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Journal of Risk and Financial Management

Provided in Cooperation with:

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Suggested Citation: Washington, Patrick Bernard; Shafiq Ur Rehman; Lee, Ernesto (2022) : Nexus between regulatory sandbox and performance of digital banks: A study on UK digital banks, Journal of Risk and Financial Management, ISSN 1911-8074, MDPI, Basel, Vol. 15, Iss. 12, pp. 1-18, <https://doi.org/10.3390/jrfm15120610>

This Version is available at:

<https://hdl.handle.net/10419/275087>

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Article

Nexus between Regulatory Sandbox and Performance of Digital Banks—A Study on UK Digital Banks

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Abstract: It is debatable whether the regulatory Sandbox contributes to financial institutions' growth. We used a panel sample of 24 challenger banks from the UK. This study has reviewed digital banks' adoption of a regulatory sandbox to foster innovation in financial sectors. We assessed the regulatory tools that encourage FinTech innovations, focusing on the aims of financial stability. Therefore, we exploit the introduction of the Sandbox as a catalyst for digital banking and its heterogeneous effects on the financial performance of digital banks. Our research showed that regulatory sandboxes have a detrimental impact on the financial performance of digital banks, increasing compliance costs and efficiency costs. This study will contribute to the limited literature on regulatory Sandbox and its policy implication for the growth and performance of digital banks. The recommendation of this study would help to improve the regulation of the development of digital technologies in the UK.

Keywords: sandbox; digital banks; virtual banks; financial performance



Citation: Washington, Patrick Bernard, Shafiq Ur Rehman, and Ernesto Lee. 2022. Nexus between Regulatory Sandbox and Performance of Digital Banks—A Study on UK Digital Banks. *Journal of Risk and Financial Management* 15: 610. <https://doi.org/10.3390/jrfm15120610>

Academic Editors: Thanasis Stengos and Christos Floros

Received: 26 September 2022

Accepted: 8 December 2022

Published: 15 December 2022

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1. Introduction

The growth of FinTech-focused innovations (i.e., digital banks) has accelerated in the past few years (EY 2019). Investment in FinTech-based banks (i.e., digital banks) was over USD 31 billion in 2017 compared to previous years, with only USD 1 billion in 2008 (Leong and Sung 2018). This heavy investment also leads to the growth of FinTech-based digital banks (BCBS 2018; Hornuf et al. 2020). Technology influences digital banks that provide their services remotely, with either little or no branch infrastructure (Ehrentraud et al. 2020).

According to the report prepared by IMF in 2020, digital banks (i.e., Neo banks) are gaining systematic importance in local markets. However, digital banks are a more significant threat to economic instability as most consumer lending operations are uncollateralized. In addition, they exhibit higher risk-taking in their securities portfolio and higher liquidity risks. These critical factors have created challenges for regulators to build effective risk management systems as these banks are untested in an economic downturn.

Regulatory sandboxes are being utilized, in several countries, to address these challenges. (Allayarov PhD et al. 2020). A sandbox is a form of regulatory innovation designed to deal with these challenges. A regulatory sandbox allows new innovators, such as neo banks, to test the trial products, new business models, and services in real-time without some of the usual rules and regulations. This box allows new firms to test the product's viability and enable the regulator to develop regulations for untested products. In addition, this sandbox function will enable firms to test their products with minimum or no regulations in a regulatory sandbox or continue with existing complete laws such as regular banking regulations.

A regulatory sandbox for the financial technology industry is a regulated environment in which financial technology companies may test their inventions while being monitored by authorities. The Sandbox decreases the cost and time required to launch technological

innovations, which attracts more investment in FinTech projects. In addition, a sandbox lowers the regulatory costs for banks. This cost reduction is because projects in a sandbox are subject to fewer regulatory constraints than projects outside of a sandbox. The websites of many regulators declare that the purposes of financial technology regulatory sandboxes are to expedite the introduction of innovative financial technology products and foster financial technology development. Therefore, it is being widely adopted by many countries, and the United Kingdom is one of the early adopters.

The United Kingdom's Financial Conduct Authority (FCA) originally introduced the notion of a FinTech regulatory sandbox in 2015, and a sandbox framework became fully operational in 2016. By the end of the year 2017, a total of 15 jurisdictions throughout the country had established regulatory sandboxes. In addition, many fintech firms (i.e., Neo Banks) have participated in sandbox programs.

Neobanks are new-age banks without any physical location, present entirely online. They provide digital, mobile-first financial solutions for payments, money transfers, and lending (Bradford 2020; Hopkinson et al. 2019). The emergence of the FinTech sector (i.e., digital banks) has piqued the interest of regulators and industry practitioners concerned about whether it will cause financial system instability. Therefore, the regulatory Sandbox is several countries' efforts to regulate the FinTech-based digital banks (i.e., challenger banks, NEO banks). However, the literature on the impact of the regulatory Sandbox on digital banks is minimal. Most of the previous literature covers the relationship between existing regulatory frameworks and the growth of FinTech-based innovations (Allayarov PhD et al. 2020; Anagnostopoulos 2018; Boot et al. 2021; Bu et al. 2021; Buchak et al. 2018; Zhou and Chen 2021). However, the relationship between the new regulatory framework (regulatory Sandbox) and its impact on digital banks is yet to unfold. Therefore, this study investigates the relationship between regulatory frameworks and their implications for digital banking performance.

This study collected data from 24 challengers' banks from UK digital banks for 2016–2021. The study found that, after implementing the first UK regulatory sandbox in 2016, many digital banks were issued licenses under the umbrella of a regulatory sandbox. As a result, these digital banks had minimal regulatory constraints compared to physical banks. However, the lack of a regulatory framework negatively influenced the performance of Neo Banks in the UK. We showed that performance indicators (the ratio of net interest income to total assets (NIM), the ratio of net income to total assets (ROA), the ratio of net income to total equity (ROE), and the yield on earning assets (YEA)) negatively influenced by the regulatory Sandbox. Our results are statistically significant.

This study will contribute to the limited literature on regulatory Sandbox and its implication for FinTech firms' performance, as this research is novel. This research is also substantial for regulators and policymakers as they are unsure about the outcome of newly developed regulations. Our findings will help them to understand and create better regulations for new and relatively small FinTech firms (i.e., digital banks).

