# The Effects of US Open Banking Adoption*

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## Abstract

The drive for open data in the financial services sector is reflected in various open banking initiatives that allow bank customers to gain greater access to their banking and transaction data and enable them to share their data with other financial institutions and FinTechs. Open banking adoption usually involves the adoption of external application programming interfaces (APIs) that allow banks to exchange data with other third-party financial institutions safely and securely. As open banking adoption of U.S. banks have previously been led by voluntary market-based initiatives., we analyze determinants of API adoption by US banks and subsequent changes in bank performance using a panel database of 1,185 US banks. We show that 3.3% of US banks in our sample have adopted APIs and that banks experience measurable improvements in earnings and modest increases in banks' market value and Tobin's Q after adoption. We also highlight heterogeneous effects after API adoption, as performance increases are greater for banks with lower levels of credit risk and lower levels of competition. Our results are consistent with previous theoretical findings that open banking might give FinTechs competitive advantages and that increased competition might disrupt the information spillover within traditional banks (He et al., 2023; Parlour et al., 2022).


*JEL classifications:* G21; G28; O32; O33

*Keywords:* API; open banking; FinTech; bank performance

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**Abstract**

The drive for open data in the financial services sector is reflected in various open banking initiatives that allow bank customers to gain greater access to their banking and transaction data and enable them to share their data with other financial institutions and FinTechs. Open banking adoption usually involves the adoption of external application programming interfaces (APIs) that allow banks to exchange data with other third-party financial institutions safely and securely. As open banking adoption of U.S. banks have previously been led by voluntary market-based initiatives., we analyze determinants of API adoption by US banks and subsequent changes in bank performance using a panel database of 1,185 US banks. We show that 3.3% of US banks in our sample have adopted APIs and that banks experience measurable improvements in earnings and modest increases in banks' market value and Tobin's Q after adoption. We also highlight heterogeneous effects after API adoption, as performance increases are greater for banks with lower levels of credit risk and lower levels of competition. Our results are consistent with previous theoretical findings that open banking might give FinTechs competitive advantages and that increased competition might disrupt the information spillover within traditional banks (He et al., 2023; Parlour et al., 2022).



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## 1. Introduction

The financial services sector has experienced a drive for open data in recent years, reflected in the variety of open banking initiatives in different countries and jurisdictions. Open banking describes the process where bank customers gain greater access to their account data (such as their transaction and credit history) and more control to share such data with other third-party providers and financial institutions, outside of the individual banks with which they are customers. Particularly European countries and the United Kingdom have taken further steps toward an open financial framework with the implementation of the EU Payment Services Directive 2 (PSD2) and the open banking initiative as the basis for open banking. In contrast, the discussions surrounding open banking in countries like the US are focused on voluntary market-based initiatives.[1] From the banks' perspective, the adoption of an open banking strategy usually involves adopting external application programming interfaces (APIs) that facilitate the link and interaction with FinTechs, payment providers, and other third-party financial institutions.

The opening up of customer data can pose a significant threat to the information monopoly of banks over their customers' data under the traditional bank model due to the resulting competition from other banks and FinTech startups (Marquez, 2002; Zachariadis & Ozcan, 2016). Furthermore, the adoption can come with considerable investment costs (due to its impact on the entire banking architecture (Dinçkol et al., 2023)) as well as cyber security risks and data privacy challenges (Benzell et al., 2022). However, proponents of open banking argue that the increase of available data and data sharing required by the adoption of an open banking strategy may expand the markets for both lending and payment services. Furthermore, the introduction of APIs by banks can increase their productivity through more efficient data sharing internally and with third parties, facilitate the automation of lending processes, and lead to more accurate risk assessments through access to more data (Babina et al., 2022).

In this paper, we analyze the determinants of API adoption by US banks and the effects of API adoption on bank performance. Based on the theory of the impact of IT innovation on firm performance (such as Brynjolfsson, 1993; Clemons, 1986) and IT adoption in banking (Hauswald & Marquez, 2003),

[1] See Babina et al. (2022) for an overview of open banking regulation in different countries.

we explore the determinants of API adoption and changes in performance after adoption. To analyze changes in performance after API adoption, we construct a unique panel dataset covering the API profiles of 1,185 US-listed banks from 2007-2022. We find that 39 banks issued external APIs within the period of 2007 to 2022, representing 3.3% of our overall sample of banks, with a wide range regarding the bank size and characteristics. We further find support for improved performance after adopting the first API. In particular, we observe a significant increase in earning-based performance, as well as some modest enhancements and improvements in the bank's market-based performance (market value, market-book ratio, and Tobin's Q). Our results are robust to various robustness tests, such as when correcting for self-selection as proposed by Heckman (1976) and testing for differences between adopting and non-adopting banks, using propensity score matching and entropy balancing to identify the control sample. In addition, we also find heterogeneous changes in bank performance after API adoption, as banks with lower levels of credit risk (measured by non-performing loans) and lower levels of competition (measured by product similarity) experience greater increases in performance after API adoption.

Our results are consistent with existing studies on FinTech competition and open banking that show that the increasing availability of bank customer data can lead to a reduction of credit risk and default (Berg et al., 2020). However, open banking and bank data portability might result in some unintended consequences for bank and FinTech competition and borrower welfare, as shown in the complementary theoretical frameworks of He et al. (2023) and Parlour et al. (2022). In particular, Parlour et al. (2022) find that allowing voluntary data porting by consumers might lead to possible unraveling and negative data externality for consumers who do not share their data. While FinTechs can benefit from additional access to customers, resulting competition can thus disrupt information spillover within traditional banks, leading to higher prices of banks' payment services. Consistent with their results, we observe that banks with low product similarity (proposed by Hoberg & Phillips (2016) to measure the intensity of direct competitors within an industry group based on similarity of 10-K filings) and product fluidity (proposed by Hoberg et al., (2014) to measure the frequency of new products and services on the market) experience stronger increases in Market-Book ratio.

Our paper contributes to the literature in three ways. First, we contribute to an emerging body of research on open banking and data portability. Our study is closely related to Benzell et al. (2022), who study how API adoption can create value through an "inverted" firm strategy[2], and Babina et al. (2022), who analyze the effects of open banking regulation on venture capital investment in FinTech firms in an international study. Our study differs from Benzell et al. (2022) as we focus on banks only whose API adoption does not necessarily adhere to an inverted firm strategy. In contrast, bank APIs can enable easier and safer sharing of bank customer data. We further argue that there is limited potential for banks to fully transform into a platform company that generates most of its value externally, making the effects of API adoption by banks inherently different than for companies from other industries. In contrast to Babina et al. (2022), we focus on voluntary adoption in the US rather than open banking regulation and their effects on venture capital in the financial services sector.[3]

The adoption of open banking can have further important implications for bank customers' and borrowers' welfare and financial inclusion, as banks might focus on attracting only a specific group of customers at the disadvantage or exclusion of other groups of customers. In this context, Goldstein et al. (2022) compare resource allocation efficiency and borrower welfare in open and closed banking scenarios, raising concerns that open banking might increase inefficiencies in resource allocation and complementing previous studies by Parlour et al. (2022) and He et al. (2023).

Second, our study relates more widely to the impact of technological innovations on the banking sector. Existing studies have examined the effect of technology on bank performance using measures such as the adoption of ATMs, internet and online banking, and payment technology (such as Berger, 2003; Beccalli, 2007; Hernández-Murillo et al., 2010; D'Andrea & Limodio, 2023), or overall bank IT expenditure and number of personal computers (Pierri & Timmer, 2022). In our paper, we use external API adoption (based on the first adopted API) and API intensity (based on the number of adopted APIs) as indicators of an open banking strategy and individual banks' intention of widening data access and

[2] The inverted firm strategy refers to the notion that firms can create value externally by opening up their data and services to third parties and becoming platforms, thereby creating an ecosystem of interactions (Benzell et al., 2023).

