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The effect of financial innovation on bank stability: *Evidence from the OECD countries*

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Summary

The rapid rate of financial innovations in the past decades has emerged a widespread academic and political debate about the effects of financial innovations. However, the Global Financial crisis of 2007-2009 has spurred renewed widespread debates on the effects of financial innovation. This period has highlighted the limitations and hazards of financial innovation while dimming the lights on its core benefits for an economy. This has led to a shift in the regulatory framework of banks. Motivated by this change, this research is going to investigate whether financial innovation affects bank stability. Measures for both inputs as outputs of financial innovation are used to test if financial innovation affects banks' stability. Using a sample of 9260 banks out of 35 OECD countries for the period 2010-2019, this research finds weak evidence for a link between financial innovation and bank stability. This is in contrast with previous studies from before the crisis. These findings show that policymakers might have succeeded in their job to mitigate the negative effects of financial innovations. Furthermore, in countries other than the United States, fintech companies positively affect the stability of banks, and off-balance sheet activities only seem to affect the stability of commercial banks negatively.

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1. Introduction

The rapid rate of financial innovation over the past few decades is widely recognized as a stylized fact. The Global Financial crisis 2007-2009 has spurred renewed widespread debates on the effects of financial innovation. This period has highlighted the limitations and hazards of financial innovation while dimming the lights on its core benefits for an economy. The main reason is that many complex financial instruments associated with innovation were extensively used as vehicles in the credit expansion that led to the crisis. In particular, mortgage securitization in the boom years did not help to reduce the informational problems that are typical of credit transactions, nor did it induce appropriate risk assessment (Sánchez, 2010).

Notwithstanding these facts, the academic literature originally has emerged the innovation-growth view on financial innovations. This view posits that financial innovation helps to improve the quality and variety of banking services (Berger, 2003), facilitate risk sharing (Allen & Gale, 1991), complete the market (Elul, 1995), and improve allocative efficiency (Houston et al., 2010). This suggests a trade-off between the “bright” and “dark” sides of financial innovation, which is confirmed by the study from Beck et al. (2016).

It was until the Global Financial Crisis that it became clear that the system of regulation governing banks had become far too relaxed. Financial authorities, hereafter, faced the challenge of discouraging practices that may lead to financial distress without inhibiting the evolution of markets and financial innovation. Hence, policymakers needed to create incentives that lead to the perfect level and type of financial innovations with the desired effect on society. The framework that exists today is, therefore, unrecognizable from what was in place in 2007. This framework has seen a shift away from national regulation and introduced a more standardized approach to the oversight of the financial sector. In particular, prudential standards have been substantially reformed under the leadership of the Basel Committee (Restoy, 2017). A potential danger for this framework is that financial innovations often respond to regulations by sidestepping regulatory restrictions that would otherwise limit activities in which people wish to engage (Calomiris, 2009).

Despite the shift in the regulatory environment of banks (primarily Basel II)[1], there is a striking paucity in the academic literature on the effects of financial innovation on bank stability in the period after the Global Financial Crisis.

Therefore, this paper examines this relationship in banks from 35 countries out of the OECD for the period 2010-2019. OECD countries are, economically speaking, the most important countries and these countries have the most data available for financial innovation, which is important as previous literature highlighted the difficulties with data availability on this topic (Frame & White, 2004). By doing an empirical analysis, in which two different hypotheses regarding bank stability will be tested, this paper tries to contribute to the academic literature by providing evidence on important factors of bank stability in the period after the crisis[2]. Studying whether financial innovation impacts bank stability also is a relevant issue because the existing literature has shown that bank sector stability has broad implications on economic output (Frame & White, 2004; Gerardi et al., 2010; Hsu et al., 2014). The link between banking sector stability and economic activity is of particular interest to policymakers who base their monetary policy decisions on economic forecasts, which in turn influence decisions made by consumers (Romer & Romer, 2000).

Furthermore, previous literature often focused on particular parts of financial innovation, such as credit derivatives, R&D expenses, or the role of an off-balance sheet business (Lee et al., 2020), due to data availability concerns (Frame & White, 2004). This research counteracts this problem by following the concept of financial innovation from Beck et al. (2016) and focusing on R&D spending in the financial sector as well as several other product or output-based measures of financial innovation. In contrast to other studies, I also include a fintech indicator. This indicator is incorporated because the influence of these companies tremendously increased after the intensified regulation of the banking sector after the crisis. Since the literature has shown that these companies can affect the stability of traditional banks, it is important to consider this dimension of financial innovation (Elsaid, 2021).

[1] Basel II primarily focused on standards that govern the capital adequacy of banks.

[2] Beck et al. (2016) reported that a bank's level of financial innovation is the most important factor associated with its growth and fragility.

The empirical analysis shows that out of the four financial innovation indicators, only two indicators are negatively significant. Specifically, I find that securitization capacity and OBS ratio negatively impact the stability of a bank. This indicates that banks are less stable if countries have more outstanding securitized assets or engage more in off-balance-sheet activities[3].

This result contrasts with pre-crisis literature on the relationship between bank stability and financial innovation in the OECD (Beck et al., 2016). This confirms comments made in the paper of Lerner & Seru (2021). They argued that the regulatory framework after the crisis, characterized by a more restrictive policy on specific activities and capital requirements, may have depressed the focus on innovation more generally, which hampered both positive and negative effects of specific forms of financial innovation on bank stability. Furthermore, fintech companies do not seem to influence bank stability[4]. Overall, there is weak evidence for a link between financial innovation and bank stability, suggesting that policymakers have succeeded in their job to stabilize the banking sector concerning financial innovations with the new regulatory framework.

This paper contributes to several strands of the literature: First, this is the first study, to my knowledge, to study the dynamic relationship between financial innovations and bank stability after the financial crisis. This is striking because we entered a new regulatory paradigm that started after the crisis. Second, I complement the dispute in the literature on how to measure financial innovation by using different input- and output variables of financial innovation. Thereby taking a more holistic approach to financial innovation. The different measures also provide more robustness. Third, this is the first study in the literature about financial innovation and bank stability, in my knowledge, which takes into account the possible endogeneity concerned with panel data.

The remainder of the paper is organized as follows: First, Section 2 summarizes the existing literature and provides hypotheses on the effect of financial innovation on bank stability. Second, Section 3 describes the empirical analysis. Subsection 3.2 defines the independent, dependent, and control variables and provides a descriptive analysis of the sample. Subsection 3.3 presents the statistical model. Section 4 discusses both the main results in comparison with previous

[3] Note that OBS ratio only significant for commercial banks.
[4] However, this result is driven by a sample selection bias towards the United States.

literature and the hypothesis as the robustness checks. Finally, Section 5 discusses the conclusions, limitations of this study, and possible directions for future research.

2. Literature review and hypothesis

The main question being asked is: What is the effect of financial innovation on bank stability in the period after the financial crisis? Given the lack of data on this topic, most studies focused on specific forms of innovation, such as financial securities (B. J. Henderson & Pearson, 2011), the introduction of credit scoring techniques (Frame & White, 2004), new forms of mortgage lending (Gerardi et al., 2010) or new organizational forms (DeYoung et al., 2007). Nevertheless, a widespread debate on financial innovation's bright and dark sides has emerged.

The traditional innovation-growth view implies that financial innovation helps to improve the quality and variety of banking services[5](Berger, 2003), facilitate risk sharing[6] (Allen & Gale, 1991), complete the market[7] (Elul, 1995), and improve allocative efficiency[8] (Houston et al., 2010). Recent studies also support this view. The paper of Lee et al. (2020) finds that banks in countries with higher levels of financial innovation exhibit better growth.

On the other hand, there is the innovation fragility view that focuses on the dark side of innovation. It says that financial innovation will lead to fragility in the financial sector. This view is fierce to wide attention after the recent global financial crisis. More specifically, this view holds financial innovation culpable for the fact that house prices both rose dramatically and then fell sharply by creating securities that were perceived to be safe but exposed to neglected risks

[5] According to Berger (2003), banks are significant users of financial technologies that employ economic and statistical models to create and value new securities, estimate return distributions, and make portfolio decisions based on financial data. These financial technologies often depend heavily on the use of IT to collect, process and disseminate the data. Technological progress, therefore increases the quality of these “back-office” services. Furthermore, technological progress created new “front-office” technologies, such as internet banking, electronic payments technologies and new forms of information exchanges.

[6] This paper argues that if financial institutions issue the same types of securities, the idiosyncratic risk can be diversified away.

[7] According to the paper of Elul (1995), introducing new products (financial innovation) into the market can lead to a situation where everyone is better off.

[8] The paper of Houston et al. (2010) shows that financial innovation promotes better information sharing among creditors, which in turn leads to higher bank profitability and lower banking risk.

(Gennaioli et al., 2012) and by helping banks develop structured products to exploit investors' misunderstandings of financial markets (B. J. Henderson & Pearson, 2011).

There is much-supporting evidence that innovation feeds the fragility of banks. For example, the paper of Allen & Carletti (2006) shows that financial innovations such as securitization change the ex-ante incentives of financial intermediaries to carefully screen and monitor the borrowers since they can diversify away all the risk by securitizing credit loans. Moreover, the paper of Rajan (2006) argued that developments in the financial sector have led to an expansion in the ability to spread risks, which led to the fact that financial institutions leave themselves exposed to certain small probability risks that their collective behaviour makes more likely. As a result, under some conditions, the financial sector may be more exposed to turmoil than in the past. Furthermore, the paper by Wagner (2007) shows that financial innovation that reduces asymmetric information can increase risk-taking due to agency problems between bank owners and managers or because of lower costs of fragility. Following these papers, Heyde and Neyer (2010) showed that securitization increased investments in illiquid, risky credit portfolios.

Moreover, the existing literature on financial innovation also predicts significant differences in its effects according to the regulatory environment in which financial innovation happens. This study has data over the period after the financial crisis, which has caused a shift in the debate to the fragility view on innovation. As a result, a new regulatory environment was created (primarily the implementation of Basel III). Financial innovation can arise as a response to regulation or religious restrictions[9]. Specifically, the paper of Beck et al. (2016) argues that the main purpose of recent financial innovations has been to facilitate regulatory arbitrage by shifting off-balance-sheet investments that would be more costly were they held on the balance sheet.

On the one hand, this cause of financial innovation implies that more restrictive regulation in terms of activity restrictions and capital might limit the possibilities of innovation which might limit the effects of both positive and negative effects. Similarly, the paper of Lerner & Seru (2021) states that financial innovation in the years after the global financial crisis shifted from locations with tight financial regulation to more permissive places. Not only may financial regulation have

[9] Examples of this are the Euro market that arose as a reaction to regulation Q from the federal reserve or the emergence of sharia-compliant financial products.

led financial incumbents to shift the location of innovative activities, but it may also have depressed their focus on innovation more generally.

On the other hand, the OECD (2020) stated that a response of regulators with a more restrictive regulatory framework to the rise of enhanced risk-taking might provide banks stronger incentives to bypass regulation and foster an increase in shadow banking, which according to the innovation-fragility view have negative effects on the stability of banks. Similarly to this view, the paper of Anginer et al. (2019) found that reforms after the crisis led to increased capital requirements and regulatory capital holdings at financial institutions. However, these increases were accompanied by shifts towards asset categories with lower risk weights. The accuracy of those risk weights is, therefore, crucial for understanding whether increases in regulatory capital holdings are a reliable signal of greater banking stability, and there is a big question mark around whether these risk weights genuinely reflect real-world risk. While on the surface, it looks like banks may be holding more capital and safer assets than before, it might provide a false sense of security which might be fed by new asset classes provided by financial innovations, as we saw before the crisis (Gennaioli et al., 2012).

Since, to my knowledge, there is no evidence of the relationship between financial innovation and bank stability in the period after the crisis when a new regulatory environment was created, it is not clear whether financial innovations in this framework had little or no effect on bank stability or whether regulatory arbitrage has caused financial innovations to increasingly compromise bank stability. This remains an empirical question, and the answer should say something about the interpretation of the regulations of the banks[10]. Therefore, in my hypothesis, there is still no reason to deviate from the mainstream view in the literature on financial innovations and bank stability, which represents the innovation fragility view:

H1. Financial innovation, measured by financial intensity, off-balance-sheet activities and securitization capacity, decreases the overall stability of a bank.

In addition to these three indicators, this research also introduces another financial innovation proxy. This indicator is the number of fintech companies founded in a country. The paper of Elsaid

[10] If the banks experience losses if they take excessive risks, instead of being bailed out at the expense of taxpayers, the banks are provided with the right incentives through bank supervision and regulation. On the other hand, if they don’t experience losses, the supervision and regulation will not reach its desired effect.

(2021) shows that the rise of these companies has led to an interest in those companies as a research subject in relation to the banking industry. These fintech companies provide financial services to customers in an innovative way that banks were not used to (Breidbach et al., 2020). Hence, fintech firms are recognized as innovation drivers in the financial services field, which makes the number of fintech firms founded in a country a proxy of the level of financial innovation. The more fintech companies are founded in a country, the higher the level of financial innovation.

This indicator is especially interesting in this research sample period since this is the period after the financial crisis. The regulatory framework after the crisis created an environment in the financial services industry where it is easier for fintech companies to provide some financial services than banks[11]. Therefore, the effects of fintech companies might be more pronounced in this sample period (2010-2019) than in other studies which is exactly why this indicator is not used that much in earlier studies, like that of Beck et al. (2016).

The effect of fintech firms on traditional banks has been explained in the literature using both consumer and disruptive theories (Elsaid, 2021).

The disruptive innovation theory indicates that new entrants to a market that apply innovative technology to offer more accessible and cost-effective goods and services may create competition in that market (Christensen, 2013). Fintech firms usually target certain financial institutions' value chain segments, aiming to provide financial products and services to loosen the tie between banking institutions and their clients (Kotarba, 2016). Moreover, the paper of Brandl & Hornuf (2020) argued that some banks are still offering old-fashioned, costly, and cumbersome financial services. Fintech firms, therefore, are taking the opportunity to provide several critical functions of traditional banks depending on technology and innovation as a source of competitive advantage. Therefore, the rise of fintech companies may directly impact existing markets and clients and threaten established and reputable institutions. The consumer theory states that a

[11] Figure 5 shows the trend of the number of fintech companies found. This figure shows that after the financial crisis, the number of fintech companies founded grew tremendously. The growth in the number of these companies is because of the fact that these companies are less subject to regulations that have emerged after the financial crisis. (Elsaid, 2021).

new service will act as a complement when utilized jointly with an old service and will serve as a substitute if it can replace the old service by satisfying the same needs (Li et al., 2017).

According to the consumer- and disruptive innovation theories, fintech firms could spark a disruptive evolution because of their new alternatives that enhance the quality and efficiency of the financial services provided and focus on customers' needs (Ferrari, 2016). Hence, it could lead to banks having to undergo a fierce competitive force, which ultimately can lead to a less stable deposit base or even a replacement of the traditional banking system (OECD, 2020). This leads to the following hypothesis:

H2. Fintech firms decrease the overall stability of a bank.

3. Methodology

3.1 Data

To analyze the effects of financial innovation on banks' stability, this study adopts bank-specific data as the primary source for the dependent variable from Bank Scope and country-specific data from the STAN R&D database, Crunchbase, and the SIFMA for the independent variable. Hereby, this study follows the paper of Beck et al. (2016) and builds a database where both country-level and bank-level variation in financial innovation is related to bank-level variation over time in bank stability.

After merging the data, the dependent variable has a total of 22,520 bank-year observations out of 35 countries. In the estimations, sample size and year may vary due to missing values for some explanatory variables in different regression models[12].

