Performance and Uncertainty: What is the Role of Experience in Fintech M&A?

Master Thesis [Strategy Economics]

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Abstract

In the last few years, fintech acquisition activity has grown considerably. This has led many acquirors to complete more than one acquisition, and some to even become serial acquirors. This raises a few key questions. First, do fintech acquisitions contribute to the performance of the acquiring firm? And second, does experience improve fintech acquisition performance? To answer the first question, I find that fintech acquisitions on average generate statistically significant positive returns, indicating that there is strategic value in fintech acquisitions. As for the second question, I find that general experience is at best a weak driver of fintech acquisition performance, and increased fintech experience leads to decreased performance. This indicates that developing pre-acquisition generalist skills such as improved target selection does not significantly improve performance, while specific skills regarding the integration stage do not help acquirors overcome issues such as acquiror-target differences in corporate culture and management styles. I do, however, find that increased fintech experience appears to decrease micro-uncertainty regarding the outcome of the acquisition, showing that organizational learning is taking place. Using reasoning from real option theory, decreased uncertainty also leads to lower expected returns, which I use as a proxy for acquisition performance. It is, therefore, possible that even though acquirors are learning and allocating resources more efficiently, decreased uncertainty from more experience can lead to lower expected returns, and therefore lower performance expectations. Therefore, the role of uncertainty is important to consider when isolating the effect of firm acquisition experience on acquisition performance.

1. Introduction

Over the last 15 years, the financial services industry has experienced significant disruption due to the rise of fintech companies. Fintech adoption rates have increased significantly (Collevecchio, Cappa, Peruffo, & Oriani, 2023), and increased regulations and improvements in technology have provided additional opportunities for fintech companies to take advantage of (Buchak, Matvos, Piskorski, & Seru, 2018), therefore creating strategic challenges for incumbent financial service providers.

This has sparked a wave of acquisitions which grew steadily until 2017, and increased significantly in 2018, as financial service providers began acquiring fintechs expecting to reap rewards in increased efficiency, cybersecurity, and competitiveness (Dranev, Frolova, & Ochirova, 2019). Additionally, firms that engage in such acquisitions often complete more than one. In a sample of 1,395 fintech acquisitions, 39.3% of acquisitions had at least one completed majority fintech acquisition in the 5 years before the focal acquisition. This is because a company often first decides to establish acquisition structures within the firm, and only then selects targets, as acquisition programs are too expensive to only complete one acquisition (Laamanen & Keil, 2008). Therefore, many acquirors who decide to engage in fintech acquisitions will acquire more than one company.

Since the likelihood of a given acquiror to engage in multiple acquisitions is quite high, acquisition experience may play an important role in how these fintech acquisitions perform, as challenges emerge both before and after acquiring fintechs. These challenges often concern target selection (Wu & Reuer, 2021) and post-acquisition integration (Al-Laham, Schweizer, & Amburgey, 2010), the repeated exposure to which may provide learning opportunities for the acquiror (Haleblian & Finkelstein, 1999).

The effect of firm acquisition experience on acquisition performance, however, has produced diverse opinions in classic acquisition literature. Hayward (2002), for example, finds that focal acquisitions tend to perform better with experience from acquisitions that are not too similar or different to the focal acquisition, whereas Haleblian and Finkelstein (1999) find that focal acquisitions tend to perform better with similar prior experience. In the context of fintech, the role of experience has also received relatively little attention, often only being included as a control variable (Collevecchio, Cappa, Peruffo, & Oriani, 2023).

To confirm whether fintech acquisitions are seen as value enhancing, and to understand how acquisition experience affects fintech acquisition performance, I arrive at the following research question:

RQ: Do fintech acquisitions lead to an improved firm outlook, and to what extent does experience affect acquisition performance?

In this paper I contribute to existing literature by providing evidence that fintech acquisitions do have strategic value and do improve firm performance. I also show that general experience is a relatively weak predictor of fintech acquisition performance, and that increased fintech experience may actually lead to decreased acquisition performance. However, after introducing the aspect of uncertainty regarding acquisition outcomes, I show that increased fintech experience decreases uncertainty, whereby using real option theory, performance may be implied to be lower at least partially due to decreased uncertainty.

In Section 2 of this paper, I provide a literature review and develop hypotheses to test the given research question. In Section 3, I describe the data and methodology used to estimate effects of experience, as well as discussing issues regarding sample selection bias. In Section 4, I present empirical results to the hypotheses developed in Section 2, and I provide robustness tests and additional analysis concerning uncertainty. In Section 5, I present concluding remarks, implications for acquiring firms, and potential limitations and avenues for further research.

2. Literature review

2.1. Fintech

Fintech, meaning "financial technology", is a relatively recent term which became popular only after 2014. The idea of linking finance and technology, however, has existed for around 150 years (Arner, Barberis, & Buckley, 2015). The first age of fintech, or fintech 1.0, began in the late 19th century which resulted in the globalization of finance by using technology such as the telegraph, railroads and steamships to increase the speed at which financial information is transmitted (Arner, Barberis, & Buckley, 2015). Eventually, firms began taking advantage of many wartime developments in the post-war period to further develop global networks by establishing a global telex network, create consumer facing innovations such as credit cards, and further simplify bank operations with tools such as handheld calculators and fax machines in the 1950's and 1960's (Arner, Barberis, & Buckley, 2015).

The digitalization of finance began in 1967, jumpstarting the second age of fintech, fintech 2.0. With this came innovations which are still used today, such as the SWIFT system and the creation of the NASDAQ, and a general increase in the usage of information and communications technologies, or IT, to replace existing paper-based mechanisms (Arner, Barberis, & Buckley, 2015). During this time, banks created IT departments with thousands of employees and were considered pioneers of IT adoption (Alt, Beck, & Smits, 2018). This new technology, however, had the potential to exacerbate already existing risks for banks. For example, new technology could enable virtual bank runs which increases liquidity risks or expand competition between established banks and new market players even across borders – possibly even hurting financial stability (Carse, 1999). These increased risks inevitably drew the eye of regulators, however, the consensus remained that such technologies would only be used by already regulated and supervised financial institutions (Alt, Beck, & Smits, 2018).

After the Great Financial Crisis in 2007 and 2008, however, trust in established financial service providers was damaged. This caused a shift in the mindset of retail customers which allowed new startups to claim legitimacy (Alt, Beck, & Smits, 2018) and take advantage of two key technologies – smartphones and the increased usage of application programming interfaces, or API's (Arner, Barberis, & Buckley, 2016). This started the third age of fintech, or fintech 3.0, with the main distinction from fintech 2.0 being that technological advancements could now be employed by non-banks (Arner, Barberis, & Buckley, 2015). For this paper, I call these new entrants fintechs, and focus on this age of fintech.

Going back to traditional perspectives on innovation, this change led the financial services industry to adopt characteristics of a Schumpeterian Mark I type of industry (Malerba & Orsenigo, 1996), as the industry widened due to young firms innovating and providing viable alternatives and even improvements to existing financial solutions.

As identified by Arner et al. (2015) fintechs operate in five major areas: finance and investment, operations and risk management, payments and infrastructure, data security and monetization, and customer interface. Additionally, fintechs often operate in narrow niches for which they can charge considerably higher premiums, as evidenced by loan data from the US (Buchak, Matvos, Piskorski, & Seru, 2018). A recent example of such a fintech from the database I use is the Swedish Advinans AB which was acquired by the Finish Nordea Bank ABP. This fintech operated in cloud-based pension and insurance management – therefore fitting into the consumer interface category by providing online financial services.

Consequently, such entrants can pose a strategic threat to incumbent financial service providers, as there is pressure from existing customers to keep up with improved services provided by fintechs (Wilson, 2020). There is evidence from China that the emergence of fintech has had negative effects on both the financial stability and ability to generate revenue of incumbent service providers (Zhao, Li, Chen, & Lee, 2021). This adds to the idea that fintechs may be able to function as effective substitutes by leveraging increased efficiency and a higher quality of services (Li, Spigt, & Swinkels, 2017), as financial service incumbents have been devoting more resources to navigating regulatory challenges (Ferrari, 2016).

2.2. Acquiring fintechs to achieve complementary effects

With the emergence of fintech 3.0, however, complementary effects between fintechs and incumbent financial service providers can be achieved, therefore contributing to creative construction (Agarwal, Audretch, & Sarkar, 2007), as it is possible for incumbents to incorporate emerging technologies in their value chain (Li, Spigt, & Swinkels, 2017). For example, incumbents could use fintechs to take advantage of existing innovation, improve profitability and efficiency by incorporating process and product innovations, and fintechs can use the banks' customer base and funding to scale solutions quickly (Wilson, 2020). To acquire such capabilities, incumbents can acquire fintechs. These acquisitions should then lead to the improved performance of incumbents (Zhao, Li, Chen, & Lee, 2021), which will be reflected in the share price of the acquiring incumbent. Additionally, acquisitions may serve to eliminate competitors to strengthen their own market share (Baker & Breshanan, 1985) as has happened in other disruptive markets, such as with killer acquisitions in pharmaceuticals (Cunningham, Ederer, & Ma, 2021). In existing literature, however, proxies for acquisition performance (namely cumulative abnormal returns) are not shown to be consistently positive. Dranev et al. (2022) for example, find that on average fintech acquisitions lead to significant positive abnormal returns, however Collevecchio et. al. (2023) found that on average abnormal returns were slightly negative. Due to there not being a clear consensus, I formulate the first hypothesis:

H1: Fintech acquisitions lead to improved expected performance for the acquiror

2.3. Experience in acquisitions

Incumbent financial service providers often offer a wide range of services. Large incumbent banks, for example, offer products for both corporate and retail consumers, including the provision of bank accounts, various lending products and investment services. Fintechs, however, typically focus on narrow niches, especially targeting underbanked customers such as small businesses with loan amounts too small to cover labor costs (Li, Spigt, & Swinkels, 2017) with specific fintech solutions such as peer-to-peer lending platforms (Zhao, Li, Chen, & Lee, 2021). Because of this, fintech acquisitions may provide a relatively narrow range of technological expertise which is likely to benefit only a portion of the acquiror's wide range of services. This, however, will depend on which of the five major areas the fintech operates in, as operations and risk management type fintechs may have more general applications than specific consumer facing solutions.

Because of the relatively narrow scope of fintech firms, it is likely that for incumbents to develop various areas of their business, multiple partnerships or acquisitions may be necessary. Additionally, as established earlier, to achieve sufficient returns for acquisitions, acquirors make the decision to acquire at a program level, develop structures, and only then decide on targets, further increasing the probability of acquirors completing multiple acquisitions (Laamanen & Keil, 2008).

This therefore raises the question – to what extent does more acquisition experience improve the performance of fintech acquisitions?

As identified by Hayward (2002), not all experience is the same, as factors such as previous acquisition similarity, performance and timing all affect how much organizational learning will take place. In a sample of 214 acquisitions in 6 industries, Hayward (2002) finds that focal acquisitions tend to perform better when prior acquisitions are not too similar or different from the focal acquisition, when prior acquisitions generate small losses, and when the gap between prior acquisitions is not too small or too large. In the context of fintech acquisitions, however, targets are similar and highly specific as defined by four distinct SIC industry codes, therefore it is not clear to what extent prior experience will be useful as experience related to the focal acquisition is likely to be either too specific or too different.

For the purposes of fintech acquisitions and this paper I categorize prior acquisition experience into *general experience* acquired from dissimilar acquisitions, and specific or *fintech experience* acquired from prior fintech acquisitions.

2.3.1. General experience

General experience can be useful for gaining a wide array of know-how regarding drivers of acquisition performance. Primarily, the benefits will be for the identification of growth opportunities (Hayward, 2002). In the fintech context where targets are high-tech, there is additional risk relative to more traditional acquisitions, which then increases both the risks and rewards in choosing targets adequately. In this case, more generally experienced acquirors will be able to judge potential targets more accurately by paying attention to target signaling, thus leading to a smaller risk of adverse target selection (Wu & Reuer, 2021). Additionally, general experience can contribute to increasing the share of value of a deal that the acquiror can capture, as acquirors can improve deal negotiation skills, and leverage these skills especially when there is asymmetry in the levels of experience between the acquiror and target, and when there is information asymmetry to overcome (Cuypers, Cuypers, & Martin, 2017).

According to Haleblian and Finkelstein (1999), however, applying such experience can be costly due to inappropriate generalization. This can happen due to managers recognizing surface similarities between prior acquisition and the focal fintech acquisition, while dissimilar underlying structures between the prior and focal acquisitions are not taken into consideration. Therefore, experience gained from prior general acquisitions may actually harm the performance of the focal acquisition. In the case of appropriate discrimination of past experience, however, the results are more likely to be neutral (Haleblian & Finkelstein, 1999).

