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Do financial technology firms influence bank performance?

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ABSTRACT

We develop a hypothesis that the growth of financial technology (*FinTech*) negatively influences 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 hypothesis through multiple additional tests and robustness tests, such as sensitivity to bank characteristics, effects of the Global Financial Crisis, and the use of alternative estimators. Our main conclusion that *FinTech* negatively predicts bank performance holds.

Keywords: *Financial technology; Bank performance*; *Predictability; Estimator*

I. Introduction

The last decade or so has seen strong growth in digital innovation, especially in financial technology (*FinTech*). However, the traditional players (financial institutions) in the financial sector have only slowly begun to participate in new technological innovations (Brandl and Hornuf, 2017). Although there have been acquisitions of *FinTech* firms by banks recently, most *FinTech* start-ups are independent of banks and are open to investment interests. Because many banks, apart from the well-known big banks, still offer old-fashioned, costly, and cumbersome financial services (Brandl and Hornuf, 2017), *FinTech* firms have the opportunity to take over several key functions of traditional banks (Li, Spigt, and Swinkels, 2017). Put differently, *FinTech* firms are likely to trigger a substitution effect, whereby banks are likely to cede some business activity. To what extent banks will be affected and how much *FinTech* firms will replace the activities currently controlled by banks is an empirical issue.

The effect of *FinTech* firms on banks can be explained by the consumer theory (Aaker and Keller, 1990) and disruptive innovation theory (Christensen, 1997). The consumer theory suggests that new services (such as those provided by *FinTech* firms) by meeting the same consumer demand can replace the old services (such as those provided by traditional banks). Based on the disruptive innovation theory, new entrants who apply innovative technology to provide more accessible and cost-effective goods and services can create competition in the market. The remits of these theories are relevant to our story where new entrants are *FinTech* firms and established incumbents are traditional banks. Complementing this line of thought is the work of Jun and Yeo (2016), who provide a model of a two-sided market with vertical constraints, emphasising on firm entry. Their model focusses on end-to-end and front-end service providers—a distinction that we do not make. Competition in our story is generated by new entrants regardless of who they are. A key feature of *FinTech* firms is that they apply innovative technology to perform tasks previously reserved for banks, such as lending, payments, or investments (Chishti and Barberis, 2016; Brandl and Hornuf, 2017; Puschmann, 2017). Recently, *FinTech* firms have been developing practical applications to improve efficiency in financial services across a range of services, including (but not limited to): contactless and instant payments; asset management services; investment and financial service advice; and information and data management/storage (Villeroy de Galhau, 2016). In this vein, Jagtiani and Lemieux (2018) argue that non-bank lenders can secure soft information relating to creditworthiness. This service is considered valuable for consumers and small business alike, particularly those that are characterized by weak credit history. On the contrary, banks operate on old information technology system and are perceived to be slow in adopting new technology (Hannan and McDowell, 1984; Laven and Bruggink, 2016; Brandl and Hornuf, 2017). The main conclusion, therefore, is that eventually *FinTech* firms can substitute the traditional banks by providing less expensive and more efficient services. Our hypothesis, therefore, is that *FinTech* growth will negatively influence bank performance.

Despite the emergence of digital innovation and its perceived effect on the financial industry, the effect of digital innovation and *FinTech* growth on the financial system are less understood. Exceptions include: (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 (2018), who test the determinants of the global *FinTech* market; (c) Brandl and Hornuf (2017), who trace the transformation of the financial industry after digitalization; and (d) Li et al. (2017), who focus on how retail banks' share prices react to *FinTech* start-ups.

We test our hypothesis using bank-level data from Indonesia. We consider Indonesia because, among emerging markets, its *FinTech* growth has been phenomenal, as shown in Figure 1. This trend in the growth of *FinTech* firms makes Indonesia an interesting case study to analyse how *FinTech* influences bank performance in an emerging market context. In general, we understand little about how *FinTech* impacts the banking sector. Using data from

41 banks, our panel models of the determinants of banking sector performance suggest that *FinTech* firms have a negative effect on Indonesian bank performance. *FinTech*, we show, also negatively predicts bank performance.

Specifically, we summarize our key findings 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 (reported in Table I), respectively.