3.2 Variable definitions and summary statistics

3.2.1 Dependent variable

Previous studies have used various measures as a proxy for banking stability. However, the most common indicator used in the banking industry is the Z-score (Abuzayed et al., 2018; Beck et al.,

[12] See paragraph 3.2 for detailed information on missing values.

2016; Boyd & Runkle, 1993; N. A. Karim et al., 2016). Based on accounting data, this indicator represents a bank's insolvency risk. This research follows the mainstream literature and uses this indicator, which is computed as follows:

$$Z - Score = \frac{ROA + E/A}{\sigma_{ROA}} \tag{1}$$

Where E/A is the equity to asset ratio, ROA is the return on average assets and σ_{ROA} its standard deviation. The return of a bank in these measures is computed from net income. The standard deviation in the Z-score is the standard deviation of the whole sample period. The equity to asset ratio is expressed as a percentage and calculated by dividing total equity by the total assets of a bank. Since the Z-score in this sample is highly skewed, this research follows Beck et al. (2016) and uses the natural logarithm of the Z-score[13]. For brevity, this research will use "Z-score" as the label for the natural logarithm of the Z-score in the remaining part of this paper[14].

The equity to asset ratio shows the number of assets on which shareholders have a residual claim. Hence, it shows if a company can be forced into liquidation. Higher equity to asset ratio means that the company funds more money with equity instead of debt, which is less risky. More specifically, the Z-score measures the number of standard deviations below the expected value of a bank's return on assets at which equity is depleted, and the bank is insolvent (De Nicoló et al., 2006). A higher Z-score, thus, means greater bank stability since the bank is more standard deviations away from insolvency and vice versa (Nisar et al., 2018).

One limitation of the Z-score is that it only takes into account accounting data. This means that market risk is excluded from this measure. Investors might prefer measures for market risk. Markets could sometimes consider risks that not are apparent from financial statements and vice versa. Balance sheets, for example, do record assets at historical cost, and markets, for example, take into account the risk of financial markets. However, since this study mostly uses data from

[13] In unreported results, the skewness and kurtosis test for normality shows that the variable "Z-score" is skewed and the natural logarithm of this variable is not.

[14] Since only the dependent variable is log-transformed, the interpretation of the variable goes as follows: for every unit of increase in the financial innovation proxy, the Z-score will increase with (exp("coefficient")-1)*100 percent. Meaning that you first have to exponentiate the coefficient, subtract one from this number, and then multiply it by 100.

unlisted banks (75%), it is hard to construct a measure for market risk due to data availability constraints.

The descriptive statistics in Table 1 show that the mean value of the Z-score is 2.712[15], which is close to the median, suggesting that outliers are not problematic. Furthermore, the minimum value is -65.15, which would indicate that the respective bank is already in technical default. According to Mokhova & Zinecker (2016), there is an increasing tendency of balance sheets with negative equities, and this can occur due to the following reasons: big losses that are not covered by retained earnings over a long period, leveraged buyouts, severe depreciation in currency positions or substantial adjustments to intangible properties. On the one hand, negative equity may signal the insolvency of a company and large losses. On the other hand, if the company's cash flow meets current bills, a company can continue to operate regardless of its level of equity.

Hence, negative equity could be a warning sign that a company is in financial distress, or it could mean that a company has spent its retained earnings and any funds from stock issuance on reinvesting in the company, which possibly can indicate a high level of financial innovation. Therefore, these negative values must be treated as valuable data[16].

Finally, Table 1 shows differences in the number of observations in variables due to missing values. These differences are both caused by the fact that the variables are coming from different sources and that there are bank-level and country-level variables. Country-level variables often don't have many missing values, whereas specific banks have many more missing values. Additional assumptions about the reasons for the missing data have to be made to do a proper analysis. However, these assumptions cannot be validated from the data at hand (Little, 2021).

After analyzing the missing data on the Z-score, there is no clear pattern to be seen. The representation of both the countries, listing status, and type of bank is relatively similar to the full sample. Although smaller banks in this sample have more missing data, this will likely not raise a survivorship bias[17], which gives more certainty about the usefulness of the sample.

[15] This mean value is comparable to other studies regarding financial innovation and bank stability (Beck et al., 2016).

[16] The negative values of equity to asset ratio and tier 1 capital variable are caused by negative equity.

[17] The survivorship bias occurs, when certain observations are removed from a sample, which causes the results to be invalid. In this case, it is intuitively logical that smaller banks often report more missings, because they have

3.2.2 Independent variable

Gauging innovative activity in the financial sector is challenging, as patents in the financial sector rarely exist and not at all in the European Union. This lack of data, as already pointed out by Frame and White (2004), has impeded the rigorous study of financial innovation across countries. As a consequence, most existing studies focus on very specific innovations.

I follow financial innovation as a concept, which includes the process of invention and diffusion of new products, services, or ideas, and focus on R&D spending in the financial sectors as well as several products or output-based measures of financial innovation. This methodology for financial innovation is taken from the paper of Beck et al. (2016).

The first explanatory variable is financial R&D expenditures relative to the total value added of the financial and insurance sector, which from now on will be called financial intensity (value-added)[18]. The higher the percentage of financial R&D expenditure in the total value-added, the higher the degree of financial innovation. The choices regarding this variable are discussed more in detail in section A.1 in the Appendix.

The value-added data comes from the STAN industry database from OECD statistics, and the data on R&D expenditures is extracted from the STAN R&D database from OECD statistics.

The descriptive statistics in Table 1 show that the mean value of this variable is 0.401[19], which is close to the median, suggesting that outliers are not problematic. Furthermore, the STAN R&D database from OECD statistics does not provide R&D expenditures information for the financial sector in 2019. To still run the regressions on the full dataset and prevent valuable data from disappearing, this study uses the dummy variable adjustment method. This method uses both a dummy, which denotes 1 if there is a missing and 0 if not, and the new adjusted variable, which

less obligations with regard to reporting data. In addition to this, the representation of the non-missing data seem to be the same as the full sample, suggesting that conclusions can still be generalized to the whole study population.

[18] The paper of Beck et al. (2016) shows that this this indicator from the manufacturing industry clearly correlates with the number of patents in the manufacturing industry, which give confidence that this indicator is a good proxy for innovative activity in the financial sector. Furthermore, this indicator is widely used in the literature as a proxy for financial innovation (Hughes, 1988). The paper of Hughes (1988) also shows potential difficulties regarding R&D intensity as proxy for innovation, however, since we apply it only on one sector, these challenges are not problematic in this research.

[19] This mean value is comparable to other studies regarding financial innovation and bank stability (Beck et al., 2016).

denotes the mean if there is a missing and the initial value if not. Thereby, the new variable represents the effect of the observed values of the securitization capacity (Jones, 1996). The dummy variable can be interpreted as the influence of the missing data on the dependent variable. Since the adjusted variable still represents the effect of only the data from 2010 till 2018, the results of this variable are less generalizable to the study population.

Additionally, the R&D measure is survey-based, making it susceptible to potential measurement errors[20][21]. Also, financial innovation involves a combination of inputs and the creation of outputs. Input-based measures relate differently to financial innovation than output-based measures. The inputs to innovation are easy to characterize; they will always be resources and assets. In this case, investment in R&D is found to be a notable component of innovative input because it leads to new products and processes. However, as an indicator of innovation, it is the one that bears the highest degree of uncertainty, given the unpredictability of the discovery process. Before the process is complete, it is unclear whether the inputs will deliver the desired outputs. Hence, outputs are unpredictable because innovation is complex, nonlinear, and risky; responds to opportunities; and inherently includes elements of chance (Ekpu, 2015). For these reasons, three other measures that refer to the "output" and specific forms of financial innovation are used as proxies to capture financial innovation.

The second explanatory variable is the ratio of the total value of off-balance sheet items and total assets, using data from Bank Scope. Bank's off-balance-sheet (OBS) activities refer to businesses that are not included in the bank's balance sheet but can directly change the bank's profits and losses. The items that are included in the off-balance sheet items are: committed credit facilities, managed securitized assets, other exposure to securitizations, guarantees, other contingent liabilities, acceptances, and documentary credits[22]. The paper of Calomaris (2009) showed that some forms of financial innovation, such as credit card receivables or subprime residential mortgages, have arisen in part as means of arbitraging regulatory capital requirements

[20] As an example, some countries primarily follow the main activity approach but redistribute the R&D of large diversified firms across the economic activities to which it relates. Since, we do not know how countries precisely measure this, it can lead to measurement errors in the level of financial innovation.
[21] The variables on R&D expenditures are all denoted in their own currency, and in the end, transformed to dollars since OECD statistics does not provide all the data in US dollar currency at current prices.
[22] For more information on these activities, see Table 3 in the appendix.

by booking assets off the balance sheets of regulated banks[23]. Hence, the higher the value of off-balance sheet items relative to total assets, the higher the degree of financial innovation.

The descriptive statistics in Table 1 show that the mean value of this variable is 0.410, which is ten times as small as the pre-crisis mean value in the sample of Beck et al. (2016). The smaller OBS ratio in my sample might indicate that the regulatory framework after the crisis has led to the fact that banks are holding way fewer assets off their balance sheet. On the other hand, it could indicate that banks have grown much bigger in the past decade, leading to a lower OBS ratio. Although the BIS (2018) shows that after the crisis, individual banks significantly enhanced their balance sheet and curbed their involvement in certain complex activities, it is likely a combination of both, given a decrease of that size. However, this cannot be validated since Beck et al. (2016) don't show the size of their banks. Furthermore, after analyzing the missing data in the OBS ratio, there are no systematic absent values, indicating that the dummy variable adjustment method (which is also applied to this variable) does not cause a misrepresentation of the study population. On top of this, the median and the mean are close to each other, suggesting that outliers are not problematic.

The third explanatory variable is an indicator for the securitization capacity of a country, proxied by the sum of the outstanding values of all securitized assets divided by GDP. The higher this percentage, the higher the level of the use of new products, services, or ideas, which means a higher level of financial innovation[24]. The data is extracted from a database prepared by the Securities Industry and Financial Markets Association (SIFMA) and the Association for Financial Markets in Europe (AFME). The GDP data is collected from the OECD statistics: national accounts database. Hence, this explanatory variable varies at the country level.

The descriptive statistics in Table 1 show that the mean value of this variable is 10.82[25], which is close to the median, suggesting that outliers are not problematic. However, the database only

[23] Originators of those securitized loans were able to maintain lower equity capital against those loans than they otherwise would have needed to maintain if the loans had been placed on their balance sheets (Calomiris, 2009).

[24] "New products, services and ideas" refers back to the definition of financial innovation used in this research based on Beck et al. (2016).

[25] This mean value is comparable to other studies regarding financial innovation and bank stability (Beck et al., 2016).

provides data for 13 countries. Therefore, for the same reasons as the other variables, the dummy variable adjustment method will be applied to this variable. This causes the adjusted variable to be the effect of the 13 countries. Hence, care must be taken in generalizing the results to the whole study population.

Furthermore, the intensified regulation of the banking sector after the financial crisis (primarily Basel III) introduced by various financial market authorities opened the door for a new kind of financial service providers to come into the picture (Elsaid, 2021; Gomber et al., 2017). Since that time, fintech startups have expanded rapidly in the financial market providing financial services to customers in an innovative way that banks were not used to. The effects of these companies on the banking industry have only been addressed in sample periods from before the crisis. However, the rapid increase of these fintech firms may cause the complex relationship between these two variables to be different. To get a further understanding of the impact of fintech companies on the financial stability of banks, this research includes a fintech indicator in the financial innovation dimension.

This indicator is the number of fintech firms founded in a particular year respective to the countries. Hence, this variable is on the country level. The more fintech companies are founded in a country, the higher the level of financial innovation. A fintech firm is placed under a country based on the location of their headquarters since firms mostly base their headquarters in the regions where they operate (J. V. Henderson & Ono, 2008). The data is collected from Crunchbase, which provides a list of fintech startups for the period 2010-2019. Section 2 elaborates more on the effects of fintech companies on the banking industry.

The descriptive statistics in Table 1 show that the mean value of this variable is 307.9[26], which is close to the median, suggesting that outliers are not problematic. Furthermore, this variable has no missing data.

3.2.3 Control variables

There may also be other variables that might systematically affect differences in the level of banking stability. These variables must be included in the regression to examine the relationship between financial innovation and banking stability. A list of potential bank-specific control variables was obtained from surveying the existing literature. Section A.3 in the Appendix provides an overview of the expectations regarding the effects of these variables. All of the below control variables, except banking freedom and regulation, are based on data from Bank Scope in the period 2010-2019.

The first control variable is the Tier-1 capital ratio. This variable is calculated by dividing the tier 1 capital by total assets[27]. By including this variable, we control for differences in banking sector development (Sari et al., 2018).

The second variable that might affect the risk of the bank is the loan-to-asset ratio. This variable is calculated by dividing the total value of all customer loans & advances by their assets. The loan-to-asset ratio controls for banks' differences in asset portfolios (Mercieca et al., 2007). This variable differs from the Z-score since loans to customers are on the asset side of the balance sheet, and the Z-score includes the equity to assets ratio, where changes on the liability or equity side influence the value of that variable. This is confirmed in Table 5, where the Z-score and the loan to asset ratio have a relatively low correlation.

The third variable that might affect the systematic risk of the bank is the ratio of other earning assets. This ratio is computed as follows: the amount of other earning assets relative to the total earning assets. Banks' other earning assets are all on-balance sheet assets that generate non-interest earnings for the financial institution, typically dividends and gains from trading and other investments. This measure is also used in a variety of other studies on bank performance (Beck et al., 2016; Lee et al., 2020).

The Fourth control variable is the bank’s market share, which is the share of each bank’s deposits to total deposits within a given country in that particular year. This measure is widely

[27] According to Investopedia (2021, p. 1), tier-1 capital is the core capital held in a bank’s reserves and is used to fund business activities for the bank’s clients. This variable is denoted in millions USD.

used in the literature as a control variable for bank performance (Beck et al., 2016; Lee et al., 2020). In relation to this, this research includes bank size as a control variable. This controls for the effect of bank size on bank performance. This variable will be captured by the natural logarithm of a bank's total assets since it leads to better interpretable coefficients[28].

In addition to bank-specific control variables, the regressions also include a set of country-control variables. In this research, the control variables below seem to have the biggest impact on bank stability since they are most widely used in the literature. Note that all these country variables change over time.

The Fifth control variable is GDP per capita (in USD). This indicator is used by many researchers (Baumann & Nier, 2004; Beck et al., 2016). By including this control variable, this study mitigates the effect of the level of prosperity of a country on bank stability.

Finally, indicators from the years 2010-2019 per country for banking freedom and regulation are included in the analysis. The paper of Barth et al. (2012) provides evidence for different outcomes regarding bank stability when a different regulatory framework or degree of banking freedom is applied to a particular country. Furthermore, the financial crisis shows that the degree of regulation and banking freedom can have a major impact on risk-taking behaviour. Especially after the financial crisis, many regulatory changes have been implemented (Basel III). Therefore, it is important to control for the cross-country differences in regulation and banking freedom to isolate the effect of financial innovation on banking stability in the period after the crisis.

The proxy for banking freedom will be ''the financial freedom index'' from the Heritage Foundation. This index gives a score from zero to a hundred, where the score indicates the extent of government regulation of financial services, the degree of state intervention and other financial firms through direct and indirect ownership, the extent of financial and capital market development, government influence on the allocation of credit, and openness to foreign competition. A higher score reflects more freedom and vice versa.

The proxy for regulation will be a combination of ''the business freedom index'', ''the labour freedom index'' and ''the monetary freedom index'' from the Heritage Foundation. This will

[28] Natural logarithms can be interpreted as follows: for example, if ln(assets) shows a coefficient of 0.06, a difference of 1% in x corresponds to an approximate 0.06% difference in y.

reflect the efficiency of government in the regulatory process, the regulatory framework of a country's labour market, and the measure of price stability with an assessment of price controls. A higher score on the index reflects lower regulation and vice versa. The descriptions of these two indices correspond to the descriptions of the paper from Mercieca et al. (2007).