The remaining parts of this study are organized as follows. In the next section, "Section 2", we will explain the data, the empirical model used as a baseline, and the technique used to evaluate the financial performance of digital banks. In Section 3, the empirical findings are discussed, and the robustness of our empirical model is analyzed. Finally, in Section 4 of this report, we will provide our results and explore the policy implications of those findings.

2. Literature Review and Hypothesis Development

Sandboxes testing products aim to establish the product's commercial viability, and those testing policies aim to assess whether particular rules or regulations should be changed based on specific use cases (Taylor et al. 2020). Several FinTech firms (also called the Neo banks) adopted regulatory Sandbox to benefit from small developing regulations or no regulations. However, since the regulatory Sandbox is in its initial implementation stage, few studies have explained its impact on FinTech firms. For instance, Hellmann et al.

(2022) envisaged the result of a regulatory sandbox on FinTech firms, such as an increase in capital in the UK. The study finds a significant positive relationship between the regulatory Sandbox and firms' capital increase.

Similarly, Goo and Heo (2020) found that adopting regulatory sandboxes positively influenced the growth of fintech venture investment. Few qualitative studies explore the importance of regulatory Sandbox in developing regulations and creating a balance between fast fintech developments and financial stability. However, very limited or no empirical studies have evaluated the impact of the regulatory Sandbox on banks (i.e., digital banks/Neo banks) which adopted the regulatory Sandbox. Therefore, this study will empirically assess this relationship.

It is well established that regulations always negatively impact bank performance (Danisman and Demirel 2019; Hsieh and Lee 2020; Klomp and De Haan 2015). Since the regulatory Sandbox already has established regulations, firms can test their products. Therefore, in light of previous studies, this study hypothesizes that "regulatory sandbox has a significant negative impact on the performance of digital banks."

3. Data and Methodology

Our sample included all banks licensed through regulatory sandboxes in the UK. We omitted those banks which do not adopt the Sandbox. To measure financial performance proxy by ROA and ROE, we used financial statements of these digital banks retrieved from banks' websites. This study will also include *CAP*, *SIZE*, *DPG*, *LLP*, *INF*, and *LG* as control variables to control for possible interactions between capital requirements, the size of banks, and deposit growth. In specifically, the Dickey–Fuller modified unit root was used in the research in order to ascertain the time series features of the variables that were represented by the model. It has been shown in the research that the modified Dickey–Fuller methodology, also known as the DF-GLS, is more powerful than the regular Dickey–Fuller method. (Elliott et al. 1992). Table 1 explanation of measurement of dependent and independent variables.

Table 2 contains some information about the dataset. Selected basic statistics are reported to get insights about the data. The statistics include data for all of the banks that were included in the sample as well as data for banks that fell between the 25th and 75th percentiles. The number of new banks which are registered in regulatory sandbox was around seven per annum over the 2016 to 2021 period. The sample of 24 bank performance statistics reveals the following message. The ROE has been an average of 7.99 percent per year, while the NIM has been an average of 4.94 percent per annum. In contrast, ROA is now at a rate of 0.40 percent every year. In addition to that, the yearly return on investment for the YEA is more than 10 percent. Approximately 12 percent is the yearly average for the CAP, which is a measure of market capitalization. When compared to the 25th percentile, the performance statistics in the 75th percentile, as was to be anticipated, are much greater. The control variables account for 91.2 percent of total income, while interest income contributes about 56 percent to the CTI on an annual basis. It is estimated that the increase of deposits is 16.32 percent on an annual basis.

Table 1. Measurement of dependent and independent variables.

	Variables	Definition/Measurements	Source	Expected Sign
Dependent Variables	ROE	Return on Equity scaled by total asset for bank <i>i</i> at time <i>t</i>	Financial statements download from digital banks' websites	+/-
	ROA	Return on assets scaled by total assets for bank <i>i</i> at time <i>t</i>	Financial statements download from digital banks' websites	+/-
Independent variables	Sandbox	If digital bank adopted regulatory Sandbox will represent 1 and 0 otherwise.	Government/Financial authority-issued sandboxes	NA
Control variables	LLP	Total number of loans outstanding for bank <i>i</i> over time <i>t</i> scaled by total loans	Financial statements download from digital banks' websites	+/-
	CAP	The total amount of capital required by the bank <i>I</i> over time <i>t</i> scaled by total asset	Financial statements download from digital banks websites	+/-
	DPG	Deposit ratio for bank <i>i</i> over time <i>t</i>	Financial statements download from digital banks websites	+/-
Macroeconomic variables	INF	UK annual inflation rate over the time <i>t</i>	Worldbank index	+/-
	GDP	UK GDP rate over the time <i>t</i>	World Bank index	+/-

Table 2. Descriptive statistics.

	MEAN	MEDIAN	SD	25%	75%	SKEWNESS	KURTOSIS
SANDBOX	6.8499	2.00	9.572	1.000	9.000	1.792	5.055
ROA(%)	0.398	1.00	4.238	0.456	1.6178	−5.965	41.271
NIM(%)	4.942	4.902	3.293	3.952	6.113	−1.968	13.124
ROE(%)	7.987	7.024	15.223	2.921	12.137	1.589	18.367
YEA(%)	10.113	9.443	2.924	8.200	11.273	1.559	6.187
CAP(%)	11.967	10.961	6.932	8.586	14.835	−0.084	10.711
LLP(%)	1.715	0.627	4.716	0.171	1.508	5.522	36.916
CTI(%)	55.975	53.499	18.199	43.989	63.595	1.656	7.999
DG(%)	16.321	12.699	19.123	5.410	22.524	1.237	7.193
FC(%)	8.927	6.726	11.305	5.157	8.224	5.799	37.276
IIS(%)	91.173	91.689	6.356	87.912	95.778	−0.993	3.471
INF(%)	7.667	5.938	13.342	3.358	9.400	2.104	10.795
GDP(%)	3.211	7.664	0.652	6.908	8.174	−0.421	1.809
SIZE	7.268	7.128	1.903	5.696	8.768	0.142	2.004

This table reports 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.