Second, *FinTech* predicts bank performance. With every new *FinTech* firm introduced into 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 that they do. Specifically, the effect of *FinTech* is stronger on (a) large banks compared to small banks, and (b) mature banks compared to younger (new) banks. We conclude our analysis by testing whether *FinTech* affects bank performance differently for state-owned versus private banks. We show that *FinTech* has a bigger effect on state-owned banks.

We confirm our results through multiple robustness tests. Using four measures of bank performance, we test the sensitivity of the relation between *FinTech* and bank performance to measures of performance. We find no evidence that measures of bank performance matter to the relation between *FinTech* and 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 uncover some positive effect of *FinTech* for younger banks, there is no evidence that *FinTech* predicts performance of these younger banks. We explain this positive effect by drawing on Giunta and Trivieri (2007) and Haller and

Siedschlag (2011). These authors find that younger firms adopt and use technological innovations much more successfully. In addition, in testing the effects of *FinTech*, we utilize a wide range of control variables consistent with the banking performance determinants literature. The role of *FinTech* in influencing performance survives these tests. We also check for the sensitivity of our results by (a) controlling for 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 these additional tests.

Our paper's main contribution is to show how *FinTech* influences bank performance. There are no studies on this subject at present. Our paper, therefore, represents the first empirical study exploring the hypothesis that *FinTech* negatively influences bank performance. Using bank-level data from Indonesia,[1] we show that *FinTech* negatively influences bank performance and that this relation is robust.

This paper is organized into three additional sections. We discuss the data and the empirical framework in Section II. A discussion of the results appears in Section III. Finally, Section IV sets forth our concluding remarks.

II. Data and empirical framework

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

[1] The literature on Indonesian banks is rich. Several studies examined the Indonesian bank performance (Aviliani, Siregar, Maulana, and Hasanah, 2015; Wu, Ting, Lu, Nourani, and Wkeh, 2016; Ekananda, 2017; Irawan and Kacaribu, 2017; Ekananda, 2017; Shaban and James, 2018; Ibrahim, 2019), efficiency (Widiarti, Siregar, and Andati, 2015; Anwar, 2016;, Purwono and Yasin, M., 2019), risk (Agusman, Monroe, Gasbarro, and Zumwalt, 2008; Hidayat, Kakinaka, and Miyamoto 2012; Agusman, Cullen, Gasbarro, Monroe, and Zumwalt, 2014), stability (Mulyaningsih, Daly, and Miranti, 2016; Karim, Al-Habshi, and Abduh, 2016; Dienillah, Anggraeni, and Sahara, 2018), and Islamic banking (Pepinsky, 2013; Gustiani, Ascarya, and Effendi, 2010; Hidayati, Siregar, and Pasaribu, 2017; Anwar and Ali, 2018).

A. Data

We collect data from multiple sources. The data on *FinTech* firms are obtained from FinTech Indonesia Association.[2] We collect the annual number of FinTech firms registered to the FinTech Indonesia Association. The *FinTech* firms are those new supply firms and settlement processes related to the banking sector, such as lending, payments, personal finance management, crowd funding, and cryptocurrencies. In Indonesia, the bulk of the FinTech activities are centered on lending (45%) followed by payments (38%). 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 these data, *NIM*, *ROA*, *ROE*, and *YEA* are proxies for bank performance—our dependent variable in regression model (1). Variables *SIZE*, *CAP*, *CTI*, *LLP*, *DG*, *IIS*, and *FC* are firm-specific control variables. We also use macroeconomic variables—gross domestic product (*GDP*) growth rate and inflation (*INF*) rate—as additional controls. These data are obtained from the *Global Financial Database*. All data are annual over the period 1998 to 2017. Specific details, including variable definitions, are provided in Table I.

A description of our dataset appears in Table II. Selected basic statistics are reported to obtain insights on the data. These statistics are for the entire sample as well as for banks at the 25th and 75th percentiles. The number of new *FinTech* firms averages 7 per annum over the 1998 to 2017 period. The bank performance statistics (for our sample of 41 banks) reveal the following. Average *NIM* is 4.94% per annum while *ROE* is 7.99% per annum. By comparison, *ROA* stands at 0.40% per annum. Moreover, *YEA* is valued at over 10% per annum. Annual average *CAP*, a measure of market capitalization, is around 12%. These performance statistics,

[2] https://fintech.id. This data is not available to public. We obtained data from Bank Indonesia which was sourced from Asosiasi FinTech Indonesia (Aftech).

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 for our sample. Growth of deposits is 16.32% per annum.

