	-0.016	-0.079	0.119***
	(2.25)	(-0.96)	(-0.37)	(4.67)
FC	-0.012	-0.001	0.023	-0.007
	(-1.55)	(-0.14)	(0.54)	(-0.47)
GDP	-0.107***	-0.103***	-0.530***	-0.249***
	(-4.26)	(-2.89)	(-2.74)	(-7.48)
INF	0.023***	0.012***	-0.032	0.024***
	(2.93)	(2.78)	(-0.66)	(3.78)
Constant	6.236*	1.979	45.065**	0.824
	(1.87)	(1.08)	(2.24)	(0.25)
AR(2)	0.402	0.234	0.476	0.892
Hansen	0.717	0.469	0.576	0.362
Observation	374	494	492	494

Table 5. Lag effect of FinTech firms on bank performance

Table 5 shows regression results of *FinTech* firms' influence on bank performance with a one-period lag. The predictive regression model takes the following form:

$$PER_{i,\,t} = \alpha + \beta_1 FinTech_{t-1} + \beta_2 PER_{i,\,t-1} + \beta_3 CAP_{i,\,t} + \beta_4 SIZE_{i,\,t} + \beta_5 CTI_{i,\,t} + \beta_6 LLP_{i,\,t} + \beta_7 DG_{i,\,t} + \beta_8 IIS_{i,\,t} + \beta_9 FC_{i,\,t} + \beta_{10} GDPC_t + \beta_{11} INF_t + \varepsilon_{i,\,t}$$

In this regression, it is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table 1. 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. The *p*-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	NIM	*ROA*	*ROE*	*YEA*
FinTech(-1)	-0.026***	-0.037***	-0.165*	-0.049***
	(-2.86)	(-3.74)	(-1.83)	(-4.47)
PER(-1)	0.174	0.072	0.151	0.375***
	(1.49)	(1.26)	(1.37)	(5.13)
CAP	0.006	0.084***	-0.774**	-0.049
	(0.20)	(2.84)	(-2.37)	(-1.20)
SIZE	-0.078	0.301***	-0.154	-0.089
	(-0.61)	(4.95)	(-0.19)	(-0.66)
CTI	-0.110***	-0.024**	-0.323***	-0.044**
	(-6.39)	(-2.31)	(-3.77)	(-2.49)
LLP	-0.060	-0.537***	-0.277	0.108
	(-1.63)	(-8.87)	(-0.50)	(1.41)
DG	-0.021***	-0.006*	0.023	-0.025***
	(-4.20)	(-1.73)	(0.65)	(-4.53)
IIS	0.065**	-0.017	-0.072	0.121***
	(2.31)	(-0.96)	(-0.34)	(4.95)
FC	-0.011*	-0.001	0.033	-0.006
	(-1.69)	(-0.09)	(0.76)	(-0.44)
GDP	-0.103***	-0.098***	-0.494**	-0.243***
	(-4.44)	(-2.98)	(-2.36)	(-7.27)
INF	0.022***	0.009**	-0.042	0.022***
	(2.97)	(2.00)	(-0.78)	(3.52)
Constant	6.099*	1.969	44.205**	0.435
	(1.88)	(1.03)	(2.00)	(0.13)
AR(2)	0.466	0.182	0.459	0.882
Hansen	0.765	0.488	0.524	0.378
Observation	374	494	492	494

Table 6. Effect of FinTech firms on bank performance sorted by bank characteristics

Table 6 presents regression results of the effect of *FinTech* firms on bank performance for panels sorted by bank characteristics, such as market value (*MV*) and firm age (*FA*). MV1 and FA1 contain the bottom-half of banks with the lowest *MV* and *FA* while MV2 and FA2 are the top-half of banks, with the highest *MV* and *FA*. The categorizations are based on the mean values of *MV* and *FA*. The regression models take the following form:

$$PER_{i,t} = \alpha + \beta_1 FinTech_t + \beta_2 PER_{i,t-1} + \beta_3 CAP_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 CTI_{i,t} + \beta_6 LLP_{i,t} + \beta_7 DG_{i,t} + \beta_8 IIS_{i,t} + \beta_9 FC_{i,t} + \beta_{10} GDPC_t + \beta_{11} INF_t + \varepsilon_{i,t}$$
$$PER_{i,t} = \alpha + \beta_1 FinTech_{t-1} + \beta_2 PER_{i,t-1} + \beta_3 CAP_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 CTI_{i,t} + \beta_6 LLP_{i,t} + \beta_7 DG_{i,t} + \beta_8 IIS_{i,t} + \beta_9 FC_{i,t} + \beta_{10} GDPC_t + \beta_{11} INF_t + \varepsilon_{i,t}$$