Empirical Framework

Our empirical model is motivated by the literature that estimates the determinants of bank performance by following the previous researchers (Ahmad et al. 2021; Barra and Zotti 2019; Chen et al. 2021; Ekinci and Poyraz 2019). Our regression model is.

$$Performance_{it} = \alpha + \beta_1 Sanbox_{it} + \beta_2 Perf_{1-t} + \beta_3 CAP_{it} + \beta_4 LLP_{it} + \beta_5 Size_{it} + \beta_6 DPG_{it} + \beta_7 LG_{it} + \beta_8 INF_t + \beta_9 GDP_t + \beta_{10} FC_t + \epsilon \tag{1}$$

where *I* for bank and *t* for time represent digital banks’ adoption or regulatory framework (in EQ1). Performance represents the financial performance of bank proxied by ROA and ROE. CAP represents the capital banks must require (Catalán et al. 2020; Ünvan and Yakubu 2020). LLP represents the ratio of non-performing loans (Hsieh and Lee 2020). SIZE represents the log of total assets of the bank (Hu and Gong 2019; Niu et al. 2020). DPG represents the deposit growth ratio. LG represents loan growth (Taylor et al. 2020). INF represents the inflation rate (Vo et al. 2020). GDP represents the rate of gross domestic product (Badarau and Lapteacru 2020). Table 1 briefly describes the measurement of dependent and independent variables.

The last column of Table 1 provides detailed descriptions of each variable and its anticipated signals. These links are touched on briefly in this section. The first control variable is the capitalization ratio (CAP), computed by dividing total equity by total assets. Previous studies on the nexus of capital and bank performance have not produced solid evidence regarding the dynamics of this connection (Bagntasarian and Mamatzakis 2019; Sannino et al. 2021; Simoens and Vander Vennet 2021). However, according to the findings of specific research, the performance of banks is improved when they have more capital.

According to this theory, banks with greater capital ratios boost their predicted profits by cutting interest costs on uninsured loans. According to Berger et al. (1987) the signaling theory, which describes additional capital as a positive signal about the bank’s prospects, is proposed as an alternate explanation. Larger equity-to-asset ratio banks may not need external financing, leading to higher earnings. According to Osborne et al. (2012), a higher CAP is associated with poorer bank performance. Debt is often believed to be less costly than capital due to the tax advantages associated with debt and the flaws in the market. These authors also give an opposing position, arguing that more capital lowers risk, resulting in a smaller compensation premium sought by investors to cover bankruptcy costs. That increased capital decreases risk inspired their idea. The “trade-off” approach, which

maintains that there is a positive link between capital and bank performance, is compatible with this premise. A large number of people support this opinion. As a consequence of this, we predict that CAP will have an influence, either favorably or adversely, on the performance of banks.

The influence of bank size (SIZE), which we proxy using banks' total assets, is likewise uncertain for various reasons. First, compared to smaller banks, large banks will have superior operational efficiency due to economies of scale and scope, resulting in cost savings (greater product and loan diversification). Consequently, we believe that the size of a bank has a favorable influence on earnings, following [Bonin et al. \(2005\)](#); [Laeven et al. \(2016\)](#).

According to [Short \(1979\)](#), large banks have access to cheaper capital, which translates into healthy profitability. In addition, large banks, according to ([Laeven et al. 2016](#)), reduce risk by diversifying their products and services, resulting in increased operational efficiency and profitability. Furthermore, [Taylor et al. \(2020\)](#) demonstrate that large banks can earn higher profits than small banks in a non-competitive environment.

Large banks can offer lower deposit rates while maintaining high lending rates because they have a larger market share. Furthermore, [Laeven et al. \(2016\)](#) [Barra and Zotti \(2019\)](#), and [Ahmad et al. \(2021\)](#) show that the size of a bank is inversely related to its profits due to bureaucracy.

The CTI variable is calculated by dividing total generated revenues by operating costs (staff salaries, property costs, and administrative costs, excluding bad and non-performing loans) (see ([Dietrich and Wanzenried 2014](#))). Bank performance should suffer as the CTI rises, implying lower bank efficiency. Previous empirical studies have found a negative relationship; see, for example, [Hess and Francis \(2004\)](#), [Ghurtskaia \(2018\)](#), and [Badarau and Lapteacru \(2020\)](#). To safeguard banks' profitability and capital positions, we utilize LLP as a surrogate for credit risk. LLP is a variable considered a reserve to cover any prospective loan default. ([Beatty and Liao 2011](#)); [Hsieh and Lee \(2020\)](#). The level of LLP indicates a bank's asset quality and can be used to forecast changes in future performance ([Beatty and Liao 2011](#)). According to [Laeven et al. \(2016\)](#) when banks give out loans with a high degree of risk, they end up with an increased number of loans that are not repaid, which has a negative impact on their profitability. According to, more credit risk exposure is related to decreasing bank profitability. In addition, it is anticipated that bad loans will affect profitability. As a consequence, we expect bank performance to suffer as a direct result of LLP.

We utilize DG to monitor bank growth. A growth-oriented or growing bank means that the firm is increasing and producing more money. However, a rise in deposit growth does not automatically indicate an increase in bank profitability. Therefore, banks must transform deposits into profitable investments. One method is to provide lending preference to applicants with poorer credit ratings.

Furthermore, deposit growth might attract and drive market rivalry. This growth has the potential to limit market earnings for banks. Consequently, from a theoretical approach, the impact of DG remains uncertain. Moreover, existing empirical evidence is conflicting. For example, [Rawan \(2019\)](#) discover a positive relationship; [Demirgüç-Kunt and Huizinga \(1999\)](#) find a negative relationship; and [Dietrich and Wanzenried \(2014\)](#) discover an insignificant relationship ([Laeven et al. 2016](#)).

FC is the last firm-specific control variable, and its value is calculated by dividing total interest expenditures by the firm's average deposits. It is anticipated that bank earnings will decrease if FC continues to climb. The findings of [Dietrich and Wanzenried \(2014\)](#), which show a positive link between inflation and profitability, indicate that FC has a negative and statistically significant influence on bank performance. On the other hand, if inflation is unanticipated and banks fail to adjust interest rates, expenses can grow faster than revenues, reducing bank earnings. These arguments give the impression that INF may have an undiscovered impact on profitability a priori.

