How Do Banks Interact with Fintechs? Forms of Strategic Alliance and Their Economic Impact

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Abstract

The increasing pervasiveness of technology-driven firms offering banking services to retail clients has led to a growing pressure regarding traditional banks to modernize their core business activities. Banks attempt to meet the new digitalization requirements by interacting with fintech startups in the form of alliances. In this paper, we investigate the factors that drive banks to form such alliances with fintechs. Furthermore, we analyze whether publicly announced bank-fintech alliances affect the market valuation of banks. We provide descriptive evidence on the different forms of alliances that occur and the segments in which these fintechs operate. Using hand-collected data covering the largest banks from Canada, France, Germany, and the United Kingdom, we show that banks are significantly more likely to form alliances with fintechs when they pursue a well-defined digital strategy and/or employ a Chief Digital Officer (CDO). We further evidence significantly positive market reactions for digital banks announcing an alliance formation with a fintech, but no reaction for traditional banks. Finally, we find that alliances are most often characterized by customer-service provider relationship between the bank and the fintech and that most of these fintechs operate in payment services.

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1. Introduction

Digitalization has influenced many industries. Most recently, the banking industry – one of the most traditional and conservative sectors in the economy – has been confronted with potentially disruptive technology-driven innovations and internet-based solutions. New ways to use innovative technology in the financial industry aim at creating more customer-oriented and user-friendly digital applications. Current developments have the potential to reshape or even crowd out the business models of more traditional banks. To confront this threat, many traditional banks have engaged in strategic alliances with some of the newcomers. In this paper, we investigate what drives banks to engage in strategic partnerships, and the economic impact they have on banks.

Many of these new solutions are developed by start-up companies, typically referred to as fintechs, which is an acronym for the phrase financial technology. Their smaller firm size and comparatively low level of complexity allows them to be more agile, innovate faster and more radically. In contrast, it appears more difficult for traditional banks to adapt to some of the new technological developments, because they need to comply with more extensive regulatory requirements and often a larger number of stakeholders need to be convinced when adopting important institutional changes. The sluggishness of traditional banks to adapt to digital challenges has not only implications at the company level, but also for the financial stability of the financial system.

Financial innovation, as measured by the filing of financial patents, has been increasing since the late 1970s (Lerner, 2002; Miller, 1986). Moreover, the financial industry had historically spent a large share of their expenses into information technology (IT), which reached over one third in the year 1992 (Scott, Van Reenen, & Zachariadis, 2017). One reason for the high share of IT expenses was that the financial industry early on employed computers as part of their business model. The quality of financial patents and financial innovations was, nevertheless, often considered low (Lerner, Speen, Baker, & Leamon, 2015). Hence, the financial industry was perceived as one of the least innovative. This has changed with the emergence of fintech startups. Financial innovations have often led to changes in financial institutions (Merton, 1995) and fintech startups have pressured traditional banks to reinvent themselves or to engage in strategic alliance with their new competitor.

The academic literature on the fintech bank relationship is still scarce. Until recently, scholars have mostly focused on specific fintech sectors. For instance, D'Acunto, Prabhala, and Rossi (2018) investigate the performance of robo-advice tools. Yermack (2017) was one of the first to analyze the governance issues related to the blockchain. Only recently, scholars have started to investigate the fintech market. Haddad and Hornuf (2018) investigate 55 countries and provide evidence that countries witness more fintech startup formations when the economy is well-developed and venture capital is easily accessible. Other relevant factors for the formation of fintechs are access to loans, secure Internet servers, mobile telephone subscriptions, and the available labor force. Cumming and Schwienbacher (2016) find that differences in the enforcement of financial regulation among start-ups and banks after the financial crisis attribute to venture capital investments in fintechs. Puschmann (2017) offers a definition of the term fintech and offers a model to categorize the industry. A recent paper by Brandl and Hornuf (2017) conducts a bank-fintech network analysis for Germany and finds that most relationships turn out to be strategic alliances. They argue that this is because most fintechs develop an algorithm or software solution, the value of which will only be determined over time when the software has been adopted to customer needs.

In this paper, we explore how banks cope with the digitalization of consumer services through startup firms by setting up strategic alliances with them. We examine the drivers and extent to which banks interact with fintech startups. Moreover, we investigate the factors that lead banks to opt for different forms of alliances in the form of product-related collaborations and financial investments (majority or minority equity stakes in fintechs). We base our theoretical analysis on transaction cost theory (Coase, 1937; Williamson, 1981) and organizational theory, within the special context of technology developments (Teece, 1986, 1998). We conjecture that banks that have declared a digital strategy and employed a Chief Digital Officer (CDO) are more likely to initiate alliances with fintechs. We further develop prediction on the relative preference of financial investments (full acquisitions or minority stakes) over partnerships.

To test these predictions we collected detailed information on strategic alliances made by the 100 largest banks in Canada, France, Germany, and the United Kingdom from 2007-2017. We found exactly 500 alliances during that period, among which 43.07 % are financial investments (4.05% acquisitions and 39.02% minority interest investments); the rest are customer-service provider relationships (53.94%) and other forms of interaction (2.99%). 21% of these banks had a digital strategy and 3% a CDO during the sample period. Consistent with our prediction, banks with a clearly defined digitalization strategy or a CDO initiated 6-10% more often an alliance with a fintech every year in our sample. In terms of number of alliances, this represents 0.6-1.4 more alliances every year. With respect to the type of alliance, financial investments are more likely than product-related partnerships in case of large banks and small fintechs. This finding is consistent with our prediction that larger banks are better able to integrate startups in their own business activities because they have invested in knowledge acquisition as part of their strategy development. Finally, digital banks are able to increase their capitalization by 3% on average for every strategic alliance initiated. Other types of banks do not obtain a gain, suggesting that they may be less able to interact with fintech startups due to different corporate culture.

Our study contributes to the literature in at least two ways. First, this is the first paper to comprehensively analyze the extent and type of strategic alliances between banks and fintechs. We thereby analyze and explain driving factors for the occurrence of alliances between banks and fintechs. Other studies have examined the fintech market more broadly (Haddad & Hornuf, 2018), without exploring whether and when they interact with traditional financial institutions. Second, we conduct an event study to investigate the effect of bank-fintech interactions on the market valuation of banks. No empirical evidence exists so far about the economic benefits for banks.

The remainder of this paper is structured as follows. In the next section, we provide a brief overview of the theory and hypotheses. In Section 3, we outline our data and describe the methodology used. The results of the study are presented in Section 4. Section 5 provides a discussion, presents policy implications, and concludes.

2. Literature review and hypotheses

Empirical evidence suggests that banks have been keen to enhance their profitability through financial innovation (Scott et al., 2017). Beck, Chen, Lin, and Song (2016) show that financial innovation is associated with bank growth. We derive testable hypotheses about what drives bank interactions with fintechs under the premise that these interactions are the result of a mutually beneficial transactions between banks and fintechs to improve their future prospects and to enhance their firm value through the implementation of financial innovations (Coase, 1960; Scott et al., 2017).

Fintechs might collaborate with banks for several reasons. Through an alliance with an established player from the financial industry, fintechs may obtain access to a broader customer base, the superior knowledge in dealing with financial regulation, and might enhance their own brand awareness. Smaller fintechs might even engage in an alliance with a bank to obtain access to a banking license, which in many cases would be too cumbersome and too expensive for a start-up company to obtain. On the other hand, banks might want to secure a competitive advantage by collaborating with fintechs that are developing or have already developed an innovative way to provide certain financial services. This may be the case if banks decide to externalize R&D activities or because some R&D activities are better done outside larger entities. In some cases, acquiring a fintech may ensure that a bank obtains an exclusive right to use a specific application or license it to competitors at their own discretion.