To study the effect of prior general experience on the performance of the focal fintech acquisition, I pose the following hypothesis:

H2: Additional general experience improves fintech acquisition performance.

2.3.2. Fintech experience

It has been shown that similar situations provide opportunities for learning, as past experience can be applied via appropriate generalization (Haleblian & Finkelstein, 1999).

Therefore, similar fintech acquisitions focusing on acquiring new technology provide opportunities for such learning to take place. Additionally, the acquiring firm can benefit from a more coherent business structure arising from relative target firm similarity (Hayward, 2002).

More specifically, prior fintech experience may be necessary to generate post-acquisition gains (Hayward, 2002) by developing integration capabilities and expanding the acquiring firm's absorptive capacity (Al-Laham, Schweizer, & Amburgey, 2010). Additionally, experience in overcoming fintech-specific post acquisition integration obstacles may help improve performance. Such issues are likely to arise as the corporate cultures and management styles of small, young, and fast fintech firms may differ significantly from established financial service providers. As outlined by Al-Laham et al. (2010) acquisitions between large pharmaceuticals and young biotech firms, a situation which is analogous to established banks acquiring fintechs, struggled in the post-acquisition phase due to differences in company culture, eventually leading to weak knowledge transfer. Given that such problems would persist between different fintech acquisitions, the situations would likely be similar enough to generate learning and generalize solutions for future acquisitions (Haleblian & Finkelstein, 1999).

As such, I hypothesize that specific fintech experience will lead to improved post-acquisition integration of new knowledge, and therefore improved performance:

H3: Additional fintech experience improves fintech acquisition performance.

2.4. Uncertainty, experience, and performance

Another important aspect of acquisition performance is uncertainty regarding the outcome of the acquisition at the time of the announcement. According to Alvarez and Stenbacka (2006) an acquisition constitutes an irreversible investment which creates a real option with uncertainty regarding the post-acquisition implementation of the acquired resources. Such uncertainty is created when there is unpredictability concerning how well the target's corporate cultures and management structures can be absorbed into the acquiring firm (Alvarez & Stenbacka, 2006). As mentioned earlier, such issues are especially likely for fintech acquisitions. Drawing parallels from risk management, such uncertainty can also be further disentangled into uncertainty caused by a lack of knowledge, and uncertainty caused by inherent variability (Hoffman & Hammonds, 1994). Real option scholars also call these types of uncertainty micro-uncertainty and macro-uncertainty, where micro-uncertainty can be managed and decreased with optimal resource allocation, but macro-uncertainty cannot (Lint

& Pennings, 1999). From this, I surmise that experience in acquisitions may help decrease micro-uncertainty, while a baseline level of uncertainty will remain due to macro-uncertainty.

In the context of real options, the level of uncertainty also has implications on the value of the real option, therefore, possibly affecting abnormal returns around the announcement date, which can then affect how scholars measure acquisition performance. As cited in Lint & Pennings (1999), Black and Scholes (1973) and Merton (1973) show that higher uncertainty leads to a higher value of the option, which by extension means that acquisitions with higher uncertainty would have a higher real option value and therefore higher abnormal returns. In the context of experience, this means that as acquirors learn and gain experience from the post-acquisition integration process, they can decrease micro-uncertainty pertaining to the acquisition, which can in turn give the appearance of lower acquisition performance as the real option value at the time of the announcement is lower.

3. Data and methodology

3.1. Dataset and selection of the sample

To study the effect of experience on fintech acquisition performance, I use a sample of fintech acquisitions. Borrowing from the methodologies of Collevecchio, Cappa, Peruffo, & Oriani (2023) and Dranev, Frolova, & Ochirov (2019), I gather acquisition data from Refinitiv Eikon. I collect two sets of data: fintech acquisitions, and general acquisitions. I use the fintech acquisition data for the final analysis, and I use general acquisition data to create a *general experience* variable.

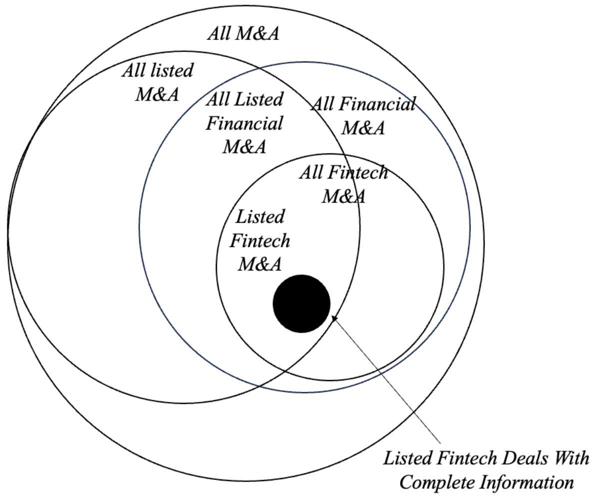
To select fintech deals, I use SIC industry codes. I do this by filtering deals from 2002 – 2023 with listed acquirors, with target SIC codes 7371 – 7374 (software companies), and with acquiror SIC codes between 6000 – 6999 (financial services providers). The rationale in using these filters is that financial services providers will acquire tech companies which create synergies with their value chain and are therefore related to the provision of financial services, which ultimately constitutes a fintech acquisition. Nevertheless, there is some risk in the SIC filters being too broad and introducing non-fintech acquisitions in the sample (Dranev, Frolova, & Ochirova, 2019).

To select general financial M&A deals, I use SIC industry codes as well. I do this by filtering deals from 2002 – 2023 with listed acquirors, and with acquiror SIC codes between 6000 – 6999 (financial services providers).

Finally, I merge the two databases, generating a final data set containing both general and fintech M&A deals.

3.2. Sample selection bias

Figure 1: A Venn diagram illustrating subsampling.



For the final analysis in this paper, I rely on a sample of fintech acquisitions. Because of this, I risk inducing bias arising from non-random sample selection, as firms may self-select into the fintech subsample due to unobserved characteristics, therefore creating a specific type of omitted variable bias (Certo, Busenbark, & Semadeni, 2016). I illustrate subsampling in Figure 1, which outlines that non-random sample selection can occur on multiple levels depending on which subsample of all M&A deals you choose to treat as the complete sample. In previous empirical work by Collevecchio et al. (2023), for example, the authors correct for sample selection bias relative to all bank M&A.

Another relevant source of sample selection bias could be non-random data-missingness (Certo, Busenbark, & Semadeni, 2016). This type of selection bias can occur when certain data, for example information on acquisition targets, cannot be obtained even for listed fintech M&A, resulting in certain acquisitions being discarded when running full specifications of regressions. Such missingness could be endogenous, as traits such as the acquiror having a higher market capitalization, a lower book-to-market ratio and an acquisition with higher abnormal returns could lead to the acquisition announcement receiving better media coverage, and by extension a higher probability of being detected by data collectors and appearing in an acquisition database like Refinitiv Eikon (Barnes, Harp, & Oler, 2014). Additionally, acquirors may choose to publicize announcements with higher abnormal returns more, making information regarding these deals more readily available, and leading to the same type of selection bias. This shows that there can also be more than one source for the same type of sample selection bias. Referring back to Figure 1, the examples mentioned above are just two of many possible sources of bias due to sub-sampling.

3.3. Variables and measures

3.3.1. Dependent variable

To study the effect of M&A activity on expected future performance, I use cumulative abnormal returns (CAR). The main idea of this variable is to estimate the effect of an exogenous shock on the stock price of a company using estimated market models which are calculated using benchmark indices (McWilliams & Siegel, 1997).

As per the methodology of McWilliams and Siegel (1997), first I estimate the rate of return of firm i on day t (R_{it}) as a result of the rate of return of a benchmark market index m on day t (R_{mt}) over a chosen, but more or less arbitrary estimation period, in this case 250 to 50 calendar days prior to the acquisition event:

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it}$$

In this paper, I use three different benchmark indices: the MSCI Global index as per the work of Collevecchio et al. (2023), MSCI Regional indices matched by acquiror region, and MSCI Country indices matched by acquiror country. I do this to ensure that results are robust to benchmark index selection.

Subsequently, I use the intercept (α_i) and stock beta (β_i) as well as the market returns (R_{mt}) to calculate the expected return (ER_{it}) of firm *i* on day *t* around the acquisition date using the following equation:

$$ER_{it} = \alpha_i + \beta_i * R_{mt}$$

After estimating the expected return on day *t*, I calculate the abnormal return on day *t* by subtracting the expected return from the actual return on day *t*, which then represents the exogeneous effect:

$$AR_{it} = R_{it} - ER_{it}$$

The abnormal returns are then accumulated around the date of the event according to a chosen window *(-n, m)* (Collevecchio, Cappa, Peruffo, & Oriani, 2023):

$$CAR_i = \sum_{-n}^{m} AR_i$$

I use multiple CAR windows in my analysis to ensure that my results are robust to subjective window selection. The windows I use are *(-2,+2)* as per the work of Collevecchio et al. (2023), *(-3, +3), (-1, 0), (-5, +5)* (Pinelli, Cappa, Peruffo, & Oriani, 2022), and (0, +5). An added benefit of using CARs instead of just abnormal returns is that it ensures that post-announcement shocks are captured even if there are errors in the Refinitiv Eikon acquisition database regarding the announcement date (Barnes, Harp, & Oler, 2014).

3.3.1.1. Data

To calculate the CAR for firm i, I use stock returns of firm i (R_{it}) and the returns of a benchmark market index m on day t (R_{mt}).

I obtain acquiror stock data from Refinitv Eikon from 2006 - 2023. Due to the 17-year window of analysis, I use acquiror datastream identifiers to mitigate the risk of stock tickers being reused by multiple firms in the sample.

As mentioned above, I use three different benchmark indices for a given firm i – a global benchmark index (MSCI Global), a regional benchmark index (MSCI Regional), and a country benchmark index (MSCI Country). Data for the MSCI Global, MSCI Regional and MSCI Country indices is obtained primarily from Refinitiv Eikon and iShares, with data for the S&P 500 index being obtained from Yahoo Finance. I show the full list of indices in Table 1, as well as selections of countries and regions used in this analysis.

Additionally, I apply filters to keep finite values for CARs, and I conduct data cleaning to remove acquisitions where any types of acquisitions are announced 5 days before or after a given announcement to ensure that abnormal returns from other acquisitions are not reflected in the CAR of the focal acquisition.

Table 1: List of benchmark indices used when calculating CARs.

Benchmark Measure	Country or Region	Index	Source
MSCI Global	Global	ISHARES MSCI WORLD UCITS ETF USD (DIST)	Refinitiv Eikon
MSCI Reginal	East Asia & Pacific	ISHARES MSCI PACIFIC EX JAPAN ETF	Refinitiv Eikon
MSCI Reginal	Europe & Central Asia	SPDR MSCI EUROPE UCITS ETF	Refinitiv Eikon
MSCI Reginal	Latin America & Caribbean	LYXOR MSCI EM LATIN AMERICA UCITS ETF - ACC	Refinitiv Eikon
MSCI Reginal	Middle East & North Africa	XTRACKERS MSCI EM (MIL) EU.MDE.& AF.ESG UCITS ET	Refinitiv Eikon
MSCI Reginal	North America	S&P 500 INDEX	Yahoo Finance
MSCI Reginal	South Asia	LYXOR MSCI INDIA UCITS ETF ACC (EUR)	Refinitiv Eikon
MSCI Reginal	Sub-Saharan Africa	ISHARES MSCI SOUTH AFRICA ETF	Refinitiv Eikon
MSCI Country	Australia	iShares MSCI Australia ETF	iShares
MSCI Country	Austria	iShares MSCI Austria ETF	iShares
MSCI Country	Belgium	iShares MSCI Belgium ETF	iShares
MSCI Country	Brazil	iShares MSCI Brazil ETF	iShares
MSCI Country	Canada	iShares MSCI Canada ETF	iShares
MSCI Country	China	iShares MSCI China ETF	iShares
MSCI Country	France	iShares MSCI France ETF	iShares
MSCI Country	Germany	iShares MSCI Germany ETF	iShares
MSCI Country	Hong Kong	iShares MSCI Hong Kong ETF	iShares
MSCI Country	Indonesia	iShares MSCI Indonesia ETF	iShares
MSCI Country	Ireland	iShares MSCI Ireland ETF	iShares
MSCI Country	Israel	iShares MSCI Israel ETF	iShares
MSCI Country	Italy	iShares MSCI Italy ETF	iShares
MSCI Country	Japan	iShares MSCI Japan ETF	iShares
MSCI Country	Malaysia	iShares MSCI Malaysia ETF	iShares
MSCI Country	Netherlands	iShares MSCI Netherlands ETF	iShares
MSCI Country	New Zealand	iShares MSCI New Zealand ETF	iShares
MSCI Country	Philippines	iShares MSCI Philippines ETF	iShares
MSCI Country	Poland	iShares MSCI Poland ETF	iShares
MSCI Country	Qatar	iShares MSCI Qatar ETF	iShares
MSCI Country	Saudi Arabia	iShares MSCI Saudi Arabia ETF	iShares
MSCI Country	Singapore	iShares MSCI Singapore ETF	iShares
MSCI Country	South Africa	iShares MSCI South Africa ETF	iShares
MSCI Country	South Korea	iShares MSCI South Korea ETF	iShares
MSCI Country	Spain	iShares MSCI Spain ETF	iShares
MSCI Country	Sweden	iShares MSCI Sweden ETF	iShares
MSCI Country	Switzerland	iShares MSCI Switzerland ETF	iShares
MSCI Country	Thailand	iShares MSCI Thailand ETF	iShares
MSCI Country	Turkey	iShares MSCI Turkey ETF	iShares
MSCI Country	UK	iShares Core FTSE 100 UCITS ETF	iShares
MSCI Country	United States	S&P 500 INDEX	Yahoo Finance

Note: Since benchmark data for all countries in the sample of fintech acquisitions is not available, CARs calculated using the MSCI Country estimates have fewer observations than when using MSCI Regional and Global benchmarks. Therefore, the list of countries in this table does not contain all countries in the dataset. A full list of sources with references for non-Refinitiv Eikon benchmarks is available in Appendix A.