[3] Our study also leverages previous qualitative research on the impact of APIs on banking strategy from Zachariadis & Ozcan (2016) as well as Dinçkol et al. (2023), which examine the role of APIs in facilitating platform banking strategies as well as changing industry architecture through API integrations.

control for their customers. While API adoption can be considered a form of digital investment, it differs from traditional bank digitalization efforts in several ways. Previous technological bank innovation often involved automating and digitizing internal processes within the bank to improve internal efficiency and reduce costs. In contrast, APIs enable banks to access data through external third-party applications and services, allowing them to share data and functionality. Therefore, APIs can help facilitate banks' collaboration with third-party providers to offer a broader range of (mostly digital) services and products without needing to develop these services internally, but rather relying on the expertise and reach of their third-party collaborators. Therefore, APIs can help banks remain competitive, by broadening their reach and expanding their customer base while enhancing the experience of existing customers.

Third, our paper is further related to the general body of FinTech research and its impact on the lending industry. Berg et al. (2022) and Vives (2019) provide an overview of the digital disruption for the banking sector and lending industry, respectively. Several papers further focus on the impact of FinTech lending on traditional bank lending (see for example, Buchak et al. (2018); Fuster et al. (2019); Gopal & Schnabl (2022), and Tang (2019)). In this context, we analyze the role of competitive pressures on the decision of adopting an open banking strategy but also discuss the implications of competitive pressures which might disrupt information spillovers from payment to lending operations within commercial banks, as suggested by Parlour et al. (2022).

Our study has significant practical and policy implications. Adopting an open banking strategy implies a fundamental transformation of the bank's internal processes as well as engagement with the overall external innovation ecosystem of third parties. We consider API adoption as a possible means for digitally engaged banks to widen their service offering to their customers, increase their customer base, and decrease their credit risk, thereby improving their performance. Furthermore, our empirical study is an essential complement to existing studies on open banking and bank digitalization strategies that have provided qualitative and theoretical evidence regarding the potential impact of open banking and data portability on bank competition and performance, and wider effects on financial inclusion and borrower welfare. API and open banking adoption can help banks enhance performance, by improving profitability and market value through widening the customer network and expanding bank service offerings. To the best of our knowledge, we are the first quantitative paper to use voluntary API adoption as a measure for open banking and evaluate its relationship with bank performance, leveraging existing work to theorize and build out hypotheses on the potential effects of open banking strategies and data portability regulation.

Additionally, we analyze the effects of voluntary open banking adoption in a less stringent regulatory environment compared to the explicit open banking mandates in Europe and the United Kingdom[4]. In the United States, rather than focusing on the technical details of open banking adoption, banks adopt APIs in a voluntary manner. However, we argue that recent banking regulations and data portability announcements that focus on protecting consumer privacy and data, such as the California Consumer Privacy Act (CCPA), have led to an increasing rate of API adoption. The results of our cross-sectional analysis reveal that effects after API adoption are heterogeneous and may depend on the level of credit risk and market competition. We thus confirm that stringent open banking regulations could have adverse effects on the banking landscape as highlighted by He et al. (2023) and Parlour et al. (2022).

The remainder of our paper is structured as follows: In section 2, we discuss the related literature to our study as the basis for our hypothesis development. We provide details of our sample selection and descriptive statistics in section 3 and present our results in section 4. Section 5 finally concludes.

## 2. Related Literature and Hypothesis Development

### 2.1 API and Bank Performance

IT has changed the way the financial industry and banks use information and data, affecting bank performance and lending decisions as well as the competitive landscape in the payment and lending

[4] In European, there are list of mandatory regulations for banks to adopt open banking strategy, such as PSD2 and General Data Protection Regulation (GDPR) which is a regulation on information privacy in the European Union (EU) and the European Economic Area (EEA). It enhances individuals' control and rights over their personal information and simplifies regulations for international business. The GDPR became effective on 25 May 2018 and supersedes the Data Protection Directive 95/46/EC. It is directly applicable with force of law on its own without the need of transposition as an EU regulation instead of a directive. However, there's an on-going debate whether existing open banking regulations in the UK and the EU have actually led to measurable performance gains for financial institutions which have adopted APIs.

industry. Previous evidence has demonstrated that bank digitalization strategies and IT investments can have a positive effect on bank output and performance. Martín-Oliver & Salas-Fumás (2008) show that IT investments of 72 Spanish commercial banks contribute significantly to bank profitability, while using internet distribution channels (for funds transfers, brokerage and securities trading transactions and deposits) leads to improvements in the banks' ROA and ROE. In addition, Scott et al. (2017) measured the impact of payment technology adoption on bank performance using a sample of more than 6,000 banks over 40 years. Their findings also report a positive aggregate result over 10 following the technology investment and innovation adoption, however this varies over time with accumulated losses over the first 2-3 years before benefits are realized.

On the other hand, there is conflicting evidence in the literature on the impact of IT investments and adoption on bank performance. According to the theory of the productivity paradox, IT adoption does not necessarily increase profitability (Brynjolfsson, 1993), as digital innovators can only benefit from their innovations if they are able to establish a significant market share before second-tier competitors act (Clemons, 1986). Empirical studies have found inconclusive beneficial effects of the digitalization of banks on performance, for example when analyzing the adoption of online banking (Sathye, 2005) or mobile payments (Staykova & Damsgaard, 2015). Therefore, it remains an open question whether adopting an open banking strategy will help improve bank performance, possibly through improving risk management and competitiveness with other competitors.

While API adoption can be considered a form of digital innovation and investment, it also differs from traditional bank digitalization efforts (such as online or mobile banking) in several ways. Previous innovation effects focused on positive effects on internal efficiency and attractiveness to the banks' existing customer base. IT innovations can significantly reduce the cost of bank customers searching for and switching banks by allowing banks to screen and monitor new customers more effectively (Hauswald & Marquez, 2003), thereby avoiding the problem of information asymmetry associated with the high cost of screening and monitoring (Agarwal & Hauswald, 2010; Degryse & Ongena, 2005). Thus, banks can gain a competitive advantage through IT adoption, as it might help understand customers' needs better, thereby increasing customer satisfaction and customer retention (Mithas et al., 2012; Dadoukis et al., 2021).

In addition to improving experience of existing customers, external APIs can generate further value outside the firm via third parties as part of an "inverted" firm strategy (Benzell et al., 2022), which generates value externally.[5] Though banks can further create internal value by leveraging APIs internally to improve existing processes, the value created by third parties might expand the boundaries of banks' service offerings and clientele. Thereby, banks with APIs can create a wider range of products and services and a banking ecosystem in which third parties help banks broaden their core business and maximize the use of resources.[6]

However, Benzell et al. (2022) note that API adoption can have limited effects on market value, as external third parties might not necessarily engage with the APIs, and IT investments might fail to produce value without complementary investment (Brynjolfsson et al., 2021). Furthermore, building a platform incurs procurement costs, and the initial investment costs of API adoption might be considerable, reducing the positive effects of API adoption at least in the initial years after adoption. Due to the tension of the possible effects of API adoption on bank performance, we propose the following alternative hypotheses:

***H1a: Banks' API adoption has a significant positive relationship with bank performance.***

***H1b: Banks' API adoption has a significant negative relationship with bank performance.***

### 2.2 API and Credit Risk

As one of the key functions of banks is to screen and monitor borrowers, IT-intensive banks can have a relative advantage when it comes to accessing and processing information to aid processes such as collateral screening, default risk assessment, and loan processing. In particular, bank IT adoption may reduce banks' credit risk through greater client information acquisition and transparency (Hauswald & Marquez, 2003) and lead to softer lending competition (Hauswald & Marquez, 2006). Branzoli et al. (2021) show banks with higher IT expenditure and usage experience higher credit growth during the Covid, while Pierri & Timmer (2022) show that high IT adoption by banks is related to lower increases

[5] This contrasts with the traditional "pipeline" strategy where the firm generates value mainly internally by designing, producing, and selling products on its own (Alstyne et al., 2016).
[6] Lindman et al. (2015) uses different business models to illustrate how businesses can create value by enriching open data.

of non-performing loans (NPL) during the financial crisis, a measure of bank distress and credit risk. Furthermore, credit providers' lending capacity is inherently determined by their screening abilities, with FinTechs having a technological advantage due to their more advanced data analysis algorithms (He et al., 2022).