Last but not least, we investigate how the GDP influences the performance of banks across the economic cycle. When there is a downturn in the economy, sometimes known as

a recession, the quality of the loan portfolio suffers. As a direct consequence, credit losses occur, cutting the bank’s profitability. Additionally, owing to the economic impacts on the net interest income generated by lending activities, earnings are likely to be affected positively by economic cycles. According to Dietrich and Wanzenried, the demand for loans goes up (goes down) during cyclical upswings and downswings, respectively (Dietrich and Wanzenried 2014). In addition, there is a large body of research that shows that economic growth helps to stimulate the financial system (Demirgüç-Kunt and Huizinga 1999; Hu and Gong 2019; Simoens and Vander Venet 2021; Ünvan and Yakubu 2020; Simoens and Vander Venet 2021; Ünvan and Yakubu 2020; Simoens and Vander Venet 2021). As a consequence of this, we estimate that the rate of GDP growth will accurately forecast the performance of banks. Error term explains that None of the independent variables have a perfect linear relationship (perfect collinearity or multicollinearity) with any of the other independent variables. (Please see Table 3 for serial correlations and autocorrelation)

Table 3. Autocorrelation.

Autocorrelation	Partial Correlation	PAC	AC	Probability	q-Statistics	
. .	. .	1	0.010	0.010	0.884	0.0213
* .	* .	2	−0.068	−0.068	0.606	1.0029
** .	** .	3	−0.239	−0.239	0.005	12.836
** .	** .	4	−0.255	−0.235	0.00	24.260
* .	** .	5	−0.276	−0.192	0.00	31.994
. *	. .	6	0.024	0.122	0.00	35.116
. .	* .	7	−0.153	0.038	0.00	35.424
. *	* .	8	−0.084	0.114	0.00	38.157
. .	. .	9	−0.191	−0.047	0.00	38.618

Source Authors own calculation. * significance at 1%, ** significance at 5% level of significance.

4. Results

4.1. Model of Reference

The conventional factors that determine banking industry performance are estimated in Table 4, which will serve as the basis for our subsequent discussion of the results. The two-step GMM system dynamic panel estimator is used to provide an estimate for the panel data regression. The results are presented in the form of columns. One column is devoted to each of the four dependent variables that serve as indicators of the performance of the banking industry. Because it was calculated without considering the variable of interest, this regression acts as the starting point for the remainder of the investigation (Sandbox). The following are some of the most interesting findings shown in Table 4. The first question addresses which of the four proxies for banking sector performance exhibits the highest level of statistically significant performance. ROE is the dependent variable for the model with the lowest predictive power; just four of the ten drivers are statistically significant. When NIM, ROA, or EA is used as the dependent variable, sixty percent of the determinants are considered statistically unimportant (insignificant). CTI and GDP, followed by CAP and INF, are significant factors independent of the variable being looked at (the dependent variable). Finally, two of the four models show a statistically significant relationship between LLP, DG, and IIS. In conclusion, FC is the sole variable with no prediction capacity.

Table 4. Determinants of bank performance of Digital banks.

	ROE	ROA	NIM	YEA
<i>PERFORMANCE(-1)</i>	0.182 * (1.77)	0.068 (1.43)	0.182 (1.42)	0.417 *** (5.37)
<i>CTI</i>	−0.336 *** (−4.18)	−0.027 *** (−3.33)	−0.187 *** (−5.52)	−0.047 *** (−3.12)
<i>CAP</i>	−0.897 *** (−3.05)	0.056 ** (2.13)	−0.006 (−0.19)	−0.085 ** (−2.22)
<i>LLP</i>	−0.337 (−0.59)	−0.551 *** (−8.56)	−0.074 ** (−2.26)	0.071 (0.93)
<i>IIS</i>	−0.056 (−0.31)	−0.024 (−1.48)	0.060 ** (2.19)	0.1086 *** (4.4)
<i>DG</i>	0.036 (0.94)	−0.003 (−1.06)	−0.018 *** (−4.51)	−0.021 *** (−3.98)
<i>FC</i>	0.063 (1.33)	0.004 (0.31)	−0.011 (−1.05)	−0.005 (−0.34)
<i>INF</i>	−0.016 (−0.32)	0.016 *** (3.84)	0.027 *** (2.91)	0.028 *** (4.63)
<i>GDP</i>	−0.483 *** (−2.59)	−0.096 *** (−3.34)	−0.102 *** (−4.23)	−0.240 *** (−7.39)
<i>SIZE</i>	−0.231 (−0.36)	0.243 *** (3.85)	−0.116 (−0.85)	−0.156 (−1.31)
CONSTANT	43.697 *** (2.62)	3.237 (1.61)	6.473 * (1.77)	2.111 (0.63)
AR(2)	0.442	0.267	0.382	0.759
HANSEN	0.526	0.587	0.723	0.345
OBSERVATION	493	493	372	493

Table 4 reports regression results from the bank performance determinants model. The model has the following form:

$$Performance_{it} = \alpha + \beta_1 Perf_{1-t} + \beta_2 CAP_{it} + \beta_3 LLP_{it} + \beta_4 Size_{it} + \beta_5 DPG_{it} + \beta_6 LG_{it} + \beta_7 INF_t + \beta_8 GDP_t + \beta_9 FC_t + \epsilon$$

The regression results from the bank performance determinants model are presented in Table 4. The model takes the following shape. In this regression, is measured by NIM, ROA, ROE, and YEA, and the control variables are described in Table 1. The two-step GMM system dynamic panel estimator is used for estimation. The null hypothesis of second-order autocorrelation in the first differenced residuals underpins the Arellano- Bond (AB) test for serial correlation. The p-value associated with the Hansen test is reported in order to determine the validity of the overidentifying restrictions. Finally, the symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2. The Impact of Regulatory Sandbox on Bank Performance of Digital Banks

First, we check to see whether any of our explanatory variables exhibit multicollinearity before moving on to the regression analysis proper. All of the variance inflation factors (VIFs) point to the conclusion that there is no substantial multicollinearity present. Second, we will begin by doing a CD test as well as a Fisher test to assess whether or not the analysis of our data should be carried out using panel estimation or pooled estimation methods. In addition, most panel data models are estimated under either fixed effects or random effects assumptions. In order to pick between these two fundamental models, we carry out a test called the Hausman test. The results of the Hausman tests, which were omitted from the table in the sake of brevity, suggest that the fixed effects model is more effective than the random effects model.

Furthermore, the lag lengths for the unit root tests were determined. The results indicate that variables are found level stationary. The test statistics −3.06, −3.48, −10.73, −3.30, −2.92, −2.80, −2.87 and −2.91, respectively and exceed the critical value (−2.75) at

the 5 percent level. In each of these cases, the null hypothesis of a unit root is rejected as the test statistics are greater than the critical values at the conventional levels.