3.3.2. Independent variables

To test the second and third hypotheses, I create two indicators of firm acquisition experience based on acquisition types. I use a rolling window of 5 years (Collevecchio, Cappa, Peruffo, & Oriani, 2023) before the time of the acquisition due to two main reasons. First, organization memory is not perfect, and relatively recent acquisitions may be more impactful than acquisitions made more than 5 years ago (Haleblian & Finkelstein, 1999), and even if experience from older acquisitions is retained within the organization, it becomes harder to generalize (Haleblian, Kim, & Rajagopalan, 2006) due to changing market trends, which is likely to be especially important for fintech M&A. The second reason is data missingness. I create the experience variables according to how many times a given company appears in the acquisition data set. Therefore, any acquisitions that are not in the data set are not reflected in the experience variables. This creates a problem, as firms with long histories (which banks are likely to be, constituting a significant portion of this sample) will be disadvantaged in this regard, as I am not able to measure experience before 2002. I am, however, able to accurately capture recent experience in a 5-year rolling window. Because of this, I gather acquisition data starting from 2002 – 2006, which I use for the creation of experience variables for acquisitions in 2007 and onwards.

3.3.2.1. General and fintech experience

I create the variables *general experience* and *fintech experience* with the same methodologies, but with different conditions. The variable *general experience* reflects how many times a given acquiror (as identified by the datastream identifier) completes non-fintech, majority acquisitions in the 5 years before the announcement, whereas the variable *fintech experience* reflects how many times a given acquiror completes fintech, majority acquisitions in the 5 years before the announcement. The final obtained values for these variables indicate the number of completed acquisitions fitting the criteria of interest.

3.3.3. Controls

I control for *acquisition rate variability* by measuring the standard deviation of average yearly acquisition numbers over a period of 5 years prior to the acquisition (Laamanen & Keil, 2008). This can be an important moderator for how well experience is expected to be utilized, as this measure can give additional information on internal firm structures related to M&A activity. For example, a large variance in acquisition rates may lead to excess strain in the acquiring firm, perhaps forcing the firm to engage in tradeoffs between managing their existing activities or properly integrating knowledge from completed acquisitions. A consistent rate may instead imply that a firm has frameworks in place to avoid excess strain, and that sufficient resources for M&A planning and completion are available (Laamanen & Keil, 2008).

Additionally, I control for *cross-border* acquisitions with a dummy variable as it is often done in existing literature (Laamanen & Keil, 2008). Out of a sample of 1,395 fintech acquisitions 29% took place across borders. In addition to that, a significant portion of those were cross-regional as well, showing that international M&A deals are popular in the scope of fintech. To further account for cross-country heterogeneity, I include *institutional differences* (Collevecchio, Cappa, Peruffo, & Oriani, 2023), as institutional differences between countries may prove to be significant barriers in fintech integration after an acquisition. I measure institutional differences between countries by using Worldwide Governance Indicators (WGI) and obtaining the absolute difference between the score of a target nation and the acquiror nation (Pinelli, Cappa, Peruffo, & Oriani, 2022). As per the work of Collevecchio et al. (2023) and Pinelli et al. (2022) I use the first dimension, voice and accountability, of the WGI to calculate a value for the institutional differences for each acquisition using specific years and countries. Data for years 2022 and 2023 is not available, and therefore values from 2021 are used for 2022 and 2023 as country scores are stable over time. The scores from the WGI unobserved components model range from -2.5 to 2.5 units of a standard normal distribution, with a higher score indicating better governance (Worldwide Governance Indicators, 2023). Therefore, the maximum attainable value for the *institutional differences* variable is 5, indicating very large institutional differences, and the minimum value is 0, indicating no differences in institutional quality. I obtain data for *institutional differences* from the WGI website (Collevecchio, Cappa, Peruffo, & Oriani, 2023; Worldwide Governance Indicators, 2023).

I also control for cases where the focal acquisition is a *minority* acquisition by using a dummy variable with values of 0 or 1. As shown by Collevecchio, Cappa, Peruffo, and Oriani (2023), minority fintech acquisitions positively impacted the expected performance of acquiring banks, as there may be more flexibility in target integration in the post-acquisition period (Spencer, Akhigbe, & Madura, 1998).

As for acquiror characteristics, I control for acquiror size which I proxy for by using the natural log of *total assets* in USD, as acquisition implications may differ depending on acquiror size (Collevecchio, Cappa, Peruffo, & Oriani, 2023). The *share of cash* on the balance sheet can also serve as a general indicator for acquiror risk, as large cash buffers may protect firms from financial difficulty and provide more flexibility in post-acquisition integration[1]. I calculate this variable by dividing the acquiror's balance sheet cash by their total assets. This variable ranges from 0 to 1, as values above 1 or below 0 are impossible to achieve – requiring either negative cash on the balance sheet, or total assets being smaller than cash on the balance sheet. To control for cases where the acquiring company is perceived to be *distressed* (with negative net income in the 12 months before the acquisition announcement) I include a dummy variable indicating negative net income. For firms that are struggling, the increased uncertainty

[1] In their paper, Collevecchio et al. (2023) use the stock beta to proxy for firm risk, but they do not find it to be a significant predictor of acquisition performance.

and strategic gains from acquiring fintech companies may be especially pronounced, therefore possibly generating higher abnormal returns than firms with positive recent performance. Conversely, however, recent negative income as a result of poor managerial performance may instead lead to negative returns. This is possible, as some fintech acquisitions may be completed just because managers want to try to do something to improve performance, which may lead to poorly executed acquisitions (Morck, Shleifer, & Vishny, 1990).

In fintech research, fintech deals are often filtered by acquiring firms being banks (Collevecchio, Cappa, Peruffo, & Oriani, 2023). I therefore include a dummy variable for when *acquirors are banks* to control for differences between banks and other acquiror industries by using acquiror SIC codes between 6011 and 6099. This is, therefore, a dummy variable with values of 0 or 1, indicating whether the acquiror is a bank as indicated by SIC industry codes.

I also include a dummy variable indicating whether the last completed fintech acquisition generated positive or negative abnormal returns to further control for the internal ability of firms to select targets and integrate the acquired technology successfully. Additionally, Hayward (2002) finds that low recent negative returns from acquisitions lead to improved performance of the focal acquisition, further outlining the salience of recent acquisition performance in the context of acquisition experience.

I include the *deal size as a share of total assets* for the acquiring firm, as relatively larger deals may have a more significant impact on the firm's operations. This is because larger deals can amplify both risks and possible rewards, as there is typically more complexity involved (Alexandridis, Fuller, Terhaar, & Travlos, 2012). I obtain this variable by dividing the deal value by the acquiror's total assets which outputs a value ranging from 0 to 1.

I also include the *years since the last completed majority acquisition* as a covariate to control for M&A related structures within the firm, as large gaps between acquisitions may signal that some fintech or general acquisition competency has deteriorated, whereas shorter gaps may indicate that a firm has not had enough time to internalize knowledge from previous acquisitions, which may also be detrimental to acquisition performance (Hayward, 2002). This variable is also split by general and fintech acquisitions, as experience and M&A structures differ for the two types. The resulting values for these variables are years after the last acquisition.

To control for differences between targets I include categorical dummy variables indicating the *public status of the target* - whether the target is private, public or a subsidiary. As for any possible within-fintech industry differences, I include a categorical variable controlling for the *fintech target industry* by using the target SIC code. The fintech industries are as follows: computer integrated systems design, computer programming services, data processing services of prepackaged software. These variables operate like status and industry fixed effects as each value of the categorical variable except the reference category receives a dummy variable estimate[2].

Since for the main analysis I use data from 2007-2023, companies will go through various business cycles and global events, the effects of which can be captured with year fixed effects. Additionally, I use region fixed effects to control for unobserved regional differences. Each year and acquiror region except the reference categories receives an estimate.

3.4. Descriptive statistics

Table 2: Descriptive statistics

Variable	N	Mean	St. Dev.	Min	Max
MSCI Country CAR (-2, +2)	26,092	0.008	0.119	-3.043	7.963
MSCI Global CAR (-2, +2)	35,218	0.007	0.113	-3.095	7.964
MSCI Regional CAR (-2, +2)	34,578	0.007	0.113	-3.046	7.963
Fintech Experience	36,590	0.221	0.813	0	12
General Experience	36,590	7.763	18.324	0	182
Acquiror Bank	36,590	0.210	0.407	0	1
Acquisition Rate Variability	36,590	1.836	1.896	0.000	16.084
Cross Border	36,590	0.294	0.456	0	1
Deal Value Share	19,971	0.074	0.140	0.000	1.000
Distressed Acquiror	36,590	0.178	0.383	0	1
Fintech Dummy	36,590	0.038	0.192	0	1
Institutional Differences	35,438	0.165	0.447	0.000	3.390
Minority	36,590	0.071	0.256	0	1
Negative Recent Fintech CAR	680	0.493	0.500	0	1
Share Intangible	35,320	0.077	0.163	0.000	1.000
Share of Cash	34,996	0.130	0.202	0.000	1.000
Total Assets (thousands, USD)	36,590	88,781.680	344,444.600	0.000	5,524,492.000
Year Gap Fintech	5,145	2.957	3.433	0.003	20.055
Year Gap General	29,771	1.493	2.218	0.003	19.847

Note: Descriptive statistics for the entire sample of 36,590 financial acquisitions from 2007 – 2023. This includes 1,395 fintech acquisitions, and 35,195 general financial acquisitions.

In Table 2 I obtain descriptive statistics for the entire sample of 36,590 acquisitions. From this table, we can note whether certain variables have possible outliers by looking at

[2] I consider controlling for *target age* as younger companies have more opportunity for growth and therefore more value (Collevecchio, Cappa, Peruffo, & Oriani, 2023) and the *target being distressed* as a target could possess mismanaged valuable assets, an offer for which would be hard to resist (Bruton, Oviatt, & White, 1994). Additionally, distressed targets could possibly be acquired at a discount, generating higher returns for the acquiror (Meier & Servaes, 2014). I do not include these variables in the final analysis, as these variables show quite severe data missingness and decrease available observations from 219 to only 65, which can be seen in Table 9.

minimums, maximums, means and standard deviations. For example, the variable *general experience* has a maximum of 182, indicating that there is a firm which has completed 182 general majority acquisitions in five years before the focal date. I verify that there are relatively few such acquisitions, only 16 out of 1,395 acquisitions with more than 50 completed prior general acquisitions. Because of many legitimate values of 0 for general experience, however, I do not use logs, as it would remove 372 observations. For total assets however, logs are necessary as there is a very large range of values with a long tail, and using logs does achieve a normal distribution in values. Additionally, total assets of 0 are removed due to other filters, as variables such as *share of cash* output infinite values when dividing by total assets of 0.