We highlight the reduction of credit risk through greater data sharing and transparency of bank customers as API adoption allow to obtain more and enriched customer data, consistent with the information generation hypothesis (Koetter & Noth, 2013). In this context, API adoption can further facilitate banks' information acquisition through more efficient data sharing with third-party providers and improve the management of credit risk through the availability of more historical transaction data, leading to more accurate assessments of credit risk scores.

However, beneficial effects might depend on the screening capabilities and credit management of adopting banks. In particular, Parlour et al. (2022) study competition between FinTech payment providers and a monopolistic bank, illustrating how FinTech competition in payment services might disrupt the information spillover of payment data used to assess consumers' credit quality within the traditional bank model. They find that allowing voluntary data porting by consumers might lead to a possible negative data externality for consumers who do not share their data and disrupt information spillover within banks. He et al. (2023) further studies the effects of open banking based on their theoretical model of credit market competition, highlighting negative concerns about open banking as it might widen the screening ability gap and over-empower FinTechs compared to banks, leaving borrowers worse off. In equilibrium, they find that lenders with stronger screening capabilities face a less severe winner's curse and earn positive profits, whilst lenders with weaker screening abilities might widen their lending offers but also suffer from a more severe winner's curse, resulting in zero average profit in equilibrium.

Thus, we conjecture that bank with lower credit risk will be affected less by the disruption of information spillover, allowing them to harness the potential provided through the increase in customer data through API adoption. As API adoption can have varying effects on bank performance for banks with different levels of credit risk management and screening abilities, we put forward the second hypothesis:

***H2: The influence of API adoption on bank performance are greater for banks with lower credit risk.***

### 2.3 API and Banking Competition

IT adoption can further help banks gain competitive advantages against their competitors, by increasing efficiencies in data sharing and loan processing, expanding their service offering, and widening their pool of customers.

Koetter & Noth (2013) show that the use of IT, proxied by IT expenditures, use of information technology (IT) contributes to bank output. Hauswald & Marquez (2003) conclude that investments in bank IT can influence the strength of bank competition by affecting information processing power. .

In contrast to other IT innovations however, banks adopt APIs to increase collaboration with third parties and possibly competitors, thereby also facilitating overview and insight into third-party providers and possible competitors. By understanding third-party systems, banks can gain insight into their business strategies and digital offerings, thereby reducing their own transaction costs and expanding their customer base, similar to interactions of Amazon with third-party providers (Zhu & Liu, 2018).

Furthermore, APIs can improve the efficiency of collaboration between banks and third parties as APIs allow for direct data exchange between different divisions, similar to the spillover effects postulated by (Parlour et al., 2022). This type of data sharing is more conducive to collaboration and access to information and can thus help to interconnect business and service processes between organizations, thereby increasing the banks' productivity and market power (or monopoly as suggested by Parlour et al. (2022).

Existing open banking research has extensively researched the impact of the growth of FinTechs on competition in the banking sector and the competitive relationship between traditional banks and FinTech lenders (Berg et al., 2022; Fuster et al., 2019; Vives, 2019). In their theoretical framework, Parlour et al. (2022) that FinTech competition might disrupt natural information spillovers within traditional banks, leading to a wider screening gap, increased monopoly power, a softening of competition, and a rise in lending rates.

However, the role of competition in the decision to adopt an open banking strategy is not well understood. To analyze how competition and product differentiation influence the effects of API adopting banks, we utilize product similarity and product fluidity measures proposed by Hoberg & Phillips (2016) and Hoberg et al. (2014) to measure the competitive pressures faced by banks with regard to competitive threats of existing competing banks and potential new entrants. While both measures are based on textual analysis of 10-K filings, product similarity measures the availability of alternatives to a company's products and services on the market, while product fluidity measures the frequency of new products and services appearing on the market. Based on the above discussion, we propose a third hypothesis:

***H3: The influence of API adoption on bank performance are greater for banks that face lower levels of competitive threats.***

## 3. Data and Sample Selection

We manually collect evidence of banks' external API adoption and intensity and analyze their effects on bank performance. Our sample consists of all publicly listed bank firms (i.e., firms with SIC (Standard Industrial Classification) codes between 6020 and 6999) level information from the Compustat and CRSP database for the years covered by our sample period (2007-2022), including banks' financial information. We exclude firm-year observations with missing values for the key variables. Our final data sample consists of 1,185 banks and 6,926 firm-year observations. API data is manually collected from the bank's official developer websites as well as from a few APIs and open-banking integration platforms, such as Programmable Web, APIdashboard, Openbanking tracker, and APItracker. Our key financial data stem from Compustat, CRSP and BankFocus.

### 3.1 Sample Selection

We extract financial data for US-listed banks from Compustat annual filings and BankFocus. We exclude companies with year-end share prices below $1, companies with total assets and book-to-equity annual observations of firms with negative values, and firms with insufficient financial data to calculate the variables of interest in our analysis. After applying these selection criteria, our final sample consists of 6,926 firm-year observations (1,185 unique banks). To eliminate the potential effect of outliers, we winsorize all continuous variables at the 1% and 99% percentiles to alleviate the potential impact of outliers.

***Measures of banks' API implementation***

API implementation is measured by a dummy variable $API\_Adopt$ (taking the value 1 in the year the first API was adopted, and 0 otherwise) and the number of APIs owned by bank $i$ in year $t$ ($API\_Intensity$) during 2007-2022. We manually collect the API information (such as API categories, description, adoption date, etc.) from the bank's official developer websites as well as from API and open-banking integration platforms, such as Programmable Web, APIdashboard, Openbanking tracker, and APItracker.[7]

***Measures of bank performance***

We use different proxies to measure bank performance, including market-based performance and earning-based performance. To measure the market-based performance, we use market value ($MRKTV$) for the market's estimate of the company's overall value, market-to-book (*Market-Book*) to indicate the market's perception of the company's potential value-added opportunities and *Tobin's* $Q$ to indicate the company's growth rate. To measure earning-based performance, we use Income before extraordinary Items (*IB*) and Earnings Per Share (*EPS*). We further control for several bank-level characteristics as is common in the literature (Hirtle et al., 2020), such as *Bank Size*, *Firm Age*, *Capital Intensity*, *Leverage*, *Tangibility*, *Cash Holding*, *Cost of Capital, Tier 1 Capital ratio,* and the number of employees (*Employee*). The specific variable names, definitions, and sources are provided in Table 1.

[7] We assign the year of the API adoption based on internet archives.

### *Measures of Competition and Competitive Threats*

To analyze the influence of competitive factors in the banking industry, we use the product similarity and product fluidity measures for individual banks, from the Hoberg-Phillips Data Library[8]. Product similarity measures the availability of alternatives to a company's products and services, while product fluidity measures the frequency of new products and services appearing on the market. Hoberg & Phillips (2016) use textual analysis of product descriptions in companies' 10-K file to identify competitors for each company. They find that firms with higher product similarity scores are more likely to mention competitive pressure posed by rivals. In contrast product fluidity measures of the ex-ante competitive threats faced by a firm in its product market that captures changes in rival firms' products relative to the firm (Hoberg et al. (2014)). Due to the more flexible TNIC classification, we can capture both competitive pressures by existing and potential rivals based on product descriptions in the 10-K filings.