B. Empirical framework

Our empirical model is motivated by the literature that estimates the determinants of bank performance (Dietrich and Wanzenried, 2011, 2014; Trujillo-Ponce, 2013; Köster and Pelster, 2017; Shaban and James, 2018). We augment this conventional model of performance determinants with the *FinTech* variable. Our regression model is:

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

We collect data for all Indonesian banks from Datastream. Data availability leads to a sample of 41 banks. Our sample of banks excludes unlisted banks since they are likely to introduce potential estimation bias. Indonesian banks are required to reveal their performance through annual reports submitted to the central bank – the Bank Indonesia. However, there are differences between listed and unlisted Indonesian banks in the level of risk disclosure that is conveyed in their annual reports. Adhering to capital market regulation, listed firms commit to extensive public disclosures and transparency in showing their performance in order to attract investors for external funds. Unlisted firms, with fewer stakeholders, however, have lack of incentives and the absence of transparency when revealing their performance in annual reports (Goktan & Muslu, 2018).

Our data sample spans 1998, when the first *FinTech* firm was established, to 2017. A two-step generalized method of moments (GMM) system dynamic panel estimator is employed to test the null hypothesis that *FinTech* negatively influences bank performance in Indonesia.

Specific definitions and expected signs on each of the variables are set forth in the last column of Table I. We briefly discuss these relations here. The first control variable is *CAP*, measured as equity scaled by total assets. Previous studies that test the capital—bank performance nexus fail to find conclusive evidence on how this relation unfolds. Some studies document a positive effect of capital on bank performance (Berger, 1995; Holmstrom and Tirole, 1997; Jacques and Nigro, 1997; Rime, 2001; Iannotta, Nocera and Sironi, 2007; Mehran and Thakor, 2011; Naceur and Omran, 2011; Berger and Bouwman, 2013), while others find the opposite (Altunbas, Carbo, Gardener and Molyneux, 2007; Lee and Hsieh, 2013) or mixed results (Dietrich and Wanzenried, 2014). Berger (1995) draws on the bankruptcy cost hypothesis to explain the relation between capital and bank profits. 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 signalling hypothesis, which describes increasing capital as a positive signal on the bank's 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 that a higher *CAP* is associated with lower bank performance. This is because capital is considered more expensive than debt due to market imperfections and tax-shield savings associated with debt. These authors also provide an alternative view, suggesting a possible positive relationship by claiming that higher capital reduces risk, thus reducing the compensation premium demanded by investors to cover 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-sized banks are set to gain from economies of scale (greater operational efficiency) and enjoy greater economies of scope (greater diversification with respect to product and loan) compared to small banks. We, therefore, predict a positive effect of bank size on profits, consistent with, for example, Pasiouras and Kosmidou (2007) and Smirlock (1985). Short (1979) argues that large banks have access to cheaper capital, which is reflected in healthy profitability. Djalilov 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 and Schumacher (2009) document that, in a non-competitive environment, large banks can obtain higher profits compared to small banks. This is because large banks, since they hold greater market share, can offer lower deposit rates and maintain high lending rates. Moreover, 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 size and bank performance nexus.

The *CTI* variable is computed as operating costs (staff salaries, property costs, and administrative costs, excluding losses due to bad and non-performing loans) scaled by total generated revenues (see Pasiouras and 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, among others, Hess and Francis (2004), Athanasoglou, Brissimis and Delis (2018), Pasiouras and Kosmidou (2007), and Dietrich and Wanzenried (2014).

To proxy credit risk, we use *LLP*, a variable considered a reserve to cover for any potential loans default, which protects bank positions in terms of profitability and capital (Beatty and Liao, 2011). The level of *LLP* indicates a bank's asset quality and can be used to judge changes in future performance (Thakor, 1987). Miller and Noulas (1997) argue that when banks are exposed to high-risk loans, they will accumulate unpaid loans and profitability will be lower. 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.

We employ *DG* to measure bank growth. A growth-oriented or growing bank indicates business expansion, thus generating greater profits. On its own though, an increase in deposit growth does not necessarily imply improved bank profits. Banks need to be able to convert deposits into productive investments. One source of achieving this is by giving loan preference to borrowers with lower credit quality. In addition, deposit-growth can attract and stimulate competition in the market. This can potentially reduce profits for banks in the market. Therefore, a priori, from a theoretical viewpoint, the effect of *DG* is unknown. 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 an insignificant relation is discovered by Dietrich and Wanzenried (2014).