For the control variables with expected ranges of 0 to 1 - *deal value share,* and *share of cash,* and for the exclusion term *share intangibles* I also remove values below 0 and above 1, as values outside those ranges are normally impossible. This removes 902 out of 20,873 observations for *deal value share,* 4 observations out of 35,000 for *share of cash,* and 38 out of 34,211 observations for *share intangibles.*

In Table 3 I split the sample by fintech and general M&A to see how the two types of acquisitions compare. The most notable differences between the two sub-samples are that 24.5% of fintech acquirors had negative net income prior to the acquisition announcement, compared to only 17.5% of general financial M&A. On average, the fintech subsample also had 0.85 completed fintech M&A deals in the 5 years prior to the announcement, compared to only 0.20 for general financial M&A. Conversely, the general M&A subsample had 7.8 completed general financial M&A deals in the 5 years prior to the focal announcement, compared to 5.8 for the fintech subsample. Regardless, both subsamples appear to have more experience doing general financial M&A. The fintech subsample also holds more cash on the balance sheet at the time of the acquisition at 21.3%, compared to 12.7% for general financial M&A, showing that fintech acquisitions may have more of a cash buffer prepared prior to acquisitions. To already give an idea about the first hypothesis, it appears that CARs for the fintech sample are positive, indicating that on average fintech acquisitions are value enhancing.

Table 3: Descriptive statistics split by fintech and general acquisitions.

Variable (0 = General, 1 = Fintech)	N	Mean	St. Dev.	Min	Max
MSCI Country CAR (-2, +2) | 0	24,974	0.008	0.119	-3.043	7.963
MSCI Country CAR (-2, +2) | 1	1,118	0.007	0.119	-2.177	0.959
MSCI Global CAR (-2, +2) | 0	33,864	0.007	0.112	-3.095	7.964
MSCI Global CAR (-2, +2) | 1	1,354	0.008	0.115	-2.182	0.961
MSCI Regional CAR (-2, +2) | 0	33,231	0.007	0.112	-3.046	7.963
MSCI Regional CAR (-2, +2) | 1	1,347	0.009	0.115	-2.176	0.959
Fintech Experience | 0	35,195	0.196	0.763	0	12
Fintech Experience | 1	1,395	0.853	1.492	0	11
General Experience | 0	35,195	7.840	18.490	0	182
General Experience | 1	1,395	5.822	13.324	0	181
Acquiror Bank | 0	35,195	0.208	0.406	0	1
Acquiror Bank | 1	1,395	0.257	0.437	0	1
Acquisition Rate Variability | 0	35,195	1.843	1.904	0.000	16.084
Acquisition Rate Variability | 1	1,395	1.670	1.657	0.000	13.535
Cross Border | 0	35,195	0.294	0.456	0	1
Cross Border | 1	1,395	0.287	0.452	0	1
Deal Value Share | 0	19,356	0.074	0.140	0.000	1.000
Deal Value Share | 1	615	0.075	0.146	0.000	0.992
Distressed Acquiror | 0	35,195	0.175	0.380	0	1
Distressed Acquiror | 1	1,395	0.245	0.430	0	1
Institutional Differences | 0	34,053	0.165	0.447	0.000	3.390
Institutional Differences | 1	1,385	0.174	0.456	0.000	3.130
Minority Flag | 0	35,195	0.071	0.257	0	1
Minority Flag | 1	1,395	0.051	0.220	0	1
Recent Negative Fintech CAR | 1	680	0.493	0.500	0	1
Share Intangible Less Goodwill | 0	33,965	0.075	0.160	0.000	1.000
Share Intangible Less Goodwill | 1	1,355	0.138	0.216	0.000	0.986
Share of Cash | 0	33,659	0.127	0.199	0.000	1.000
Share of Cash | 1	1,337	0.213	0.249	0.000	1.000
Total Assets (thousands, USD) | 0	35,195	87,014.190	340,052.600	0.000	5,524,492.000
Total Assets (thousands, USD) | 1	1,395	133,374.400	438,814.200	0.000	3,841,314.000
Year Gap Fintech | 0	4,506	3.032	3.455	0.003	20.055
Year Gap Fintech | 1	639	2.428	3.226	0.003	18.530
Year Gap General | 0	28,664	1.489	2.215	0.003	19.847
Year Gap General | 1	1,107	1.585	2.315	0.003	18.768

Table 4: Correlation matrix for the fintech subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
MSCI Global CAR (-2, +2) (1)	1																	
MSCI Regional CAR (-2, +2) (2)	0.973	1																
MSCI Country CAR (-2, +2) (3)	0.936	0.957	1															
Share Intangible (4)	0.038	0.031	0.036	1														
General Experience (5)	-0.095	-0.060	-0.073	-0.115	1													
Fintech Experience (6)	0.040	0.039	0.019	-0.048	0.259	1												
Acquisition Rate Variability (7)	-0.036	-0.003	-0.034	-0.214	0.666	0.204	1											
Cross Border (8)	-0.060	-0.063	-0.098	0.268	0.186	0.011	0.013	1										
Institutional Differences (9)	-0.022	-0.036	-0.043	0.130	0.282	0.021	0.099	0.732	1									
Minority (10)	0.031	0.029	0.030	0.125	0.051	-0.075	-0.035	-0.039	-0.027	1								
Total Assets (11)	-0.055	-0.024	-0.021	-0.170	0.175	0.062	0.089	0.089	0.079	-0.074	1							
Share of Cash (12)	0.095	0.080	0.085	-0.204	-0.149	0.143	-0.091	-0.225	-0.098	-0.068	-0.202	1						
Distressed Acquiror (13)	-0.020	-0.024	-0.032	0.009	-0.117	-0.137	-0.099	-0.014	-0.068	-0.103	-0.125	0.027	1					
Acquiror Bank (14)	0.032	0.062	0.072	0.209	-0.153	0.040	-0.162	0.087	0.120	-0.005	0.206	-0.052	-0.033	1				
Negative Recent Fintech CAR (15)	0.062	0.037	0.054	-0.014	0.083	-0.008	0.047	-0.023	0.070	-0.017	0.112	0.007	-0.125	-0.083	1			
Deal Value Share (16)	0.069	0.057	0.050	0.292	-0.077	0.031	-0.035	0.088	-0.012	0.022	-0.128	-0.012	0.108	0.041	-0.021	1		
Year Gap Fintech (17)	0.012	0.022	0.047	0.046	-0.082	-0.462	-0.152	0.021	-0.068	0.074	-0.005	-0.089	0.100	0.077	-0.035	-0.094	1	
Year Gap General (18)	0.075	0.038	0.063	0.161	-0.278	-0.124	-0.315	-0.025	0.074	0.028	-0.131	0.025	-0.053	0.165	-0.051	0.076	0.166	1

Note: To calculate the correlations for all variables in the matrix, all incomplete observations are removed. This leaves 219 fintech deals with complete information.

In Table 4 I show a correlation matrix to help establish basic relations between variables of interest in the fintech subsample. From this table, I note that there appears to be a negative correlation between general experience and CARs, whereas higher fintech experience is correlated with higher CARs, therefore giving initial support for the third hypothesis, while going against the second hypothesis. We can also notice that correlations between all measures of CARs and explanatory variables are of the same direction and of a similar magnitude. From this table, we can see that CARs have positive correlations with minority acquisitions, larger shares of cash on the balance sheet, acquirors being banks, recent negative fintech CARs, larger deal values and larger gaps between both the focal fintech acquisition and the last fintech and general acquisitions. There are preliminary negative relations between CARs and cross-border acquisitions, higher institutional differences, larger total assets, and the acquirors being distressed.

3.5. Methodology

To combat sample selection bias outlined in Section 3.2, I use the Heckman two-step estimation procedure as per the work of Collevecchio et al. (2023) and others.

3.5.1. Two-step Heckman model

The usage of Heckman models has been increasing in popularity in the last 15 years as an effective way to combat selection bias (Certo, Busenbark, & Semadeni, 2016). The intuition lies in modelling the probability of appearing in the selected sample in the first stage, and then modelling the relations between variables of interest and the dependent variable in the second stage (Certo, Busenbark, & Semadeni, 2016). In this case I model the probability of an acquisition appearing in the fintech subsample in the first stage, and the effect of acquisition experience on performance in the second stage.

3.5.2. The Probit first stage

To model the probability of an acquisition appearing in the fintech sample, I must select a reference sample from Figure 1. I then treat this sample as the overall population from which fintech deals are "selected" in a non-random way. In existing literature by Collevecchio et al. (2023), the authors treat the overall population of acquisitions as all acquisitions announced by banks, whereas their selected sample consists of fintech acquisitions announced by banks. I employ the same methodology, and by extension, use the overall sample of listed financial M&A as the overall population, and listed fintech M&A as the sub-sample of interest.

To model the first stage, an exclusion restriction term which does not influence the dependent variable of the second stage is necessary (Certo, Busenbark, & Semadeni, 2016). In the paper by Collevecchio et al. (2023) the authors use the acquiror's intangible assets as a share of total assets as their exclusion restriction, arguing that the share of intangible assets can serve as a proxy for a given firm's innovation activities. For example, technology-based assets such as patented and unpatented technology, databases and trade secrets are valued as intangible assets (Mard, Hitchner, & Hyden, 2007). Therefore, the share of intangible assets can be a good indicator of a firm's willingness to engage in knowledge-intensive acquisitions[3].

As per the suggestions of Certo et al. (2016), I verify with a correlation matrix in Table 4 that there are near-zero correlations ranging from 3.1 to 3.8 percent between the dependent variables in the second stage and the exclusion term (share of intangible assets).

Borrowing from Certo et al. (2016) I show the specification for the Probit first stage in Equation 1:

$$d_i = a + \beta_1 z_i + \beta_2 x_{1i} + \beta_3 x_{2i} + \beta_n w_{ni} + u_i \tag{1}$$

[3] Additionally, I consider subtracting balance sheet *goodwill* from *intangible assets* to attempt to more accurately proxy for firm innovation efforts. I reason that goodwill is generated as a result of a difference in the book value of assets of the acquisition target and the fair value paid by the acquiror. Goodwill therefore contains the value of expected synergies which are unique to each acquisition (Mard, Hitchner, & Hyden, 2007), and can therefore differ between different types of acquisitions as well. Technology-based intangible assets such as patented and unpatented technology, databases and trade secrets, however, meet the separability condition and as such, are valued as intangible assets (Mard, Hitchner, & Hyden, 2007), which more closely represent firm innovation efforts. I test for exclusion restriction strength by using first stage correlations of the independent variables of interest (x_{1i}, x_{2i}), and the Inverse Mills Ratio. These correlations, however, are lower when using *intangible assets less goodwill*, and therefore do not show that intangible assets less goodwill is a better exclusion restriction. First stage specifications using *intangible assets less goodwill* can be seen in Appendices C and D.

In Equation 1, (d_i) denotes the selection parameter, the dummy variable indicating whether observation (i) is in the fintech subsample. The selection parameter is then modelled using 3 groups of variables: (z_i) being the exclusion restriction *share of intangible assets*, (x_{1i}, x_{2i}) being the independent variables of interest *fintech* and *general experience* respectively, and (w_{ni}) denoting a group of acquiror and target control variables which are relevant in predicting the probability of observation (i) appearing in the sample as identified by selection parameter (d_i). Finally, there is the constant (a) and the first stage error term (u_i).

3.5.3. The OLS second stage

The OLS second stage of the two-step Heckman estimation operates much like a regular OLS estimation. In the second stage I model the effect of the main independent variables, *fintech* and *general experience*, on the dependent variable, CARs, with various control variables to account for deal, acquiror and target characteristics. I show the second stage OLS specification in Equation 2:

$$y_i = a + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_n w_{ni} + \beta_m v_{mi} + e_i \tag{2}$$

In Equation 2, (y_i) denotes the dependent variable of interest CAR for acquisition (i). Just like for the first stage (x_{1i}, x_{2i}) denote the independent variables of interest *fintech* and *general experience.* Variable group (w_{ni}) denote a group of (n) number of acquiror and target control variables which are relevant in predicting the probability of observation appearing in the fintech subsample, as well as being relevant predictors of acquisition performance. Variable group (v_{mi}) denote a group of (m) number of additional acquiror, target and acquisition level control variables which are more relevant for predicting acquisition performance. Once again, (a) denotes the constant term, while (e_i) denotes the second stage error term.