The descriptive statistics in Table 1 show that the median and the mean of all of the variables, except for "other earning assets" and "bank market share", are close to each other, suggesting that outliers are not problematic. By further analyzing the outliers at the 1% level of other earning assets, no pattern can be found[29], which means that there is no specific cause for the outliers of this variable. Hence, this variable can be adjusted without concerns of losing valuable data. Therefore, this research winsorizes the variable "Other earning assets" at the 5% and 95% levels, which solves the issue[30]. Furthermore, after analyzing the outliers on market share, there can be seen that most of the banks with a high market share are commercial banks (569 out of 759). Hence, adjusting this variable might cause a loss of valuable data (also known as the survivorship bias). Therefore, I choose not to winsorize this data and keep the outliers in the sample[31]. Finally, there is no strong correlation between each of the control variables, as shown in Table 5[32].

[29] Outliers at the 1% level are values that are approximately more than 2.335 standard deviations away from the mean.

[30] Winsorizing is a method to deal with outliers, in which the upper- or lower cases are changed so that they are close to other values in the data set. In this case, the median and mean differ no more than one standard deviation if the variable "other earning assets" is winsorized at the 5% and 95% level.

[31] By choosing this, I am aware of the potential influence of the outliers. However, excluding this data will likely cause more harm to the sample than leaving this in the sample, since this data clearly has a pattern/meaning.

[32] The correlation between Tier-1 capital and the variable Other earning assets is relatively high in this sample, however, multicollinearity is still not a problem since correlations from above 0.6 are worrying. Furthermore, when regressing those two variables, we get a adjusted R-squared of 0.3383 and a VIF of 1. This means that other earning assets, can somewhat explain Tier-1 capital ratio, however, for multicollinearity problems to arise, the explained variance by other earning assets has to be higher. Moreover, the VIF of 1 implies that there is no correlation among the two variables.

TABLE 1. DESCRIPTIVE SUMMARY STATISTICS OF RAW DATA, 2010 TO 2019

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**N (Banks x Years)**	**Number of banks**	**Number of countries**	**Mean (St. dev)**	**Min**	**Max**
Dependent variable						
Z-score	22,520	2,902	35	2.712 (3.197)	-65.15	101.2
Independent variables						
Financial intensity (Value added)	81,324	9,179	34	0.401 (0.331)	0.00113	4.742
OBS-ratio	19,421	2,514	35	0.410 (6.171)	-3.381	806.8
Securitization/GDP	9,620	962	13	10.82 (11.41)	0.0286	50.43
Number of Fintech companies	92,600	9,260	35	307.9 (204.8)	0	624
Control Variables						
Tier1Capital	13,244	2,225	35	5,090 (16,205)	-2,679	214,432
Loan to Asset ratio	23,087	2,889	35	57.45 (24,61)	-68.98	99.85
Other Earning Assets	22,913	2,902	35	10,960 (65,029)	-1.167	1.853e+06
Bank market share	21,300	2,637	35	0.0164 (0.0519)	0	0.824
GDP per Capita	92,600	9,260	35	52,951 (9,578)	15,252	117,184
Financial Freedom index	91,770	9,177	34	71.42 (6.546)	40	90
Regulation Index	92,600	9,260	35	84.11 (5.483)	59.67	92.37
Total Assets	24,134	2,998	35	8.821 (2.142)	-6.482	15.32

N measures all the observed values in the period 2010-2019. St. dev measures the standard deviation of the variable of the whole sample and is reported below the mean in parentheses. Furthermore, the median is not shown for brevity reasons. Not all observations are the same since missing values are not included. A comma is a separator for thousands, and a dot is a separator for decimals. In total, 9260 banks out of 35 OECD countries satisfied the conditions for the research subject. Financial intensity (value-added) is computed by financial R&D expenditures relative to the total value added of this sector, OBS-ratio is computed by dividing the total value of all off-balance sheet items by the total assets of a particular bank, and Securitization/GDP is computed by the sum of the outstanding values of all securitized assets divided by GDP. Note that the 35 countries include Austria, Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States. The 34 countries for the Financial freedom index exclude Korea, the 34 countries for the financial intensity variable exclude Switzerland, and the 13 countries for securitization only include Turkey, Austria, Finland, Germany, France, Portugal, Ireland, Greece, Italy, Spain, Belgium, United Kingdom, and the Netherlands.

3.3 Model Specification

Conclusively, this research is going to use OLS regressions with the above-mentioned set of bank- and country-level control variables to reduce the probability that unobserved variables are correlated with the variables in the regression.

Additionally, country- and period fixed effects are incorporated into the model to effectively capture variation within countries by controlling for unobserved predictors that are time-invariant and controlling for the trends towards higher/lower financial innovation over time, documented in Figure 2 till Figure 5 in the appendix (Best & Wolf, 2013)[33]. Hereby we follow the method of Beck et al. (2016).

These fixed effects are implemented by using the dummy variable estimation. One disadvantage of this method is that it causes the R^2 to be inflated since this method allows each country and year to be different, which might be doing most of the explaining without exactly knowing what is driving that. Hence, all the country- and year dummy variables enter the regression significantly, adding some predicting power. Therefore, care should be taken in drawing conclusions based on the R^2. The following setup is used:

$$Z - score_{i,k,t} = \beta_1 FI_{i,t} + \beta_2 OBS_{k,t} + \beta_3 Securitization_{i,t} + \beta_4 Fintech_{i,t} + \beta_5 X_{k,t} + \beta_6 Y_{i,t} + V_i + \tau_t + \varepsilon_{i,k,t} \quad (2)$$

In this setup, the indices i, k, and t stand respectively for the country, bank, and time. Z-score is the bank stability measure. β_1 till β_4 are the proxies for financial innovation, where FI stands for financial intensity (value-added), OBS stands for the total value of off-balance sheet items relative to total assets, Securitization stands for the securitization capacity of a country, and Fintech stands for the number of fintech start-ups in a particular year. Furthermore, X is a vector of bank-specific controls, and Y is a vector of country-level controls, both discussed in section 3.2. Finally, the V_i represents country fixed effects, τ_t represents period fixed effects and $\varepsilon_{i,k,t}$ represents the error term. Furthermore, Table 6 shows a low correlation between the independent- and dependent variables, meaning that a multiple regression model is possible. This type of regression

[33] Running a Hausman test on the data shows that fixed effects are more appropriate than random effects on this panel data (this is an unreported result).

is preferable to separate regressions since it takes into account the effect of indicators on each other. This model, however, will be performed by using adjusted variables based on the dummy variable adjustment method (described in section 3.2), which prevents the sample size would limit itself to 13 countries. Since the literature has shown that this method causes biased estimators, this research shows both the multiple regression model without the dummy variable adjustment method and the separate regressions per financial innovation indicator to show the robustness and that multicollinearity issues are not a problem.

Moreover, the Breusch-Pagan test detects heteroscedasticity in the model. Heteroskedasticity occurs when the variance of the error terms is unequal over a range of measured values. An unequal variance may cause the results to be invalid[34]. In addition to this, the error terms of the variables are correlated with each other since observations between years and within countries are not independent of each other[35]. These issues can be solved by allowing the error terms to be arbitrarily correlated with each other within predefined clusters (Cameron et al., 2006). More specifically, this means that the standard errors will be transformed into robust standard errors while clustering them both within countries and across periods. This is done by generating a new variable indicating a country plus a year. Then regressions are run with clusters on this variable to solve both the heteroskedasticity and the autocorrelation in the error terms.

Additionally, it is notable to mention that the sample is very dependent on the US (77% of the observations), which means that our results might be biased toward the US. Since most financial innovation comes from this country, this might not be problematic for this study. However, to determine whether this research can be representative of the whole OECD, a robustness check where this country is excluded will be done. The same will be done for the type of bank, where the observations stem for almost 60% of the cases from commercial banks.

Furthermore, since the numbers of subsidiaries are very far apart from each other (from 0 to 1979 subsidiaries) and the literature has shown that subsidiaries can have a significant influence on the scale and quality of innovation, additional analysis on the impact of subsidiaries on the

[34] The Breusch-Pagan test is unreported, but shows that the p-value of the Chi-Square test statistic is lower than 0.05, suggesting that the null hypothesis can be rejected. This means that there is no constant variance among the residuals.

[35] This problem is also known as the problem of “autocorrelation”.

relationship between financial innovation and bank stability will be done (Iwanicz-Drozdowska & Witkowski, 2021; Kahn & Winton, 2004; Phene & Almeida, 2008)[36]. To test whether the number of subsidiaries has any impact on this relationship, an interaction term is introduced between financial innovation and the number of subsidiaries. This interaction term then shows if the effect of financial innovation on the stability of banks depends on the number of subsidiaries.

Table 7 in the appendix shows the correlation of the variable "subsidiaries" with the other variables. This table shows that there is high to moderate positive correlation between some variables. However, when regressing these variables with "subsidiaries" as a dependent variable, the variance inflation factor shows no values above 2, meaning that correlation is not problematic (multicollinearity does not play a role) when including subsidiaries in an interaction term.

Finally, Leszczensky & Wolbring (2022) highlighted the common problem in panel data of reverse causality. In this research, this problem may also arise as countries with higher financial innovation affect bank stability, however, banks with a certain level of stability also affect the degree of innovation of a country. Furthermore, it could be the case that endogeneity in the form of an omitted variable bias occurs, meaning that there is a variable that is not included in the model, which influences a variable that is incorporated in the model. Thereby, creating biased estimators. Section A.5 in the Appendix discusses in detail how this research deals with these issues.

4. Empirical results

4.1 Main Analysis

The main focus of this research is to examine the effect of financial innovation on bank stability in the OECD countries in the period after the crisis. The empirical results are presented in Table 2. The regressions provide mixed results, where the following results stand out:

[36] The paper of Iwanicz-Drozdowska & Witkowski (2021) showed that there is a strong parent-subsidiary nexus, where subsidiaries can have a strong impact on their parents. Moreover, the paper of Phene & Almeida (2008) shows that both sourcing capability and combinative capability, which are different for companies with different numbers of subsidiaries, have a significant influence on the scale and quality of innovation. In addition to these papers, the paper of Kahn & Winton (2004) shows that securitization of loans often goes in combination with creating "bipartite" bank holding structures, where subsidiaries are created to hold those securities on their balance sheet.

First, the multiple regression in model 1 in Table 2 shows that there is a relationship between financial innovation and bank stability. Specifically, two out of the four innovation proxies enter the separate regressions significantly at the 1% and 5% levels, where both OBS-ratio shows and Securitization capacity show a negative coefficient. Furthermore, the intensity of financial innovation and fintech companies do not seem to have a significant impact on bank stability, according to model 1.

The negative coefficient of *securitization capacity* shows that banks are more unstable in countries with a greater capacity to securitize assets. This is in line with both the hypothesis (H1) and recent literature on financial innovation with samples of the European banking sector (Allen & Carletti, 2006; González et al., 2016; Michalak & Uhde, 2012; Shin, 2009).

Where the classic view in the literature suggests that securitized products can help reduce banks' risk, providing the best possible diversification and risk reduction, increased efficiency, greater liquidity, and transferring credit risk in the markets (Batten & Hogan, 2002), it is argued by more recent papers that banks may relax their policy on monitoring borrowers (Allen & Carletti, 2006), leverage up their capital structure (Shin, 2009) and increase their investments in illiquid, risky credit portfolio's, thus creating a channel of contagion. Moreover, Gonzàlez et al. (2016) show that securitization leads to more fragility in the European banking sector, arguing that the reinvestment process created by securitization created fragility, whereas it should provide greater diversification when reinvesting resources into a new conservative asset. Most of the credit risk occurs in the first-loss tranche, which usually remains on the bank's balance sheet. Hence, the results of Table 2 support the view of the recent literature.

Similarly, the negative coefficient of the *OBS ratio* shows that if banks hold more off-balance sheet items relative to their total assets, banks become more unstable. This is both in line with the innovation-fragility hypothesis (H1) and the literature that relates OBS activities with bank risk in OECD countries (Beck et al., 2016). The paper of Karim et al. (2013) provided evidence that banks in OECD countries after 2003 used off-balance-sheet activities for regulatory arbitrage rather than for risk diversification reasons, which left banks without sufficient capital to cover the risks they were facing. Where banks first used OBS activity as a risk-reducing tool whereby parent companies could venture into new business lines without exposing shareholders to the concurrent risks, the explosion of OTC derivatives trading and asset-backed security issuance fed banks' desire to avoid holding costly capital against their assets after 2003. Furthermore, this paper showed that Off-balance sheet activity contributed significantly to crisis probabilities after 2003. The paper of Papanikalaou (2013) also pointed out that regulatory arbitrage was the game that took place for more than two decades between banking firms and regulatory authorities, where the former were innovating and developing new financial instruments to help elude the scrutiny of supervisors and increase their returns, while the latter were tightening the rules to avoid excessive risk-taking and safeguard the stability of the banking system.

Although this evidence would suggest to make fundamental regulatory changes, the regulatory activity after the crisis, according to Rixen (2013), can be described as “more of the same”. While some institutions are strengthened, their basic workings and formal powers are not enhanced. Also, the institutional landscape remains fragmented. Consequently, a coherent policy toward shadow banking and off-balance sheet activities has not been formulated. In particular, those countries with large financial sectors are hesitant to agree on strict and binding international standards, which will largely be countries of the OECD. So far, their crisis response does not often target the crucial links between shadow banks, off-balance-sheet activities, and financial instability. It can now be characterized by a large number of specialized and detailed rules for individual cases. Similarly, the paper of Anginer et al. (2019) shows their concern about asymmetric information in current policies.

Hence, from a regulatory perspective, not much has changed, making the results from column 1 in Table 2 consistent with the pre-crisis literature (Beck et al., 2016; González et al., 2016; D. Karim et al., 2013; Papanikolaou, 2013).

Second, the regressions in Table 2 show that there is no significant relationship between the number of fintech companies founded in a particular country and the stability of banks in that country. This result is not in line with both hypothesis 2 and previous literature. The paper of Siek & Sutanto (2019) argues that a potential reason for this can be that customers currently still rely on traditional banks for safety reasons. Fintech companies are often small and undeveloped, so these institutions often carry certain levels of uncertainty were many customers are not waiting for. According to the OECD (2020), this uncertainty includes: First, the parallel payment system that isn't adequately monitored by central banks. Second, a proportion of fintech firms rely on BigTech firms that provide third-part services (e.g. data storage or analytics), some of them in the cloud, which makes these fintech companies vulnerable to cyberattacks. Third, the existence of large online money market funds, which are not insured, leaves them vulnerable to runs.

Third, this research captured financial innovation with input and output variables. However, it appears that only output variables of financial innovation enter the regressions significantly. This is not in line with Beck et al. (2016), who also established a significant relationship between the input variable "financial intensity" and the stability of banks. A potential reason for the insignificance of the input variable, therefore, can be that the input variable "Financial intensity (value-added)" bears the highest degree of uncertainty. Although it is often so that more financial R&D expenditures will lead to more products and processes, it does not need to be so. The process of financial innovation is complex, nonlinear, risky, responds to opportunities, and inherently includes elements of chance (Ekpu, 2015). Therefore, it might be that the input variable in this research sample cannot establish a relationship with the stability of banks because the process of financial innovation is complex in which other variables or elements of chance play a large role (Hai et al., 2022). Since this sample is almost identical to Beck et al. (2016), it might be interesting to look further at why the input variable after the crisis is no longer significant. As Hai et al. (2022) showed that financial innovation is nonlinear and risky, the regulatory framework after the crisis might have created even more complexity which drives the result of model 1 in Table 2.