Now we'll investigate whether or not the Sandbox impacts the performance of digital banks. The results of an investigation on the simultaneous impact of a regulatory sandbox on each of the four measurements of digital bank performance are summarized in Table 5. In each of the four models, the slope coefficient on the influence of the Sandbox is shown to have a statistically distinct value from zero. The implication of Sandbox brings a reduction in 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). According to these slope coefficients, adding one additional digital bank to the financial services industry causes a reduction in NIM, ROA, ROE, and YEA of 0.38 percent, 7.30 percent, 1.73 percent, and 0.38 percent of the mean value, respectively. (As seen in Table 1, the mean values of NIM, ROA, ROE, and YEA are 4.94 percent, 0.40 percent, 7.99 percent, and 10.11 percent, respectively.)

Table 5. Contemporaneous effect of regulatory Sandbox on digital bank performance.

	ROA	NIM	YEA	ROE
SANDBOX	−0.028 *** (−3.03)	−0.018 *** (−2.66)	−0.037 *** (−3.52)	−0.137 *** (−2.73)
<i>PER(-1)</i>	0.061 (1.27)	0.167 (1.42)	0.367 *** (4.81)	0.147 (1.37)
<i>CTI</i>	−0.027 *** (−2.62)	−0.111 *** (−6.19)	−0.045 ** (−2.47)	−0.317 *** (−3.96)
<i>DG</i>	−0.006 * (−1.84)	−0.022 *** (−4.11)	−0.027 *** (−4.57)	0.023 (0.63)
<i>LLP</i>	−0.543 *** (−8.93)	−0.064 * (−1.75)	0.108 (1.33)	−0.291 (−0.53)
<i>IIS</i>	−0.017 (−0.95)	0.064 ** (2.25)	0.119 *** (4.68)	−0.078 (−0.36)
<i>INF</i>	0.012 *** (2.78)	0.023 *** (2.93)	0.024 *** (3.78)	−0.032 (−0.66)
<i>GDP</i>	−0.103 *** (−2.89)	−0.107 *** (−4.26)	−0.249 *** (−7.48)	−0.530 *** (−2.74)
<i>SIZE</i>	0.300 *** (5.45)	−0.091 (−0.69)	−0.096 (−0.71)	−0.177 (−0.24)
<i>FC</i>	−0.001 (−0.14)	−0.012 (−1.55)	−0.007 (−0.47)	0.023 (0.54)
<i>CAP</i>	0.086 *** (2.99)	0.006 (0.17)	−0.049 (−1.19)	−0.761 ** (−2.57)
CONSTANT	1.979 (1.08)	6.236 * (1.87)	0.824 (0.25)	45.065 ** (2.24)
AR(2)	0.234	0.402	0.892	0.476
HANSEN	0.469	0.717	0.362	0.576
OBSERVATION	494	374	494	492

The findings of the regression analysis carried out on the bank performance determinants model with the addition of the Sandbox variable are shown in Table 5. The following is the shape that the regression model takes.

$$Performance_{it} = \alpha + \beta_1 Sanbox_t + \beta_2 Perf_{1-t} + \beta_3 CAP_{it} + \beta_4 LLP_{it} + \beta_5 Size_{it} + \beta_6 DPG_{it} + \beta_7 LG_{it} + \beta_8 INF_t + \beta_9 GDP_t + \beta_{10} FC_t + \epsilon_{i,t}$$

Table 5 reports regression results from the bank performance determinants model augmented with the *Regulatory sandbox* variable. The regression model has the following form: In this regression, is measured by NIM, ROA, ROE, and YEA, and the description of the control variables arenoted 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.

The following collection of studies addresses the question of whether or not the use of a regulatory sandbox by digital banks can accurately forecast bank performance. Our research shows that Sandbox has a negative impact on 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). These slope coefficients imply that the NIM, ROA, ROE, and YEA will decrease by 0.53 percent, 9.32 percent, 2.07 percent, and 0.48 percent (of their sample means), respectively, for every new FinTech firm that enters the market. This result has implications regarding the economic significance of the data (see Table 6)

Table 6. Lag effect of regulatory Sandbox on bank performance.

	YEA	ROA	NIM	ROE
<i>SANDBOX(-1)</i>	−0.048 *** (−4.48)	−0.037 *** (−3.74)	−0.026 *** (−2.86)	−0.165 * (−1.83)
<i>PER(-1)</i>	0.374 *** (5.23)	0.072 (1.26)	0.174 (1.49)	0.151 (1.37)
<i>CAP</i>	−0.048 (−1.20)	0.084 *** (2.84)	0.006 (0.20)	−0.774 ** (−2.37)
<i>LLP</i>	0.108 (1.41)	−0.537 *** (−8.87)	−0.060 (−1.63)	−0.277 (−0.50)
<i>CTI</i>	−0.044 ** (−2.49)	−0.024 ** (−2.31)	−0.110 *** (−6.39)	−0.323 *** (−3.77)
<i>IIS</i>	0.121 *** (4.95)	−0.017 (−0.96)	0.065 ** (2.31)	−0.072 (−0.34)
<i>DG</i>	−0.025 *** (−4.53)	−0.006 * (−1.73)	−0.021 *** (−4.20)	0.023 (0.65)
<i>INF</i>	0.022 *** (3.52)	0.009 ** (2.00)	0.022 *** (2.97)	−0.042 (−0.78)
<i>GDP</i>	−0.243 *** (−7.27)	−0.098 *** (−2.98)	−0.103 *** (−4.44)	−0.494 ** (−2.36)
<i>FC</i>	−0.006 (−0.44)	−0.001 (−0.09)	−0.011 * (−1.69)	0.033 (0.76)
<i>SIZE</i>	−0.089 (−0.66)	0.301 *** (4.95)	−0.078 (−0.61)	−0.154 (−0.19)
CONSTANT	0.435 (0.13)	1.969 (1.03)	6.099 * (1.88)	44.205 ** (2.00)
HANSEN	0.378	0.488	0.765	0.524
AR(2)	0.882	0.182	0.466	0.459
OBSERVATION	494	494	374	492

We investigate if the banks’ features have any bearing on the effect that regulatory sandboxes have on bank performance. The studies done by [Dietrich and Wanzenried \(2014\)](#), and Matousek, Rughoo, Sarantis, and Assaf provided the push for further research into the role that bank features play in the formation of this association (2015). According to the findings of this research, the features of the bank have a substantial influence on the bank’s performance. As a consequence of the results of this research, we investigate two elements of bank characteristics: market value (MV) and company age (FA). Companies with a high market capitalization are more competitive and efficient than companies with a lower market capitalization because companies with a higher market capitalization have more visibility and liquidity. Consequently, we believe that the effect of the regulatory Sandbox on high MV (MV2) banks will differ from what it will have on banks with low MV (MV1). In addition, we believe that the impacts of financial technology will vary with the user’s age (maturity).