Many banks have adopted a digitalization strategy that outlines how the digital transformation should take place. One way to implement this transformation is to assign responsibility for this process to a designated manager, and some banks have created the position of a CDO. While research has been conducted, for example, on the role that the Chief Executive Officer (CEOs) and Chief Financial Officer (CFOs) play for earnings management (J. X. Jiang, Petroni, & Wang, 2010) or whether hiring a CFO changes fraudulent financial reporting (Geiger & North, 2006), little is known about the impact of hiring a CDO, which only recently has been established as a board position. Given the specific tasks assigned to the CDO and the recent context in which these positions have been created, we expect banks with a CDO to interact more frequently with fintechs than other banks. Similarly, banks with a clear digitalization strategy are more likely to initiate alliances with fintechs. We summarize these predictions in our first hypothesis:

Hypothesis 1 (digitalization strategy): The implementation of a digitalization strategy increases a bank's propensity to engage in alliances with fintechs.

Banks might have different motives to engage in an alliance with a fintech, also simply because banks pursue different strategic development plans. Given that for many fintechs it is too costly to obtain a banking license, they have decided to partner with banks that are sometimes startup firms themselves. Some of these banks have specialized in the provision of IT services to corporate clients and extend their banking license to these clients. For example, fintechs offering crowdlending services often do not have a banking license to extend commercial loans (e.g., German Auxmoney). Once a loan is fully funded on the crowdlending website, the loan request is transferred to a partner bank (e.g., SWK Bank) that extends the loan to a borrower and then sells it to the lender (i.e., the crowd). This process works through application programming interfaces (APIs) and allows for seamless costumer experience. This type of banking is therefore often referred to as API-banking. The banks involved in this business are often small startup firms and are interested in a customer-service provider relationship with fintechs. They have regularly little intention to acquire the fintech.

Traditional banks have different motives when they engage in an alliance with fintechs. On the one hand, product-related collaboration enable banks to broaden their portfolio. Offering fintech application on their website helps them to maintain their customer base, without having to invent specific services themselves. Often, this would be a cumbersome task, as many banks operate software systems that are barely compatible with modern end-user applications (Brandl & Hornuf, 2017). Moreover, acquiring a fintech is risky, because many fintechs offer software solutions. Software solutions must be customized to end-user needs and updated at regular intervals. Whether the particular fintech can achieve this task satisfactorily is highly uncertain. Thus, waiting until the software solution has been customized and is running on mass markets might be a better strategy. By acquiring a fintech, banks might easily bet on the wrong horse. Large banks, which are typically less flexible in continuously adapting, may prefer to acquire an established product than take the risk of early partnerships.

On the other hand, acquiring a fintech allows banks to internalize the knowledge of the fintech and get sole possession of the fintech knowledge . Thus, larger banks may be more able to afford such acquisitions and redeploy it by integrating it in its existing line of business and distribution channel. We therefore expect bank size to affect the form of alliances chosen, as summarized in the next hypothesis.

Hypothesis 2A (type of alliance): Large banks are more likely to invest in a fintech, while small banks engage in customer-service provider relationships.

In addition, the attractiveness of a financial investment (acquisition) is likely to decline as a fintech grows in size. Indeed, larger fintechs typically have reached a certain maturity level beyond the pure development of a new product or service, and at times even developed their own distribution channel. This reduces the value in an acquisition, since synergy gains with incumbent banks is reduced.

Hypothesis 2B (type of alliance): Banks are more likely to invest in small fintechs, than in large fintechs.

An important follow-up question is whether alliances between banks and fintechs ultimately create economic value. Because many banks have only recently engaged in alliances with fintechs, it is still too early to investigate the effect bank-fintech alliances on performance measures of banks or their corporate structure. Nevertheless, event studies are an established method to evaluate the market expectations about future cash flows that might result from structural changes such as mergers, joint ventures or strategic alliances (Amici, Fiordelisi, Masala, Ricci, & Sist, 2013;

Gleason, Mathur, & Wiggins, III, 2003; Marciukaityte, Roskelley, & Wang, 2009). Given the increasing importance of digitalization for the financial industry and its ultimate impact on the survival of incumbent banks, we expect bank shareholders to perceive new interactions with fintechs as value enhancing. If stock prices reflect future earnings of banks and formal interactions with fintechs are value enhancing, this should be reflected in the stock price once a new alliance is announced to the market.

All banks are however unlikely to benefit from an alliance in the same way. The extent to which banks can create value depends on its capacity to generate synergies with the fintech startups. These alliances may act as knowledge platforms for banks. Given the particular nature of these knowledge-intense alliances, banks need to engage in significant organizational learning (see Dodgson, 1993; Inkpen, 2000; Inkpen & Crossan, 1995; and Lane & Lubatkin, 1998 for studies on the importance of learning in inter-firm alliances), which is more difficult for larger, more traditional banks. Some banks have a greater 'absorptive capacity' than others due to their corporate structure and activities. Greater absorptive capacity facilitates synergies and especially stability of the alliance (Fang & Zou, 2010). In particular, banks that are already active in distributing digital products and services (which we call digital banks) or have a developed digitalization strategy are likely to benefit more than traditional banks. We summarize these predictions in Hypotheses 3A and 3B:

Hypothesis 3A (announcement effect by digital banks): Public announcements of a newly started alliance made by digital banks have a stronger positive effect on the bank's share price.

Hypothesis 3B (announcement effect by banks with digital strategy): Public announcements of a newly started alliance made by banks with a clear digital strategy or a CDO have a stronger positive effect on the bank's share price.

3. Data and method

In this section we presents our data. We then describe the methods used and our empirical model. In order to identify our research questions, we apply cross-sectional, panel data, and event study methods.

3.1 Data

In a recent study, Haddad & Hornuf (2018) rank countries by their number of fintech startups and show that the United States are on top of the list, followed by the United Kingdom, Germany and France. As the United States have by far the largest fintech market, we decided to exclude them in order to keep a comparable sample. Thus, our sample consists of the top 100 largest legally independent banks in Canada, France, Germany and the United Kingdom as measured by their total assets. The list of banks was collected from all active banks as of spring 2017, using information from the respective national supervisory authority. The banks from these four countries have the highest GDPs in the Comprehensive Economic and Trade Agreement (CETA) area and represent different economics models: While Canada and the UK are considered market-based economies, France and Germany are bank-based economies (Demirguc-Kunt & Levine, 1999).

To assemble a comprehensive overview of existing bank-fintech alliances, we use a broad Internet search encompassing three steps. First, we searched on all bank websites to find official press releases concerning alliances with fintechs. Second, we investigated the startup side and searched on the Crunchbase database for alliances with banks. Third, we run a comprehensive search for news articles on Factiva, also to get more information regarding the respective forms of interaction. Alliances are coded according to the following criteria: (1) an *acquisition* occurs when the bank acquires at least 50% of the fintech; (2) a *product-related partnership* / *customer-service provider relationship* is defined as a contract-linked alliance. To qualify as an alliance three additional requirements had to be fulfilled: (1) the interaction was announced between January 1, 2007 and January 1, 2018; (2) there is at least one bank involved in the interaction together with at least one fintech; (3) the bank's headquarter is located in one of the four countries that are part of our study (Canada, France, Germany or the UK). Our sample comprises of 400 banks which formed 500 bank-fintech alliances. On average, banks engage in 0.11alliances with a fintech per year. However, there is strong variation among banks, since some initiated up to 51 alliances during the time 2007-2017.

To investigate whether onto what extent banks engage in alliances with fintechs, we have constructed two dependent variables: a binary variable that is equal to 1 if bank i has at least one alliance with a fintech in year t, and 0 otherwise, as well as the number of new alliances (*Nbr. New Alliances*) that bank i started in year t.