Fourth, Table 2 shows a negative coefficient for the variable "Total Assets" in all the models, suggesting that larger banks have lower Z-scores and, thus, are more unstable. The coefficients of models 1,2 and 3 are the lowest, with a value of around -0.06, which means that for every 1% increase in the total assets of a bank, the bank is 0.06% closer to insolvency. This is in contrast with other work (Mercieca et al., 2007; Michalak & Uhde, 2012). For example, DeYoung & Rice (2004) argue that larger sized banks can invest a lot of money in ICT, so they can build up know-how and technologies for high-quality risk management and a larger size allows the bank to operate more business lines, with a wider range of customers, suggesting that a larger sized bank is more stable.

The paper of Anginer et al. (2019) provides evidence for the fact that bank solvency risk is more sensitive to regulatory capital ratios for smaller banks than for larger banks. Regulatory capital for large banks is a less effective disciplining device for those that are better able to manipulate their balance sheets to circumvent regulatory measures. One potential reason for this finding, therefore, could be that larger banks are more unstable in the new regulatory framework after the crisis because regulatory measures, on average, are less effective as a disciplining device for larger banks than for smaller banks. Large banks might still be able to manipulate their balance sheets, whereas, for small banks, this is not possible. However, note that the paper of Rixen (2013) described the new regulatory framework as "more of the same", suggesting that the regulatory framework could not have changed that much in the behaviour of banks.

Moreover, the paper of Afonso et al. (2015) mentions that some banks are ''too big to fail''. These banks will always get support to avoid the adverse consequences of disorderly bank failures. However, this promise of support comes at a cost: large, complex, or interconnected banks might take on more risk if they expect future rescues. Hence, the results of Table 2 might indicate that larger-sized banks have more systematic risk because they know they can expect support if they are in poor financial conditions. Even though the global financial crisis showed this issue, Table 2 shows that this phenomenon of "too big to fail" might still create risk in the banking industry. Moreover, Grimaldi et al. (2016) estimated the average size of banks in the OECD in 2014 at around $50 billion, while this sample's average asset size in 2014 was around $70 billion, which makes it more likely that "too big to fail" practices might drive this result.

Finally, the signs and significance of both *OBS-ratio* and *Securitization capacity* are consistent throughout each model, suggesting that both multicollinearity problems are not present in these variables and that the dummy variable adjustment method has not caused the variables to be different. However, the number of fintech companies seems to enter significantly in model 2, which only used available data—suggesting that fintech companies in this sample are a significant predictor of bank stability. This shows either that the dummy variable adjustment method caused a biased estimator or that the sample selection of model 2 caused the variable *fintech* to become significant since this model contains fewer observations. Although it can never be confirmed what reason is driving this result, it seems that the latter reason is more likely. The separate regressions, with all the observations included, namely, show an insignificant *fintech* variable. This means that when some observations are eliminated, the number of fintech companies becomes significant, which is also known as the problem of sample selection bias. In the following section, a deeper dive into this issue will be done.

In summary, there is evidence of a negative impact of financial innovation on the stability of banks. At least two out of the four innovation proxies seem to be consistent predictors of stability throughout the different models. The consistency of those variables makes the evidence even stronger. The *fintech* variable seems to have no significant impact on the stability of banks, however, as section 4.2 will show, this is most likely driven by a selection bias.

TABLE 2. OLS REGRESSION OF FINANCIAL INNOVATION AND BANK STABILITY FROM 2010 TO 2019

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Financial Int.	-0.00987	0.0422	-0.0380			
	(0.0140)	(0.0743)	(0.0517)			
OBS-Ratio	-0.00866**	-0.0478*		-0.00863**		
	(0.00414)	(0.0256)		(0.00417)		
Securitization Cap	-0.00821***	-0.00890***			-0.00672**	
	(0.00209)	(0.00298)			(0.00261)	
Fintech	7.07e-05	0.00111***				4.86e-05
	(0.000170)	(0.000204)				(0.000172)
Tier-1 Capital	5.84e-06***	9.50e-06***	6.12e-06***	5.84e-06***	8.44e-06***	5.84e-06***
	(6.26e-07)	(7.90e-07)	(7.18e-07)	(6.18e-07)	(7.36e-07)	(6.19e-07)
LA	-0.00244***	-0.00234***	-0.00239***	-0.00243***	-0.00272***	-0.00242***
	(0.000369)	(0.000681)	(0.000438)	(0.000368)	(0.000612)	(0.000368)
OEA	-1.45e-05***	-1.43e-05***	-1.47e-05***	-1.46e-05***	-1.11e-05***	-1.46e-05***
	(1.29e-06)	(1.69e-06)	(1.48e-06)	(1.29e-06)	(1.54e-06)	(1.30e-06)
Market Share	0.938***	1.719***	0.934***	0.961***	1.759***	0.961***
	(0.164)	(0.219)	(0.181)	(0.165)	(0.221)	(0.165)
GDP	1.67e-05***	1.70e-05***	2.51e-05***	2.01e-05***	2.34e-05***	2.00e-05***
	(3.44e-06)	(5.88e-06)	(4.77e-06)	(3.60e-06)	(5.40e-06)	(3.61e-06)
Fin. Freedom	-0.000730	0.00971**	-0.00152	-0.00224	0.00144	-0.00234
	(0.00202)	(0.00470)	(0.00264)	(0.00200)	(0.00463)	(0.00201)
Regulation Index	0.00934***	0.0220***	0.0163***	0.0118***	0.0103**	0.0120***
	(0.00351)	(0.00633)	(0.00368)	(0.00323)	(0.00487)	(0.00319)
Total Assets	-0.0685***	-0.142***	-0.0685***	-0.0686***	-0.159***	-0.0686***
	(0.0149)	(0.0130)	(0.0176)	(0.0149)	(0.0111)	(0.0149)

Constant	0.678*	-1.535*	-1.186**	-0.538	0.0707	-0.547
	(0.356)	(0.796)	(0.471)	(0.399)	(0.712)	(0.396)
Observations	11,307	2,207	8,740	11,307	3,749	11,307
Number of Countries	34	13	33	34	13	34
Number of Banks	1958	481	1846	1958	577	1958
R-squared	0.386	0.413	0.394	0.384	0.379	0.384
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

The sample period is from 2010 to 2019, with the exception of model 3 (2010-2018). Section 3.2 explains differences in the number of countries and banks in different models. In model 1, the financial innovation proxies are subject to the dummy variable adjustment method, while the other models do not use this method. Models 3 till model 6 are separate regressions of the financial innovation proxies. These models will show robustness and control for potential collinearity issues. The dependent variable is the logged Z-score or Sharpe ratio in all the models. Log(Z-score)= log((ROA + E/A)/ σ(ROA)), where ROA is the return on average assets, E/A is the equity to asset ratio, and σ(ROA) is the standard deviation of ROA of the whole sample period. Higher Z-score implies more stability and less bank risk-taking. The dependent variable is regressed on innovation proxies (Financial intensity(value-added), OBS-ratio, securitization capacity, and the number of fintech companies founded) and a group of bank- and country-specific control variables. The estimations are OLS regressions with country- and year-fixed effects in all the models to control for unobserved heterogeneity at the country and time level. The coefficients are not reported for brevity. All regressions are cross-sectional time series with one observation per bank each period. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Furthermore, all the errors in the models are normally distributed.

4.2 Robustness checks

Additionally, the results will be subjected to several robustness tests: First, the regressions will be performed with the exclusion of banks from the United States. Second, the regressions will be performed with the exclusion of commercial banks, and, finally, the effect of subsidiaries on the relationships will be tested by including an interaction term. Hereafter, I adopt 2SLS/IV estimators with instrumental variables for the endogenous variables to mitigate endogeneity concerns associated with panel data. Furthermore, the problem of an omitted variable bias[37] might be present in the data.

The results of the robustness check are presented in Table 10 and Table 11 in the Appendix. For reasons of brevity, the control variables are excluded. Moreover, these regressions did not give

[37] This bias occurs when a variable is left out of the model, which both impact the independent variable as the dependent variable. The effect of the omitted variable, then, will be captured by the independent variable. This causes this variable to have a biased coefficient.

any special results and showed the robustness of the control variables for all the models. A detailed discussion of the results of the robustness tests can be found in section A.8 in the Appendix. A summary of these results is given below:

First, the variable *fintech* becomes highly significant and positive when excluding the United States from the sample. Hence, the insignificant result in the main analysis is driven by US banks.

A potential reason for these could be found in the classification of their financial sector. As opposed to the majority of the sample, the United States has a market-based financial system (Demirguc-Kunt & Levine, 1999)[38]. Another explanation for this result is provided by the paper of Wang et al. (2021), who argued that hardware and software must be in place to achieve in-depth integration with fintech in traditional banks[39].

Second, the variable *OBS ratio* becomes insignificant when excluding commercial banks. This means that the commercial banks drive the significant relationship between the OBS ratio and stability in the main analysis. The paper of Cantú et al. (2019) provides a potential reason for this, showing that commercial banks generally supply more credit than other bank types, making these banks more susceptible to the moral hazard problem described in section A.8.1.2.

Third, it can be said that the effect of subsidiaries on the relationship between financial innovation and bank stability is inconsistent. This is shown by different signs and significance of the interaction terms throughout different specifications shown in Table 10 and Table 14.

Finally, the 2SLS/IV estimator shown in Table 11 shows that there was endogeneity or reverse causality in the original model (Table 2) since the coefficients/ standard errors changed significantly. Moreover, the significant relationship of off-balance sheet item activities and the

[38] In bank-based financial systems, banks play a leading role in mobilizing savings, allocating capital, overseeing the investment decisions, overseeing the investment decisions of corporate managers, and providing risk management vehicles. In market-based financial systems, securities markets share center stage with banks in getting society's savings to firms, exerting corporate control, and easing risk management. The emergence of these fintech companies is more likely to be seen as serious competitive threat in bank-based systems than in market-based systems, since it threatens the status quo more. Therefore, fintech companies may only have a strong effect on banks in bank-based countries.

[39] In the US, the average size of the banks is 56.100.000.000 and outside the US the average size of the banks is: 77.700.000.000. Therefore, it is possible that in-depth integration with fintech in the United States is more difficult to achieve than in other countries. Hence, a significant relationship between bank stability and fintech is more unlikely in the US (also see section A.8.1.1 for more detail).

insignificant relationship of fintech companies with bank stability seems to be driven by endogeneity issues. Therefore, these 2SLS/IV estimators confirm both selection biases.

5. Discussion and conclusion

This paper tests the relationship between several financial innovation proxies and bank stability in OECD countries. Using an updated dataset with both yearly bank-level data and country-level data from 35 countries in the OECD, this study finds little evidence for the *innovation-fragility* view during the period 2010 to 2019. More specifically, out of the four financial innovation indicators, only securitization capacity and OBS-ratio are consistently negatively significant throughout different regressions. This suggests that banks are less stable if countries have more outstanding securitized assets or engage more in off-balance-sheet activities. However, note that off-balance-sheet activities only predict bank stability in commercial banks[40].

Where pre-crisis literature on the relationship between bank stability and financial innovation in the OECD found four consistent significant proxies, this research only finds two consistent significant proxies (Beck et al., 2016). The effect of a possible omitted variable bias in this research is mitigated, meaning that an omitted variable does not drive the insignificancy of these proxies. Therefore, it must be that something in the nature of innovations has changed[41]. This either confirms comments made in the paper of Lerner & Seru (2021) or the paper of Sánchez (2010). Lerner & Seru (2021) argued that the regulatory framework after the crisis, characterized by a more restrictive policy on certain activities and capital requirements, may have depressed the focus on innovation more generally which hampered both positive and negative effects for specific forms of financial innovation on bank stability. Sanchez (2010) argues that prudential regulation and supervision may lead to innovations being sufficiently transparent and understandable for markets to work efficiently and society to continue to benefit from an

[40] These banks are very important in our system, so this result has major implications for society (Yakubu & Affoi, 2014).

[41] However, care must be taken with interpreting this conclusion, since something inherent in the data collection process can also drive the result. For example, the data availability for the variables in the paper of Beck et al. (2016) might have been better whereby they were not forced to do statistical tricks like the dummy variable adjustment method. This problem is also mentioned as one of the limitations of this study.

unceasing modernization of finance and the financial system. Hence, this suggests that there has been a change in the nature of the innovations. Innovations now have different effects on the stability of banks. Future research could look at what exactly has changed in the nature of specific types of innovations.

Furthermore, the increased capital requirements and stricter lending conditions that banks faced after the Global Financial Crisis made it hard for small businesses and individuals to secure credit, thus creating an unmet demand for financial services. This, in turn, has led to the fact that fintech companies have become increasingly important. For this reason, this research examines the relationship between these companies and bank stability in the period after the crisis. The results show that banks are more stable if countries outside the United States contain more fintech startups. According to the literature, this is either through an increase in competition which enhances monitoring quality or reduces the tendency to over-lend or through strategic partnerships with each other (see section A.8.1.1 in the Appendix for more detail). This result has both implications for regulators, who must stimulate the competition effect the fintech companies have on banks, and for bank managers, who might want to start a strategic partnership to generate positive spill-over effects. Hence, the regulatory framework may have not only hampered the negative effects of financial innovation but also created another positive consequence. These results imply that policymakers have succeeded in their job to stabilize the banking sector concerning financial innovations with the new regulatory framework.

However, this study also has several limitations, some of which open an avenue for future research. First, due to data availability constraints, this research only uses an accounting-based risk measure. Since previous literature has shown that accounting measures sometimes consider risks that are not apparent in financial statements and investors might care more about market risk, future research must also incorporate market measures into the literature on the relationship between financial innovation and bank stability after the crisis (González et al., 2016).

Second, this study only determines the effects on the risk in the banking sector. The results of this study show that the emergence of fintech companies contributed to the stability of the banking sector. However, the OECD (2020) mentioned that regulators must be alert to new forms of systematic risk due to the new fintech companies. Since the banking sector and other sectors in the financial sector are greatly interconnected, future studies must investigate whether the emergence of these companies does not worsen the systematic risk of the financial sector (Peltonen et al., 2018).

Third, the data contained a fair amount of missings. To prevent loss of usable data, I was forced to use the dummy variable adjustment method on both Financial intensity(value-added), OBS ratio and securitization capacity. This caused the problem of biased estimators, as described by Jones (1996). Although I tried to show the robustness of results throughout the different specifications with different numbers of observations, care must be taken in generalizing the results as the missings are not at random.

Fourth, where the variables did reach statistical significance, the variables are not that economically significant. For example, the main analysis shows a coefficient of -0.00821 for securitization capacity, suggesting that if the securitization capacity increases by 1%, banks are 0,8% standard deviation closer to insolvency (measured by the Z-score). Assuming an average bank with a Z-score of 2.7[42], it means that the amount of outstanding securitized assets of a country must increase by 105% before it is technically insolvent. This increase is unlikely in the short term, given the strict regulatory framework and challenging environment (Manzi et al., 2022). Therefore, care must be taken in interpreting the results.

Additionally, this research took a general approach. I did not look into the specific characteristics of banks. Therefore, future research may look at the impact of financial innovation on the stability of banks moderated by the different business models in banks, which can have an impact on how banks approach non-traditional business practices (DeYoung & Torna, 2013).

[42] In this sample, the average Z-score is 2.7. Thereby, the standard deviation is assumed to be 3.197, taken from Table 1.

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Appendix

A.1. Choices regarding input measure of financial innovation

This research takes this proxy for the whole financial sector, rather than a proxy for the bank sector since R&D expenditures by other financial institutions than banks might trigger actions by banks since they're afraid that they lose market share against other financial institutions, not classified as banks.