### *API classification*

Our API adoption dataset contains public APIs that financial institution use to communicate data and information externally (with third-parties and partners). To classify APIs, we use a broader approach based on the information they process: we cluster APIs by HTTP method[9] combination (Craig et al., 2016; Serbout et al., 2022) and determine whether an API can only request data from a specified resource (Read-only) or also send data to a server to create/update a resource (Read-Write)[10]. First, *Read-only* APIs provide data access to third-party providers who can only see and 'consume' data without making any amendments to the original database or initiating any actions such as account creation or issuing of contracts or services. These are relevant when access to data is needed, such as bank account, transactional and balance information. On the other hand, *Read-Write* APIs enable a

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[8] Hoberg and Phillips Data Library can see from: https://hobergphillips.tuck.dartmouth.edu

[9] The Hypertext Transfer Protocol (HTTP) is designed to enable communications between clients and servers. HTTP works as a request-response protocol between a client and server. The two most common HTTP methods are: GET and POST. GET is used to request data from a specified resource, while POST is used to send data to a server to create/update a resource.

[10] Read and write APIs information can see from: https://www.openbanking.org.uk/glossary/read-write-api/#:~:text=Read%2FWrite%20APIs%20enable%20third,initiate%20payments%20from%20those%20accounts

stronger connection and deeper integration between parties, allowing different systems to communicate data and initiate transactions on their behalf following explicit customer consent. The payment initiation process is a typical application where read-write APIs can be useful. In our data, 51.127% of APIs of US public banks are *Read-only* whereas 48.87% of APIs are *Read-Write*. Any bank in our sample with more than one API can have both *Read-only* and *Read-Write* APIs.

### 3.2 Descriptive Statistics

We present the summary statistics of the overall sample (Full Sample) and the subsamples of banks that have APIs or not in Table 2. The table reports selected mean and standard deviations (SD) for relevant variables of our analyses for the full sample and two subsamples. The statistics are from 2007 to 2022, covering the major period of growing API adoption.

[Insert Table 2 about here]

The summary statistics in Table 2 give insight into the characteristics of banks with and without APIs. We find that only around 3.3% of the US-listed banks in our sample have adopted APIs (39 out of 1,185 banks). Banks that have adopted public APIs tend to have larger average Capital Intensity (*CAP*) and total assets and have higher levels of earning-based performance (*IB* and *EPS*) and market-based performance (*MRKTV, Market-Book,* and *Tobin's Q*), compared to banks that have not adopted public APIs. Furthermore, banks with APIs have larger sizes and more employees, higher leverage and cash holdings, lower cost of capital, generally lower credit risk (as determined by non-performing loans (*NPL*), loan loss provisions (*LLP*), and *Z-Score*), higher operational efficiency (*Efficiency*), and relatively lower product similarity (*Similarity*) and product fluidity (*Fluidity*). We formally test the determinants of API adoption using a logistic regression in Section 4.1.

Table A1 in Appendix A further shows the overall correlation between the main independent and dependent variables and bank characteristics. The correlation coefficients show positive correlations of API adoption and API intensity with market-based performance (*MRKTV*, *Market-Book* and *Tobin's Q*), *IB* and *EPS*, and negative correlation with credit risk (*NPL*, *LLP* and *Z-Score*) and competition metrics (*Similarity* and *Fluidity*).

### 3.3 API Adoption by Banks Over Time

We analyze the API adoption of banks over time and present our results in Figure 1 and Figure 2.

[Insert Figure 1 and Figure 2 about here]

Figure 1 shows the growth and cumulative APIs for the sample period of 2007 to 2022. The bar chart illustrates the cumulative number of banking APIs, while the line chart illustrates the number of APIs added each year. There is a sizeable increase in API adoption in 2020 and 2021, pointing towards an increasing trend of adopting APIs in the banking industry. Figure 2 shows the number of individuals adopting banks in the sample period.

## 4. Empirical Results

### 4.1 Determinants of API Adoption

Studies have shown that bank characteristics such as profitability, bank size, presence in urban markets, membership in bank holding companies, branching intensity, capital-to-asset ratio, non-performing loan ratio, etc., play an essential role in adopting bank websites and online banking services (Furst et al., 2001; DeYoung et al., 2007; Hernandez-Murillo et al. 2010). To analyze the factors that determine API adoption based on bank-specific characteristics, we apply the following logistic regression:

$$API_{bank_i} = \alpha_{it} + \beta Bank\ Characteristics_{i,t} + \omega_t + \epsilon_{i,t} \tag{1}$$

where *API_bank*$_i$, is a dummy variable which equals one if bank $i$ has adopted APIs during the sample period and 0 otherwise. We include the following measures for bank characteristics prior to API adoption: the age of the bank in years (*Firm Age*), the size of the bank (*Bank Size*) measured as the log of bank $i$'s total assets, the percentage of non-performing loans (*NPL*) and loan loss provision (*LLP*), and the degree of financial leverage (*Leverage*), calculated as the ratio between selected financial assets of the banking sector and its total equity, and measures of liquidity such as cash holdings (*Cash Holding*). We further include measures of operational efficiency (*Efficiency*), number of employees (*Employee*), and *Capital Intensity*, as well as the competition metrics (*Similarity* and *Fluidity*) (see

Table 1 for variable definitions). Table 3 presents the results of the logistic regression in Equation (1) based on a sample of 3,976 firm-year observations. We include bank characteristics based on observations in the years before the API was adopted, and year-fixed effects $\omega_t$.

[Insert Table 3 about here]

We find that bank size and operating efficiency are positive determinants of API adoption, as banks with more resources and funds are more likely to cover the considerable investment costs of adopting APIs. We also found a negative and statistically significant relationship between the number of employees and the probability of adopting APIs.

### 4.2 API Adoption and Bank Performance

We further examine the changes in bank performance after API adoption using a two-step regression approach by Heckman (1976). In the first stage regression, we use a Probit model to estimate the selection equation and generate the inverse mills ratio (*IMR*) to account for self-selection which is included in the second stage regression. The Probit model includes control variables and broadband access within the state that the bank is headquartered in (*Broadband*), provided by the Internet Access for High-Speed Services data on broadband adoption[11], as an exogenous variable. As the adoption of APIs is implemented at the bank's headquarters, broadband penetration can have a positive effect on the decision to adopt and develop APIs, with minor consequences to banks' overall performance. In the second stage regression, shown in equation (3), we include IMR to account for self-selection bias. $Controls_{i,t}$ are a set of time-varying firm control variables, respectively; and $\epsilon_{i,t}$ is the error term. Specifically, we estimate the following model:

$$Pr\,(API_{i,t}) = \alpha_{i,t} + \beta Broadband_{i,t} + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \tag{2}$$

$$Perf_{i,t} = \alpha_{i,t} + \beta API_{i,t-1} + \gamma Controls_{i,t} + \delta IMR_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \tag{3}$$

[11]We get the data from FCC's semi-annual report on broadband adoption, this data includes information on the total number of broadband subscribers in a state, the prevalence of different broadband speeds, and adoption rates. Broadband information is gathered from: https://www.fcc.gov/BroadbandData

where $i$ and $t$ denote firms and years, respectively. The main variable of interest in the baseline model is $API_{i,t-1}$ ($API\_Adopt$), which is an indicator set to one for the bank $i$ in or before year $t-1$ has adopted APIs, and zero for the bank $i$ in year $t-1$ did not own APIs. The regression model includes year-fixed effects $\omega_t$ and firm fixed effect $\varphi_i$. For the dependent variable $Performance_{i,t}$, we use three measures of bank performance indicators: market-based and earning-based performance. To measure the market-based performance, we use market value ($MRKTV$), market-to-book (*Market-Book*), and *Tobin's Q*. We use Income before extraordinary Items (*IB*) and Earnings Per Share (*EPS*) to measure earning-based performance. The results of the baseline regressions are shown in Table 4:

[Insert Table 4 about here]

Table 4 shows the effects of API adoption on bank performance in the subsequent year. Column (0) shows the Heckman first stage regression, columns (1)-(5) illustrate the second-stage regression results of the lagged effect of API adoption on bank performance, including IMR to account for self-selection. Overall, the results show a general increase in performance measures after API adoption. According to Table 4, For earning-based performance, as shown in column (4), this change represents a 9.23% increase (= 0.665 percent increase) compared to the average *IB* of 7.198.