In this regression, it is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table 1. The estimation method is the two-step GMM system dynamic panel estimator. We report the coefficient $_1$ of the FinTech variable. Finally, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Contemporaneous effect				
	NIM	*ROA*	*ROE*	*YEA*
MV1	-0.014*	-0.026**	-0.121*	-0.041***
	(-1.86)	(-2.50)	(-1.93)	(-3.05)
MV2	-0.024***	0.000	-0.153*	-0.139***
	(-4.97)	(-0.04)	(-1.85)	(-3.90)
FA1	0.052*	-0.010	-0.042	0.020**
	(1.87)	(-0.75)	(-0.31)	(2.42)
FA2	-0.018*	-0.028**	-0.106	-0.037***
	(-1.69)	(-2.43)	(-1.42)	(-2.87)
Panel B: Lag effect				
	NIM	*ROA*	*ROE*	*YEA*
MV1	-0.019**	-0.032**	-0.145*	-0.051***
	(-2.19)	(-2.55)	(-1.87)	(-2.95)
MV2	-0.026**	0.000	-0.250***	-0.124***
	(-2.55)	(-0.02)	(-3.19)	(-4.00)
FA1	0.096	-0.008	-0.192	0.009
	(1.38)	(-0.29)	(-0.99)	(0.53)
FA2	-0.017	-0.034**	-0.126	-0.043***
	(-1.15)	(-2.45)	(-1.55)	(-3.34)

Table 7. Effect of FinTech firms on bank performance sorted by ownership

Table 7 indicates regression results of the effect of *FinTech* firms on the performance of state- and private-owned banks. The regression model takes the following form:

$$PER_{i,t} = \alpha + \beta_1 FinTech_t * STATE_i + \beta_2 FinTech_t * (1 - STATE_i) + \beta_3 PER_{i,t-1} + \beta_4 CAP_{i,t} + \beta_5 SIZE_{i,t} + \beta_6 CTI_{i,t} + \beta_7 LLP_{i,t} + \beta_8 DG_{i,t} + \beta_9 IIS_{i,t} + \beta_{10} FC_{i,t} + \beta_{11} GDPC_t + \beta_{12} INF_t + \varepsilon_{i,t}$$

$$PER_{i,t} = \alpha + \beta_1 FinTech_{t-1} * STATE_i + \beta_2 FinTech_{t-1} * (1 - STATE_i) + \beta_3 PER_{i,t-1} + \beta_4 CAP_{i,t} + \beta_5 SIZE_{i,t} + \beta_6 CTI_{i,t} + \beta_7 LLP_{i,t} + \beta_8 DG_{i,t} + \beta_9 IIS_{i,t} + \beta_{10} FC_{i,t} + \beta_{11} GDPC_t + \beta_{12} INF_t + \varepsilon_{i,t}$$

The first regression estimates the contemporaneous effect (Panel A) of *FinTech* while the second regression estimates the predictive ability (Panel B) of *FinTech*. In this regression, it is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of control variables is noted in Table 1. is a dummy variable that equals 1 if the firm is state owned and 0 otherwise (private owned). 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. The *p*-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Contemporaneous effect				
	NIM	*ROA*	*ROE*	*YEA*
*FinTech*STATE*	-0.008	-0.043**	-0.276*	-0.036***
	(-0.35)	(-2.20)	(-1.79)	(-2.65)
FinTech(1-STATE)*	-0.020***	-0.026***	-0.100*	-0.038***
	(-2.87)	(-3.21)	(-1.79)	(-2.94)
PER(-1)	0.173	0.057	0.151	0.363***
	(1.55)	(1.14)	(1.35)	(4.28)
CAP	0.006	0.082***	-0.823**	-0.048
	(0.19)	(2.94)	(-2.52)	(-1.10)
SIZE	-0.103	0.308***	0.068	-0.097
	(-0.77)	(5.40)	(0.09)	(-0.69)
CTI	-0.107***	-0.027**	-0.340***	-0.044**
	(-6.03)	(-2.51)	(-3.91)	(-2.38)
LLP	-0.067**	-0.542***	-0.243	0.110
	(-2.13)	(-9.16)	(-0.42)	(1.29)
DG	-0.022***	-0.006*	0.026	-0.026***
	(-4.54)	(-1.88)	(0.69)	(-4.43)
IIS	0.064**	-0.016	-0.037	0.119***
	(2.17)	(-0.98)	(-0.20)	(4.72)
FC	-0.012	-0.002	0.043	-0.007
	(-1.55)	(-0.29)	(0.90)	(-0.48)
GDPC	-0.103***	-0.106***	-0.540***	-0.249***
	(-3.94)	(-3.14)	(-2.70)	(-7.45)

INF	0.024***	0.011**	-0.033	0.024***
	(2.91)	(2.37)	(-0.69)	(3.73)
Constant	6.146*	2.110	41.077**	0.840
	(1.78)	(1.16)	(2.12)	(0.26)
AR(2)	0.442	0.257	0.498	0.906
Hansen	0.764	0.525	0.451	0.364
Observation	374	494	492	494