The R&D expenditures are measured relative to an economic indicator since this controls for the size of the overall financial sector. It is often the case that the bigger the financial sector, the higher the R&D expenditures, so to make a cross-country comparison, I need a relative R&D expenditure proxy.

Furthermore, about which economic indicator is chosen, I choose R&D expenditures relative to the total value added instead of R&D expenditures relative to the total revenue because value-added helps explain why companies can sell their goods or services for more than they cost to produce. Hence, adding value to products and services is very important as it gives consumers an incentive to make a purchase, thus increasing a company's revenue and bottom line. As opposed to value-added, revenue does not tell whether a product adds value to a market. Therefore, the concept of value added is more aligned with the goal of financial innovation, which is that it adds value to a product/market (Philippas & Siriopoulos, 2011).

The definition of value-added, according to OECD statistics, is the contribution to national GDP. This contribution is calculated as the difference between production and intermediate inputs. Value Added comprises Labour Costs (Compensation of Employees), Consumption of Fixed Capital, Taxes fewer Subsidies on production, and Net Operating Surplus and Mixed-Income.

R&D expenditures are defined following the Frascati Manual (2015): total intramural (within-firm) and extramural (acquired from outside) expenditures on R&D. An enterprise fall within the financial and insurance industry when its most economic output falls in that industry; this may be identified directly from sales or indirectly proxied. As such, all business enterprise R&D expenditures of a diversified enterprise are allocated to the same industry as its main activity.

This definition enables, as far as possible, the alignment and compatibility of data with other economic statistics.

A.2. Definition of OBS-ratio parts

TABLE 3. DEFINITIONS OF COMPONENTS OF OBS-RATIO

Variables	**Definition**
Committed credit facilities	Committed credit facilities refer to a business in which the bank promises to provide loans to customers in the future under certain conditions; in this process, even if the customer does not obtain a loan, the bank still charges a handling fee.
Guarantees	Guarantees refer to a business the bank undertakes to repay the debt for guaranteed parties (Zhang et al., 2020).
Acceptances and documentary credits	Acceptances and documentary credits refer to a business that the bank that becomes the guarantor of the transaction of bills.
Managed securitized assets	Managed securitized assets refer to business-related backstop liquidity facilities providing last-resort support in securities offering for an unsubscribed portion of shares.
Under other exposure to securitizations	The main portion of “Under other exposure to securitizations” is the number of securitized loans.
Other contingent liabilities	Other contingent liabilities refer to obligations other than “guarantees” that currently do not meet the accounting definition of liability because the contingency is not probable. However, if certain events occur they may become a liability.

This table shows the definition of some parts of the off-balance-sheet activities.

A.3. Expected signs of control variables

TABLE 4. EXPECTED RELATIONS OF THE CONTROL VARIABLES WITH Z-SCORE BASED ON THE LITERATURE

Variable	**Sign**	**Explanation**
Bank-level		
Tier-1 capital ratio	+	According to Investopedia (2021), tier-1 capital is the same as a bank's core equity capital and disclosed reserves. Hence, the higher the tier-1 capital relative to their total assets, the higher the capital buffers, and thus, the lower the chance they become insolvent. This is also confirmed by the paper of Sari et al. (2018), who argue that more tier-1 capital results in better risk management.
Loan to asset ratio	-	A higher loan-to-asset ratio indicates that the bank has more of its assets in loans, which means that if there is more borrower default, the bank is closer to insolvency (Adusei, 2015). Hence, a higher loan-to-asset ratio will lead to higher chances of insolvency (lower Z-scores).
Other earning assets	-	Banks' other earning assets are all on-balance sheet assets that generate non-interest earnings for the financial institution, typically dividends and gains from trading and other investments. According to Brunnermeier et al. (2020), non-interest income is positively related to the total systematic risk of banks. Therefore, the higher the other earnings assets, the higher the systematic risk (the lower the Z-score).
Bank's market share	-	The paper of Mirzaei et al. (2013) shows that, in advanced economies, concentration is negatively associated with bank soundness, suggesting that a high market share of a bank may encourage risk-taking.

Asset size	+	Larger-sized banks can invest a lot of money in ICT to build up know-how and technologies for high-quality risk management. Furthermore, a larger size allows the bank to operate more business lines with a broader range of customers, suggesting that a larger-sized bank is more stable (DeYoung & Rice, 2004).
Country-level		
GDP	+ Or -	This macro-economic variable can either have a negative or a positive effect: It can be positive because a high GDP implies high productive capacity, where real income also rises. This rise means that demand for goods and services increases, suggesting that there is also more demand for loans. This increase in demand would lead to a more stable customer deposit base (higher Z-scores) (Olokoyo et al., 2021). It can be negative because high GDP can improve the business environment and lower bank entry barriers. This promotes competition in the banking industry, which reduces stability (Adusei, 2015).
Banking Freedom	+	According to Mercieca et al. (2007), more banking freedom will lead to less insolvency risk, meaning that a higher score of this variable leads to higher Z-scores.
Regulation index	+	According to Barth et al. (2012), increased regulation of bank activities goes hand in hand with an increased likelihood of insolvency. A Higher score on the regulation index means lower regulation. Hence, a higher score means that there is more stability (higher Z-scores).

This table shows the effects of each control variable according to the literature. A positive sign in this table means that the higher the value of the control variable, the higher the stability. A higher Z-score means that the bank is further away from insolvency. This is vice versa for a negative sign.

A.4. Correlation matrices

TABLE 5. CORRELATION MATRIX FOR DEPENDENT VARIABLES AND CONTROL VARIABLES.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Zscore	1.000								
(2) Tier1Capital	-0.096	1.000							
(3) LA	-0.274	-0.156	1.000						
(4) OEA	-0.080	0.582	-0.157	1.000					
(5) Bank Market Share	-0.079	0.318	0.004	0.233	1.000				
(6) GDP	0.002	-0.028	0.129	-0.034	-0.162	1.000			
(7) FinancialFreedom	0.076	0.005	0.069	0.037	-0.019	0.502	1.000		
(8) RegulationIndex	-0.060	0.007	0.130	-0.025	-0.225	0.415	0.140	1.000	
(9) Totalassets	-0.366	0.579	0.043	0.367	0.388	-0.023	-0.088	-0.042	1.000

The above table shows the correlation of all the control variables, with both the dependent as the other control variables.

TABLE 6. CORRELATION MATRIX FOR (IN)DEPENDENT VARIABLES

Variables	(1)	(2)	(3)	(4)	(5)
(1) Z-Score	1.000				
(2) Financial Intensity	-0.044	1.000			
(3) Securitization Capacity	-0.105	-0.131	1.000		
(4) Fintech	0.014	-0.154	0.252	1.000	
(5) OBS-Ratio	0.032	0.000	0.014	-0.010	1.000

The above table shows the correlation of the dependent- and independent variables.

TABLE 7. CORRELATION MATRIX FOR SUBSIDIARIES AND OTHER VARIABLES.

Variables	(1)
(1) Subsidiaries	1.000
(2) Z-score	-0.006
(3) Financial Intensity	0.006
(4) OBS-ratio	-0.005
(5) Securitization	-0.006
(6) Fintech	-0.137
(7) Tier1Capital	0.665
(8) LA	-0.134
(9) OEA	0.458
(10) Bank Market Share	0.255
(11) GDP	-0.091
(12) Financial Freedom	-0.041
(13) Regulation Index	-0.123
(14) Total Assets	0.412

The above table shows the correlation of the variable “subsidiaries” (labeled with “1”), with both the dependent and independent as the other control variables.

A.5. Reverse causality and omitted variable bias

As section Model Specification describes, Leszczensky & Wolbring (2022) highlighted the problem of reverse causality. Suppose the assumption is made that the relationship between financial innovation and stability is one way around. In that case, the effect size might be biased since the relationship also goes the other way around. Hence, the financial innovation variables might be endogenous due to reverse causality between financial innovation and stability. Furthermore, independent variables in the model might be influenced by variables that are not included in the model (omitted variable bias).

More specifically, the problem is that the financial innovation variables may be correlated with the error terms of the model because the stability of banks or other variables might be able to influence the degree of financial innovation of a country. To deal with this endogeneity and reverse causality, this research follows Bos et al. (2013) and Lee et al. (2020) by using lags of the endogenous regressors that are not correlated with the error term (instrument exogeneity) as instruments in an IV/2SLS estimator. Then the effect of financial innovation on stability can be isolated (Leszczensky & Wolbring, 2022).

Hence, in this research, levels of the endogenous variables are used as instruments for the endogenous variables. The lag structure of the instrumental variables depends on the order of serial correlation in the residuals. If there is no serial correlation in the residuals in levels, the instruments of that particular level can be used. To test whether there is no serial correlation, this research performs an Arellano Bond test for serial correlation. This test is based on an examination of residuals in first differences (Bos et al., 2013). An important assumption is that these lagged variables are exogenous[43].

Furthermore, The Hansen test is performed to examine the instrument exogeneity assumption. Under the null hypothesis in this test, the instruments are valid. Finally, to explore the relevance

[43] An argument against the exogeneity of these lags is that the dependent variable in the current period may reflect expectations in the past. If this is the case and behavior in the past is based on expectations in the future, these lags as instruments are not exogenous. For example, if the stability of a bank in the current period may reflect expectations concerning stability in previous periods, and this expectation may have affected financial innovation in the past.

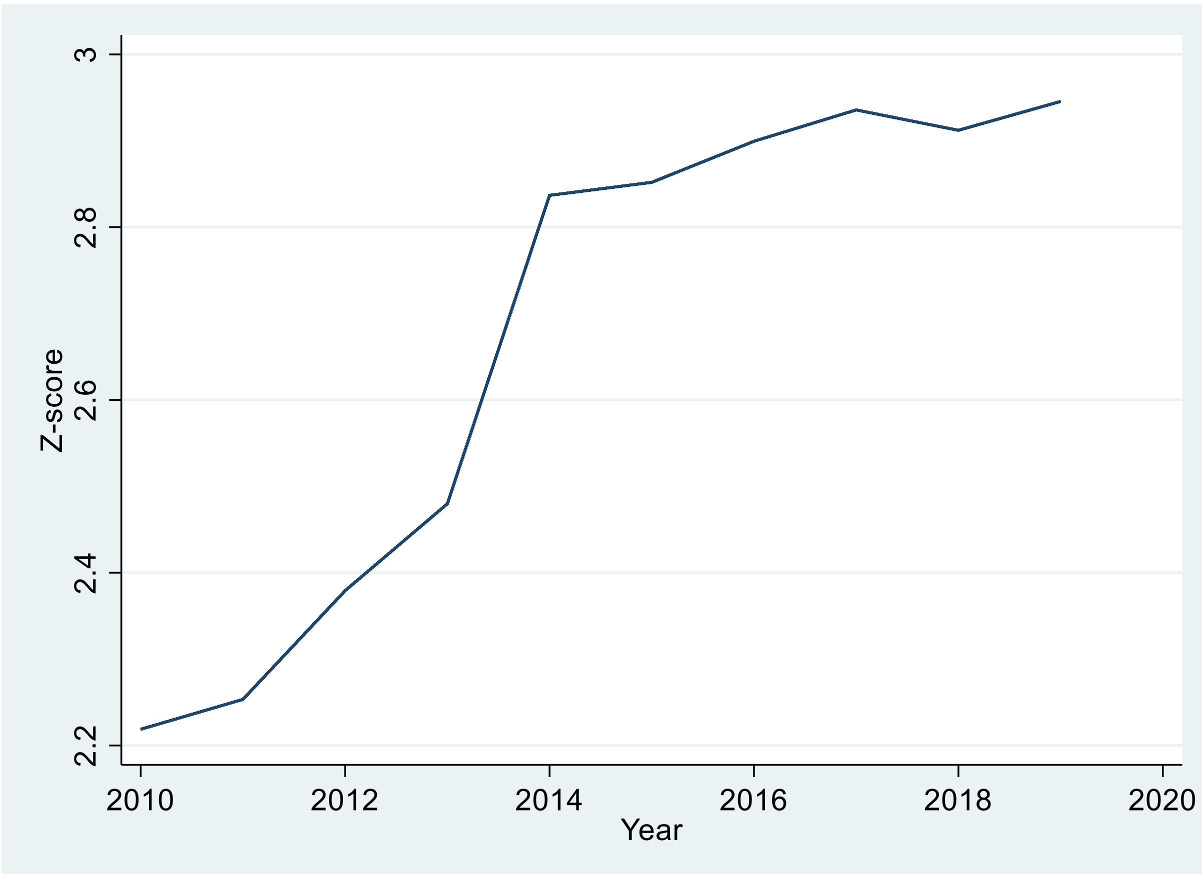
of the instruments, the F-statistics of the instruments in regressions of the endogenous variables are examined[44].

The Arellano Bond test is reported in Table 8. It shows that for both “Financial intensity (value-added)” and “OBS-ratio” and “Securitization capacity” and “Fintech”, there is no serial correlation in the residuals when using the first- and second lag of this independent variable. Furthermore, the Hansen test in Table 8, shows values higher than 0.05 in each model, which confirms the exogeneity of these instruments (and holds the null hypothesis) and the F-statistics in the regressions of Table 9 show that these instrumental variables have high explaining power and, hence, are very strong. Thus, the effect of financial innovation on the stability of banks can be isolated by using the above-mentioned instrumental variables in an IV/2SLS estimator. The intuition behind this method is that the instrumental variables isolate the effect of financial innovation on stability so that the relationship between financial innovation and bank stability is one way around. The instrumental variables, namely, are not influenced by stability levels in the current period. Since it is impossible to include different endogenous regressors with other instrumental variables in the same regression, the 2SLS/IV estimators regress the independent variables separately.

[44] To check whether the instruments are strong enough to predict the effect of the endogenous variable, regressions with the instrumental variables on the endogenous variables are run.

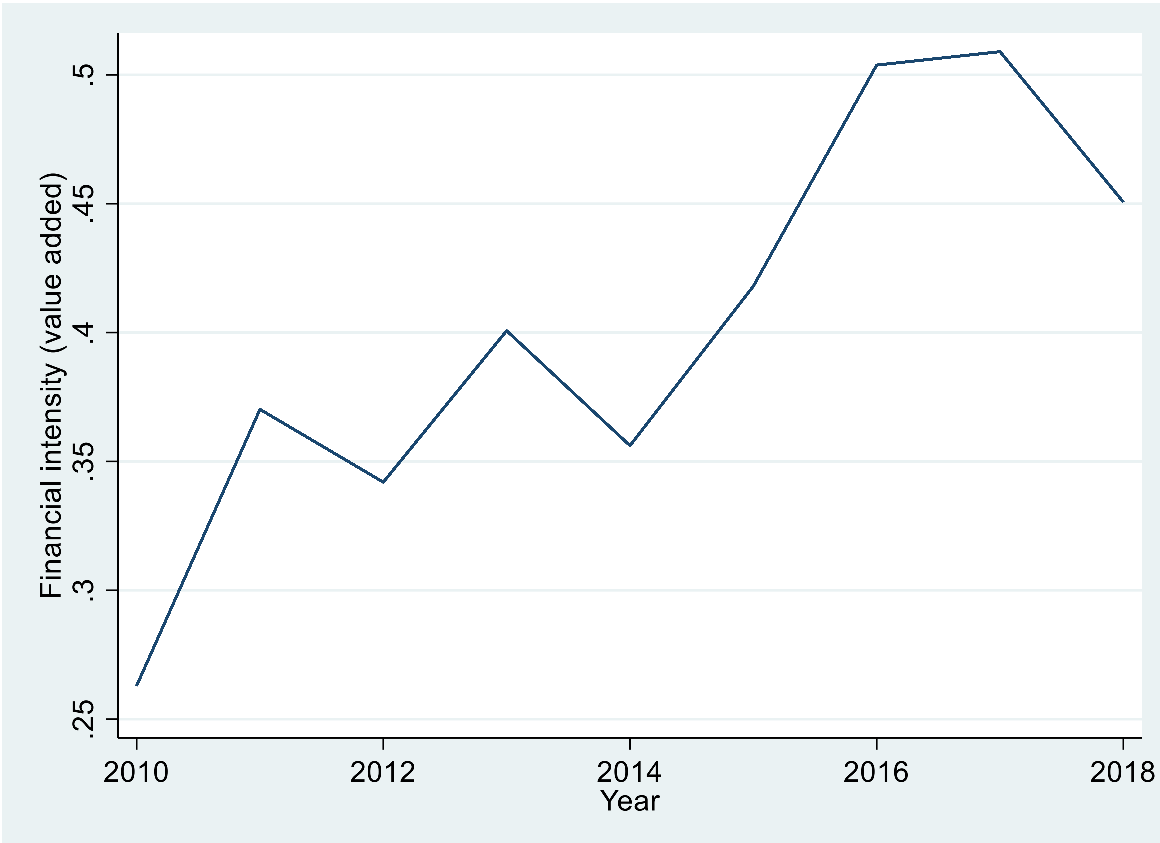
A.6. Trends in the stability of banks and financial innovation measures

FIGURE 1. THE OVERALL TREND OF AVERAGE Z-SCORE IN 35 COUNTRIES FROM 2010 TO 2019.