To exclude any effects due to the financial crisis in 2008-09, we further shorten the sample period to 2010 to 2022. The results remain significant and qualitatively similar and are shown in Table A7. In addition, we further employ alternative measures of API, such as the number of APIs ($API\_Intensity$), to perform robustness checks. Overall, the positive effects of API implementation on bank performance are robust to conventional API measures and different model, which are shown in Table A4 Panels A, B and C. To be more specific, the results of $MRKTV$, *IB*, and *EPS* specifications consistently show statistically and economically significant positive coefficients of API intensity, indicating a positive effect on bank performance. In earnings-based performance, more APIs can result in more significant profit opportunities and cross-selling potential, further boosting bank earnings. Additionally, as the number of APIs increases, banks might be able to expand their service offering for existing customers and attract new customers with their more comprehensive service offerings.

#### *4.2.1 Propensity Score Matching Analysis*

To address potential self-selection bias and mitigate systematic differences in characteristics between treatment and control banks, we use propensity score matching technique (PSM) based on Rosenbaum & Rubin (1983). In particular, our treatment group of "API banks" has at least one API per bank during our sample period, whereas the control group of "non-API banks" has no APIs. We use year-by-year matching, using the bank characteristics from the year prior to the adoption of an API to match each API bank in the treatment group with a similar non-API bank in the control group. To balance the treatment and control groups, we use a nearest neighbor one-to-four matching with 0.5% caliper (without replacement) and identify 253 pairs of bank-year observations in the treatment and control groups to match all control variables used in the baseline regression model. We report matching statistics, including diagnostic statistics for differences in bank characteristics (control variables as in Equation (3) between the treatment and control groups in Panel A of Table 5. Mean treatment effects are reported in Table A2. To estimate the propensity score of treated firms, we use a logistic regression of the treatment indicator (API) on the relevant firm-level variables (i.e., *Bank Size*, *Firm age*, *Capital Intensity*, *Leverage*, and *Cost of capital*). The regression model includes year-fixed effects $\omega_t$ and firm fixed effects $\varphi_i$:

$$Perf_{i,t} = \alpha_{i,t} + \beta API_{i,t-1} + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \tag{4}$$

The results from the OLS regression of PSM analysis are presented in Panel B of Table 5. The results based on the PSM sample are consistent with our baseline finding that API adoption has a positive relationship with bank performance, particularly comparing "API banks" with "non-API banks".

[Insert Table 5 about here]

#### *4.2.2 Entropy Balancing Analysis*

To correct for endogeneity bias, such as omitted variables, or model misspecification issues (Roberts and Whited, 2013), we apply Hainmueller (2012)'s entropy balanced matching technique. Entropy balancing applies a weighting function to the sample such that the distributional properties of the control variables for the treatment and control group are similar (Hainmueller, 2012), to reduce bias in estimating treatment effects. To ensure that the treatment and control groups are balanced on covariates, we compare the mean and variance of firm characteristics between the treatment and control groups (see Table A3). Results using the entropy balancing technique are presented in Table 6.

[Insert Table 6 about here]

Consistent with the baseline regressions in Equation (3), results in Table 6 show significant increases in bank performance after API adoption, confirming a positive relationship between API and bank performance.

#### *4.2.3 Privacy legislation as exogenous shock*

We use the level of privacy legislation in different states of the U.S. International Association of Privacy Professionals (IAPP)[12] as an exogenous variable that will affect the rate of API adoption in US states. U.S. state privacy laws limit the collection, use, sharing, and transfer of consumer information by firms and provide normative guidance for data analysis in U.S. banks. Under the Privacy Legislation Act, residents have greater control over how their personal information is used by Internet companies and other organizations (Patel et al., 2023). As a result, banks might be more inclined to adopt APIs to fulfill privacy protection requirements, as sharing data with other third parties through APIs are a more secure method compared to alternative methods such as screen scraping. Table 7 presents the results of the OLS regressions which include the level of privacy legislation in each state where the bank is headquartered.

[Insert Table 7 about here]

As indicated in column (0) of Table 7, privacy legislation has a positive impact on API adoption by banks with headquarters in states that have enacted privacy legislation, demonstrating the effects of the exogenous variables on API adoption ($API\_Adopt$), implying that APIs are more likely to be

[12] Since 2018, the IAPP has closely tracked privacy legislation developments in the U.S. at the state level. This resource, published by the IAPP Research and Insights team, shows the rapid growth of U.S. state-level privacy initiatives from 2018 through 2022 to provide historical context. The IAPP additionally tracks the status of U.S. state privacy legislation in our tool, the "US State Privacy Legislation Tracker," and published a 2022 state privacy legislation wrap-up infographic titled "Privacy Matters in the US States." Sources: https://iapp.org/resources/article/the-growth-of-state-privacy-legislation-infographic/

adopted by banks after stricter data security requirements due to privacy protection legislation have come into effect. In columns (1) to (5), we present the results of the second-stage regression to estimate the impact of marginal effects after API adoption using the predicted value of API adoption from the first stage regression. The results show a positive and significant coefficient of *API_Adopt* for *Market-Book* and *EPS*, while coefficients for the other performance indicators become insignificant. Given that any API adoption after privacy legislation might be driven by regulatory compliance rather than adoption to increase value for bank customers or third-party partnerships, banks are less likely to see any improvements in performance after API adoption compared to banks that have adopted APIs early.

#### *4.2.4 Effects of different API Categories on Bank Performance*

We further analyze differential effects of different types of APIs, in particular Read-only (R) or Read and Write (R/W) APIs (see Section 3.1). Using an OLS regression model, we analyze the changes in performance after the adoption of Read-Write APIs and Read-only APIs. We use the ratio of Read-only APIs (*R_Ratio*) to present the relative number of Read-only APIs of bank $i$, relative to its total number of APIs in year $t$. We constructed the following model to test the impact of API categories on bank performance using a matched sample based on PSM to ensure a balanced sample:

$$Perf_{i,t} = \alpha_{i,t} + \beta API\ ratio_{i,t-1} + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \tag{4}$$

The regression results are shown in Table 8. Panels A and B of Table 8 present the lagged impact of the ratio of the Read-Write API and the Read-only API on bank performance. In addition, we further conduct a robustness test of the number of Read-only APIs (*R_Intensity*) and number of Read-Write APIs (*R/W_Intensity*), and the results are shown in Table A5.

[Insert Table 8 about here]

While both Read-only APIs and Read-Write APIs can enhance bank performance to some extent, their effects on performance do differ. As Read-only APIs enable access to bank customers' transaction and credit information, they might improve service provision for existing customers as well as widen the banks' networks by providing access to potential new customers, thereby improving banks' market value and earnings. We find that after adopting the read-only API, market-based performance (*MRKTV*, *Market-Book* and *Tobin's Q*) has improved. As shown in column (2), this change represents a 4.06% increase (= 0.047 percent increase) compared to the average *Tobin's Q* of 1.156. On the other hand, Read-Write APIs allow more dynamic data sharing in real time, and thereby can provide more detailed information of existing customers and enable better assessment of financial credit risks.