To test Hypothesis 1, we use the *Number of Alliances* and a binary variable *Alliance* equal to 1 if at least one alliance exists and 0 otherwise as dependent variables. *Chief Digital Officer,* a binary variable equal to 1 if bank i employs a CDO in year t and 0 otherwise, and *Digital Strategy,* a binary variable equal to 1 if bank i has a digital strategy in year t and 0 otherwise are being used as main explanatory variables. Both variables were hand-collected by systematically reading the annual reports that were published by the banks in our sample. When a CDO entered the board, this was easily observable from the annual reports and often published in the year the respective person was hired. The variable CDO provides another indicator for the digital orientation of a bank, since the core task of a CDO is the design and support of technology-driven change processes. We consider the bank to have adopted a digitalization strategy if it has an officially declared strategy. More specifically, whether a bank has a digital strategy is tested using a thorough analysis of all annual reports during the considered time period. The existence of a digital strategy is only confirmed if concrete digitalization-related implementation plans are announced there. Accordingly, more general statements on digitalization are not enough to identify a digital strategy.

Following (Peng, Jeng, Wang, & Chen, 2017), we consider a variety of control variables including company characteristics such as whether the bank is publically listed (*Bank is Listed*) and whether it is a universal bank (*Universal Bank*) as well as financial indicators such as the natural logarithm of total assets (*ln(Bank Total Assets*)) and return on average assets (*Bank ROAA*). General information about the banks, such as a balance sheet data is retrieved from the bank's annual reports and the database Fitch Connect. The data on bank characteristics as well as the number of bank-fintech interactions are collapsed in a 2007-2017 annual panel dataset.

To test Hypotheses 2A and 2B, we use the variable *Financial Investment,* a dummy variable equal to 1 if a bank invests in a fintech and0 if the alliance is characterized by a customer-service provider relationship. We then use *ln(Bank Total Assets)* and a variable indicating the fintech´s number of employees (*Fintech Employees*) as the main explanatory variables. In addition to the control variables used to test Hypothesis 1, we include variables indicating selected fintech-characteristics. These variables comprise *Fintech Front End Solution,* a binary variable equal to 1 if a fintech offers front end solutions and 0 if it offers back end solutions, *Fintech HQ Country of Interest,* which is equal to one if the fintech operates in the same land where the partnering bank has its headquarters, a variable indicating the fintech´s number of patents (*Fintech Nbr. Patents)*, and its founding date.

With regard to the fact that banks might get involved in partnerships with more than one fintech within one year, data in panel format would not allow for an appropriate analysis in this case. Accordingly, we create an additional dataset with fintech- and partnership-variables to allow a cross-sectional investigation.

Table 1 provides a description of the variables. Some information, such as financial data of certain privately-owned banks can only be collected from banks that are subject to some forms of disclosure requirements.

- Table 1 about here -

3.2 Methodology

3.2.1 Panel data analysis

To test Hypothesis 1 (*Alliance (d)*), we apply panel probit regressions. We follow Peng et al. (2017) and use panel data for the regressions and include bank country and year effects to avoid any biased estimations resulting from individual heterogeneity. With regard to the fact that our sample includes both large/established fintechs and small/unestablished fintechs (measured by their founding year and number of employees), we apply separate regressions for the full sample and a restricted version of the sample. In the restricted version, we exclude fintechs with more than 1000 employees and fintechs, which were older than 10 years when they started their partnership with a bank. Furthermore, we use separate regressions for the main explanatory variables *Digital Strategy* and *Chief Digital Officer*, since they are significantly correlated (0.29; p-value = 0.000).

The two baseline equations for the panel probit regressions are:

$$Pr(Alliance_{it} = 1) = F(Digital\ Strategy_{it} + Bank\ is\ listed_i + Digital\ Bank_i + Universal\ Bank_i + Bank\ HQ\ Country\ of\ Interest_i + \ln(Bank\ Age_{it}) + Year_t + Country_i + \delta_{it}),$$

$$Pr(Alliance_{it} = 1) = F(Chief\ Digital\ Officer_{it} + Bank\ is\ listed_i + Digital\ Bank_i + Universal\ Bank_i + Bank\ HQ\ Country\ of\ Interest_i + \ln(Bank\ Age_{it}) + Year_t + Country_i + \delta_{it}),$$

where *Alliance* is the dependent variable and F(.) represents a negative binominal distribution function as in Baltagi (2008). *Digital Strategy* and *Chief Digital Officer* are the main explanatory variables, followed by a number of control variables representing selected bank characteristics. A full set of year and country dummies is included in both models to control for the unobserved effect of time and location on the dependent variables. δ_{it} is a vector of additional control variables used in models (3), (4), (7), and (8) (Table 3).

To test whether the bank´s strategic orientation also impacts the number of fintech the bank interacts with, we follow York and Lenox (York & Lenox, 2014) and apply negative binominal regressions using *Nbr. New Alliances* as the dependent variable. We decide not to use a poisson regression due to the unequal mean and variance of the dependent variable. The baseline equations are:

$$Pr(y_{i1}, y_{i2}, \dots, y_{iT}) = F(Digital\ Strategy_{it} + Bank\ is\ listed_i + Digital\ Bank_i + Universal\ Bank_i + Bank\ HQ\ Country\ of\ Interest_i + \ln(Bank\ Age_{it}) + Year_t + Country_i + \delta_{it}),$$

$$Pr(y_{i1}, y_{i2}, \dots, y_{iT}) = F(Chief\ Digital\ Officer_{it} + Bank\ is\ listed_i + Digital\ Bank_i + Universal\ Bank_i + Bank\ HQ\ Country\ of\ Interest_i + \ln(Bank\ Age_{it}) + Year_t + Country_i + \delta_{it}),$$

where y_{it} refers to the dependent variable *Nbr. New Alliances*. In case of both equations, F(.) represents the same model as used for the probit regressions (Table 4). A Hausman test is used to identify whether the respective model is a fixed effects or random effects model. We select the random-effects model if the Hausman test is not statistically significant.

3.2.2 Cross-sectional analysis

To test Hypotheses 2A and 2B, we use probit regressions and extend our model with variables indicating selected fintech characteristics and the respective form of interaction (see Section 3.1). As in case of the panel analysis, we calculate separate regressions based on the full sample and a restricted version in which we exclude mature fitechs.

The baseline equations are:

$$Pr(Financial\ Investment_i = 1) = F(\ln(Bank\ Total\ Assets_i) + Fintech\ Employees_i + Digital\ Strategy_i + Bank\ is\ listed_i + Digital\ Bank_i + Universal\ Bank_i + Bank\ HQ\ Country\ of\ Interest_i + \ln(Bank\ Age_i) + Country_i + \delta_i + \gamma_j),$$

$$Pr(Financial\ Investment_i = 1) = F(\ln(Bank\ Total\ Assets_i) + Fintech\ Employees_i + Chief\ Digital\ Officer_i + Bank\ is\ listed_i + Digital\ Bank_i + Universal\ Bank_i + Bank\ HQ\ Country\ of\ Interest_i + \ln(Bank\ Age_i) + Country_i + \delta_i + \gamma_j),$$

where *Financial Investment* is the dependent variable and *Bank Total Assets* and *Fintech Employees* the main explanatory variables. The functions F(.) contain an additional element γ_j, representing a vector of fintech- and partnership-variables.

3.2.3 Event study

To estimate the market reaction of the announcement of a new bank-fintech alliance, we apply an event study where we follow the widely used methodology by Brown and Warner (Brown & Warner, 1980, 1985) and MacKinlay (MacKinlay, 1997). This aim is somewhat similar to those studies that investigate how strategic alliances and joint venture-announcements affect stock prices (Amici et al., 2013; Chiou & White, 2005).

Due to the nature of our research design, we restrict the calculation of the Cumulative Abnormal Returns (CARs) to publicly traded banks of our sample. To be included in the sample we require that (i) the date of the first public announcement about the partnership as mentioned above can be clearly identified and (ii) stock prices data are available to calculate the ARs for a minimum of 46 days prior the first press announcement. Therefore, we manually search the ISIN-Code on various retail brokers and financial data providers like www.onvista.de or www.finanztreff.de for each bank in our sample.

From these ISIN-Codes, we then extract stock prices and accounting data from Thomson Reuters Datastream. After this, we are left with 140 announcements of 30 banks, of which 40 announcements are from Germany (5 banks), 49 from UK (11 banks), 28 from Canada (8 banks) and 23 from France (6 banks).