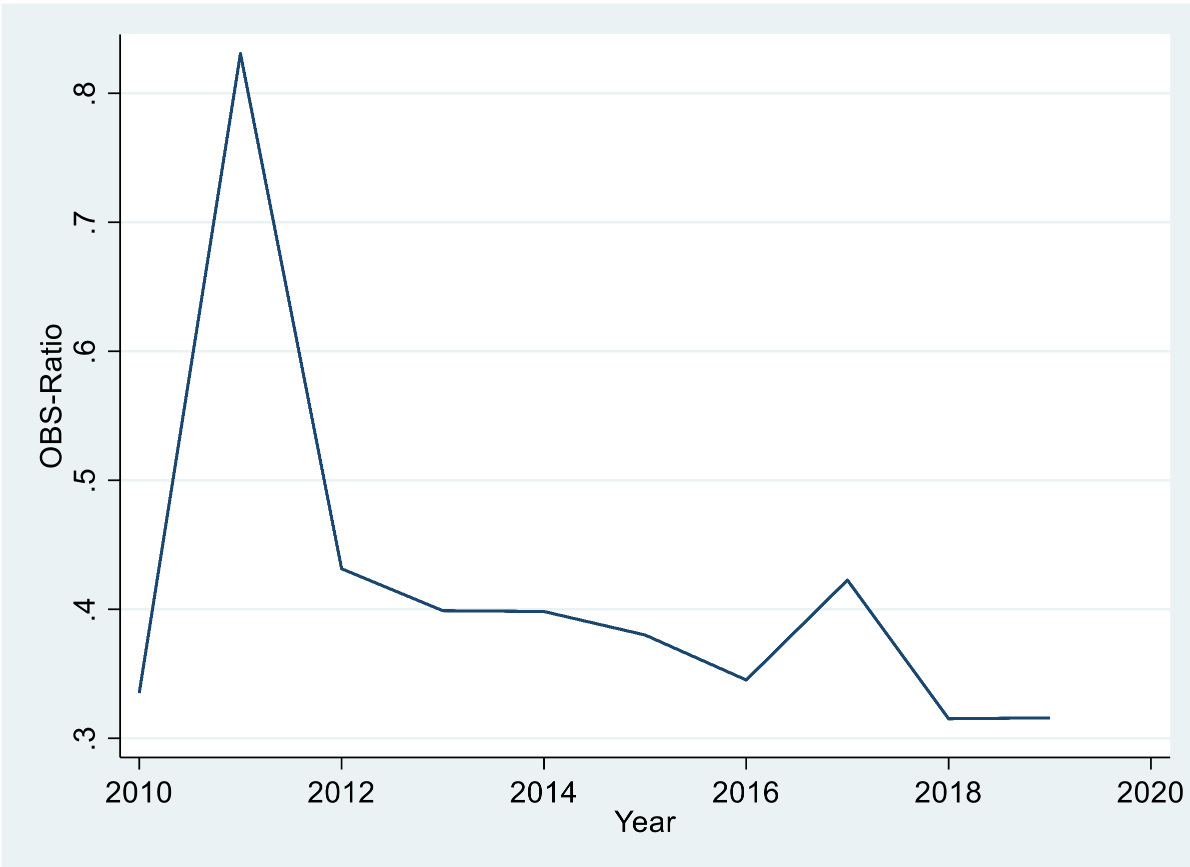
The figure shows the overall trend of the averaged Z-score per year in 34 countries from 2010 to 2019. The 35 countries include Austria, Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Turkey, United Kingdom, and the United States. The data comes from Bank Scope.

FIGURE 2. THE OVERALL TREND OF AVERAGE FINANCIAL INTENSITY (VALUE-ADDED) IN 34 COUNTRIES FROM 2010 TO 2018.



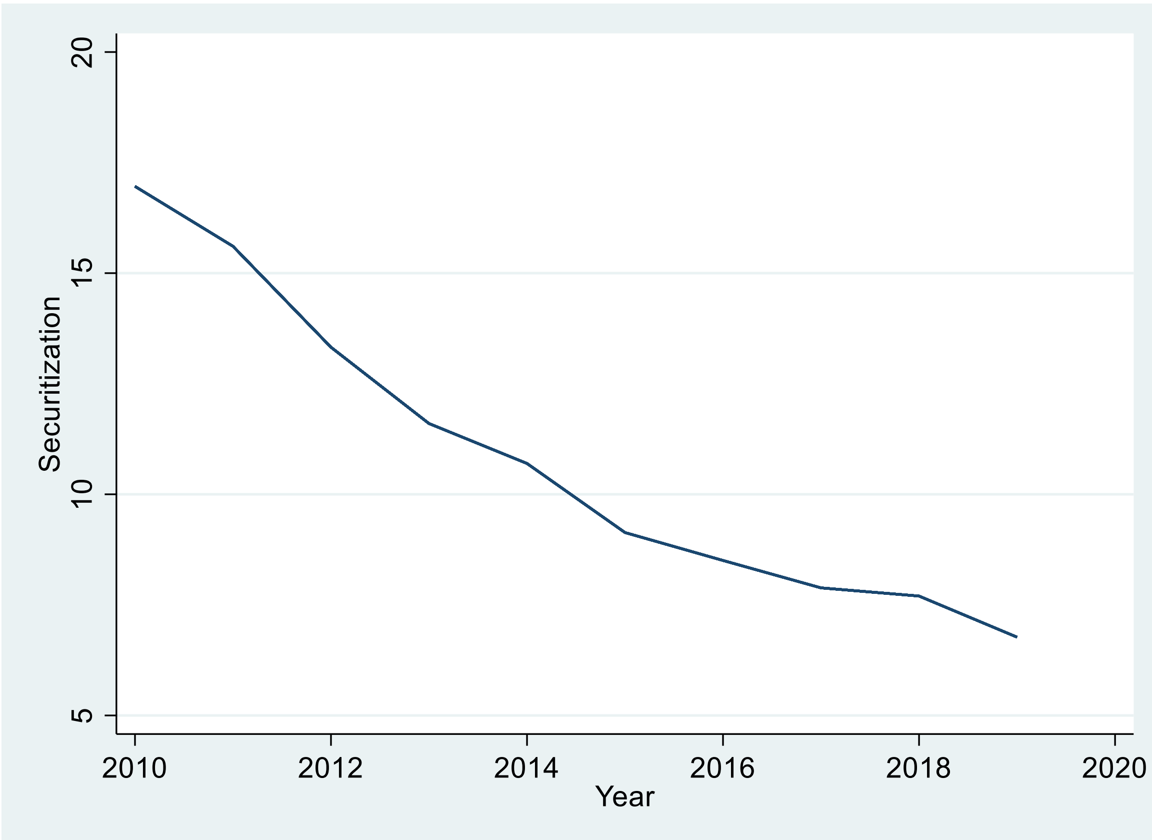
The figure shows the overall trend of the averaged Financial intensity based relative on the total value added per year in 34 countries from 2010 to 2019. The 34 countries include Austria, Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States. The data comes from the STAN R&D database from OECD statistics.

FIGURE 3. THE OVERALL TREND OF AVERAGE OBS-RATIO IN 35 COUNTRIES FROM 2010 TO 2019.



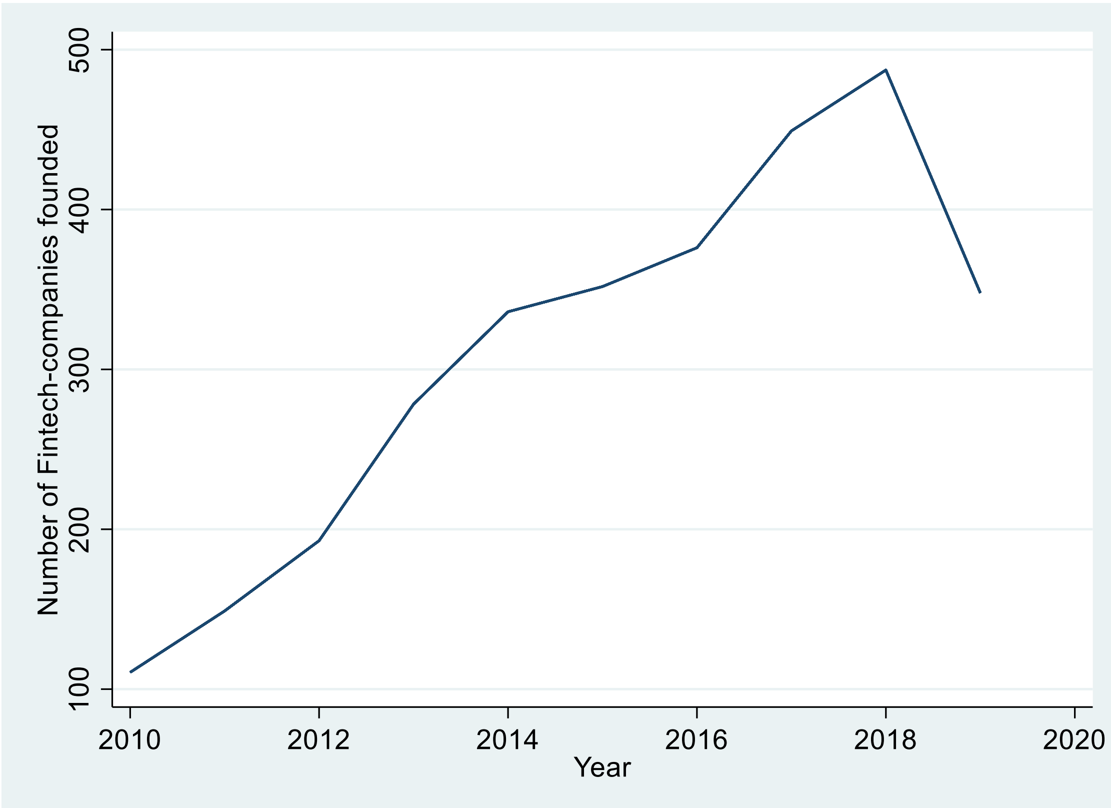
The figure shows the overall trend of the averaged off-balance sheet items relative to total assets per year in 35 countries from 2010 to 2019. The 35 countries include Austria, Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States. The data comes from Bank Scope.

FIGURE 4. THE OVERALL TREND IN AVERAGE SECURITIZATION CAPACITY IN 13 COUNTRIES FROM 2010 TO 2019.



The figure shows the overall trend of the averaged securitization capacity per year in 13 countries from 2010 to 2019. The 13 countries include Turkey, Austria, Finland, Germany, France, Portugal, Ireland, Greece, Italy, Spain, Belgium, the United Kingdom, and the Netherlands. The data comes from a database, prepared by the Securities Industry and Financial Markets Association (SIFMA) and the Association for Financial Markets in Europe (AFME)

FIGURE 5. THE OVERALL TREND IN THE NUMBER OF FINTECH COMPANIES FOUNDED IN 35 COUNTRIES FROM 2010 TO 2019.



The figure shows the overall trend of the number of fintech companies founded per year in 35 countries from 2010 to 2019. The 35 countries include Austria, Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States. The data comes from Crunchbase.

A.7. Tests for the 2SLS/IV estimation

TABLE 8. ARELLANO-BOND TESTS FOR SERIAL CORRELATION

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Financial intensity (value added)	0.060			
	(0.102)			
OBS-Ratio		-0.006**		
		(0.002)		
Securitization Capacity			-0.001	
			(0.013)	
Fintech				-0.000**
				(0.000)
Constant	2.667***	2.412***	3.132***	2.882***
	(0.112)	(0.044)	(0.193)	(0.093)
Observations	14,975	9,747	5,486	19,010
Number of Banks	2,651	1,683	913	2,890
AR(1)	0.102	0.308	0.158	0.740
AR(2)	0.387	0.291	0.535	0.305
Hansen Test	0.221	0.220	0.359	0.312
Sargan Test	0	0	0	0

The above table shows Arellano-Bond tests for serial correlation. The dependent variable in each model is the Z-score. In every model, the first- and second-order levels of the proxy of financial innovation are used as instrumental variables. AR(1) and AR(2) stand for the autoregressive processes, from which the first is based on the immediately preceding value and the latter is based on the previous two values. Hence, this shows if the serial correlation is present in the model. The Hansen test checks for exogeneity of the instrumental variables. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 9. F-TEST FOR STRONG INSTRUMENTS

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 5
L.Financial Intensity (value added)	0.703***			
	(0.00356)			
L2.Financial Intensity (value added)	0.270***			
	(0.00354)			
L.OBS-Ratio		0.0217***		
		(0.00255)		
L2.OBS-Ratio		0.0226***		

		(0.00254)		
L.Securitization Capacity			0.987***	
			(0.0104)	
L2.Securitization Capacity			-0.113***	
			(0.00909)	
L.Fintech				1.730***
				(0.00742)
L2.Fintech				-0.904***
				(0.00814)
Constant	0.350***	0.355***	0.0360***	39.33***
	(0.0183)	(0.0158)	(0.000468)	(0.491)
Observations	62,919	14,118	7,696	74,080
R-squared	0.951	0,0110	0.989	0.884
F-test	605623	78,31	344683	283115

The above table shows the OLS regressions of the instrumental variables on the endogenous regressors of the main analysis, which are the financial innovation proxies. In model 1 this is the variable "Financial intensity (value-added)". In model 2 this is the variable "OBS-Ratio". In model 3 this is the variable "Securitization Capacity" and in model 4 this is the variable "Fintech". The F-test shows if the instrumental variables are strong or not. If the F-statistic is above 10, then the instruments are threatened as strong. *** p<0.01, ** p<0.05, * p<0.1.

A.8. Robustness checks

Furthermore, the results will be subjected to several robustness tests: First, the regressions will be performed with the exclusion of banks from the United States. Second, the regressions will be performed with the exclusion of commercial banks, and, finally, the effect of subsidiaries on the relationships will be tested.

Hereafter, I adopt 2SLS/IV estimators with instrumental variables for the endogenous variables, which in this research are the proxies for financial innovation, to mitigate endogeneity concerns associated with panel data. The problem is that reverse causality may cause biased estimators since financial innovation can influence stability, but stability can also influence financial innovation. Furthermore, the issue of an omitted variable bias[45] might be present in the data.