Our findings are summarized in Table 6. Based on firm characteristics, we see distinct patterns in the sandbox effect. According to MV, regulatory Sandbox has a negative impact

on both large and small banks, but the result is more significant on large digital banks. Smaller businesses, for example, may be able to adapt to technological innovation more quickly than larger businesses (Dos Santos and Peffers 1995; Sannino et al. 2021; Vo et al. 2020). According to the literature, larger firms must bear significantly higher reorganization costs than smaller firms due to legacy systems. Scott et al. (2017) argue that small businesses can better adjust to internal and external changes in their operations regarding technological transformations. Larger companies, on the other hand, may take longer to respond due to legacy systems that require significant modification.

Table 6 reports regression results of Fin Tech firms' influence on bank performance with a one -period lag. The predictive regression model takes the following form:

$$Performance_{it} = \alpha + \beta_1 Sanbox_{t-1} + \beta_2 Perf_{i,1-t} + \beta_3 CAP_{it} + \beta_4 LLP_{it} + \beta_5 Size_{it} + \beta_6 DPG_{it} + \beta_7 LG_{it} + \beta_8 INF_t + \beta_9 GDP_t + \beta_{10} FC_t + \epsilon_{i,t}$$

Table 6 reports regression results of regulatory sandbox influence on bank performance with a one- period lag. The predictive regression model takes the following form: In this regression, 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.

Table 7 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:

$$Performance_{it} = \alpha + \beta_1 Sanbox_t + \beta_2 Perf_{i,1-t} + \beta_3 CAP_{it} + \beta_4 LLP_{it} + \beta_5 Size_{it} + \beta_6 DPG_{it} + \beta_7 LG_{it} + \beta_8 INF_t + \beta_9 GDP_t + \beta_{10} FC_t + \epsilon_{i,t}$$

$$Performance_{it} = \alpha + \beta_1 Sanbox_{t-1} + \beta_2 Perf_{i,1-t} + \beta_3 CAP_{it} + \beta_4 LLP_{it} + \beta_5 Size_{it} + \beta_6 DPG_{it} + \beta_7 LG_{it} + \beta_8 INF_t + \beta_9 GDP_t + \beta_{10} FC_t + \epsilon_{i,t}$$

Table 7 reports regression results of the effect of Regulatory sandbox 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: These categorizations are based on the mean values of MV and FA. The regression models take the following forms: In this regression, 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 of FinTech variable. Finally, *, **,and *** denote significance at the 10%, 5% and 1% levels, respectively.

When NIM, ROA, and YEA are the dependent variables, respectively, Sandbox has a negative influence on mature banks, with a slope of -0.018 (t -stat. = -1.69), -0.028 (t -stat. = -2.43), and -0.037 (t -stat. = -2.87), respectively. Younger banks have a positive effect when NIM and YEA are the dependent variables, with a slope coefficient of 0.052 (t -stat. = 1.87) and 0.020 (t -stat. = 2.42), respectively. This result indicates a positive correlation between the two. Previous studies have shown that younger companies have a better track record of successfully absorbing and putting into practice technological innovation. This result is due to their increased adoption of technological innovation (Anagnostopoulos 2018; Ehrentraud et al. 2020).

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

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

Predictability is also affected by the characteristics of the bank. For example, regulatory Sandbox predicts performance regardless of bank size; however, regulatory Sandbox is more critical to small than large banks. Sandbox, on the other hand, predicts performance only for mature banks and not for relatively young banks based on age.

We have private and state-owned digital banks (government banks that lunch their FinTech subsidiaries) in our sample. The findings are summarized below. We focus on controlling for bank ownership in additional results reported in Table 8. sandbox’s impact on the performance of state-owned banks is notable. Regulatory Sandbox does not have any effect on NIM, but it does have a negative influence that is statistically significant on ROA (−0.043, *t*-stat. = −2.20), ROE (−0.276, *t*-stat. = −1.79), and YEA (−0.036, *t*-stat. = −2.65). Regulatory Sandbox does not have any effect on NIM. However, when it comes to the capability of Sandbox to forecast performance, we find that it accurately predicts NIM (−0.027, *t*-stat. = −3.15), ROA (−0.034, *t*-stat. = −3.29), and YEA (−0.050, *t*-stat. = −3.06). On the other hand, Sandbox does not provide any predictions about ROE for state-owned banks.

Table 8. Effect of FinTech firms on bank performance sorted by ownership.

PANEL A: CONTEMPORANEOUS EFFECT				
	YEA	ROA	NIM	ROE
SANDBOX*STATE	−0.036 *** (−2.65)	−0.043 ** (−2.20)	−0.008 (−0.35)	−0.276 * (−1.79)
SANDBOX*(1-STATE)	−0.038 *** (−2.94)	−0.026 *** (−3.21)	−0.020 *** (−2.87)	−0.100 * (−1.79)
PER(−1)	0.363 *** (4.28)	0.057 (1.14)	0.173 (1.55)	0.151 (1.35)
CAP	−0.048 (−1.10)	0.082 *** (2.94)	0.006 (0.19)	−0.823 ** (−2.52)

Table 8. Cont.