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 predict that banks will be less profitable if the share of interest income relative to total income is high (Dietrich and Wanzenried, 2011, 2014). In other words, we expect a negative effect of *IIS* on bank performance.

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 way *INF* influences bank profits depend on whether the rate of increase in inflation is slower compared to wages and other operating expenses. Studies such as Bourke (1989), Molyneux and Thornton (1992), Pasiouras and Kosmidou (2007), Athanasoglou et al. (2008), Claeys and Vander Vennet (2008), García-Herrero, Gavilá and Santabárbara (2009), Kasman, Tunc, Vardar and Okan, (2010), and Trujillo-Ponce (2013) show that inflation and profits are positively related. However, if inflation is unanticipated and banks fail to adjust their interest rates, costs may escalate faster than revenues, thus adversely affecting bank profits. These discussions imply that a priori there is an unknown effect of *INF* on profits.

Finally, we turn to the role of *GDP*, which influences bank performance through the business cycle. When the economy is not doing well (recession), the quality of the loan portfolio worsens. This leads to credit losses, which reduces bank profits. In addition, profits are likely be pro-cyclical given that economic influences net interest income through lending activity. It is the demand for lending that is increasing (decreasing) in cyclical upswings (downswings) as argued by Dietrich and Wanzenried (2014). Additionally, there is a vast literature that shows that economic growth stimulates the financial system (e.g., Demirguc-Kunt and Huizinga, 1999; Bikker and Hu, 2002; Athanasoglou et al., 2008; Albertazzi and Gambacorta, 2009). We, therefore, expect that the *GDP* growth rate will predict bank performance positively.

III. Results

A. Benchmark model

We begin the discussion of our results with Table III, where we estimate the traditional determinants of banking sector performance. The panel data regression is estimated using the two-step 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. Several observations are noteworthy from Table III. The first regards which of the four proxies for banking sector performance perform best from a statistical point of view. The weakest model has the dependent variable as *ROE*: 4 of the 10 determinants are statistically significant. When the dependent variable is *NIM*, *ROA*, or *EA*, 60% of the determinants are statistically irrelevant (insignificant). The variables that are significant regardless of the dependent variable are *CTI* and *GDP*, followed by *CAP* and *INF*. *LLP*, *DG*, and *IIS* are statistically significant in two of the four models. Finally, *FC* is the only variable with no explanatory power.

B. Effect of FinTech on bank performance

We now examine how, if at all, *FinTech* affects bank performance. We begin with Table IV, 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). These slope coefficients imply that with one extra *FinTech* firm entering 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 I).

In our next set of results, we test whether *FinTech* predicts bank performance. As with the contemporaneous results, we find from results presented in Table V 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). In terms of economic significance, these 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 means), respectively (see Table IX).

We test whether the effect of *FinTech* on bank performance is shaped by bank characteristics. The motivation for examining bank characteristics in shaping this relation has roots in Iannotta et al. (2007), Dietrich and Wanzenried (2011, 2014), Matousek, Rughoo, Sarantis and Assaf (2015), Köster and Pelster (2017), and Talavera, Yin and Zhang (2018). These studies show that bank characteristics are instrumental in shaping bank performance. Motivated by these studies, we consider two aspects of bank characteristics, market value (*MV*) and firm age (*FA*). High *MV* firms, because they have greater visibility and are expected to be more liquid, are more competitive and efficient. We, therefore, expect that the way *FinTech* impacts high *MV* (MV2) banks will differ compared to low *MV* (MV1) banks. In addition, with age (maturity), we expect the effects of *FinTech* to be heterogeneous.

Our results are reported in Table VI. We observe 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 stronger for large banks. A possible explanation is that smaller firms can adapt to technological innovation faster than larger firms (Dos Santos 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 substantially more costs in reorganizing because of their legacy systems compared to smaller firms. When there are technological transformations, Scott et al. (2017) argue that it is the small firms that are more apt at adjusting to internal and external changes related to their operations. On the other hand, larger firms may respond slowly due to legacy systems that demand substantial modification.

Mature banks are negatively affected by *FinTech*, 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*, *ROA*, 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 technological innovation. This is because they adopt technological innovation more (Giunta and Trivieri, 2007; Haller and Siedschlag, 2011).