Following existing literature (Amici et al., 2013), we run an event study to examine whether the stock returns of our bank sample display abnormal returns (AR) around the announcement date. We adopt the market model (MacKinlay, 1997) to estimate the normal returns for every bank as a function of the MSCI-based market portfolio return.

To find a suitable benchmark market portfolio, we apply the MSCI index for each respective country, which measures the performance of the large and mid-cap segments of each market (MSCI, 2018). The parameters of the market model to obtain ARs are estimated over a 200-trading day window, ending 20 days before the event day to avoid bias in the parameters estimations due to changes in firm characteristics around the event date (Brown & Warner, 1985).

We follow previous event studies dealing with the announcement of strategic alliances and joint ventures in banks (Amici et al., 2013; Chiou & White, 2005), and focus on the short event windows (-1;0), (0;+1) and (-1;+1). We also perform robustness checks with different windows, as sometimes investors may forecast such an event or stock reactions may last more days. The CAARs are thus estimated over the following event windows: (-15;+15), (-10;+10), (-5;+5) and (-3;+3). We obtain the CARs for each event window and aggregate ARs to the Cumulative Average Abnormal Return (CAAR). To find whether the CAAR is statistically different from zero, we use parametric and non-parametric tests (Bickel & Doksum, 1977; Lehman, 1975).

In the multivariate analysis, we control this view and provide further insights into what drives stock price reactions. To find the factors which may further influence the shareholder value created, we use an ordinary least squares regression (OLS) and follow previous studies (e.g. Amici et al., 2013;

Chiou & White, 2005). To estimate the multivariate linear model, we use the previously outlined controls (if applicable) for each of the three short windows. In Table7, Regressions (1)-(8) take only bank-variables into consideration:

$$CAR_{Bank} = \alpha + \sum_{j=1}^{5} \beta_j Bank_j + \sum_{j=1}^{4} \theta_j Country_j + \varepsilon_{it},$$

whereas Regressions (5)-(8) use additionally an interaction term of *Chief Digital Officer (d)* and *Acquisition (d)* (8)-(12) use the whole set of variables as in the deal-level regression:

$$CAR_{Bank} = \alpha + \sum_{j=1}^{5} \beta_j Bank_j + \sum_{j=1}^{6} \delta_j Fintech_j + \sum_{j=1}^{4} \theta_j Country_j + \varepsilon_{it},$$

Where CAR is the cumulative abnormal return for the *i*th bank for each representative event window.

Since some information regarding the explanatory variables were not available, our sample for the multivariate analysis on the first public information contains only 139 respectively 126 observations.

4. Empirical results

Our analysis begins with a descriptive examination of the frequency of occurrence of different fintech segments and forms of alliance in Canada, France, Germany, and the United Kingdom (Section 4.1). We then go on to analyze Hypotheses 1 and 2 using panel data analysis (Section 4.2.1) and a cross-sectional analysis (Section 4.2.2). Finally, we present the results of the event study (Section 4.2.3).

4.1 Descriptive statistics

Summary statistics for the panel and deal-level analysis are presented in Tables 2.1 and 2.2.

- Table 2.1 about here -

- Table 2.2 about here -

Figure 1 provides an overview of the distribution of fintech-segments and Figure 2 the distribution of the most common forms of bank-fintech alliances, by country. Figure 1 shows that a large number of fintechs operate in the payment services sector. Many fintechs in Germany additionally provide a combination of asset management services and payment services, which seem to be less common in the other countries under consideration, especially in Canada and in the United Kingdom. Although financing does not appear to be part of the core business of the fintechs in our sample, it is still represented in all countries by at least some of the fintechs. In comparison to Germany, Canada and France, a relatively large number of fintechs in the UK provide bank-level software such as digital tools for customer relationship management (CRM). Furthermore, many fintechs in the UK cannot be assigned to one of the predefined segments, indicating that they might have more diversified portfolios or operate in niche segments. Although cyber security is a topic of increasing relevance in the financial services sector, we do not find many bank-fintech alliances in this field. With regard to the forms of interaction between banks and fintechs, we classify them into four categories: acquisition, minority interest, product-related partnership, and other forms of interaction (see Table 1 for the definition of the categories). For all the four countries under consideration, both buying minority interest stakes and product-related partnerships are the two most common forms of interaction between banks and fintechs. It thus seems that a comparatively loose form of interaction is preferred. However, the extent to which the interaction is formalize through control varies greatly between the two forms, since banks have greater control in the case of a minority stake than in a pure product-related partnership. Furthermore, we find a relatively high number of full acquisitions in France, even though they account for a small proportion overall.

- Figures 1 and 2 about here -

4.2 Regression results

4.2.1 Panel data regressions

To investigate the influence of a bank´s strategic orientation on its willingness to interact with fintechs, we use two econometric estimation methods as outlined in Section 3.2. First, we apply panel probit regressions (Table 3), to examine whether the implementation of a *Digital Strategy* or the employment of a *Chief Digital Officer* has an effect on the emergence of bank-fintech partnerships. Regressions (1) – (4) are based on the full sample, which we restrict in Regressions (7) – (12) to fintechs that have no more than 1000 employees and were not older than 10 years when they got involved in an alliance. The coefficients of *Digital Strategy* in Regressions (1), (3), (5), and (7) are all found to be significantly positive at the 0.1%-level, suggesting that a bank´s strategic focus on digitalization could be an important factor in predicting the occurrence of at least one alliance with a fintech. The coefficients of *Chief Digital Officer* are significantly positive at the 0.1%-level in Regressions (2) and (6). In addition, the coefficients of *Bank is listed* in Regressions (1), (2), (4), (5), (6), and (8) are significantly positive at the 0.1%-level and the coefficients of *Universal Bank* in Regressions (1) – (8) at the 5%- and 1%-level. Furthermore, the coefficients of *ln(Bank Total Assets)* in Regressions (3) – (4) and (7) – (8) are all found to be significantly positive, implying that listed banks, universal banks, and large banks are exceptionally attracted in getting involved in partnerships with fintechs. A comparison of the results of the full sample (Regressions (1) – (4)) with the results of the restricted sample (Regressions (5) – (8)) shows only minor changes overall.

- Table 3 about here -

In order to find out whether a *Digital Strategy* and a *Chief Digital Officer* also influence the number of alliances a bank gets involved in, we use in Table 4 negative binominal regressions.

- Table 4 about here -

As for the random-effects probit regression, we divided the sample into two groups, one including the full sample and one excluding mature fintechs. Most of the results are consistent with the results of the probit regressions. The coefficients of *Digital Strategy* in Regressions (1), (3), (5), and (7) are again significantly positive at the 0.1%-level. Interestingly, the coefficients of *Chief Digital Officer* are significantly positive in case of all negative binominal regressions, indicating that the bank´s strategic orientation is not only a relevant predictor for the occurrence of a bank-fintech-alliance, but also for the number of fintechs a bank interacts with. Furthermore, the coefficients of *Bank is listed* and *ln(Bank Total Assets)* are significantly positive in case of all the regressions. Accordingly, large and listed banks seem to be particularly interested in interacting with more than one fintech at a time. The coefficient of *Bank ROAA* is significantly negative at the 1%-level in Regression (3) and at the 5%-level in Regressions (4) and (7). This could indicate that banks with a poor profitability may be particularly interested in a high number of partnerships with fintechs, perhaps to spread risk across several alliance partners or accelerate a transformation process.

4.2.2 Deal-level regressions

To test Hypotheses 2A and 2B, we modify the structure of our dataset as described in section 3.2.2 and integrate explanatory variables indicating selected fintech-characteristics.