### 4.3 Cross-Sectional Analysis

We further explore the cross-sectional heterogeneity of the effects depending on bank characteristics. Specifically, we provide further evidence regarding the cross-sectional differences of the effects of API adoption and intensity on bank performance measures based on a variety of variables: (i) using the level non-performing loans (*NPL*) and loan loss provisions (*LLP*) to measure banks' credit risk and credit quality, and (ii) banks' product similarity (*Similarity*) and product fluidity (*Fluidity*) to measure competitive pressure for individual banks (Hoberg et al., 2014; Hoberg & Phillips, 2016). In particular, we include a set of dummy variables ($Bank\_Character_i$) based on different bank characteristics with equal one if: (i) the bank's *NPL* is higher than the median of sample banks' (*High_NPL*) and the bank's *LLP* is higher than the median of sample banks' (*High_LLP*), (ii) the bank similarity index is higher than the median of banks' in the sample (*High_Similarity*) and product fluidity is higher than the median of banks' in the sample (*High_Fluidity*). We estimate the following regression model, which extends Equation (3) by incorporating an interaction term between API and bank characteristics.

$$Perf_{i,t} = \beta API_{i,t-1} + \partial\, API_{i,t-1} \times Bank\_Character_i + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \qquad (5)$$

#### *4.3.1 The Role of Banks' Credit Risk*

We assess whether the change in bank performance after API adoption differs for banks with different levels of credit risk. We use the rate of non-performing loans and loan loss provisions. *High_NPL* and *High_LLP* as a proxy for credit risk. In general, the higher the NPL and LLP, the greater the credit risk. The results are presented in Table 9.

[Insert Table 9 about here]

According to Table 9, the increase in performance after API adoption for banks with a low level of risk management and a high level of non-performing loans (*High_NPL*= 1) as well as loan loss provision (*High_LLP*= 1) are much lower compared to banks with low NPL. In contrast, banks with lower levels of *NPL* and *LLP* see greater performance increases, particularly for *MRKTV*, *Market-Book*, and *Tobin's Q*, *IB,* and *EPS*.

While banks with greater credit risk might have greater potential to benefit for additional and better quality data, we argued in in section 2.2 that banks with lower credit risk and better screening abilities might benefit more from an open banking environment. In particular, He et al. (2023) suggest that open banking activities of banks with different levels of risk management may experience differing impacts on performance as weaker lenders with lesser screening abilities will be subject to a more severe winner's curse. Furthermore, Parlour et al. (2022) argue that banks rely on an efficient information spillover of payment data to assess credit risk, which can be disrupted by data portability and consumer privacy laws as customers are entitled to not share their data with the bank. Consistent with these theoretical predictions, we conjecture that bank with lower levels of credit risk will be subject to a less severe winner's curse, and experience less disruption of information spillover. Thus, our results that show that banks with lower credit risk experience greater performance increases and are in line with these theoretical results.

#### *4.3.2 The Role of Banks' Product Similarity and Fluidity*

To test the heterogenous effects for banks that are subject to different levels of competition, we include an interaction effect of API adoption and a dummy that indicates high levels of product similarity within sample banks (*High_Similarity*) and high levels of product fluidity within the bank industry (*High_Fluidity)*. The results for both analyses are presented in Table 10.

[Insert Table 10 about here]

The results show the positive effects on bank performance are enhanced for banks with lower levels of industry similarity (*High_Similarity*) and lower levels of product fluidity (*High_Fluidity*) but weaker for banks that experience greater competitive pressures. In line with previous discussions on FinTech competition, Parlour et al. (2022) shows that FinTech competition might have adverse effects on the information spillover within banks, and API adoption can have more substantial effects on bank performance in a less competitive market environment. Our results thus supports H3 that higher levels of competition in the bank industry might disrupt internal information spillover, and lead to adverse effects, such as higher prices of loans for consumers.

## 5. Conclusion

In contrast to previous studies on open banking and Fintech competition, this paper provides an empirical framework to assess the effects of adopting an open banking strategy from the adopting banks' perspective. In contrast to European countries where there is an open banking mandate from regulators, our empirical results shed light on the implications of an open banking strategy for US banks. We find that bank performance improves after API adoption, supporting recent literature that IT adoption and IT investment by banks can have positive effects on firm performance (Dadoukis et al., 2021). However, we illustrate that effects are heterogeneous, as banks with lower levels of credit risk and competitive pressure gain more benefits from data sharing and open banking environment compared to banks with higher levels of credit risk and subject to more banking competition.

Our study has specific practical and policy implications, as open banking initiatives and policies can have significant consequences for the banking landscape as well as for FinTech competition. Compared with the open banking mandates adopted in Europe and the UK, our heterogeneous findings provide insights into the effects of voluntary open banking on the US banking industry. Our results show that open banking regulation might have heterogeneous effects on different types of banks and that an increasing amount of data sharing and data portability and create certain unintended consequences, as indicated by existing open banking research (Parlour et al. 2022; He et al., 2022). Furthermore, implementing excessively stringent regulations may add additional regulatory burdens on smaller banks and increase discrepancies between banks even further. While it is beyond the scope of this paper, future work might explore the differences in open banking regulation in other countries besides the US and the implications for the banking industry and bank customers.

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**Tables and Figures**

**Figure 1. Number of Adopted APIs by Year**

This figure shows the growth and cumulative number of adopted bank APIs for the sample interval from 2007 to 2022. The bar chart shows the cumulative number of bank APIs, and the line chart shows the number of new APIs for each year.

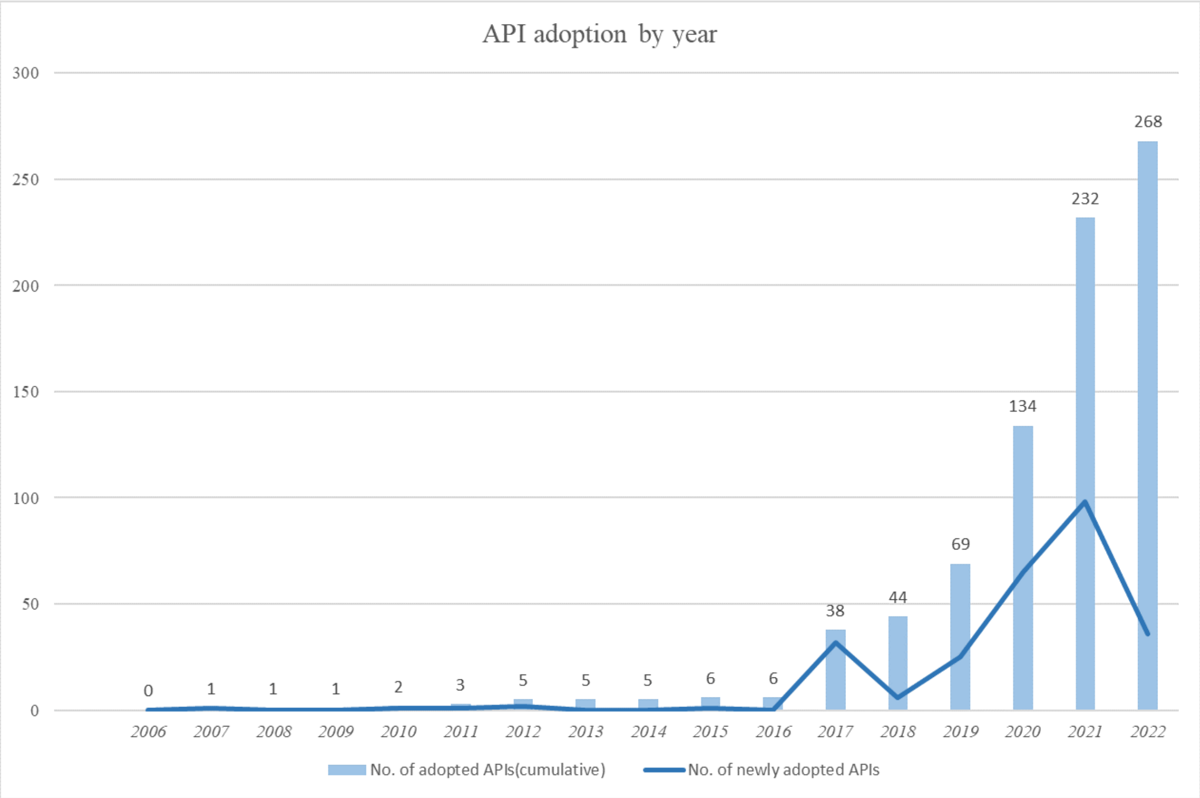


**Figure 2. Number of Individual Adopting Banks per Year**

This figure shows the growth and cumulative number of banks that adopted APIs (API-banks) for the sample interval from 2005 to 2022. The bar chart shows the cumulative number of API-banks, and the line chart shows the number of new API-banks for each year.