A.8.1. Selection bias

A.8.1.1. Exclusion of United States

On top of this, the sample in this research mainly consists of banks from the United States (77%). Therefore, this research checks if the main findings are robust for the United States to prevent a selection bias[46]. In addition, model 2 in Table 2 shows that if many countries are excluded from the sample, the *fintech* variable changes in significance, which suspects a sample selection bias.

Therefore, this research checks if the results are robust towards the United States. Table 10 presents the results of this robustness test. For reasons of brevity, the regression results for the control variables are excluded. Moreover, these regressions did not give any special results and showed the robustness of the control variables for all the models. Below the notable results will be discussed:

[45] This bias occurs when a variable is left out of the model, which both impact the independent variable as the dependent variable. The effect of the omitted variable, then, will be captured by the independent variable. This causes this variable to have a biased coefficient.

[46] This bias occurs when the sample used is not a representative of the population intended to be analyzed. Since, the United States takes up the most observations in the sample, it might be that the results are driven by characteristics out of the United States. Therefore, regressions are run without this country, to see if the results also hold for other countries.

First, the sensitivity analyses confirm both the significant negative effect of *OBS-ratio, Securitization capacity* on the stability of banks, and the insignificance of the input variable *financial intensity*, suggesting that the results for at least these two financial innovation variables in the main analysis do not seem to be driven by sample selection bias. The consistency of these variables makes the evidence for the relation between stability and the financial innovation proxies even stronger.

Second, the variable *fintech* becomes highly significant and positive when excluding the United States from the sample. This means that the number of fintech companies founded in a particular year for countries outside of the US is essential for the stability of banks in those countries. More specifically, if more fintech companies are founded in countries outside the US, the banks in those countries will be more stable.

This result is not in line with the results of the main analysis, where *fintech* remains insignificant in the separate regressions, making the results of the main analysis susceptible to the sample selection bias. Hence, the insignificant result in the main analysis is driven by US banks.

The exact reasons for this selection bias are hard to determine. Apparently, US banks had some characteristics which caused the relationship between the number of fintech companies and bank stability to be insignificant. By studying the literature, two potential reasons for this bias can be found:

First, the biggest difference between the United States and the rest of the sample is that the majority of the countries have a bank-based financial system. In contrast, the United States has a market-based financial system (Demirguc-Kunt & Levine, 1999). In bank-based financial systems, banks play a leading role in mobilizing savings, allocating capital, overseeing the investment decisions, overseeing the investment decisions of corporate managers, and providing risk management vehicles. In market-based financial systems securities, markets share center stage with banks in getting society's savings to firms, exerting corporate control, and easing risk management. The emergence of these fintech companies is more likely to be seen as a serious competitive threat in bank-based systems than in market-based systems since it threatens the status quo more. Therefore, fintech companies may only strongly affect banks in bank-based countries.

Second, Wang et al. (2021) argue that to achieve in-depth integration with fintech in traditional banks, it is necessary to have the required hardware and software infrastructure. Therefore, the change in the quality and efficiency of financial services in banks due to the fintech companies differs according to the required hardware and software level. In this sample, the banks in the US on average, are smaller than those in other countries[47]. A potential reason for the results in Table 10, therefore, can be that in countries other than the US, banks often have the required hardware and software infrastructure to enhance the quality and efficiency of their financial services. To verify this, an OLS regression with the interaction between the size of a bank and the number of fintech companies founded is done. Table 15 in the appendix shows the results. This table shows, indeed, that the size of a bank affects the impact that fintech companies have on bank stability since both the *fintech* and the interaction effect are positive and significant. Suggesting that the number of fintech companies positively impacts the stability of banks, but that effect is stronger if those banks are bigger.

A striking result, however, is that the effect in the countries outside the United States is the reverse of what might be expected according to the hypothesis (H2). Despite the majority in the literature supporting hypothesis 2, there is also a current supporting the other side. Below three views from this current in the literature are summarized:

First, Goetz (2018) found evidence for the fact that an increase in banking competition due to new fintech firms forces banks to be more efficient, which increases bank stability. An important channel through which banks improve stability is by increasing their asset quality by monitoring efforts (Boyd & De Nicoló, 2005). Similarly, banks may reduce their tendency to engage in over-lending.

Second, Thakor (2019) argued that banks that perceive fintech lenders as serious competitive threats would focus more on their competitive advantage. Where, according to Jakšič & Marinc (2019), fintech companies are more transaction-oriented, traditional banks have competitive advantages over fintech companies in relationship lending. Where relationship banks charge a

[47] In the US the average size of the banks is: 56.100.000.000 and outside the US the average size of the banks is: 77.700.000.000.

higher spread in normal times, they offer more favourable continuation-lending terms and fewer defaults in response to bad times (Bolton et al., 2016).

Third, Brandl & Hornuf (2020) showed that banks usually attempt to build strategic partnerships with fintech companies to gain access to the desired technology. Through cooperation with fintech companies, banks may gain knowledge about the technology required to provide innovative financial services, banks can seek to benefit from the development of new customer segments, products and services, expand into new markets and develop new capabilities. By using financial technology, traditional banks can improve their traditional business model by reducing bank operating costs, improving service efficiency and strengthening risk control. At the same time, fintech firms can earn customer trust and market reach or look for financial resources and infrastructures through cooperation.

Since the OECD countries outside the US are bank-based systems, where the status quo is more threatened than in market-based systems by the arrival of the fintech companies, it is possible that the mechanisms above drive the significant positive relationship between fintech and bank stability.

Finally, model 1 till model 5 in Table 12 in the appendix show both multiple- and simple regression models of the available data without the US banks included. These models show no different effects in each model, suggesting that the results presented in Table 10 are robust and show no collinearity issues. Therefore, the evidence that US banks drive the *fintech* indicator in the main analysis becomes stronger. Furthermore, this strengthens the established relationships between the other three financial innovation proxies.

In summary, the negative impact of Off-balance sheet activities, securitization capacity, and the insignificant financial intensity variable do not seem to be driven by the United States, which makes this evidence stronger. However, the insignificant relationship in the main analysis of the fintech companies with bank stability seems to be driven by the United States since excluding this country will lead to a highly significant fintech variable. Therefore, the problem of sample selection bias seems to occur, which weakens the evidence of this insignificant relationship.

A.8.1.2. Exclusion of Commercial banks

The sample in this research mainly consists of banks that classify as Commercial banks (60%). Therefore, this research checks if the main findings are robust for bank type to prevent a selection bias[48]. Table 10 presents the results of this robustness test. For reasons of brevity, the regression results for the control variables are excluded. Moreover, these regressions did not give any special results and showed the robustness of the control variables for all the models. Below the notable results will be discussed:

First, the sensitivity analyses again confirm the significant negative effect of *securitization capacity* on the stability of banks, suggesting that the results from the main analysis for this variable are robust for the exclusion of commercial banks. The consistency of this relation between stability and the securitization capacity makes this evidence even stronger.

Second, the variable OBS ratio remains negative but becomes insignificant when excluding commercial banks. This means that the commercial banks drive the significant relationship between the OBS ratio and stability in the main analysis. The paper of Cantú et al. (2019) showed that commercial banks generally supply more credit than other bank types. This makes these types of banks more susceptible to the moral hazard problem described in the literature (Gropp & Vesala, 2004; Nachane & Ghosh, 2002). With the introduction of deposit insurance, depositors no longer have the incentive to ask for compensation for the bank's risk-taking. Without facing any additional costs, the bank will maximize its financial leverage through OBS activities that are not subject to regulations (Khasawneh & Hassan, 2010). Hence, banks that supply more credit make more use of the flat-deposit insurance system, which creates a moral hazard. This can lead to banks engaging more in OBS activities. The results in Table 10, therefore, could mean that the negative relationship between OBS activities and stability only applies to commercial banks because these are the banks that are the most susceptible to this moral hazard problem.

[48] This bias occurs when the sample used is not a representative of the population intended to be analyzed. Since, the United States takes up the most observations in the sample, it might be that the results are driven by characteristics out of the United States. Therefore, regressions are run without this country, to see if the results also hold for other countries.

However, further research must be done to confirm if moral hazard problems in commercial banks are the real drivers behind this result in Table 10.

Second, as opposed to the robustness check for the United States, the fintech indicator in this robustness check shows the same results as the main analysis. This suggests that the effect of the number of fintech companies founded on the stability of banks in the main analysis is robust for the exclusion of commercial banks. The consistency of this variable makes the evidence for the insignificance in the relationship between the number of fintech companies founded and the stability of banks even stronger.

Finally, model 1 till model 5 in Table 13 in the appendix show both multiple- and simple regression models of the available data without the Commercial banks included, to both check for collinearity in the multiple regression and robustness of the results. These models confirm the relationships of off-balance-sheet activities, securitization capacity, and financial intensity with the stability of banks shown in Table 10. This strengthens the evidence for the fact that commercial banks drive the negative and significant results in the main analysis. Furthermore, model 1 in Table 13 shows that the *fintech* indicator becomes positively significant when excluding commercial banks and only available data is used. This evidence can mean that commercial banks drive the insignificant relationship between the number of fintech companies and bank stability, but the inconsistency of this positive significance throughout the models in both Table 10 and Table 13 does not confirm this. On top of this, model 1 in Table 13 is the only model which excludes the United States, which makes it more likely that this evidence is another confirmation of the sample selection bias associated with the number of fintech companies in section A.8.1.1.

In Summary, the negative impact of securitization capacity, the insignificance impact of Financial intensity (value-added), and Fintech companies on bank stability do not seem to be driven by the Commercial banks, which makes this evidence stronger. However, off-balance-sheet activities lose their significance when excluding commercial banks, suggesting that this variable is prone to sample selection bias, which makes the evidence of the main analysis weaker. However, since commercial banks play the most important role in modern economic organization, this result has great implications for society (Yakubu & Affoi, 2014).

A.8.2. The impact of subsidiaries

In the sample of this research, the number of subsidiaries per bank varies heavily (from 0 to 1979). Moreover, existing literature has shown that subsidiaries can influence the effects of financial innovation (Iwanicz-Drozdowska & Witkowski, 2021; Phene & Almeida, 2008)[49]. Therefore, to test the robustness of the results of the main analysis, this research conducts an additional analysis on the impact of subsidiaries on the relationship between financial innovation and bank stability.

This additional test will be done by introducing an interaction term between the number of subsidiaries and financial innovation into the regression models. This term is simply the multiplication of the two variables. If this interaction term is significant, it can be concluded that there is an interaction between financial innovation and subsidiaries in the data. This means that the effect of financial innovation on the stability of banks depends on the number of subsidiaries a bank has.

However, if a model contains an interaction term between two variables, the coefficients of the main effects of these variables represent their value for the situation in which the other variable has the value of zero[50]. Therefore, this research "centers" on the interaction variable[51]. By doing this, the coefficients of the main effects will change, but the interaction variable itself does not change. Only the distribution of the variable changes. The main effects of the standalone variables of both variables included in the interaction term, then, can be interpreted as if the other variable is equal to the average value of itself.

Table 10 presents the results of this robustness test. For reasons of brevity, the regression results for the control variables are excluded. Moreover, these regressions did not give any special

[49] For more details on how subsidiaries can influence the effects of financial innovation on a bank, see section Model Specification

[50] This refers to the golden rule of interaction analysis.

[51] By centering the variables, the mean of the variables will be subtracted of every value. Then you have data for the interaction term, where the zero becomes meaningful. Now, the zero is the mean of the centered variable and the mean of a variable is often sensible. For example, if there is an interaction term between financial innovation and subsidiaries which is centered, the main effect of financial innovation on stability of banks can now be interpreted as: the effect of financial innovation on bank stability of banks with the average number of subsidiaries.

result, and the control variables showed robustness for the number of subsidiaries. Below the notable results will be discussed:

First, the interaction terms in model 1 of Table 10 are significant in each model. Where *financial intensity* and *securitization capacity* show a negative sign, *fintech* and *OBS-ratio* show a positive sign. Furthermore, the significance and signs of the main coefficients without the interaction effects are the same as in the main analysis[52]. This suggests both stronger evidence for the effects in the main analysis, but also that the effects of financial innovation on bank stability are dependent on the number of subsidiaries.

More specifically, the financial intensity of financial innovation and the capacity of a country to securitize assets negatively affect the bank stability, but that effect is mitigated if the bank has more subsidiaries. A potential reason for the mitigating effect of subsidiaries on financial intensity can be found in the paper of Phene & Almeida (2008). They argue that knowledge plays a central role in innovation: it serves both as input and output. The knowledge can be obtained from a variety of sources. Multinational firms enable themselves to assimilate knowledge from both headquarters and other subsidiaries in different parts of the world and other firms located in the host- and home countries. Hence, firms with more subsidiaries can assimilate more knowledge, which according to Tsai (2001), contributes to the unit's ability to innovate. Therefore, more subsidiaries, according to the paper of Phene & Almeida (2008), positively influence the quality of innovation. Therefore, in firms with more subsidiaries, the effect of spending more on R&D relative to value-added (which is the intensity of financial innovation) might be less negative due to the increase in knowledge assimilation.

A potential reason for the positive interaction of securitization capacity and subsidiaries can be found in the paper of Kahn & Winton (2004). This paper shows that banks use subsidiaries to hedge the negative consequences of risky loans. The separated structure also lowers incentives for asset substitution behaviour in the safer subsidiary, effectively lowering the value of the insolvency put there and adding value (Kolasinski, 2009). This evidence shows that it might be more efficient for banks to make bipartite structures and separate safe and risky loans into

[52] Note that these are the effects, where the number of subsidiaries is at the mean.

subsidiaries (this process is known as securitization). More subsidiaries will make this process of risk-shifting easier. Therefore, the negative effect of securitized assets on the stability of banks can be mitigated by setting up bipartite structures with many subsidiaries (Ligon & Malm, 2018). However, one might also argue that subsidiaries make it easier to engage in risk-shifting practices and shadow banking, which according to previous literature, provide more fragility (Allen & Carletti, 2006; Batten & Hogan, 2002; González et al., 2016; Shin, 2009). This might also explain the negative interaction effect of securitization capacity and subsidiaries.

Moreover, according to Table 10, more subsidiaries will mitigate the positive impact of fintech companies. An intuitive reason for this result is that if a bank has more subsidiaries, it gives the feeling that they are really powerful and are assimilating more knowledge and newer technologies by acquiring new firms. Therefore, especially these banks with more subsidiaries might underestimate the rise of fintech companies, which have proven to weaken their deposit base (OECD, 2020). However, further research into the power and sentiment of these parent companies in conjunction with subsidiaries must be done to conclude.

In summary, it can be said that the effect of subsidiaries on financial innovation is inconsistent. This is both confirmed by the different signs in Table 10 and by the significance in the other regressions to check the robustness of the results, shown in Table 14 in the appendix, where both *OBS-ratio* and *Fintech* lose their significant interaction effect. Nevertheless, the positive interaction effects seem to remain significant in most of the models, which makes the evidence that more subsidiaries positively affect the impact of financial innovation on bank stability stronger than the evidence that more subsidiaries negatively affect the impact of financial innovation. Furthermore, both the relationships of the main variables and the sample selection bias established in section 4 hold. The *fintech* indicator, namely, is only significant in the model without US banks (model 1 in Table 14). This makes the evidence of the main analysis stronger.