3.5.4. Validity

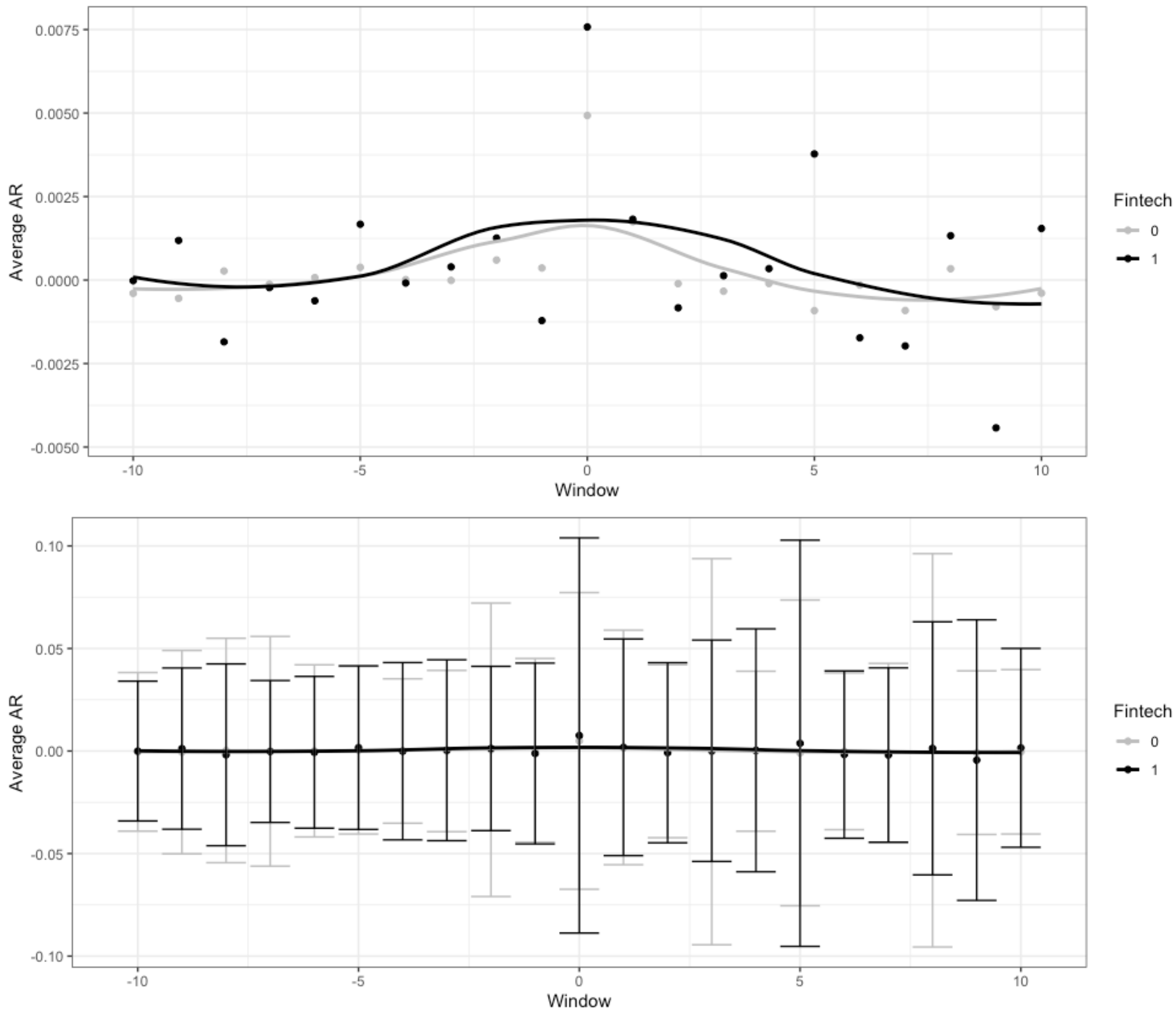
To confirm that there is sample selection bias and applying Heckman is justified, independent variables of interest (x_{1i}, x_{2i}) need to be significant predictors in the first stage in Equation 1, and that there must be a significant correlation between the error terms (u_i) and (e_i) (Certo, Busenbark, & Semadeni, 2016). To verify that the Heckman estimation is applied correctly with respect to the exclusion restriction, I use the correlation between the independent variables of interest (x_{1i}, x_{2i}) and the inverse mills ratio in the first stage (Certo, Busenbark, & Semadeni, 2016).

4. Results

4.1. H1: Fintech acquisitions lead to improved expected performance for the acquiror

To begin testing the first hypothesis that fintech M&A activity leads to improved expected firm performance, I look at whether abnormal returns around the focal date are positive or negative. Additionally, this gives insight on CAR window selection.

Figure 2: Average abnormal returns before and after the announcement date.



Note: Average abnormal returns plotted 10 days before and 10 days after the acquisition date split by a fintech acquisition indicator. The x-axis indicates the day before or after the announcement date, day 0 indicating the focal date. The y-axis shows the level of average abnormal returns. I include error bars in the second figure to show the standard deviation of abnormal returns on each day. For reference and comparison, I include non-fintech abnormal returns as well.

From Figure 2, there are a few extraordinary values for average abnormal returns - on day 0 (0.75 percentage points), day 5 (0.37 percentage points) and day 9 (-0.44 percentage points). On all the other days around the focal date, abnormal returns appear to hover in the -0.12 to 0.12 percentage point range. In the second graph in Figure 2 I include the standard deviation of abnormal returns. Here we see that the variation in returns is not constant over time with the focal date and day 5 after the acquisition showing the highest variation in abnormal returns. The post-announcement period also appears more volatile in general, as the standard deviation of abnormal returns in the 10 post-announcement days is 5.8% (5.3% if we exclude day 5), compared to 4.0% in the pre-announcement period. This shows that there is more uncertainty on the focal date and in the post-announcement period because of an acquisition announcement. Additionally, the standard deviation in general is much larger than mean, therefore I employ t-tests in to verify if they are statistically significantly different from zero.

I run such t-tests in Table 5, and I include 5 different CAR windows to maintain robustness with respect to window selection. Additionally, I include three different benchmark index selections to compare results and capture abnormal returns as accurately as possible.

Table 5: T-tests to test whether mean abnormal returns are statistically significantly different from zero.

Variable	Mean Estimate	p - value	Observations	Confidence Low	Confidence High
CAR (-2, +2) MSCI Global	0.009	0.015	1145	0.002	0.016
CAR (-1, 0) MSCI Global	0.006	0.066	1131	0.000	0.012
CAR (-3, +3) MSCI Global	0.008	0.038	1145	0.000	0.016
CAR (-5, +5) MSCI Global	0.013	0.017	1145	0.002	0.023
CAR (0, +5) MSCI Global	0.013	0.007	1145	0.004	0.022
CAR (-2, +2) | MSCI Regional	0.009	0.009	1138	0.002	0.016
CAR (-1, 0) | MSCI Regional	0.006	0.055	1124	0.000	0.013
CAR (-3, +3) | MSCI Regional	0.010	0.014	1138	0.002	0.017
CAR (-5, +5) | MSCI Regional	0.014	0.007	1138	0.004	0.024
CAR (0, +5) | MSCI Regional	0.013	0.005	1138	0.004	0.023
CAR (-1, 0) | MSCI Country	0.005	0.172	914	-0.002	0.013
CAR (-2, +2) | MSCI Country	0.007	0.086	938	-0.001	0.015
CAR (-3, +3) | MSCI Country	0.000	0.961	938	-0.006	0.006
CAR (0, +5) | MSCI Country	0.005	0.240	938	-0.004	0.015
CAR (-5, +5) | MSCI Country	0.006	0.233	938	-0.004	0.016

Note: I choose windows of (-2, +2), (-1, 0), (-3, +3), (-5, +5), and (0, +5) as indicated in Section 3.3.1, and Figure 2. As mentioned in Table 1, CARs calculated using the MSCI Country indices have fewer observations due to not all countries in the dataset having a dedicated stock exchange and benchmark index.

As can be seen in Table 5, depending on the measure there is quite a lot of variation in average CARs, as means range from 0.0 percentage points to 1.4 percentage points. Using the t-tests however, most specifications yield results which are statistically significantly different from zero and positive. For country specific (-1, 0), (-3, +3), (0, +5), and (-5, +5) window estimates, however, the means are not statistically significantly different from zero.

The results also appear to be very similar when using the MSCI Global and MSCI Regional benchmark indices, however, the means are noticeably lower when using MSCI Country benchmarks. This could be because the MSCI Country index is more relevant for a given company, therefore meaning that the stock price of a given company will exhibit a higher correlation with the MSCI Country benchmark than MSCI Regional or Global benchmarks resulting in lower abnormal returns. This is likely as the highest average 25-day rolling correlation for a given stock is calculated for the MSCI Country index (34%) compared to the MSCI Regional index (26%) and the MSCI Global index (18%) (for more information, please see Appendix B).

Based on these results, there is evidence that CARs caused by fintech acquisition announcements are statistically significant and positive, indicating that fintech acquisitions in general are seen as value-enhancing, therefore confirming the first hypothesis.

4.2. H2: Additional general experience improves fintech acquisition performance.

To estimate the effects of acquisition experience on performance, I run a two-step Heckman estimation in Tables 6 and 7.

Table 6: First stage of the two-step Heckman estimation.

	Dependent variable:
	Fintech Dummy
Share Intangible	0.878***
	(0.132)
General Experience	-0.015***
	(0.004)
Fintech Experience	0.298***
	(0.017)
Ln(Total Assets)	-0.003
	(0.011)
Balance Sheet Cash Share	0.574***
	(0.129)
Distressed Acquiror	-0.018
	(0.078)
Bank	0.146*
	(0.077)
Constant	-3.431***
	(0.303)
Target Status	Yes
Acquiror Region	Yes
Year Fixed Effects	Yes
Observations	33,266
Log Likelihood	-1,042.633
chi^2	551.460*** (df = 28)

*p<0.1; **p<0.05; ***p<0.01

Note: As per the suggestion of Certo et al. (2016) I also calculate the correlations between the independent variables of interest (*fintech* and *general experience*) and the Inverse Mills Ratio to verify the strength of the exclusion restriction. I find correlation values of 0.36 and 0.32 respectively, which indicates that the exclusion restriction is relevant. In their paper Certo et al. (2016) report values of 0.44 for a medium exclusion restriction, and 0.31 for a strong exclusion restriction, however, they do not provide specific thresholds for when an exclusion restriction can be considered strong, as it depends on various factors. Coefficients for year fixed effects, acquiror regions and target status are truncated to save space. I use Equation 1 from Section 3.5.2 for the specification of the first stage.

I show first stage of the Two-Step Heckman estimation in Table 6. I find that the effect of the *share of intangible assets* is statistically significant, as an increase in the *share of intangible assets* of a given firm predicts an increase in the probability of self-selecting into the fintech sub-sample. Additionally, the magnitude of the exclusion restriction appears to be non-negligible. This means that the exclusion restriction is both relevant and strong. The coefficient for *general experience* is statistically significant and negative meaning that more *general experience* has a small negative and statistically significant effect on the probability of a firm self-selecting into the fintech sample.

Table 7: The second stage of the two-step Heckman estimation.