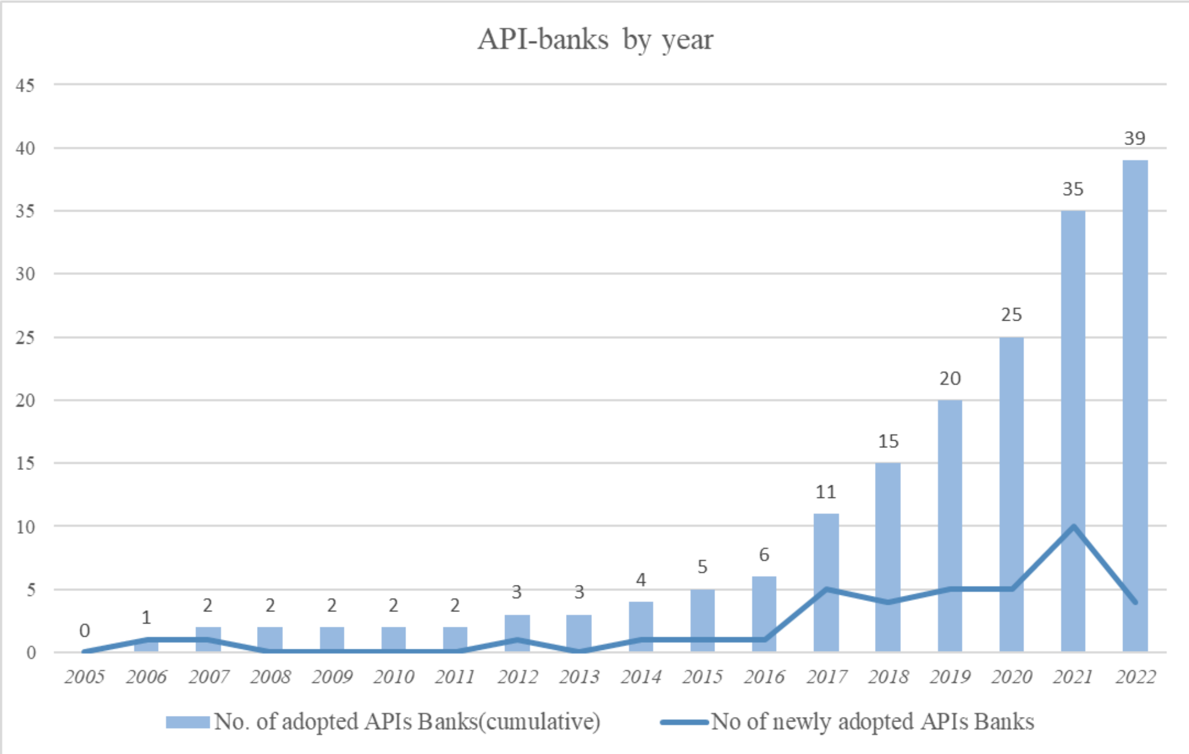


**Table 1. Variable Description**

| Variable name | Definition |
|---|---|
| ***Panel A: Variables for API Adoption and Instrumental Variable*** | |
| $API\_Adopt_{i,t}$ | Dummy variable equals 1 if bank $i$ has operating APIs in period t [Bank websites and API platforms] |
| $API\_Intensity_{i,t}$ | Number of APIs owned by bank $i$ in year $t$ [Bank websites and API platforms] |
| $API\_bank_i$ | Dummy variable, whether bank $i$ has operating APIs during sample period (2007-2022) [Bank websites and API platforms] |
| *R_Ratio* | The number of Read-only APIs to the total number of APIs in bank $i$ in t years [Bank websites and API platforms] |
| *R/W_Ratio* | The number of Read-Write APIs to the total number of APIs in bank $i$ in t years [Bank websites and API platforms] |
| *R_Intensity* | Number of Read-only APIs owned by bank $i$ in year $t$ [Bank websites and API platforms] |
| *R/W_Intensity* | Number of Read-Write APIs owned by bank $i$ in year $t$ [Bank websites and API platforms] |
| ***Panel B: Measures of Bank Performance*** | |
| *MRKTV* | Natural logarithm of market value of equity [Compustat] |
| *Tobin's Q* | Ratio of market value of bank shares to the replacement cost of the assets represented by the shares [Compustat] |
| *Market-Book* | Ratio of market value (market capitalization) to book value of equity) [Compustat] |
| *IB* | Income before extraordinary Items/1000 [Compustat] |
| *EPS* | Earnings per Share Ratio of net income/number of common shares [Compustat] |
| ***Panel C: Bank and industry characteristics*** | |
| *Firm Age* | Year minus the IPO year or the first year Compustat reports data for the firm [Compustat] |
| *Bank Size* | Logarithm of total assets [Compustat] |
| *Capital Intensity* | Ratio of capital expenditures to total assets, CAPX/AT [Compustat] |
| *Leverage* | Long-term debt plus debt in current liabilities, divided by total assets (DLTT+DLC)/SEQ [Compustat] |
| *Cash Holding* | Cash and short-term investments divided by total assets. CHE/AT [Compustat] |
| *Cost of Capital* | Total interest expense divided by the total amount of debt: XINT/DLC [Compustat] |
| *Tier 1 capital* | The ratio of a bank's equity capital with its total risk-weighted assets (RWAs) [Compustat] |
| *Employee* | We use the natural logarithm of 1 plus the number of employees in the regression, the number of employees in thousands. [Compustat] |
| *Efficiency* | Operational efficiency as the ratio of bank's inputs to outputs, (input measured by deposits, non-interest expenses (net of loan losses), fixed assets and loan loss provisions) and output by total loans and leases, other earning assets [Compustat] |
| *NPL* | Ratio of non-performing loans to total loans [BankFocus] |
| *LLP* | Ratio of loan loss provision to total loans [BankFocus] |
| *Similarity* | The total similarity measures the pairwise product similarities for each firm with competitor firms in 10-k filings, see Hoberg and Phillips (2016) [Hoberg-Phillips Database] |
| *Fluidity* | The competitive threat a firm faces by measuring the overlap between the product descriptions of firms and corresponding rivals. Firms that score higher on product liquidity are more likely to face significant competitive threats. See Hoberg (2014) [Hoberg-Phillips Database] |
| *Broadband* | State-level broadband subscription rates for Internet access. Takes values in the range [0,1], with values near 0 indicating low broadband subscription and near 1 indicating high residential broadband subscription [FCC's semi-annual report] |

**Table 2. Summary Statistics**

This table presents summary statistics for the main variables in the regressions for 6,926 firm-year observations for 1,185 banks from 2007 to 2022. Variable descriptions are provided in Table 1. Column (1) shows the descriptive statistics number of observations (N), mean and standard deviation (SD) for the overall sample, columns (2) and (3) show the descriptive statistics for the 1,146 banks without APIs and the 39 banks with APIs, respectively.