Predictability is also dependent on bank characteristics. We see that regardless of bank size, *FinTech* predicts performance; however, *FinTech* matters more to small banks than to large banks. With age, on the other hand, *FinTech* predicts performance only for mature banks and not for relatively young banks.

In our sample, we have both private banks and state-owned banks. Results can be summarized as follows. In additional results reported in Table VII, we focus on controlling for bank ownership. The effect of *FinTech* on the performance of state-owned banks is noteworthy. 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* for state-owned banks. With respect to private 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, we see that the negative effect of *FinTech* is stronger for state-owned banks compared to private banks. This is because 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.[3] Additionally, state-owned firms are slow in adopting technological

[3] This point is made with respect to firms by Troshani, Jerram, and Hill (2011).

innovation due to budget-timing restrictions (Caudle, Gorr, and Newcomer, 1991). They depend on budgeting cycle constraints driven by political influences or periodic changes in political priorities (Caudle et al., 1991). In another strand of literature, studies point out that the state-owned banks are less competitive compared to private banks. Cull, Peria, and Verrier (2017), for instance, argue that the inefficiency in operating and low intermediation quality due to high agency costs that characterize state-owned banks reduce their competitiveness. Several studies end up comparing competition between state-owned banks and private banks through examining their performance. They found strong evidence favouring private banks in Latin America (Micco, Panizza, and Yane, 2007), Asia (Williams and Nguyen, 2005; Micco et al., 2007; Cornett, Guo, Khaksari, and Tehranian, 2010); MENA (Farazim Feyen, Rocha, 2013); and Europe (Bonin, Hasan, and Wachtel, 2005a,b; Iannotta, Nocera, and Sironi, 2007; Yildirim and Philippatos, 2007). Therefore, the state-owned banks are affected more than private banks when competition in the market increases due to new entrants (*FinTech*).

We conclude the discussion of results with a note on the effect of some of the core variables on bank performance judging only from Table III as results are more or less consistent. We find mixed results on the signaling hypothesis consistent with the literature. For example, while *CAP* positively influences *ROA*, it negatively impacts *ROE* and *YEA*. *SIZE* has a positive effect (but significant only when *ROA* is the dependent variable). This is consistent with our argument that large banks enjoy economies of scale, access to cheaper capital, and risk diversification. *CTI* consistently appears with a negative sign on performance corroborating our argument (supported by the literature) that an increase in *CTI* implies declining bank efficiency. Finally, *LLP* appears with a negative sign when *NIM* and *ROA* are dependent variables because a higher *LLP*, as we argued earlier, implies cover for default loans.

C. Robustness tests

We mount two lines of inquiry to confirm robustness, the lack of which could compromise our main conclusions. The first is the effect of the GFC. Several studies (see Berger and Bouwman, 2013; Matousek et al., 2015; Vazquez and Federico, 2015; Olson and Zoubi, 2017) show that the GFC impacted the banking sector. One limitation of our work, therefore, is that we do not specifically control for the GFC effect. We do so now by including a dummy variable in the regression model. This variable has a value of 1 for the years 2007 and 2008 and a value of 0 for the remaining years. The results suggest that the effect of *FinTech* on bank performance is insensitive to the inclusion of the GFC control (see Table VIII). *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 VIII, reveal that the effects of *FinTech* on bank performance are insensitive to the use of an alternative estimator.

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

IV. Concluding remarks

This paper is inspired by the phenomenal growth of *FinTech* firms in Indonesia and, indeed, globally. Exceedingly little is known about whether such firms 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. With a dataset comprising a panel of 41 banks (spanning the period 1997 to 2017), we estimate both a banking performance determinant and a predictability model. We augment this traditional banking performance 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: ratio of net interest income to total assets (*NIM*), ratio of net income to total assets (*ROA*), ratio of net income to total equity (*ROE*), and 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 state-owned banks are relatively more negatively impacted by *FinTech* compared to lower valued, younger, and private 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.