	Dependent variable: MSCI Global				
	CAR (-2, +2)	CAR (-3, +3)	CAR (-1, 0)	CAR (-5, +5)	CAR (0, +5)
	(1)	(2)	(3)	(4)	(5)
General Experience	0.0001	0.0004	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fintech Experience	-0.007	-0.007	-0.015*	-0.034**	-0.025**
	(0.010)	(0.011)	(0.008)	(0.016)	(0.011)
Acquisition Rate Variability	0.002	0.001	0.002	0.005	0.004
	(0.004)	(0.004)	(0.002)	(0.005)	(0.004)
Cross Border	-0.005	-0.009	-0.016	-0.013	-0.002
	(0.016)	(0.018)	(0.011)	(0.024)	(0.015)
Institutional Differences	-0.004	0.009	0.004	0.001	-0.007
	(0.021)	(0.024)	(0.015)	(0.032)	(0.020)
Minority	0.006	0.007	0.005	0.008	-0.008
	(0.016)	(0.018)	(0.011)	(0.024)	(0.015)
Ln(Total Assets)	-0.00000	-0.0003	0.003**	0.006**	0.004*
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Balance Sheet Cash Share	-0.018	-0.039	-0.003	-0.035	-0.002
	(0.028)	(0.032)	(0.021)	(0.046)	(0.029)
Distressed Acquiror	0.007	0.026*	0.011	0.034	0.014
	(0.013)	(0.015)	(0.010)	(0.022)	(0.014)
Bank	-0.009	-0.013	-0.019*	-0.038*	-0.022
	(0.013)	(0.015)	(0.010)	(0.022)	(0.014)
Recent Negative Fintech CAR	0.020**	0.028***	0.012*	0.018	0.010
	(0.009)	(0.010)	(0.006)	(0.014)	(0.009)
Deal Value Share	0.007***	0.007***	0.007***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year Gap Fintech	0.003	0.004*	0.001	0.002	-0.001
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Year Gap General	0.003	0.001	0.003	0.004	0.003
	(0.004)	(0.004)	(0.002)	(0.005)	(0.003)

Public Target	-0.001	0.004	-0.010	-0.009	0.005
	(0.014)	(0.016)	(0.010)	(0.023)	(0.015)
Subsidiary Target	0.001	-0.001	0.007	0.023	0.017
	(0.014)	(0.015)	(0.010)	(0.022)	(0.014)
Target Computer Programming Services	0.035	0.027	0.035**	0.034	0.009
	(0.025)	(0.028)	(0.018)	(0.038)	(0.024)
Target Data Processing Services	0.044*	0.047	0.041**	0.042	0.024
	(0.026)	(0.029)	(0.018)	(0.039)	(0.025)
Target Prepackaged Software	0.036	0.032	0.028*	0.033	0.009
	(0.023)	(0.025)	(0.016)	(0.034)	(0.022)
Acquiror Emerging Markets	0.005	0.030	0.013	0.012	0.005
	(0.026)	(0.029)	(0.019)	(0.043)	(0.027)
Acquiror Europe Central Asia	0.002	-0.001	0.016	0.015	0.015
	(0.013)	(0.015)	(0.010)	(0.021)	(0.014)
Acquiror North America	-0.008	-0.011	0.009	-0.008	0.006
	(0.013)	(0.015)	(0.010)	(0.022)	(0.015)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	0.125	0.203	0.227**	0.454**	0.194
	(0.146)	(0.163)	(0.107)	(0.230)	(0.148)
Observations	33,266	33,266	33,263	33,266	32,292
R^2	0.432	0.394	0.582	0.292	0.483
Adjusted R^2	0.309	0.262	0.490	0.138	0.364
rho	-0.604	-0.702	-0.858	-0.900	-0.920
Inverse Mills Ratio	-0.044 (0.035)	-0.063 (0.040)	-0.061** (0.027)	-0.152*** (0.057)	-0.102*** (0.037)

*p<0.1; **p<0.05; ***p<0.01

Note: Coefficients for year fixed effects are truncated to save space. I use Equation 2 from Section 3.5.3 for the specification of the second stage.

As can be seen in Table 7, the coefficients for *general experience* in the second stage are consistently very small, positive, and statistically insignificant in all specifications. In Table 8 I also compare results for the same (-5, +5) window CARs, but with different benchmark indices. I find that the results between different benchmark indices are much more stable than when using different windows. The coefficient for *general experience* is only statistically significant and positive in one specification when using MSCI Regional indices as benchmarks.

Overall, there is some evidence that *general experience* has a small positive effect on acquisition performance, therefore I partially reject the second hypothesis. Regardless, the effect of *general experience*, even when significant, is likely to be very small, as it fails to be a meaningful statistically significant predictor in most specifications and has a comparatively small effect when compared to *fintech experience* and other control variables, as the only statistically significant result for *general experience* predicts that an additional completed majority general acquisition in the last 5 years increases the CARs of the focal acquisition by 0.2 percentage points.

As for control variables, there is evidence that acquisitions by larger firms as proxied by *total assets*, *distressed* firms, acquirors with *recent negative fintech CARs*, larger deals, and deals with larger gaps after the last fintech deal tend to perform better. Acquisitions where the acquiror is a *bank*, however, exhibit lower CARs. While the directions of estimated coefficients are largely consistent between different CAR windows, the magnitudes and levels of significance vary.

As mentioned in the methodology section, for sample selection bias to be confirmed, the variable of interest, in this case *general experience,* must be a significant predictor in the first stage, and there must be a significant correlation between the error terms in the first and second stages (Certo, Busenbark, & Semadeni, 2016), which is identified by the rho in the second stage output in Table 7. I find that both conditions are fulfilled as the effect of *general experience* is statistically significant in the first stage, and the rho of the second stage ranges from -0.60 to -0.92, showing that sample selection bias regarding *general experience* is a problem and therefore, the Heckman two-step estimation is appropriate.

4.3. H3: Additional fintech experience improves fintech acquisition performance.

In Table 7 I also estimate the effect of *fintech experience.* In 3 out of 5 specifications there are statistically significant negative and non-negligible coefficients for *fintech experience*. The results indicate that an additional completed majority fintech acquisition in the last 5 years decreases CARs for the focal acquisition announcement by 1.5 – 3.4 percentage points. Additionally, coefficients for *fintech experience* are negative in all specifications even when statistically insignificant. In Table 8 I again compare results for different benchmark indices but the same (-5, +5) CAR window. The results for *fintech experience* are very similar for MSCI Global and Regional benchmark indices but are insignificant when using the MSCI Country level benchmarks. Therefore, the negative effect for *fintech experience* is robust to some extent to both CAR window selection and benchmark index selection. Because of these results, I reject the third hypothesis.

Additionally, by evaluating the first and second stage outputs in Table 6 and Table 7, I conclude that there is sample selection bias in estimating this effect, as the coefficient for *fintech experience* is statistically significant in the first stage, and the rho in the second stage, as mentioned before, is quite high. Therefore, the use of the Heckman two-step estimation is also appropriate in this case.

Table 8: Sensitivity analysis with respect to benchmark index selection in the second stage.

	Dependent variable: CAR (-5, +5)		
	MSCI Global	MSCI Regional	MSCI Country
	(1)	(2)	(3)
General Experience	0.002	0.002*	0.001
	(0.001)	(0.001)	(0.001)
Fintech Experience	-0.037**	-0.036**	-0.020
	(0.018)	(0.015)	(0.015)
Acquisition Rate Variability	0.002	0.004	0.003
	(0.007)	(0.005)	(0.005)
Cross Border	-0.018	-0.013	-0.001
	(0.025)	(0.022)	(0.024)
Institutional Differences	-0.005	-0.0004	-0.002
	(0.032)	(0.029)	(0.031)
Minority	0.010	0.011	0.009
	(0.024)	(0.022)	(0.023)
Ln(Total Assets)	0.007**	0.005**	0.002
	(0.003)	(0.003)	(0.003)
Balance Sheet Cash Share	-0.017	-0.036	-0.031
	(0.047)	(0.043)	(0.045)
Distressed Acquiror	0.036	0.036*	0.001
	(0.023)	(0.021)	(0.022)
Bank	-0.044*	-0.028	-0.007
	(0.023)	(0.021)	(0.022)
Recent Negative Fintech CAR	0.020	0.012	0.004
	(0.014)	(0.013)	(0.014)
Deal Value Share	0.008***	0.009***	0.002
	(0.001)	(0.001)	(0.001)
Year Gap Fintech	0.002	0.001	0.003
	(0.003)	(0.003)	(0.003)
Year Gap General	0.004	0.001	-0.005
	(0.006)	(0.005)	(0.005)
Constant	0.470**	0.459**	0.242
	(0.238)	(0.213)	(0.216)
Target Status	Yes	Yes	Yes
Target Industry	Yes	Yes	Yes
Acquiror Region	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	32,258	33,266	33,236
R^2	0.310	0.337	0.102
Adjusted R^2	0.151	0.192	-0.134
rho	-0.914	-0.916	-0.743
Inverse Mills Ratio	-0.161*** (0.060)	-0.149*** (0.053)	-0.086 (0.055)

*p<0.1; **p<0.05; ***p<0.01

Note: Alternative variations of the second stage of the two-step Heckman estimation using different benchmark indices, but identical specifications to the main regression in Table 7. I use Equation 2 from Section 3.5.3 for the specification of the second stage.

4.4. Additional specifications and robustness

To ensure that the results in previous sections are not spurious, and to eliminate concerns regarding multicollinearity, I check for robustness with respect to model specification, and conduct cascading regression analysis in Table 9.

In almost all specifications except for Column 3, the effect of *fintech experience* is statistically significant and negative, indicating that results regarding *fintech experience* are largely robust with respect to model specification. The magnitude of the coefficient for *fintech experience* also increases when adding groups of control variables. The effect of *general experience*, however, is statistically insignificant and very small in all specifications, indicating that the results for *general experience* are also robust with respect to model specification.

One interesting aspect that Table 9 also shows is the tradeoff between adding more control variables and maintaining a larger sample size. For example, by adding acquiror controls in Column 4, I decrease the sample size from 1,081 to 219 highlighting the issue of data missingness. Additionally, by decreasing the sample size, rho appears to decrease quickly from -0.2 in Column 1 to about -0.9 in Column 5, indicating that issues with sample selection bias due to additional data missingness increase as I limit the available sample size for the second stage. Additionally, I check for robustness with respect to the first stage specifications in Appendices C and D and find that the significance of the effect of *fintech experience* is robust, however, results for *general experience* may vary given different first stage specifications.

This in combination with previous analysis shows that the effect of *general* and *fintech experience* is the most volatile with respect to CAR window selection, while benchmark index selection plays a smaller role. Additionally, the main results, especially concerning *fintech experience*, are robust to first and second stage model specification. This analysis highlights the importance of scholars using and presenting results for various CAR windows, as there is a high risk of cherry-picking if robustness is not reported.

Table 9: Cascading regressions using different second stage specifications.

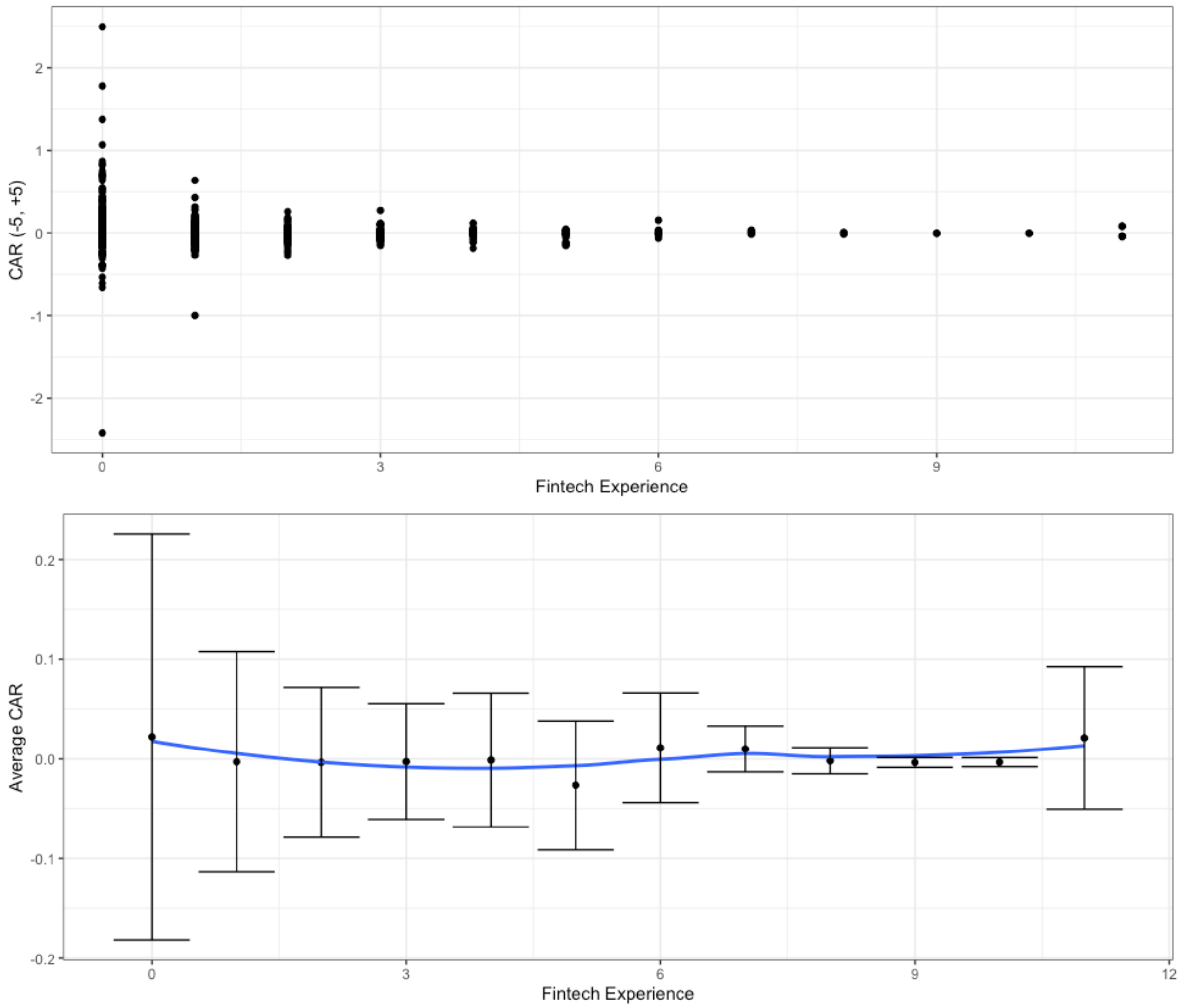
	Dependent variable:					
	CAR (-5, 5) MSCI Global					
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Experience	-0.013**	-0.014**	-0.008	-0.026*	-0.034**	-0.032*
	(0.006)	(0.006)	(0.006)	(0.014)	(0.016)	(0.017)
General Experience	-0.001	-0.0004	0.0002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Acquisition Rate Variability				0.003	0.005	0.003
				(0.005)	(0.005)	(0.005)
Cross Border		-0.006	-0.003	-0.003	-0.013	0.001
		(0.014)	(0.014)	(0.023)	(0.024)	(0.024)
Institutional Differences		-0.013	-0.015	-0.003	0.001	-0.084***
		(0.015)	(0.015)	(0.031)	(0.032)	(0.032)
Minority		0.030	0.041*	0.009	0.008	-0.004
		(0.022)	(0.021)	(0.024)	(0.024)	(0.028)
Ln(Total Assets)			-0.008***	0.005*	0.006**	0.003
			(0.001)	(0.003)	(0.003)	(0.005)
Balance Sheet Cash Share				-0.023	-0.035	-0.113*
				(0.044)	(0.046)	(0.066)
Distressed Acquiror				0.031	0.034	0.109***
				(0.021)	(0.022)	(0.033)
Bank				-0.029	-0.038*	0.032
				(0.021)	(0.022)	(0.034)
Recent Negative Fintech CAR				0.018	0.018	0.043**
				(0.014)	(0.014)	(0.019)
Deal Value Share				0.008***	0.008***	0.282
				(0.001)	(0.001)	(0.212)
Year Gap Fintech				0.002	0.002	-0.006**
				(0.003)	(0.003)	(0.003)
Year Gap General				0.005	0.004	0.002
				(0.005)	(0.005)	(0.011)
Target Age						-0.002***
						(0.001)
Target Distressed						-0.0002*
						(0.0001)
Constant	0.137**	0.147**	0.125**	0.403*	0.454**	0.695**
	(0.056)	(0.057)	(0.056)	(0.212)	(0.230)	(0.339)
Target Industry					Yes	Yes
Target Status					Yes	Yes
Acquiror Region	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,136	34,128	34,128	33,266	33,266	33,101
Second stage observations	1,089	1,081	1,081	219	219	54
R^2	0.026	0.030	0.064	0.283	0.292	0.820
Adjusted R^2	0.006	0.007	0.041	0.150	0.138	0.204
rho	-0.209	-0.234	-0.075	-0.835	-0.900	-1.038
Inverse Mills Ratio	-0.034* (0.021)	-0.039* (0.021)	-0.012 (0.021)	-0.123** (0.050)	-0.152*** (0.057)	-0.169** (0.079)