SIZE	−0.097 (−0.69) (4.28)	0.308 *** (5.40) (1.14)	−0.103 (−0.77) (1.55)	0.068 (0.09) (1.35)
CAP	−0.048 (−1.10)	0.082 *** (2.94)	0.006 (0.19)	−0.823 ** (−2.52)
SIZE	−0.097 (−0.69)	0.308 *** (5.40)	−0.103 (−0.77)	0.068 (0.09)
CTI	−0.044 ** (−2.38)	−0.027 ** (−2.51)	−0.107 *** (−6.03)	−0.340 *** (−3.91)
LLP	0.110 (1.29)	−0.542 *** (−9.16)	−0.067 ** (−2.13)	−0.243 (−0.42)
DG	−0.026 *** (−4.43)	−0.006 * (−1.88)	−0.022 *** (−4.54)	0.026 (0.69)
IIS	0.119 *** (4.72)	−0.016 (−0.98)	0.064 ** (2.17)	−0.037 (−0.20)
FC	−0.007 (−0.48)	−0.002 (−0.29)	−0.012 (−1.55)	0.043 (0.90)
GDPC	−0.249 *** (−7.45)	−0.106 *** (−3.14)	−0.103 *** (−3.94)	−0.540 *** (−2.70)
INF	0.024 *** (3.73)	0.011 ** (2.37)	0.024 *** (2.91)	−0.033 (−0.69)
CONSTANT	0.840 (0.26)	2.110 (1.16)	6.146 * (1.78)	41.077 ** (2.12)
AR(2)	0.906	0.257	0.442	0.498
HANSEN	0.364	0.525	0.764	0.451
OBSERVATION	494	494	374	492
PANEL B: LAG EFFECT				
	YEA	ROA	NIM	ROE
SANDBOX(-1)*STATE	−0.050 *** (−3.06)	−0.034 *** (−3.29)	−0.027 *** (−3.15)	−0.092 (−1.11)
SANDBOX(-1)*(1-STATE)	−0.051 *** (−2.93)	−0.052 ** (−2.10)	−0.014 (−0.50)	−0.418 (−1.61)
PER(-1)	0.371 *** (4.45)	0.067 (1.19)	0.174 (1.53)	0.147 (1.26)
CAP	−0.049 (−1.18)	0.082 *** (2.87)	0.006 (0.20)	−0.820 ** (−2.48)
SIZE	−0.090 (−0.65)	0.302 *** (5.04)	−0.092 (−0.70)	−0.213 (−0.24)
CTI	−0.044 ** (−2.49)	−0.026 ** (−2.30)	−0.108 *** (−6.13)	−0.343 *** (−3.66)
LLP	0.112 (1.29)	−0.537 *** (−9.00)	−0.066 ** (−2.15)	−0.290 (−0.50)
DG	−0.025 *** (−4.52)	−0.006 * (−1.68)	−0.022 *** (−4.55)	0.022 (0.58)
IIS	0.122 *** (4.63)	−0.018 (−1.04)	0.067 ** (2.31)	−0.118 (−0.55)
FC	−0.006 (−0.42)	−0.002 (−0.18)	−0.011 (−1.57)	0.035 (0.76)
GDPC	−0.244 *** (−7.04)	−0.101 *** (−2.96)	−0.101 *** (−4.28)	−0.518 ** (−2.10)
INF	0.022 *** (3.56)	0.010 ** (2.12)	0.023 *** (2.96)	−0.034 (−0.69)
CONSTANT	0.458 (0.14)	2.124 (1.17)	5.794 * (1.74)	50.541 ** (2.18)
AR(2)	0.873	0.184	0.503	0.482
HANSEN	0.377	0.537	0.789	0.644
OBSERVATION	494	494	374	492

Table 8 reports regression results of the effect of FinTech firms on the performance of state—and private -owned banks. The regression models take the following form

$$Performance_{it} = \alpha + \beta_1 Sanbox_t * State + \beta_2 Perf_{i,1-t} + \beta_3 CAP_{it} + \beta_4 LLP_{it} + \beta_5 Size_{it} + \beta_6 DPG_{it} + \beta_7 LG_{it} + \beta_8 INF_t + \beta_9 GDP_t + \beta_{10} FC_t + \epsilon_{i,t}$$

$$Performance_{it} = \alpha + \beta_1 Sanbox_{t-1} * State + \beta_2 Perf_{i,1-t} + \beta_3 CAP_{it} + \beta_4 LLP_{it} + \beta_5 Size_{it} + \beta_6 DPG_{it} + \beta_7 LG_{it} + \beta_8 INF_t + \beta_9 GDP_t + \beta_{10} FC_t + \epsilon_{i,t}$$

Table 8 reports regression results of the effect of *regulatory sandbox* on the performance of state- and private- owned banks. The regression models take the following forms estimates the predictive ability (Panel B) of FinTech. In this regression, 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.

When looking at private banks, we find that Sandbox simultaneously impacts all four performance metrics. However, it can only be used to forecast ROA (-0.052 , t -stat. = -2.10) and YEA (-0.051 , t -stat. = -2.93). In general, we find that the adverse effects of sandboxes are felt more strongly by state-owned financial institutions than by private financial institutions. This result is because state-owned (public) banks, compared to private enterprises, are more likely to be tardy in adopting and implementing technological improvements. On the other hand, state-owned businesses have a more bureaucratic culture and are thus more likely to accept innovations reactively. As a result, private digital banks often proactively adopt innovations. In addition, state-owned businesses are notoriously hesitant to embrace new technologies since political considerations constrain them.

Limitations bring about timing constraints in the budget. They depend on limits placed on budgeting cycles as a result of political pressures and periodic adjustments in the government's political goals. Another set of evidence suggests that privately held banks are more competitive than state-owned financial institutions. The inefficiency of operations at state-owned banks and the poor intermediation quality resulting from high agency costs reduce these institutions' competitiveness. Several studies arrive at these conclusions by contrasting the levels of competition provided by state-owned and private banks by analyzing their respective performance levels. As a consequence, when the level of competition in the market increases due to new entrants, the performance of state-owned banks is worse than that of private banks (FinTech).

Because the findings are relatively consistent, we will complete the discussion of the results with a comment on the impact of some of the primary factors on the performance of digital banks. This comment will be based exclusively on Table 4, as it contains all of the findings. In line with the results of the previous research, we discover conflicting evidence on the signaling theory. For example, CAP has a good influence on ROA but a negative impact on ROE and YEA. On the other hand, CAP also has a favorable impact on YEA. The magnitude of an effect is important (but significant only when ROA is the dependent variable). This fact lends credence to our argument that big banks enjoy various benefits, including risk diversification, economies of scale, and cheaper capital costs. Our contention that a rise in CTI signals a decline in bank efficiency is bolstered by the fact that CTI always has a negative impact on performance. In conclusion, LLP has a negative sign when NIM and ROA are dependent variables. This result is because, as was said earlier, a larger LLP means that loan coverage for defaults is greater.