The results show a significant negative coefficient of *Fintech Employees* at the 0.1%-level in Regressions (1) and (2), indicating that small fintechs are preferred for financial investments. The coefficients get insignificant when excluding mature fintechs (Regressions (3) and (4)), suggesting that the effect diminishes when only considering relatively young fintechs with less than 1000 employees. Furthermore, the coefficients of *ln(Bank Total Assets*) are found to be significantly positive at the 1%-level in Regressions (1) and (2), indicating that – considering both small and mature fintechs – large banks are more likely to invest in fintechs, than small banks. Again, the effect diminishes when excluding mature fintechs, suggesting that the bank´s size plays a limited role for the decision whether or not to invest in small fintechs. Furthermore, the coefficients of universal bank are all found to be significantly negative at the 5%-level in Regressions (1) – (4). Accordingly, specialist banks seem to be more likely to invest in fintechs, than universal banks. The reason behind this might well be that fintechs serves niches that are of particular interest to specialist banks.

- Table 5 about here -

4.2.3 Event Study analysis

To examine whether any stock price reactions occur after an official partnership announcement, we calculate abnormal returns for different event windows. To this extent, we run OLS regressions on our financial performance measure CAAR for short event windows (-1;0), (0;+1) and (-1;+1) as suggested in Amici et al. (2013), Chiou & White (2005), but also a longer event window (0;+100).

- Table 6 about here -

Regarding Hypothesis 3A, Table 6 presents estimated CAARs for our sample. Although all short-term reactions in the windows considered are generally negative, only the very short event windows (-1;0) and (-1;+1) indicate statistically significant differences. The CAAR for the partnership announcement is -0.52 for the (-1;0) window and -0.53 for the (-1;+1) window, with large variation around the mean. For the very long event window (0;+100), the direction of the CAAR turns around and becomes positive, yet not statistically significant. These results indicate that the market, in the short-term, does not value fintech-partnership announcements when the first public information about it leaks to the market. The results further suggest that there is no information leakage or rumours on the upcoming partnership prior to the first formal information, but also that there is strong heterogeneity in the banks in our sample.

In order to investigate what further determines shareholder value creation, we run multivariate regressions for the short event windows (-1;0), (0;+1) and (-1;+1) and a longer event window (0;+100).

- Table 7 about here -

To test Hypothesis 3B, we report the results for three models (bank-variables model, bank- and acquisition-variables model, and bank-fintech-variables model) for the respective event windows in Table 7. First, we focus on coefficient estimates regarding the bank variable *Digital Bank*. This variable is statistically significant for the (-1;+1) event window and partly significant for the (-1;0) and (0;+1) event windows. Four event windows in Regressions (5) – (8) were tested considering the control variables *Chief Digital Officer (d)* and *Acquisition (d)*. Regressions (5) and (7) show the anticipated negative association with the bank's CAR. In Regression (7), the coefficient for *Acquisition (d)* is positive and statistically significant at the 5%-level. We further find that the coefficient for the variable *Digital Strategy (d)* is positive and statistically significant at the 5%-level or less throughout all models for the very long event window (0;+100).

Surprisingly, none of the other bank- or fintech-variables have a statistically significant relationship with shareholder value created.

5. Concluding remarks

As a concluding remark, it can be noted that the way how banks establish alliances with FinTechs varies both between and within the countries examined. As a common denominator, however, it can be noted that alliances across the four countries examined are most often characterized by a customer-service provider relationship. This is particularly interesting in that this form of alliance is less institutionalized compared to the other forms of alliance studied and offers little to no interfaces in the product development process. At this point, the question may be raised to what extent banks use this form of alliance to outsource their innovation and thereby become increasingly dependent on alliance partners. This further raises the question of whether alliances between banks and fintechs are a temporary phenomenon or a long-term business model and what motives are being pursued by the respective parties. We recommend a deeper analysis of these questions for future research projects. Another result of our study shows that fintechs operate in different segments across the countries investigated, with the payment services segment being the most prevalent overall. It would be interesting to learn more about whether the comparatively weak representation of other segments such as "financing" is more due to technical challenges or, for example, a lack of customer acceptance.

Our findings confirm Hpothesis 1, as the implementation of the topic of digitalization in the bank´s corporate strategy has a positive effect on the emergence of alliances with fintechs. We further conclude that large, listed, and universal banks are more involved in the establishment of alliances with at least one fintech, than smaller, unlisted, and specialist banks. In addition, the bank´s financial situation (measured by the return on average assets) seems to be relevant for explaining the number of alliances a bank gets involved in. Accordingly, banks with weak profitability seem to be particularly interested in collaborating with more than one fintech. The background could be that the respective banks have a high pressure to change in order to remain competitive.

Our results further suggest that neither a bank's implementation of a digitalization strategy nor the employment of a CDO significantly increases the likelihood of a financial investment instead of a customer-service provider relationship. Even though this finding contradicts our hypothesis and previous literature about board-positions (e.g. Geiger & North, 2006; X. Jiang & Li, 2009), it can be assumed that CDOs do not simply focus on acquring fintechs but more on how to manage the variety of alliances in order to extend the bank's knowledge. In order to satisfy investors and other stakeholders it can be assumed that banks try to show credible digitalization efforts by fully acquiring and integrating fintechs. Yet, we can confirm Hypothesis 2A as larger banks seem to possess higher purchasing power and therefore get financially involved in their alliances with fintechs. Through the acquisition of a stake in the fintech, banks might try to avoid hazardous actions by the fintech, as financial investments constitute a higher involvement in the fintech's decision making and allows stronger control about its actions. As large banks tend more often to establish alliances with fintechs, they have the financial power to establish themselves as attractive incubators and accelerators and spread their risk by investing in various fintechs. This is especially attractive for banks as long as the fintechs are young and occupied by large uncertainty. As they become larger, our results show that the effect diminishes.

Our event study points out that, in our whole sample, the announcement of a alliance has a negative effect on the bank's firm value in the short-term windows. Even though the negative market reaction is not very large, it might show the investors opinion about unsatisfying digitalization efforts in order to (re)gain competitive advantage. Surprisingly, our models suggest that stocks of direct banks benefit from alliance announcements in the short term as investors can assume that they can apply the fintech's knowledge much better to strenghten their market position. However, in the long term, it seems that investors reward the bank's alliances with fintechs. This is especially true for banks following a digitalization strategy.

Overall, the present paper contributes to existing literature by explaining which factors play a role for the emergence of alliances between banks and fintechs, what factors are relevant for a bank to acquire a fintech instead of getting involved in an alliance, and how the announcement of a press announcement regarding a newly started alliance affects the bank´s market value.

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Table 1
This table provides the definition of variables included in the regression models.

Variable Name	Definition
Dependent variables	
Financial Investment (d)	Binary variable equal to 1 if a bank acquires at least a minority stake of a fintech and equal to 0 if the alliance is characterized by a customer-service provider relationship Source: Factiva, Company websites, Crunchbase, Thomson Reuters.
CAR(-X;+Y)	The cumulative abnormal return for the event window (-X;+Y). Event date 0 constitutes the date of the first public announcement of the alliance. In the analysis, we specify different window ranges Source: Thomson Reuters Datastream.
Alliance (d)	Binary variable equal to 1 if the bank cultivates at least one alliance with a FinTech. Source: Factiva, Company websites.
Joint Venture (d)	Binary variable equal to 1 if a joint business arrangement between bank and fintech in which both parties pool their resources for the purpose of the accomplishment of a specific task was set up. Source: Factiva, Company websites, Crunchbase.
Nbr. New Alliances	Number of new alliances in the year of interest; Source: Factiva, Company websites.
Form of Alliance	Categorical variable equal to 1 if the alliance is an acquisition, 2 if minority interest, 3 if product related partnership (customer service-provider relationship) and 4 if the alliance is characterized by another form of interaction; Source: Factiva, Company websites, Crunchbase.
Bank characteristics	
Bank is Listed (d)	Binary variable equal to 1 if the bank is publicly listed; Source: Onvista.
Bank HQ Country of Interest (d)	Binary variable equal to 1 if the bank's headquarter ist located in the country as the fintech that participates in the alliance. Source: Fitch connect.
Bank Loan-To-Assets Ratio	Ratio of a bank's loans over its assets as a measure of asset structure. It measures the total loans outstanding as a percentage of total assets and can be uses for assessing a bank's liquidity. A higher ratio indicates a bank is loaned up and, thus, a low liquidity which brings a higher risk in terms of defaults. Source: Fitch connect.
Bank ROAA	Ratio of a bank's return over its average assets as a measure of profitability. Source: Fitch connect.
Chief Digital Officer (d)	Binary variable equal to 1 if the bank employs a Chief Digital Officer. Source: Annual reports, LinkedIn, Company website.
Digital Bank (d)	Binary variable equal to 1 if the bank is a direct bank without any branch network, offering only remote services via online- and telephone banking. Source: Company websites.
Digital Strategy (d)	Binary variable equal to 1 if the bank announced a credible digitalization strategy. Source: Annual reports.
ln(Bank Age)	Natural logarithm of the bank's age in years. Source: Fitch connect.
ln(Bank Total Assets)	Natural logarithm of the bank's total assets in Euros. Source: Fitch connect.
Universal Bank (d)	Binary variable equal to 1 if the bank participates in many kinds of banking activities; e.g., if the bank is both commercial bank and an investment bank, or provides other financial services as well. Source: Company websites.