*p<0.1; **p<0.05; ***p<0.01

4.5. Uncertainty, fintech experience, and performance

The robust negative results for *fintech experience* in Sections 4.3 and 4.4 indicate that increased *fintech experience* reduces acquisition performance. As surmised from Section 2, this could be due to an inability to learn from prior fintech acquisitions to remedy difficulties in the effective knowledge transfer in the integration phase. Here, examining acquisition uncertainty may help verify whether organizational learning is taking place, as with more experience in allocating resources micro-uncertainty can be reduced (Lint & Pennings, 1999), which I measure by calculating the standard deviation of CARs in Figure 3.

Figure 3: Cumulative abnormal returns plotted by degree of *fintech experience.*



Note: The x-axis shows how many majority fintech acquisitions a given acquirer has completed in the 5 years before the focal acquisition. The y-axis shows the average CARs using a (-5, +5) window and the MSCI Global benchmark index. The errors bars in the second figure show the standard deviation of CARs for that specific level of experience. Additionally, it is worth mentioning that there are only 15 observations with more than 6 completed fintech acquisitions. Therefore, the very low uncertainty for observations with high *fintech experience* is possibly due to the small sample size and may be unreliable. I also complete this analysis for *general experience* in Appendix E, which shows a similar pattern.

In Figure 3 I show the distribution of CARs for each level of prior *fintech experience,* as well as the standard deviation of CARs for a given level of *fintech experience.* From this graph I note that the largest standard deviation of CARs occurs for acquisitions with no previous *fintech experience*, and the standard deviation gradually decreases with every additional completed fintech acquisition in the 5 years prior to the focal acquisition. This decrease in the standard deviation of CARs therefore indicates that micro-uncertainty is reduced with additional *fintech experience.*

5. Discussion and conclusion

To summarize the results, I find that fintech acquisitions in general do improve the performance of the acquiring company. More general financial M&A experience also possibly has a very small positive effect on the performance of the focal acquisition. More fintech experience, however, has a statistically significant negative impact on acquiror performance. Additionally, I find evidence that more fintech experience leads to lower uncertainty regarding acquisition outcomes at the time of the announcement.

Connecting back to the literature and the development of the hypotheses, fintech acquisitions generating statistically significant positive returns indicates that there is strategic value in existing financial service providers acquiring fintechs. Additionally, this shows that there are complementarities to be achieved as indicated by the creative construction hypothesis (Agarwal, Audretch, & Sarkar, 2007), and that it is possible for acquirors to integrate the acquired technologies in their value chain (Zhao, Li, Chen, & Lee, 2021).

As for the effects of general experience, an inconsistent small positive effect indicates that there may be some support for the hypothesis that increased general experience may help acquirors develop generalist skills such as selecting targets more adeptly to help avoid adverse selection (Wu & Reuer, 2021) and develop deal making negotiation skills to capture a larger share of profit for a given deal (Cuypers, Cuypers, & Martin, 2017). Given the very small effect and sparse significance of general experience, however, acquirers are much more likely to see a very neutral effect as predicted by Haleblian and Finkelstein (1999).

The effects of fintech experience being negative, however, is quite surprising, as this shows that in general, additional fintech experience does not improve acquisition performance, and likely does not lead the improved ability of firms to extract value from acquisitions in the post-acquisition period (Hayward, 2002). The negative results instead provide support that post-acquisition tensions caused by differences in management styles (Al-Laham, Schweizer, & Amburgey, 2010) are not improved by additional acquisition experience, and indeed cause problems for post-acquisition extraction and integration of acquired technologies even after several acquisitions. To investigate this problem further, in Section 4.5 I study how the variance of acquisition returns changes as acquirors gain more specific fintech experience. The results indicate that more experienced acquirors generate less volatility, which indicates that with subsequent acquisitions firms can mitigate some micro-uncertainty using more efficient resource allocation (Lint & Pennings, 1999). This means that learning is indeed taking place as predicted by Haleblian and Finkelstein (1999), which should lead to positive outcomes when measuring firm performance. Connecting these ideas with real option theory, however, it is understood that lower uncertainty is expected to lead to lower abnormal returns (Black & Scholes, 1973; Merton, 1973), which may at least partially explain why additional fintech experience produces reduced abnormal returns. These findings regarding uncertainty, however, serve only as additional analysis as additional robustness testing is needed as shown in Appendix E.

This information can then be distilled into three key implications for would-be acquirors. First, fintech acquisitions are a viable strategy to acquire technology and products to then improve the business outlook of the acquiring company. Second, general experience is not a significant driver of fintech acquisition performance, therefore general experience is not a requirement for fintech acquirors. And third, while there is no evidence that additional fintech experience improves performance, there is evidence that additional fintech experience does appear to decrease uncertainty pertaining to acquisition outcomes and does likely lead to organizations learning. For scholars, this research shows the importance of considering uncertainty when studying the effects of experience on acquisition performance, as well as advancing the understanding of fintech acquisition performance.

The main limitations of this analysis are mostly empirical. Due to sample selection bias, and the Heckman estimation only tackling one direction of sample selection bias, it is possible that results may differ depending on which sample is treated as the complete sample. Additionally, the two-step Heckman estimation only tackles endogeneity caused by sample selection (Certo, Busenbark, & Semadeni, 2016), therefore omitted variable bias still poses a risk. For example, two important unobserved variables in this study are measures of the level of M&A structures present in firms in the sample, and the capacity for organizational learning of a given firm. While I control for such characteristics by using various proxies such as *acquisition rate variability* and *recent negative fintech CARs*, the risk of omitted variable bias may still be present. As for further research, I have outlined the importance of considering uncertainty when studying the effects of experience. Therefore, more research could be done on how other sources of acquisition heterogeneity affect acquisition uncertainty and generated CARs. Conducting research using volatility adjusted CARs may also help more accurately capture the expected performance, and help researchers more conclusively isolate the effects of variables of interest which affect uncertainty. Additionally, examining more sources of heterogeneity in experience may further help isolate the effect of acquisition experience.

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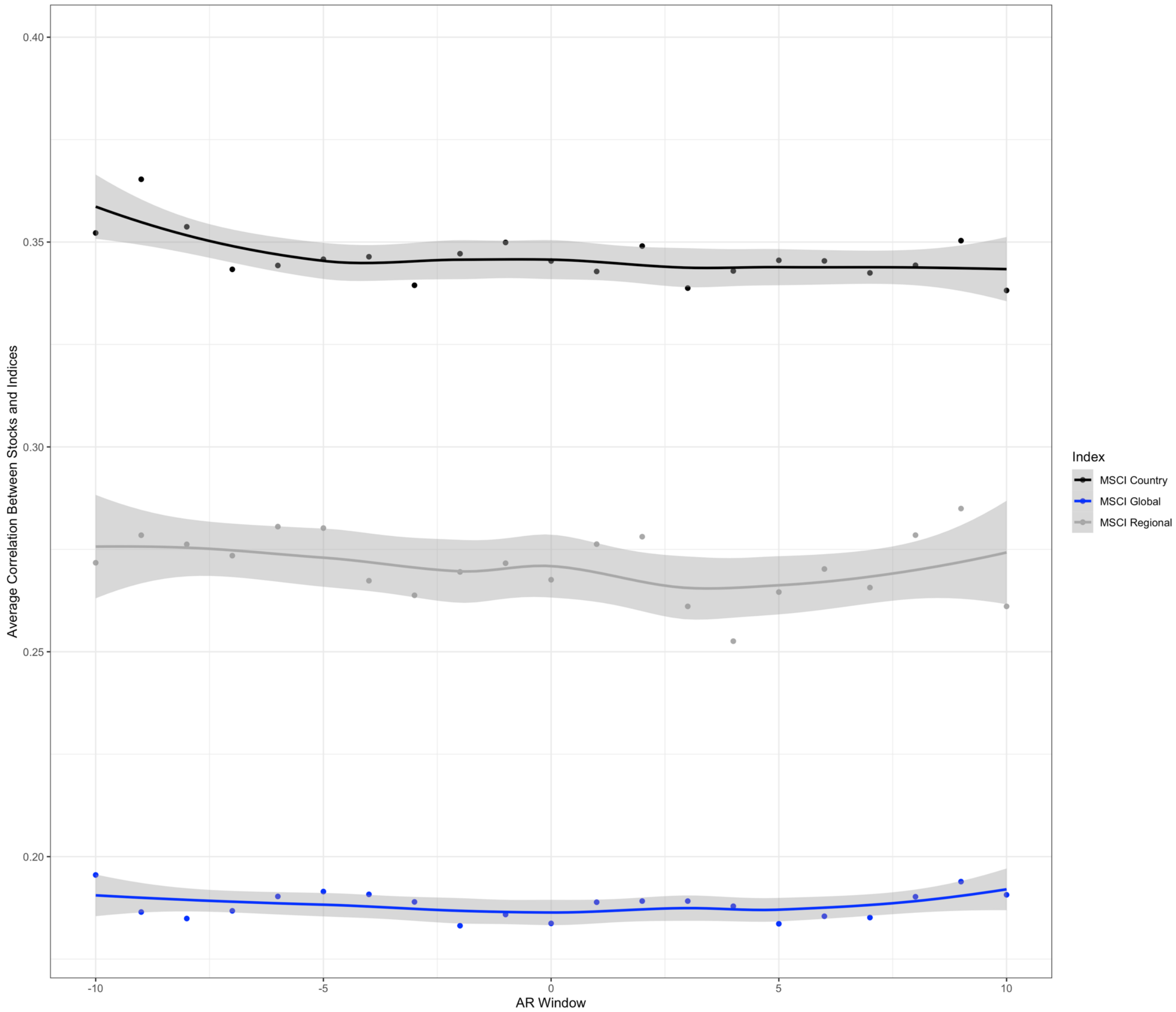
7. Appendix A