Panel B: Lag effect

	NIM	*ROA*	*ROE*	*YEA*
*FinTech(-1)*STATE*	-0.027***	-0.034***	-0.092	-0.050***
	(-3.15)	(-3.29)	(-1.11)	(-3.06)
FinTech(-1)(1-STATE)*	-0.014	-0.052**	-0.418	-0.051***
	(-0.50)	(-2.10)	(-1.61)	(-2.93)
PER(-1)	0.174	0.067	0.147	0.371***
	(1.53)	(1.19)	(1.26)	(4.45)
CAP	0.006	0.082***	-0.820**	-0.049
	(0.20)	(2.87)	(-2.48)	(-1.18)
SIZE	-0.092	0.302***	-0.213	-0.090
	(-0.70)	(5.04)	(-0.24)	(-0.65)
CTI	-0.108***	-0.026**	-0.343***	-0.044**
	(-6.13)	(-2.30)	(-3.66)	(-2.49)
LLP	-0.066**	-0.537***	-0.290	0.112
	(-2.15)	(-9.00)	(-0.50)	(1.29)
DG	-0.022***	-0.006*	0.022	-0.025***
	(-4.55)	(-1.68)	(0.58)	(-4.52)
IIS	0.067**	-0.018	-0.118	0.122***
	(2.31)	(-1.04)	(-0.55)	(4.63)
FC	-0.011	-0.002	0.035	-0.006
	(-1.57)	(-0.18)	(0.76)	(-0.42)
GDPC	-0.101***	-0.101***	-0.518**	-0.244***
	(-4.28)	(-2.96)	(-2.10)	(-7.04)
INF	0.023***	0.010**	-0.034	0.022***
	(2.96)	(2.12)	(-0.69)	(3.56)
Constant	5.794*	2.124	50.541**	0.458
	(1.74)	(1.17)	(2.18)	(0.14)
AR(2)	0.503	0.184	0.482	0.873
Hansen	0.789	0.537	0.644	0.377
Observation	374	494	492	494

Table 8. Robustness tests

Table 8 shows results of robustness tests for the *FinTech* firms' influence on bank performance. We employ two additional tests. First, we control for the global financial crisis period and estimate the regression with a GMM system two-step estimator as before. Second, we estimate the model with panel fixed effects (firm and year effects). The coefficient of *FinTech* and its *t*-statistic are reported, and ** and *** denote significance at the 5% and 1% levels, respectively. The contemporaneous effects of *FinTech* are reported in Panel A while Panel B reports *FinTech*'s ability to predict bank performance.

Panel A: Contemporaneous effect				
	NIM	*ROA*	*ROE*	*YEA*
Control for global financial crisis	-0.017**	-0.030***	-0.137***	-0.036***
	(-2.54)	(-3.50)	(-2.73)	(-3.57)
Fixed effects	-0.062***	-0.062**	0.267	-0.071***
	(-3.02)	(-2.38)	(0.97)	(-2.81)
Panel B: Lag effect				
	NIM	*ROA*	*ROE*	*YEA*
Control for global financial crisis	-0.023***	-0.038***	-0.177**	-0.048***
	(-2.69)	(-3.64)	(-2.33)	(-4.36)
Fixed effects	-0.047**	-0.045**	0.272	-0.043**
	(-2.52)	(-1.99)	(1.13)	(-2.03)

Table 9. Economic significance

Table 9 describes the economic significance of all statistical results presented in earlier tables. It shows how *NIM*, *ROA*, *ROE* and *YEA* sample means are affected by every new FinTech firm introduced into the market.

Panel A: Contemporaneous effect				
	NIM	*ROA*	*ROE*	*YEA*
Main regression	-0.38%	-7.30%	-1.73%	-0.38%
MV1	-0.28%	-6.55%	-1.51%	-0.41%
MV2	-0.49%	0.00%	-1.92%	-1.37%
FA1	1.05%	-2.52%	-0.53%	0.20%
FA2	-0.36%	-7.05%	-1.33%	-0.37%
*FinTech*STATE*	-0.16%	-10.83%	-3.46%	-0.36%
*FinTech *(1-STATE)*	-0.40%	-6.55%	-1.25%	-0.38%
Control for global financial crisis	-0.34%	-7.56%	-1.72%	-0.36%
Fixed effects	-1.25%	-15.62%	3.34%	-0.70%
GMM difference two-step	-0.04%	-16.62%	-0.63%	-0.48%
Panel B: Lag effect				
	NIM	*ROA*	*ROE*	*YEA*
Main regression	-0.53%	-9.32%	-2.07%	-0.48%
MV1	-0.38%	-8.06%	-1.82%	-0.50%
MV2	-0.53%	0.00%	-3.13%	-1.23%
FA1	1.94%	-2.02%	-2.40%	0.09%
FA2	-0.34%	-8.56%	-1.58%	-0.43%
*FinTech(-1)*STATE*	-0.55%	-8.56%	-1.15%	-0.49%
FinTech(-1)(1-STATE)*	-0.28%	-13.10%	-5.23%	-0.50%
Control for global financial crisis	-0.47%	-9.57%	-2.22%	-0.47%
Fixed effects	-0.95%	-11.34%	3.41%	-0.43%
GMM difference two-step	-0.14%	-12.59%	-0.91%	-0.74%