Fintech characteristics

Bank-level	The fintech provides bank-level technology solutions. Source: Company website, Crunchbase, LinkedIn.
Fintech Employees (rank)	Rank of the fintech's employees as a measure of size. Categories: 1-10, 11-50, 51-100, 101-1000, >1000. Source: Crunchbase company website, LinkedIn.
Fintech Age	Age of the fintech in years. Source: Crunchbase company website, LinkedIn.
Fintech Front End Solution (d)	Binary variable equal to 1 if the fintech offers front-end solutions. Source: Crunchbase company website, LinkedIn.
Fintech HQ Country of interest (d)	Binary variable equal to 1 if the fintech is located in the same country as the headquarter of the bank. Source: Crunchbase company website, LinkedIn.
Fintech Nbr. Patents	Number of patents the FinTech until December 2017; Source: Max-Planck-Institute.
Fintech Segment	Categorical variable equal to 1 if the fintech provides financing services, 2 if asset management, 3 if payment services, 4 if bank-level software, 5 if asset management and payment services, 6 if cyber security services, and 7 if the fintech operates in another segment. Source: Company websites, Crunchbase, LinkedIn.

Table 2.1.
Summary statistics of panel data for the full sample of 4400 bank-year observations by the 100 largest banks in Canada, France, Germany, and UK from 2007 to 2017. The table provides the mean, different standard deviations, and the number of banks and observations of the panel.

Variable	Mean	SD (Overall)	SD (Between)	SD (Within)	Number of Banks	Number of Observations
Dependent variables						
Alliances (d)	0.12	0.32	0.20	0.25	400	4400
Nbr. New Alliances	0.11	0.72	0.35	0.63	400	4400
Explanatory variables						
Digital Strategy (d)	0.21	0.41	0.25	0.34	327	3394
Chief Digital Officer (d)	0.03	0.16	0.10	0.13	353	3871
Bank is listed (d)	0.15	0.35	0.35	0.00	400	4400
Digital Bank (d)	0.07	0.26	0.26	0.00	400	4400
Universal Bank (d)	0.40	0.49	0.49	0.00	400	4400
Bank HQ Country of Interest	0.82	0.38	0.38	0.00	398	4378
Ln(Bank Age)	3.83	0.96	0.96	0.00	371	4081
Ln(Bank Total Assets)	16.65	2.41	2.26	1.06	375	3345
Bank Loan-to-Assets Ratio	0.57	0.26	0.26	0.08	366	3211
Bank ROAA	0.01	0.04	0.04	0.03	374	3191

Table 2.2.

Summary statistics of deal-level data for the full sample of 500 alliances identified between banks and fintechs in Canada, France, Germany and UK from 2007 to 2017. The table provides the number of observations, mean, median, standard deviation, minimum and maximum of the deal-level data.

Variable	Nbr. Obs.	Mean	Median	Std. Dev.	Minimum	Maximum
Dependent variables						
Financial Investment (d)	455	0.44	0	0.50	0	1
Explanatory variables						
Digital Strategy (d)	470	0.86	1	0.35	0	1
Chief Digital Officer (d)	489	0.23	0	0.42	0	1
Fintech Employees (rank)	462	2.40	2	1.19	1	5
Ln(Bank Total Assets)	362	18.99	19.79	2.26	12.53	22.73
Bank is listed (d)	500	0.56	1	0.50	0	1
Digital Bank (d)	500	0.11	0	0.31	0	1
Universal Bank (d)	500	0.67	1	0.47	0	1
Bank HQ Country of Interest	500	0.87	1	0.34	0	1
Ln(Bank Age)	498	4.08	4.14	0.93	1.10	5.86
Bank ROAA	460	0.00	0	0.01	-0.07	0.04
Fintech Front End Solution	463	0.71	1	0.46	0	1
Fintech HQ Country of Interest (d)	493	0.65	1	0.48	0	1
Fintech Nbr. Patents	500	1.67	0	8.49	0	158
Fintech Age	456	5.67	4	6.41	0	45

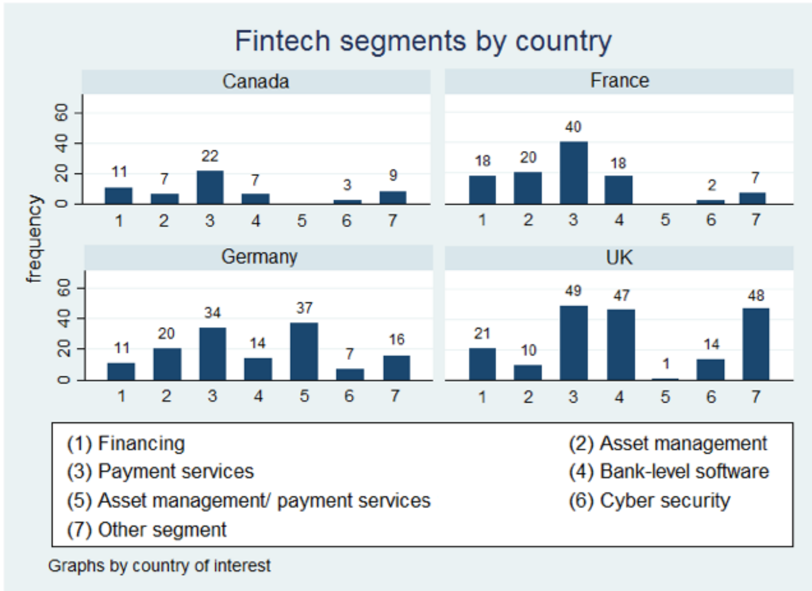

Fig. 1. Fintech segments by bank country. This figure presents the frequency of occurrence of bank alliances with fintechs by segment and country. The sample includes 492 fintechs from 27 countries collected from 2007 to 2017. The bars represent the number of fintechs in each segment and grouped by the country of the bank.