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Figure I: FinTech firms in Indonesia in 1998-2017

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

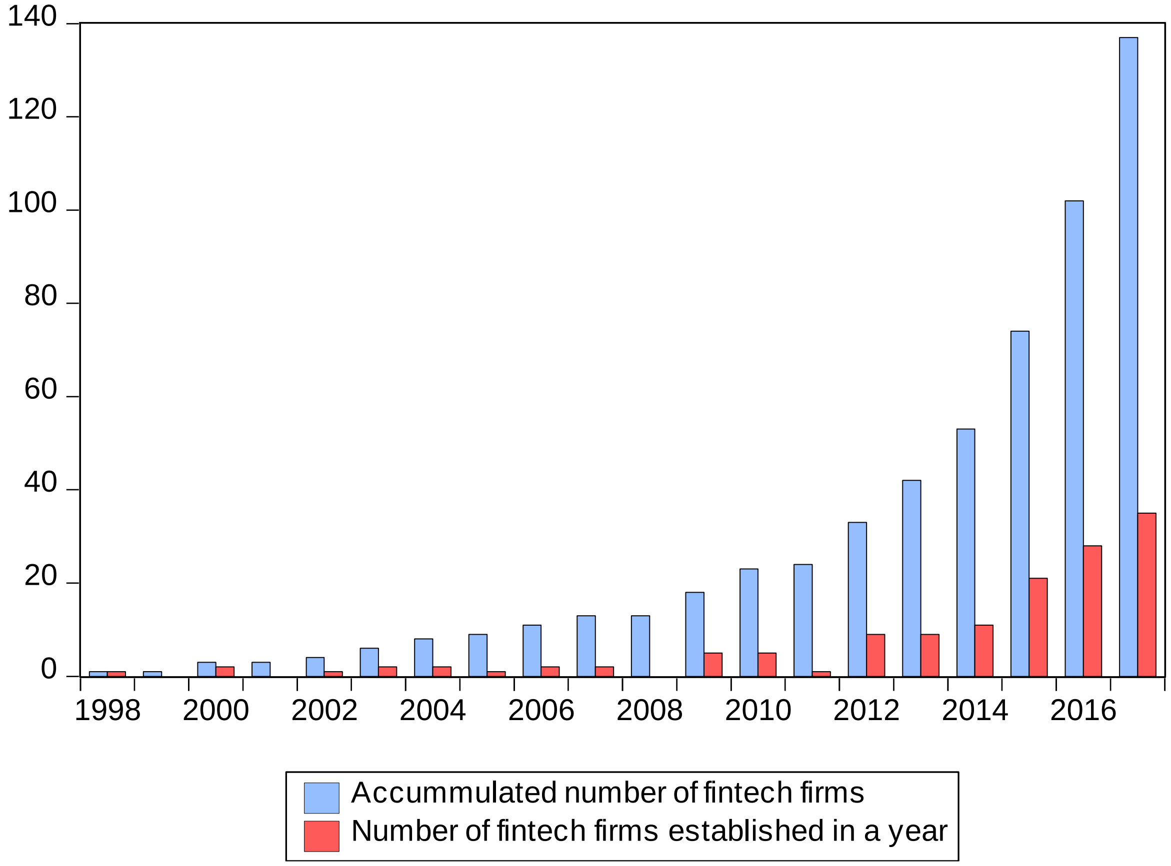

Table I: Variable description

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 II: Descriptive statistics

This table reports selected descriptive statistics for the variables. The statistics include the mean, median, standard deviation (SD), 25% percentile, 75% percentile, skewness, and Kurtosis.

	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 (%)	3.210	4.912	5.725	2.777	5.954	-2.770	10.233
INF (%)	7.669	5.939	13.343	3.359	9.400	2.103	10.793

Table III: Determinants of bank performance

This table reports 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, PER is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table I. 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 IV: Contemporaneous effect of FinTech firms on bank performance

This table reports 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, PER is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table I. 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 V: Lag effect of FinTech firms on bank performance

This table reports 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, PER is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table I. 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 VI: Effect of FinTech firms on bank performance sorted by bank characteristics

This table reports 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, those with the highest *MV* and *FA*. These categorizations are based on the mean values of *MV* and *FA*. The regression models take the following forms:

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

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

In this regression, PER is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of the control variables are noted in Table I. The estimation method is the two-step GMM system dynamic panel estimator. We report the coefficient β_1 of *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 VII: Effect of FinTech firms on bank performance sorted by ownership

This table reports regression results of the effect of *FinTech* firms on the performance of state- and private-owned banks. The regression models take the following forms:

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

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

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, PER is measured by *NIM*, *ROA*, *ROE*, and *YEA*, and the description of control variables is noted in Table I. $STATE$ 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 VIII: Robustness tests

This table reports 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 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 IX: Economic significance

This table reports 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%