TABLE 10. OLS REGRESSIONS CONCERNING ROBUSTNESS CHECKS FROM 2010 TO 2019

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Financial intensity (value added)	-0.00229	-0.0244	-0.0134
	(0.0133)	(0.0164)	(0.0137)

OBS-Ratio	-0.00836**	-0.000286	-0.0104**
	(0.00417)	(0.00414)	(0.00417)
Securitization Capacity	-0.00685***	-0.00886***	-0.00941***
	(0.00206)	(0.00260)	(0.00206)
Fintech	0.000904***	9.84e-05	0.000105
	(0.000245)	(0.000204)	(0.000164)
Financial intensity (value added) * Subsidiaries			0.000173*
			(0.000104)
OBS-ratio * Subsidiaries			-0.000328**
			(0.000162)
Securitization capacity * Subsidiaries			2.58e-05***
			(4.25e-06)
Fintech * Subsidiaries			-4.44e-07***
			(1.15e-07)
Subsidiaries			0.000351***
			(4.38e-05)
Constant	1.237***	0.0187	0.723**
	(0.355)	(0.447)	(0.354)
Observations	7,715	6,163	11,307
Number of Countries	33	33	34
Number of Banks	1228	1084	1958
R-squared	0.352	0.403	0.392
Control Variables	YES	YES	YES
Country FE	YES	YES	YES
Year FE	YES	YES	YES
Excluding US	YES	NO	NO
Excluding Comm. banks	NO	YES	NO

Model 1 shows an OLS regression, where banks out of the United States are excluded. Model 2 shows an OLS regression, where Commercial banks are excluded, and Model 3 shows an OLS regression with an interaction term between subsidiaries and the financial innovation proxies. Table 12 to Table 14 show robustness for the above estimators. The sample period is from 2010 to 2019. The control variables are not shown for brevity. Section 3.2 explains differences in the number of countries and banks in different models. The dependent variable is the logged Z-score or Sharpe ratio in all the models. Log(Z-score)= log((ROA + E/A)/ σ(ROA)), where ROA is the return on average assets, E/A is the equity to asset ratio and σ(ROA) is the standard deviation of ROA of the whole sample period. Higher Z-score implies more stability and less bank risk-taking. The dependent variable is regressed on innovation proxies (Financial intensity(value-added), OBS-ratio, securitization capacity, and the number of fintech companies founded) and a group of bank- and country-specific control variables. The estimations are OLS regressions with country- and year fixed effects in all the models to control for unobserved heterogeneity at the country and time level. The coefficients are not reported for brevity. All regressions are cross-sectional time series with one observation per bank each period. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Furthermore, all the errors in the models are normally distributed.

A.8.3. Endogeneity

In this research, the problem of both endogeneity and reverse causality may arise as countries with higher financial innovation affect bank stability. However, banks with a certain level of stability also affect the degree of innovation of a country. If the assumption is made that the relationship between financial innovation and stability is one way around, the effect size might be biased since the relationship is also going the other way around. It might also be that there might be an omitted variable that influences the financial innovation proxies. Hence, the financial innovation variables might be endogenous due to reverse causality or an omitted variable bias between financial innovation and stability.

By using 2SLS/IV estimators, it is possible to remove both the omitted variable bias and the reverse causality of the relationship. Since sections A.8.1.1 and A.8.1.2 showed that the relationships of off-balance-sheet activities and the number of fintech companies with bank stability are driven by a sample selection bias, the omitted variable bias is likely present in this data. More specifically, this means that both commercial banks and US banks contain characteristics which are not included in the models, but these variables influence the effect of financial innovation proxies. Therefore, I expect differences in relationships in these estimators.

Furthermore, this research uses lags of the financial innovation proxies as instrumental variables to isolate the effect of financial innovation on the stability of banks. Since running a multiple 2SLS/IV regression is impossible, only separate regressions will be performed.

Table 11 presents the results of this 2SLS/IV estimator for different financial innovation proxies[53]. For reasons of brevity, the regression results for the control variables are excluded. Moreover, these regressions did not give any special results. Below the notable results will be discussed:

First, the coefficients of the financial innovation proxies have changed. This means that the reverse causality and endogeneity now is filtered out. More specifically, the standard errors are

[53] Model 2 does not provide an R-squared because there is a negative model sum of squares of -792, which means that the residual sum of squares (RSS) exceeds the total sum of squares (TSS). The model sum of squares is just the improvement over the sum of squares about the mean given by the full model. The 2SLS model, thus, performs worse than the mean of all the variables in the model. However, the R-squared has no statistical meaning in the context of 2SLS/IV, so it does not lead to problems.

bigger than those in the main analysis (Table 2). In addition to this, the coefficients of the financial innovation proxies have become larger, meaning that when the effect of stability or an omitted variable on financial innovation is filtered out, the financial innovation effect on stability is larger. This suggests that in Table 2, where the endogeneity still is in the model, the coefficients of the financial innovation proxies are diminished by the effect of the endogeneity because the coefficients there are lower. Hence, the effect of financial innovation is now isolated and endogeneity no longer plays a role.

Second, where the variable *OBS-Ratio* was significant in the main analysis, it becomes insignificant when the endogeneity is filtered out. This is in line with the previously established selection bias. Section A.8.1.2 argued that commercial banks drove the significance of this variable, meaning that some variables prone to commercial banks influenced this variable. However, it could also mean that reverse causality played a role in explaining the significant relationship between these two variables.

Third, the variable *Fintech* enters the regression positive and significant if the endogeneity is filtered out. The insignificant relationship in the main analysis, thus, was driven by either omitted variables or reverse causality issues. This is again in line with the previously established selection bias in section A.8.1.1. This section showed that US banks drive the insignificancy of the number of fintech companies.

In summary, the 2SLS/IV estimators show that there was endogeneity or reverse causality in the original model (Table 2) since the coefficients/ standard errors changed significantly. Moreover, the significant relationship of off-balance-sheet item activities and the insignificant relationship of fintech companies with bank stability seems to be driven by endogeneity issues. These 2SLS/IV estimators, therefore, confirm robustness checks in section A.8.1. Finally, the consistency of results on the relationship between *securitization capacity* and bank stability makes this evidence even stronger.

TABLE 11. 2SLS/IV ESTIMATORS WITH LAGGED VALUES OF THE FINANCIAL INNOVATION PROXIES AS INSTRUMENTAL VARIABLES FROM 2010 TO 2019

	(1)	(2)	(3)	(4)
VARIABLES	Model 1	Model 2	Model 3	Model 4
Financial intensity (value added)	0.0722			
	(0.110)			
OBS-ratio		-0.00833		
		(0.00511)		
Securitization Capacity			-0.00797**	
			(0.00376)	
Fintech				0.000969**
				(0.000399)
Constant	-1.025*	-0.294	0.598	-0.621
	(0.526)	(0.422)	(0.795)	(0.490)
Observations (bank-year)	7,515	10,088	3,175	10,088
R-squared	0.377	0.366	0.352	0.362
Number of Countries	28	34	13	34
Number of Banks	1779	1941	569	1941
Control Variables	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

The sample period is from 2010 to 2019, except for model 1 (where the sample period is 2010 to 2018). The control variables are not shown for brevity. Section 3.2 explains differences in the number of countries and banks in different models. The dependent variable is the logged Z-score or Sharpe ratio in all the models. Log(Z-score)= log((ROA + E/A)/ σ(ROA)), where ROA is the return on average assets, E/A is the equity to asset ratio, and σ(ROA) is the standard deviation of ROA of the whole sample period. Higher Z-score implies more stability and less bank risk-taking. The dependent variable is regressed on innovation proxies (Financial intensity(value-added), OBS-ratio, securitization capacity, and the number of fintech companies founded) and a group of bank- and country-specific control variables. The estimations are 2SLS/IV regressions with country- and year-fixed effects in all the models to control for unobserved heterogeneity at the country and time level. The coefficients are not reported for brevity. To solve the endogeneity, the 2SLS/IV estimators use instrumental variables for the endogenous regressors. This research uses the first two lags of each financial innovation proxy as instrumental variables. This also means that fewer observations are available because the lags don't allow the use of observations from the first two years of the sample. Table 8. Arellano-Bond tests for serial correlation and Table 9. F-test for strong instruments shows why these variables are good instrumental variables. For more detailed information about this estimator, see section Model Specification All regressions are cross-sectional time series with one observation per bank each period. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Furthermore, all the errors in the models are normally distributed.

TABLE 12. DIFFERENT OLS REGRESSIONS OF FINANCIAL INNOVATION AND BANK STABILITY EXCLUDING US BANKS

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Financial intensity (value added)	0.0422	-0.0255			
	(0.0743)	(0.0513)			
OBS-Ratio	-0.0478*		-0.00816*		
	(0.0256)		(0.00417)		
Securitization Capacity	-0.00890***			-0.00672**	
	(0.00298)			(0.00261)	
Fintech	0.00111***				0.000895***
	(0.000204)				(0.000189)
Constant	-1.535*	-0.482	0.270	0.0707	0.0895
	(0.796)	(0.487)	(0.413)	(0.712)	(0.416)
Observations	2,207	5,850	7,715	3,749	7,715
Number of Countries	13	32	33	13	33
Number of Banks	481	1117	1228	577	1228
R-squared	0.413	0.356	0.351	0.379	0.350
Control Variables	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Excluding US	YES	YES	YES	YES	YES

The sample period is from 2010 to 2019. Except for models 1 and 2 (2010-2018). These models control the multiple regression in Table 10 for collinearity and selection bias. For reasons of brevity, the control variables are not shown. The dependent variable is the logged Z-score or Sharpe ratio in all the models. Log(Z-score)= log((ROA + E/A)/ σ(ROA)), where ROA is the return on average assets, E/A is the equity to asset ratio and σ(ROA) is the standard deviation of ROA of the whole sample period. Higher Z-score implies more stability and less bank risk-taking. The dependent variable is regressed on innovation proxies (Financial intensity(value-added), OBS-ratio, securitization capacity, and the number of fintech companies founded) and a group of bank- and country specific control variables. The estimations are OLS regressions with country- and year-fixed effects in all the models to control for unobserved heterogeneity at the country and time level. The coefficients are not reported for brevity. All regressions are cross-sectional time series with one observation per bank each period. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Furthermore, all the errors in the models are normally distributed.

TABLE 13. DIFFERENT OLS REGRESSIONS OF FINANCIAL INNOVATION AND BANK STABILITY EXCLUDING COMM. BANKS

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Financial intensity (value added)	-0.0361	-0.0815			
	(0.0860)	(0.0669)			
OBS-Ratio	-0.0231		-0.000199		
	(0.0359)		(0.00419)		
Securitization Capacity	-0.00652*			-0.00683**	
	(0.00335)			(0.00277)	
Fintech	0.000675**				4.38e-05
	(0.000266)				(0.000203)
Constant	-2.194***	-2.326***	-1.523***	-1.405**	-1.529***
	(0.587)	(0.482)	(0.477)	(0.569)	(0.480)
Observations	1,947	4,758	6,163	2,360	6,163
Number of Countries	13	32	33	13	33
Number of Banks	370	1016	1084	385	1084
R-squared	0.428	0.408	0.401	0.426	0.401
Control Variables	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Excluding Comm. Banks	YES	YES	YES	YES	YES

The sample period is from 2010 to 2019. Except for models 1 and 2 (2010-2018). These models control the multiple regression in A.8.1.2 for collinearity and selection bias. For reasons of brevity, the control variables are not shown. The dependent variable is the logged Z-score or Sharpe ratio in all the models. Log(Z-score)= log((ROA + E/A)/ σ(ROA)), where ROA is the return on average assets, E/A is the equity to asset ratio, and σ(ROA) is the standard deviation of ROA of the whole sample period. Higher Z-score implies more stability and less bank risk-taking. The dependent variable is regressed on innovation proxies (Financial intensity(value-added), OBS-ratio, securitization capacity, and the number of fintech companies founded) and a group of bank- and country-specific control variables. The estimations are OLS regressions with country- and year-fixed effects in all the models to control for unobserved heterogeneity at the country and time level. The coefficients are not reported for brevity. All regressions are cross-sectional time series with one observation per bank each period. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Furthermore, all the errors in the models are normally distributed.

TABLE 14. DIFFERENT OLS REGRESSIONS OF FINANCIAL INNOVATION AND BANK STABILITY WITH INTERACTION EFFECTS OF SUBSIDIARIES

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Financial intensity (value added) * Subsidiaries	0.000464***	1.10e-05			
	(6.46e-05)	(8.48e-05)			
OBS-ratio * Subsidiaries	-4.34e-06		-0.000167		
	(0.000300)		(0.000161)		
Securitization capacity * Subsidiaries	2.65e-05***			2.21e-05***	
	(5.57e-06)			(5.40e-06)	
Fintech * Subsidiaries	-5.46e-07				1.74e-07
	(4.83e-07)				(1.54e-07)
Financial intensity (value added)	0.0820	-0.0389			
	(0.0771)	(0.0511)			
OBS-ratio	-0.0371		-0.00987**		
	(0.0260)		(0.00434)		
Securitization capacity	-0.00780**			-0.00804***	
	(0.00315)			(0.00262)	
Fintech	0.000896***				4.97e-05
	(0.000245)				(0.000169)
Subsidiaries	0.000134	0.000306***	0.000305***	0.000309***	0.000310***
	(0.000499)	(4.00e-05)	(3.90e-05)	(4.32e-05)	(4.69e-05)
Constant	-0.876	-1.157**	-0.507	0.132	-0.526
	(0.750)	(0.470)	(0.399)	(0.710)	(0.396)
Observations	3,131	8,740	11,307	3,749	11,307
Number of Countries	13	33	34	13	34
Number of Banks	553	1846	1958	577	1958
R-squared	0.388	0.397	0.387	0.383	0.387
Control Variables	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

The sample period is from 2010 to 2019. Except for models 1 and 2 (2010-2018). These are the models to control the multiple regression in section A.8.1.2 for collinearity and selection bias. For reasons of brevity, the control variables are not shown. The dependent variable is the logged Z-score or Sharpe ratio in all the models. Log(Z-score)= log((ROA + E/A)/ σ(ROA)), where ROA is the return on average assets, E/A is the equity to asset ratio, and σ(ROA) is the standard deviation of ROA of the whole sample period. Higher Z-score implies more stability and less bank risk-taking. The dependent variable is regressed on innovation proxies (Financial intensity(value-added), OBS-ratio, securitization capacity, and the number of fintech companies founded) and a group of bank- and country-specific control variables. The estimations are OLS regressions with country- and year-fixed effects in all the models to control for unobserved heterogeneity at the country and time level. The coefficients are not reported for brevity. All regressions are cross-sectional time series with one observation per bank each period. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Furthermore, all the errors in the models are normally distributed.

A.9. Possible explanation for selection bias towards the United States

TABLE 15. OLS REGRESSION WITH INTERACTION EFFECT OF SIZE OF THE BANK AND FINTECH COMPANIES

VARIABLES	(1) Model 1
Fintech	0.00177***
	(0.000294)
Fintech * Size	0.000203***
	(2.55e-05)
Total Assets	-0.109***
	(0.0105)
Constant	-0.185
	(0.363)
Observations	11,307
R-squared	0.400
Number of Countries	34
Number of Banks	1958
Control Variables	YES
Country FE	YES
Year FE	YES

The sample period is from 2010 to 2019. For reasons of brevity, the control variables are not shown. The dependent variable is the logged Z-score or Sharpe ratio in all the models. Log(Z-score)= log((ROA + E/A)/ σ(ROA)), where ROA is the return on average assets, E/A is the equity to asset ratio, and σ(ROA) is the standard deviation of ROA of the whole sample period. Higher Z-score implies more stability and less bank risk-taking. Size is measured as the natural logarithm of a bank's total assets. The variable fintech is the number of fintech companies founded in a particular year in a country. The estimations are OLS regressions with country- and year-fixed effects in all the models to control for unobserved heterogeneity at the country and time level. The coefficients are not reported for brevity. All regressions are cross-sectional time series with one observation per bank each period. Heteroskedasticity-robust standard errors clustering within countries and time (double clustering) are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Furthermore, all the errors in the models are normally distributed.