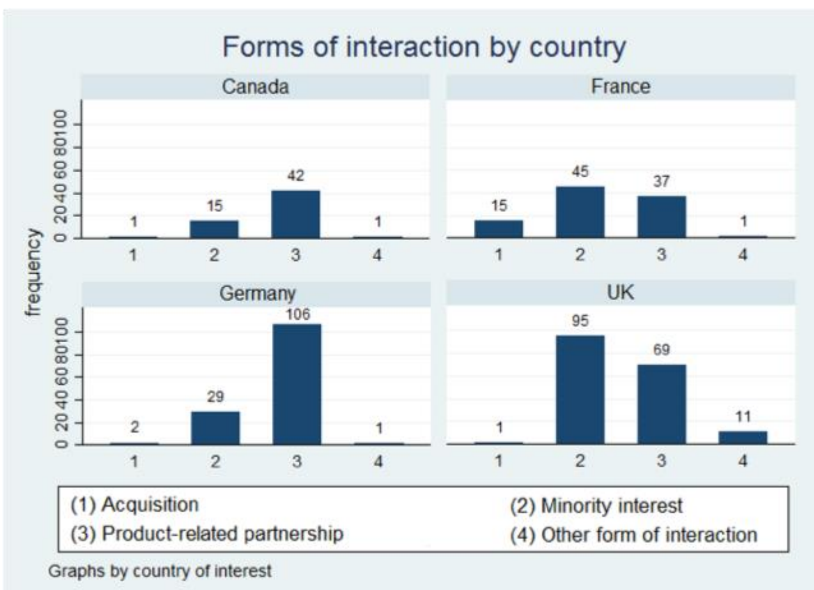

Fig. 2. Forms of interaction by country. This figure presents the frequency of occurrence of interacting fintechs by form and country. The sample includes 470 interacting fintechs from 28 countries collected from 2007 to 2017. The bars represent the frequency of the different arrangements of interaction with banks in Canada, France, Germany, and UK.

Table 3
Panel data analysis for *Digital Strategy, Chief Digital Officer* and *Alliance (d)*. This table presents the results of random-effects probit regressions modeling the probability that at least one interaction between bank i and a fintech occurs in year t (dependent variable = 1) or not (dependent variable = 0). The coefficients show the average marginal effects. Standard errors in parentheses. Models 1-4 uses the full sample; Models 5-8 fintechs with more than 1000 employees and fintechs which were older than 10 years at time of the alliance. All the variables are defined in Table 1. * denotes significance at the 5% level, ** denotes significance at the 1% level, and *** denotes significance at the 0.1 % level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	full sample				*excluding mature fintechs*			
	Dep. Var. = Alliance (dummy)							
Explanatory variables								
Digital Strategy (d)	0.062***		0.066***		0.062***		0.066***	
	(0.009)		(0.011)		(0.009)		(0.011)	
Chief Digital Officer (d)		0.098***		0.062		0.098***		0.062
		(0.019)		(0.034)		(0.019)		(0.034)
Bank is listed (d)	0.057***	0.085***	0.059	0.086***	0.057***	0.085***	0.059	0.086***
	(0.015)	(0.015)	(0.031)	(0.019)	(0.015)	(0.015)	(0.031)	(0.019)
Digital Bank (d)	0.032	0.032	0.035	0.069**	0.032	0.032	0.035	0.069**
	(0.018)	(0.017)	(0.030)	(0.025)	(0.018)	(0.017)	(0.030)	(0.025)
Universal Bank (d)	0.029**	0.020*	0.034*	0.043*	0.029**	0.020*	0.034*	0.043*
	(0.010)	(0.009)	(0.014)	(0.017)	(0.010)	(0.009)	(0.014)	(0.017)
Bank HQ Country of Interest (d)	0.003	0.011	0.002	0.030	0.003	0.011	0.002	0.030
	(0.015)	(0.013)	(0.018)	(0.025)	(0.015)	(0.013)	(0.018)	(0.025)
ln(Bank Age)	0.012*	0.012*	0.011	0.024**	0.012*	0.012*	0.011	0.024**
	(0.005)	(0.005)	(0.007)	(0.009)	(0.005)	(0.005)	(0.007)	(0.009)
ln(Bank Total Assets)			0.011***	0.011***			0.011***	0.011***
			(0.003)	(0.003)			(0.003)	(0.003)
Bank Loan-to-Assets Ratio			-0.019	-0.004			-0.019	-0.004
			(0.024)	(0.030)			(0.024)	(0.030)
Bank ROAA			-0.118	-0.265			-0.118	-0.265
			(0.150)	(0.582)			(0.150)	(0.582)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n (Obs.)	3212	3629	2375	2691	3212	3629	2375	2691
N (Banks)	310	331	289	308	310	331	289	308
Wald chi2	127.614	533.195	298.362	306.679	127.614	533.195	298.362	306.679
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4

Panel data analysis for *Digital Strategy, Chief Digital Officer* and *Number of Partnerships*. This table presents the results of random-effects negative binominal regressions. The dependent variable represents the number of new alliances of bank i in year t. The coefficients show the average marginal effects. Standard errors in parentheses. Models 1-4 uses the full sample; Models 5-8 fintechs with more than 1000 employees and fintechs which were older than 10 years at time of the alliance. All the variables are defined in Table 1. A Hausman test is used to identify whether fixed effects or random effects should be applied to each respective model. * denotes significance at the 5% level, ** denotes significance at the 1% level, and *** denotes significance at the 0.1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		full sample				*excluding mature fintechs*		
				Dep. Var. = Number of Alliances				
Explanatory variables								
Digital Strategy (d)	1.396***		1.091***		1.509***		1.207***	
	(0.216)		(0.215)		(0.259)		(0.259)	
Chief Digital Officer (d)		0.971***		0.620**		0.984***		0.527*
		(0.228)		(0.227)		(0.264)		(0.258)
Bank is listed (d)	0.990***	1.366***	0.658**	0.955***	1.270***	1.599***	0.680**	0.960***
	(0.231)	(0.229)	(0.210)	(0.213)	(0.265)	(0.268)	(0.243)	(0.244)
Digital Bank (d)	0.392	0.631*	0.805**	0.778**	0.516	0.858*	0.734*	0.810**
	(0.313)	(0.306)	(0.268)	(0.276)	(0.350)	(0.342)	(0.314)	(0.314)
Universal Bank (d)	0.543**	0.539**	0.456*	0.434*	0.541*	0.535*	0.403	0.367
	(0.200)	(0.198)	(0.184)	(0.192)	(0.231)	(0.228)	(0.217)	(0.223)
Bank HQ Country of Interest (d)	-0.117	0.006	-0.196	-0.038	-0.274	-0.033	-0.266	0.005
	(0.275)	(0.274)	(0.254)	(0.266)	(0.319)	(0.320)	(0.294)	(0.311)
ln(Bank Age)	0.116	0.159	0.127	0.176*	0.164	0.217*	0.107	0.175
	(0.095)	(0.094)	(0.088)	(0.089)	(0.110)	(0.107)	(0.101)	(0.100)
ln(Bank Total Assets)			0.253***	0.233***			0.312***	0.305***
			(0.047)	(0.046)			(0.055)	(0.053)
Bank Loan-to-Assets Ratio			-0.329	-0.038			-0.113	0.104
			(0.368)	(0.367)			(0.447)	(0.439)
Bank ROAA			-13.331**	-15.583*			-15.363*	-13,571
			(4.560)	(6.636)			(6.302)	(8.734)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n (Obs.)	3212	3629	2375	2691	3212	3629	2375	2691
N (Banks)	310	331	289	308	310	331	289	308
Wald chi2	366.382	390.27	402.393	412.562	279.552	310.763	314.940	326.301
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 5

Cross-sectional regression results for *Financial Investment* versus *Customer-Service Provider Relationship*. This table presents the results of Probit regression. The coefficients show the average marginal effects. Standard errors are clustered by banks (in parentheses). The dependent variable *Financial Investment* is equal to 1 if the invests in a fintech and equal to 0 if the alliance is characterized by a customer-service provider relationship. Models 1 and 2 use the full sample; Models 3 and 4 fintechs with more than 1000 employees and fintechs which were older than 10 years at time of the alliance. All the variables are defined in Table 1. * denotes significance at the 5% level, ** denotes significance at the 1% level, and *** denotes significance at the 0.1% level.