4.3. Robustness Evaluations

We validate the robustness of our results by pursuing two other lines of investigation; failure to do so might jeopardize our primary findings. The first is the effect that the Great Depression had on the economy. As a direct consequence, one of the shortcomings of our research is that we do not directly account for the influence of the GFC. We can achieve this goal by using a dummy variable inside the regression model. This variable has a value of one for the years 2007 and 2008. However, for the other years, it has a value of zero. According to the research, the inclusion of the GFC control has no bearing on sandboxes' effect on the functioning of digital banks as financial institutions (see Table 9). There is continuing evidence that FinTech has a negative and statistically significant effect on each of the four metrics that assess bank performance.

Table 9. Robustness tests.

PANEL A: CONTEMPORANEOUS EFFECT				
	ROA	NIM	YEA	ROE
GFC	−0.030 *** (−3.50)	−0.017 ** (−2.54)	−0.036 *** (−3.57)	−0.137 *** (−2.73)
FE	−0.062 ** (−2.38)	−0.062 *** (−3.02)	−0.071 *** (−2.81)	0.267 (0.97)
PANEL B: LAG EFFECT				
	ROA	NIM	YEA	ROE
GFC	−0.038 *** (−3.64)	−0.023 *** (−2.69)	−0.048 *** (−4.36)	−0.177 ** (−2.33)
FE	−0.045 ** (−1.99)	−0.047 ** (−2.52)	−0.043 ** (−2.03)	0.272 (1.13)

Table 9 reports results of robustness tests for the regulatory sandbox influence on bank performance of digital banks. 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 sandbox 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.

This Table 10 reports the economic significance of all statistical results presented in earlier tables. It shows how NA, ROA, ROE and YEA sample means are affected by every new FinTech firm introduced into the market.

Table 10. Economic significance.

Panel A: Contemporaneous effect				
	ROA	NIM	YEA	ROE
Main regression	−7.30%	−0.38%	−0.38%	−1.73%
MV1	−6.55%	−0.28%	−0.41%	−1.51%
MV2	0.00%	−0.49%	−1.37%	−1.92%
FA1	−2.52%	1.05%	0.20%	−0.53%
FA2	−7.05%	−0.36%	−0.37%	−1.33%
Sandbox*STATE	−10.83%	−0.16%	−0.36%	−3.46%
Sandbox*(1-STATE)	−6.55%	−0.40%	−0.38%	−1.25%
GFC	−7.56%	−0.34%	−0.36%	−1.72%
Fixed effects	−15.62%	−1.25%	−0.70%	3.34%
GMM difference two-step	−16.62%	−0.04%	−0.48%	−0.63%

Table 10. Cont.

<i>Panel B: Lag effect</i>				
	ROA	NIM	ROE	YEA
<i>Main regression</i>	−9.32%	−0.53%	−0.48%	−0.48%
<i>MV1</i>	−8.06%	−0.38%	−0.50%	−0.50%
<i>MV2</i>	0.00%	−0.53%	−1.23%	−1.23%
<i>FA1</i>	−2.02%	1.94%	0.09%	0.09%
<i>FA2</i>	−8.56%	−0.34%	−0.43%	−0.43%
<i>Sandbox(-1)*STATE</i>	−8.56%	−0.55%	−0.49%	−0.49%
<i>Sandbox(-1)*(1-STATE)</i>	−13.10%	−0.28%	−0.50%	−0.50%
<i>GFC</i>	−9.57%	−0.47%	−0.47%	−0.47%
<i>Fixed effects</i>	−11.34%	−0.95%	−0.43%	−0.43%
<i>GMM difference two-step</i>	−12.59%	−0.14%	−0.74%	−0.74%

Our second question concerns the use of an alternative estimator. We employ a panel estimator with fixed effects (firm and year) widely used in the literature. The findings in Table 9 show that the effects of FinTech on bank performance are unaffected by using a different estimator. We conclude from these robustness tests that the regulatory sandbox effects we document are unaffected by the GFC and the use of a different (popular) estimator.

5. Conclusions

This article was motivated by the spectacular expansion of digital banking worldwide, particularly in the United Kingdom. Regarding whether or not the recently formed regulatory sandboxes affect the digital banking industry, there is a lot of doubt. We establish our hypothesis as a result of this gap in the existing research, which states that the expansion of regulatory sandboxes has a negative impact on the bank performance of digital banks. We generate a data sample that is one of a kind and focuses on digital banks and FinTech companies in the UK. We use a dataset including a panel of 24 banks from 2016 to 2021 to estimate a banking performance determinant and a forecasting model. The time period covered by the dataset is from 2016 to 2021. Our sandbox metric is an addition to the conventional banking performance model already being used. Because it is not fully understood how, if at all, Sandbox influences the performance of the digital banking sector; we employ four performance indicators: the ratio of net interest income to total assets (NIM), the ratio of net income to total assets (ROA), the ratio of net income to total equity (ROE), and the yield on earning assets (YEA). We show, using several models, that the regulatory Sandbox negatively influences all four performance indicators. Our findings are supported by statistical significance. According to a subset of our results, high-value mature banks are more severely affected by Sandbox than lower-value younger private digital banks. This result is because FinTech is more likely to disrupt traditional banking models. Our results are reliable because they are unaffected by the majority of proxies for bank performance, various control variables, controls for the Great Recession, controls for varying company panel compositions, and a different estimator.

This study has contributed to the limited available literature on regulatory Sandbox and its implication for FinTech firms' performance, as there is no study to date. This research is also substantial for regulators and policymakers as they are unsure about the outcome of newly developed regulations. Our findings will help them to understand and create better regulations for new and relatively small FinTech firms (i.e., digital banks).

This study also has data limitations as the data collected was hand-collected. However, future research can be conducted utilizing already established databases on FinTech. Furthermore, the prospective researcher can use the index to measure the regulatory sandbox adoption by using the financial statement of banks and online search engines.

Author Contributions: Writing—original draft preparation, methodology, formal analysis, S.U.R.; writing—review and editing, formal analysis, P.B.W.; supervision, E.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Center Advancing Financial Equity and funded by Institute4me.org (under the Financing the Race Grant).

Data Availability Statement: Data can be provided on demand.

Conflicts of Interest: The authors declare no conflict of interest.

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