Table 10: Benchmark index reference list

Index	Source	Reference
S&P 500 INDEX	Yahoo Finance	(Yahoo Finance, 2023)
iShares MSCI Australia ETF	iShares	(iShares, 2023)
iShares MSCI Austria ETF	iShares	(iShares, 2023)
iShares MSCI Belgium ETF	iShares	(iShares, 2023)
iShares MSCI Brazil ETF	iShares	(iShares, 2023)
iShares MSCI Canada ETF	iShares	(iShares, 2023)
iShares MSCI China ETF	iShares	(iShares, 2023)
iShares MSCI France ETF	iShares	(iShares, 2023)
iShares MSCI Germany ETF	iShares	(iShares, 2023)
iShares MSCI Hong Kong ETF	iShares	(iShares, 2023)
iShares MSCI Indonesia ETF	iShares	(iShares, 2023)
iShares MSCI Ireland ETF	iShares	(iShares, 2023)
iShares MSCI Israel ETF	iShares	(iShares, 2023)
iShares MSCI Italy ETF	iShares	(iShares, 2023)
iShares MSCI Japan ETF	iShares	(iShares, 2023)
iShares MSCI Malaysia ETF	iShares	(iShares, 2023)
iShares MSCI Netherlands ETF	iShares	(iShares, 2023)
iShares MSCI New Zealand ETF	iShares	(iShares, 2023)
iShares MSCI Philippines ETF	iShares	(iShares, 2023)
iShares MSCI Poland ETF	iShares	(iShares, 2023)
iShares MSCI Qatar ETF	iShares	(iShares, 2023)
iShares MSCI Saudi Arabia ETF	iShares	(iShares, 2023)
iShares MSCI Singapore ETF	iShares	(iShares, 2023)
iShares MSCI South Africa ETF	iShares	(iShares, 2023)
iShares MSCI South Korea ETF	iShares	(iShares, 2023)
iShares MSCI Spain ETF	iShares	(iShares, 2023)
iShares MSCI Sweden ETF	iShares	(iShares, 2023)
iShares MSCI Switzerland ETF	iShares	(iShares, 2023)
iShares MSCI Thailand ETF	iShares	(iShares, 2023)
iShares MSCI Turkey ETF	iShares	(iShares, 2023)
iShares Core FTSE 100 UCITS ETF	iShares	(iShares, 2023)

8. Appendix B

Figure 4: Rolling 25-day average correlations between individual firm stocks and benchmark indices.



Note: The y-axis shows the degree of correlation, the x-axis shows the day before or after the announcement, with an AR window of 0 meaning the day of the announcement. I use a rolling correlation window to check whether in the post-announcement period there is a jump in correlation between a given MSCI index and the stock, as such a correlation would indicate that the change in the stock price of a given company may be reflected in the benchmark index as well. The most probable index to show this phenomenon is the MSCI Country index, and while it does have the highest correlation, it does not show a spike in correlation in the post-acquisition period. Therefore, changes in the stock price of the firm are on average not reflected in the benchmark indices.

9. Appendix C

Table 11: Comparing three possible specifications of the first stage.

	Dependent variable:		
	Fintech Dummy		
	(1)	(2)	(3)
Share Intangible	0.768***	0.865***	
	(0.123)	(0.134)	
Share Intangible Less Goodwill			0.808***
			(0.221)
General Experience	-0.020***	-0.014***	-0.015***
	(0.003)	(0.004)	(0.004)
Fintech Experience	0.333***	0.313***	0.320***
	(0.017)	(0.018)	(0.018)
Ln(Total Assets)		-0.007	-0.012
		(0.011)	(0.011)
Balance Sheet Cash Share		0.539***	0.478***
		(0.133)	(0.130)
Distressed Acquiror		-0.030	-0.037
		(0.080)	(0.080)
Bank		0.162**	0.154**
		(0.079)	(0.078)
Public Target		0.008	-0.011
		(0.081)	(0.080)
Subsidiary Target		-0.228***	-0.228***
		(0.069)	(0.068)
Acquiror Emerging Markets		-0.408***	-0.397***
		(0.139)	(0.135)
Acquiror Europe Central Asia		-0.122*	-0.108
		(0.074)	(0.073)
Acquiror North America		-0.210***	-0.174**
		(0.078)	(0.077)
Intercept	-2.659***	-3.426***	-3.313***
	(0.036)	(0.305)	(0.303)
Year Fixed Effects		Yes	Yes
Observations	33,087	32,258	32,292
Log Likelihood	-1,060.426	-990.115	-1,003.086
chi^2	412.813*** (df = 3)	542.793*** (df = 28)	517.293*** (df = 28)

*p<0.1; **p<0.05; ***p<0.01

Note: I choose between specifications by using the correlations between variables of interest in the first stage, and the inverse mills ratio, a lower correlation indicating a more relevant exclusion restriction (Certo, Busenbark, & Semadeni, 2016). I find the lowest correlations (0.37, 0.30) for Column 2, followed by Column 3 (0.36, 0.37) and finally Column 1 (0.40, 0.67). This indicates that adding more controls to the first stage improves the strength of the exclusion restriction. Based on this analysis, I use the Column 2 specification for all regressions in the paper.

10. Appendix D

Table 12: The same specifications in the second stage with different first stage specifications from Appendix B

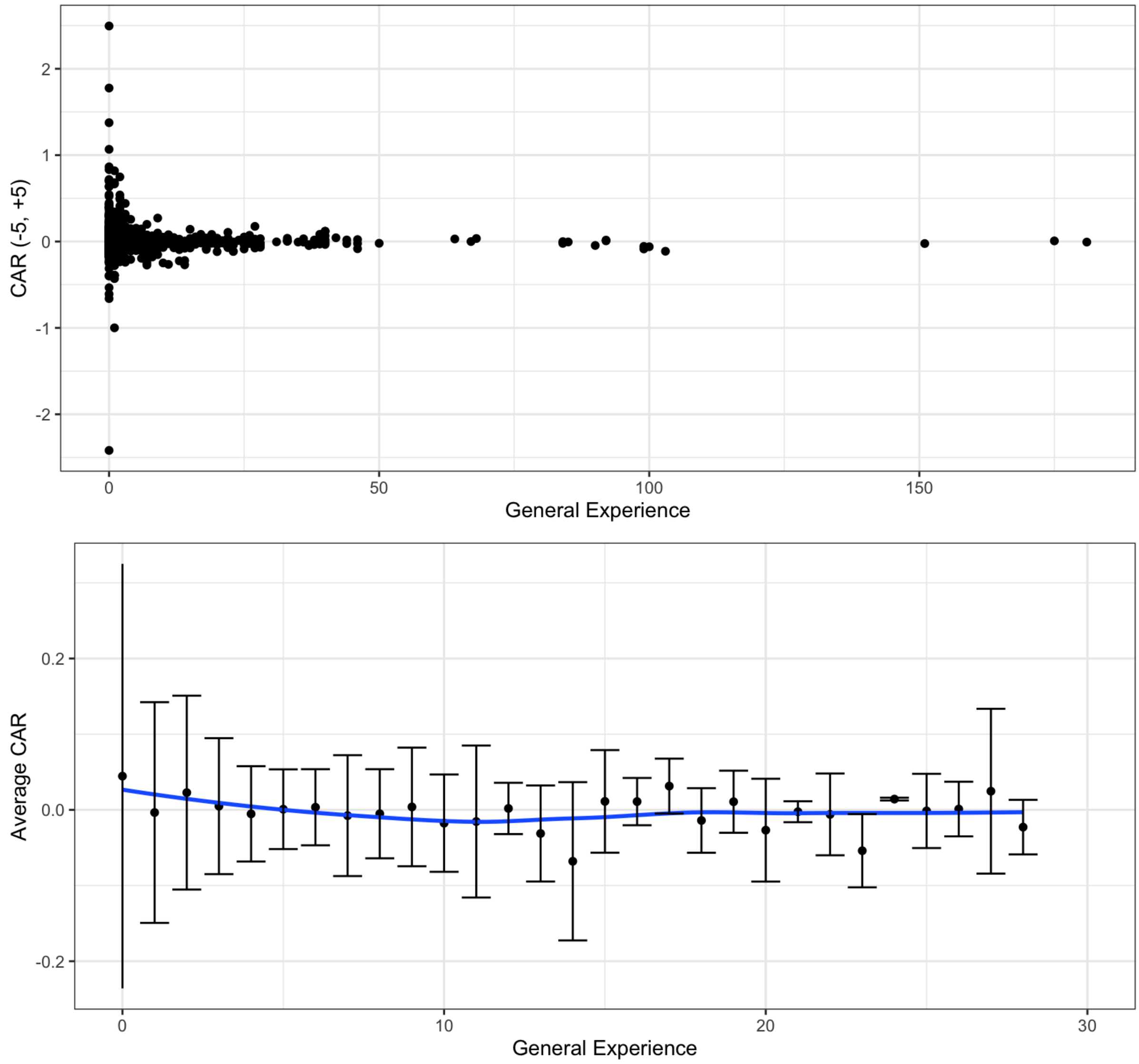
	Dependent variable: CAR (-5, +5)		
	(1)	(2)	(3)
General Experience	0.003*	0.002	0.005*
	(0.002)	(0.001)	(0.002)
Fintech Experience	-0.048**	-0.037**	-0.087**
	(0.021)	(0.018)	(0.041)
Acquisition Rate Variability	0.003	0.002	0.002
	(0.007)	(0.007)	(0.007)
Cross Border	-0.018	-0.018	-0.018
	(0.025)	(0.025)	(0.025)
Institutional Differences	-0.005	-0.005	-0.010
	(0.032)	(0.032)	(0.031)
Minority	0.009	0.010	0.014
	(0.024)	(0.024)	(0.023)
Ln(Total Assets)	0.006**	0.007**	0.009**
	(0.002)	(0.003)	(0.005)
Balance Sheet Cash Share	0.059	-0.017	-0.091
	(0.037)	(0.047)	(0.078)
Distressed Acquiror	0.031	0.036	0.037
	(0.020)	(0.023)	(0.031)
Bank	-0.022	-0.044*	-0.072*
	(0.018)	(0.023)	(0.037)
Recent Negative Fintech CAR	0.020	0.020	0.023
	(0.014)	(0.014)	(0.014)
Deal Value Share	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
Year Gaps	Yes	Yes	Yes
Target Status	Yes	Yes	Yes
Target Industry	Yes	Yes	Yes
Acquiror Region	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	0.432*	0.470**	1.121**
	(0.224)	(0.238)	(0.521)
Observations	33,087	32,258	32,292
R^2	0.311	0.310	0.314
Adjusted R^2	0.153	0.151	0.155
rho	-0.944	-0.914	-1.029
Inverse Mills Ratio	-0.187*** (0.069)	-0.161*** (0.060)	-0.348** (0.144)

*p<0.1; **p<0.05; ***p<0.01

Note: Column 1 corresponds to the Column 1 first stage specification in Appendix C, Column 2 corresponds to the Column 2 first stage specification in Appendix C, etc. I concur with findings by Certo et al. that different first stage specifications and exclusion restrictions largely only affect the standard errors of the second stage. I find that certain specifications of the first stage like Columns 1 and 3 from Appendix C generate significant results for *general experience,* however I consider these to be inferior specifications due to higher correlations of the independent variables in the first stage and the inverse mills ratio.

11. Appendix E

Figure 5: Cumulative abnormal returns plotted by degree of *general experience*.



Note: The x-axis shows how many majority general acquisitions a given acquirer has completed in the 5 years before the focal acquisition. The y-axis shows the average CARs using a window of (-5, +5) and the MSCI Global benchmark index. The errors bars in the second figure show the standard deviation of CARs for that specific level of experience. As can be seen in the graph, acquirors with no *general experience* generate much more volatility, and as acquirors gain more *general experience,* the volatility decreases especially with the first few completed acquisitions. When running regressions after accounting for data missingness, however, only 5 observations with *general experience* of 0 remain, indicating that at most only 5 observations will show a drastic decrease in volatility which could lead to lower abnormal returns. This could explain why the coefficients for *general experience* remained positive. 28 out of 219 observations in the final sample, however, had *fintech experience* of 0, which meant that a larger share of the sample could experience a rapid decrease in volatility with additional experience, which could explain why we see more negative results for *fintech experience* than *general experience.*