	(1)	(2)	(3)	(4)
		full sample	*excluding mature fintechs*	
		Dep. Var.: Financial Investment (d)		
Explanatory variables				
Digital Strategy (d)	-0.069		-0.078	
	(0.083)		(0.104)	
Chief Digital Officer (d)		-0.082		-0.113
		(0.118)		(0.122)
Fintech Employees (rank)	-0.098***	-0.095***	-0.037	-0.034
	(0.026)	(0.026)	(0.035)	(0.036)
ln(Bank Total Assets)	0.057**	0.050**	0.048*	0.041
	(0.019)	(0.018)	(0.022)	(0.021)
Bank is listed (d)	0.107	0.132	0.16	0.186
	(0.114)	(0.126)	(0.123)	(0.134)
Digital Bank (d)	0.181	0.185	0.205	0.204
	(0.121)	(0.119)	(0.121)	(0.119)
Universal Bank (d)	-0.157*	-0.137*	-0.204*	-0.176*
	(0.070)	(0.067)	(0.080)	(0.080)
Bank HQ Country of Interest (d)	-0.051	-0.080	-0.003	-0.055
	(0.076)	(0.104)	(0.073)	(0.105)
ln(Bank Age)	0.010	0.004	0.022	0.014
	(0.044)	(0.041)	(0.046)	(0.043)
Bank ROAA	4501	2589	2.515	0.654
	(7.238)	(7.091)	(6.930)	(7.344)
Fintech Front End Solution (d)	-0.032	-0.039	-0.034	-0.043
	(0.054)	(0.055)	(0.060)	(0.061)
Fintech HQ Country of Interest (d)	-0.143**	-0.138**	-0.094	-0.084
	(0.055)	(0.053)	(0.060)	(0.059)
Fintech Nbr. Patents	0.001	-0.000	0.000	-0.001
	(0.005)	(0.005)	(0.006)	(0.005)
Fintech Age	-0.005	-0.006	-0.021*	-0.022*
	(0.004)	(0.005)	(0.010)	(0.011)
Country Dummies	Yes	Yes	Yes	Yes
N (Banks)	331	346	282	295
Pseudo ar2	0.273	0.285	0.268	0.285
Wald chi2	51362	58935	57.687	58.797
Prob > chi2	0.000	0.000	0.000	0.000

Table 6

CAR returns for bank-fintech alliances. This table reports descriptive statistics of CARs for various event windows, based on 140 alliances done by all the 21 publicly listed banks in our sample for the period from 2007 to 2017. Daily Abnormal Returns are obtained using the market model with a 200-trading day window, ending 20 days before the event day to avoid bias in the parameters estimations due to changes in firm characteristics around the event date.
* denotes significance at the 5% level, ** denotes significance at the 1% level, and *** denotes significance at the 0.1 % level.

		t-test	Wilcoxon sign-rank			
Event window	CAAR (%)	t-statistic	z-statistic	Minimum (%)	Maximum (%)	Percentage of positive CAR (%)
-1 to +1	-0.52	-2.050*	-1.82	-7.25	6.10	43.69
-1 to 0	-0.53	-2.475*	-2.538*	-5.43	4.59	38.95
0 to +1	-0.18	-0.823	-0.928	-5.81	6.03	44.25
-3 to +3	-0.72	-1.893	-1.564	-12.06	8.25	42.70
-5 to +5	-0.25	-0.353	-0.021	-9.50	7.64	52.74
-10 to +10	-0.70	-1.117	1.591	-15.24	17.55	46.95
0 to 100	2.89	1.506	-1.082	-40.94	38.78	58.16
N 140						

Table 7

Determinants of shareholder value creation from bank-fintech alliances. This table provides results of OLS regression, where the dependent variables are the standardized CARs for the selected event windows (-1;0), (0;+1), (-1;+1) and (0;+100). Standard errors shown in parentheses are clustered by banks. All the variables are defined in Table 1. * denotes significance at the 5% level, ** denotes significance at the 1% level, and *** denotes significance at the 0.1 % level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	bank-variables				bank- and acquisition- variables				bank- and fintech- variables			
					Dep. Var. = CAR							
Event Windows	-1 to +1	-1 to 0	0 to +1	0 to +100	-1 to +1	-1 to 0	0 to +1	0 to +100	-1 to +1	-1 to 0	0 to +1	0 to +100
Digital Strategy (d)	-0.018	-0.014	-0.007	0.187*	-0.019	-0.015	-0.007	0.193*	-0.012	-0.01	-0.002	0.199*
	(0.011)	(0.009)	(0.009)	(0.079)	(0.011)	(0.009)	(0.009)	(0.077)	(0.011)	(0.010)	(0.009)	(0.081)
Chief Digital Officer (d)	0.005	0.002	-0.001	-0.055	0.007	0.001	0.001	-0.058	0.007	0.003	-0.002	-0.059
	(0.006)	(0.005)	(0.005)	(0.043)	(0.006)	(0.005)	(0.005)	(0.045)	(0.007)	(0.006)	(0.005)	(0.049)
Acquisition (d)					0.03	0.005	0.031*	-0.004	-0.015	0.008	-0.011	-0.052
					(0.017)	(0.015)	(0.014)	(0.126)	(0.013)	(0.011)	(0.010)	(0.092)
Chief Digital Officer x Acquisition					-0.040*	0.005	-0.037*	-0.04				
					(0.020)	(0.017)	(0.016)	(0.142)				
Universalbank (d)	0.003	-0.001	0.001	-0.1	0.007	0.002	0.005	-0.106	0.000	0.003	-0.003	-0.166
	(0.009)	(0.008)	(0.008)	(0.070)	(0.010)	(0.009)	(0.008)	(0.073)	(0.012)	(0.010)	(0.009)	(0.084)
Digital Bank (d)	0.032**	0.029**	0.025*	0.008	0.026*	0.026*	0.019	0.017	0.030*	0.024	0.029*	0.029
	(0.012)	(0.010)	(0.010)	(0.089)	(0.012)	(0.011)	(0.010)	(0.090)	(0.015)	(0.013)	(0.012)	(0.106)
ln(Bank Age)	-0.002	-0.001	-0.003	-0.005	-0.002	-0.002	-0.004*	-0.009	-0.002	-0.001	-0.003	-0.007
	(0.002)	(0.002)	(0.002)	(0.019)	(0.003)	(0.002)	(0.002)	(0.019)	(0.003)	(0.003)	(0.002)	(0.021)
ln(Bank Total Assets)	0.002	0.004	0.003	0.013	0.002	0.004	0.003	0.016	0.002	0.003	0.004	0.020
	(0.002)	(0.002)	(0.002)	(0.018)	(0.003)	(0.002)	(0.002)	(0.018)	(0.003)	(0.002)	(0.002)	(0.020)
ROAA	-0.358	0.013	-0.407	7.366	-0.252	0.126	-0.209	6.353	-0.060	0.403	-0.283	6.558
	(0.550)	(0.469)	(0.451)	(4.123)	(0.567)	(0.499)	(0.457)	(4.117)	(0.666)	(0.597)	(0.529)	(4.822)
Fintech Front End Solutoion (d)									-0.004	-0.002	-0.004	-0.043
									(0.004)	(0.004)	(0.004)	(0.032)
Fintech Employees (rank)									0.001	0.000	0.001	-0.008
									(0.002)	(0.002)	(0.002)	(0.016)
Fintech HQ Country of Interest (d)									-0.002	-0.006	0.003	0.040
									(0.005)	(0.004)	(0.004)	(0.035)
Fintech Nbr. Patents									0.000	0.000	0.000	-0.002
									(0.000)	(0.000)	(0.000)	(0.003)
Fintech Age									0.003	0.001	0.003	0.002
									(0.004)	(0.003)	(0.003)	(0.025)
Intercept	-0.04	-0.059	-0.047	-0.299	-0.035	-0.056	-0.043	-0.349	-0.033	-0.035	-0.062	-0.357
	(0.043)	(0.037)	(0.036)	(0.326)	(0.044)	(0.039)	(0.036)	(0.322)	(0.055)	(0.049)	(0.044)	(0.398)
Country Dummies	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	139	139	139	139	128	128	128	128	116	116	116	116
R2	0.105	0.094	0.152	0.126	0.135	0.105	0.207	0.131	0.14	0.135	0.17	0.188
P	0.143	0.225	0.016	0.06	0.134	0.347	0.006	0.157	0.453	0.502	0.231	0.141