| No. of banks | (1) Full-Sample (N=1185) | | | (2) Banks without APIs (N=1146) | | (3) Banks with APIs (N=39) | |
|---|---|---|---|---|---|---|---|
| *VARIABLES* | N | Mean | SD | Mean | SD | Mean | SD |
| ***Panel A: Variables for API adoption*** | | | | | | | |
| *API_Adopt* | 6,926 | 0.074 | 1.216 | 0.000 | 0.000 | 0.245 | 0.431 |
| *API_Intensity* | 6,926 | 0.044 | 0.205 | 0.000 | 0.000 | 1.674 | 5.575 |
| *API_bank* | 6,926 | 0.036 | 0.594 | 0.000 | 0.000 | 1.000 | 0.000 |
| *API_R/W* | 6,926 | 0.006 | 0.067 | 0.000 | 0.000 | 0.126 | 0.287 |
| *API_R* | 6,926 | 0.003 | 0.039 | 0.000 | 0.000 | 0.059 | 0.167 |
| ***Panel B: Measures of bank performance*** | | | | | | | |
| *MRKTV* | 6,926 | 1.020 | 0.075 | 0.935 | 3.432 | 23.130 | 30.340 |
| *Tobin's Q* | 6,926 | 1.156 | 0.602 | 1.019 | 0.075 | 1.043 | 0.063 |
| *Market-Book* | 6,926 | 1.067 | 0.684 | 1.142 | 0.593 | 1.490 | 0.718 |
| *IB* | 6,926 | 7.198 | 12.150 | 0.081 | 0.445 | 1.821 | 2.610 |
| *EPS* | 6,926 | 3.083 | 0.943 | 7.095 | 12.280 | 9.716 | 8.085 |
| ***Panel C: Bank and industry characteristics*** | | | | | | | |
| *Firm Age* | 6,926 | 7.587 | 1.709 | 2.406 | 0.902 | 3.105 | 0.924 |
| *Bank Size* | 6,926 | 0.122 | 0.096 | 7.442 | 1.509 | 10.750 | 2.536 |
| *Capital Intensity* | 6,926 | 1.103 | 1.432 | 0.123 | 0.098 | 0.100 | 0.044 |
| *Leverage* | 6,926 | 0.068 | 0.070 | 1.085 | 1.403 | 1.483 | 1.937 |
| *Cash Holding* | 6,926 | 6.111 | 143.40 | 0.067 | 0.068 | 0.105 | 0.105 |
| *Cost of Capital* | 6,926 | 12.860 | 4.959 | 6.373 | 147.000 | 0.970 | 6.069 |
| *Tier 1 Capital* | 6,926 | 6.025 | 1.676 | 12.860 | 4.990 | 12.790 | 4.241 |
| *Employee* | 6,669 | 0.012 | 0.011 | 5.887 | 1.516 | 8.743 | 2.257 |
| *EFF* | 6,926 | 1.187 | 1.157 | 0.011 | 0.010 | 0.025 | 0.017 |
| *NPL* | 6,926 | 0.486 | 0.955 | 1.196 | 1.168 | 1.016 | 0.897 |
| *LLP* | 6,926 | 48.330 | 19.540 | 0.486 | 0.961 | 0.467 | 0.833 |
| *Similarity* | 6,926 | 0.081 | 0.061 | 48.810 | 19.410 | 36.720 | 19.250 |
| *HHI* | 6,926 | 10.540 | 3.633 | 0.081 | 0.059 | 0.080 | 0.094 |
| *Fluidity* | 6,669 | 0.951 | 0.811 | 10.590 | 3.623 | 9.208 | 3.630 |
| *Z-score* | 6,926 | 0.951 | 0.811 | 0.955 | 0.817 | 0.853 | 0.640 |
| *Broadband* | 6,926 | 0.655 | 0.155 | 0.794 | 0.139 | 0.649 | 0.153 |

**Table 3. Logistic Regression of API Adoption on Bank Characteristics**

This table shows the results of the logistic regression of whether bank *i* has adopted API (*API_bank*) on bank characteristics:

$$API\_bank_i = \alpha_i + \beta Bank\ Characteristics_{i,t} + \omega_t + \epsilon_{i,t} \quad (1)$$

The table reports regression coefficients and t-statistics (in parentheses). The regression model is shown in Equation (1), with dependent variable $API\_bank_i$ regressed on variables of bank characteristics prior to the adoption of the first API. The independent variables' definitions are provided in Table 1. All continuous variables are winsorized at the 1st and 99th percentile. All models control for year-fixed effects. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| *VARIABLES* | $API\_bank_i$ | $API\_bank_i$ |
| $Firm\ Age_i$ | -0.240 | -0.247 |
| | (-0.98) | (-1.08) |
| $Bank\ Size_i$ | 2.255*** | 2.524*** |
| | (8.55) | (9.58) |
| $Cash\ Holding_i$ | 2.247 | 1.739 |
| | (1.25) | (0.98) |
| $Efficiency_i$ | 33.084*** | 36.523*** |
| | (2.85) | (3.17) |
| $Employee_i$ | -1.303*** | -1.522*** |
| | (-4.49) | (-5.54) |
| $Capital\ Intensity_i$ | -21.124*** | -20.083*** |
| | (-3.67) | (-3.51) |
| $Leverage_i$ | -0.067 | -0.009 |
| | (-0.69) | (-0.10) |
| $NPL_i$ | -0.456*** | |
| | (-2.95) | |
| $Similarity_i$ | -0.022*** | |
| | (-2.88) | |
| $LLP_i$ | | -0.481*** |
| | | (-3.45) |
| $Fluidity_i$ | | -0.003 |
| | | (-0.07) |
| Constant | -10.319*** | -12.753*** |
| | (-10.06) | (-12.27) |
| Year FE | Yes | Yes |
| Observations | 3,976 | 3,976 |

**Table 4. Regression of Bank Performance on API**

The table reports baseline regression coefficients and t-statistics (in parentheses) using the Heckman two-stage analysis. This table shows the effect of API adoption on the bank performance. The column (0) shows the Heckman first-stage Probit regression of *API_Adopt* (a dummy variable representing whether bank $i$ adopted APIs in and before year $t$) on control variables and *Broadband* (is an exogeneous variable with values between [0,1]) that measure the strength of Internet access in the state where the bank is headquartered. *Broadband* is a continuous variable, with 1 indicating the strongest broadband subscription. *IMR* denotes the inverse Mills ratio generated from the first step which is included in the second step of this model. In the second-stage OLS regression, we use dependent performance variables (Market Value (*MRKTV*), *Market-Book*, *Tobin's Q*, Net Income (*IB*), and *EPS*). The control variables are defined in Table 1. All models include year and firm fixed effects. The continuous variables are winsorized at the 1st and 99th percentiles. ∗∗∗, ∗∗ and ∗ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| | (0) | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|---|
| *VARIABLES* | $API_t$ | $MRKTV_t$ | *Tobin's* $Q_t$ | *Market-Book*$_t$ | $IB_t$ | $EPS_t$ |
| *Broadband*$_t$ | 0.545 | | | | | |
| | (0.63) | | | | | |
| *API_Adopt*$_{t-1}$ | | 3.827*** | 0.015** | 0.209*** | 0.665*** | 3.288*** |
| | | (7.88) | (2.24) | (2.79) | (9.77) | (6.96) |
| *Firm Age*$_t$ | -0.177 | -2.791*** | 0.007** | 0.043 | -0.291*** | -0.328 |
| | (-1.50) | (-12.75) | (2.29) | (1.22) | (-9.13) | (-1.54) |
| *Bank Size*$_t$ | 0.735** | 1.315*** | -0.027*** | -0.264*** | 0.093** | 1.421*** |
| | (2.52) | (5.05) | (-7.47) | (-6.32) | (2.44) | (5.61) |
| *Capital Intensity*$_t$ | -10.023*** | 4.012 | -0.132*** | -1.425*** | 0.279 | -13.604*** |
| | (-2.64) | (1.51) | (-3.61) | (-3.39) | (0.73) | (-5.28) |
| *Leverage*$_t$ | -0.124 | 0.039 | 0.000 | -0.038*** | -0.008 | 0.025 |
| | (-1.47) | (0.83) | (0.26) | (-5.05) | (-1.19) | (0.54) |
| *Cash Holding*$_t$ | 1.749 | -0.181 | -0.025* | 0.026 | -0.154 | -2.526*** |
| | (1.29) | (-0.18) | (-1.85) | (0.17) | (-1.07) | (-2.61) |
| *Cost of Capital*$_t$ | -0.008 | 0.000 | 0.000*** | 0.000** | 0.000 | -0.001 |
| | (-1.12) | (0.37) | (2.98) | (2.29) | (0.64) | (-0.79) |
| *Tier 1 Capital*$_t$ | 0.019 | -0.031* | 0.000* | 0.004 | -0.002 | -0.012 |
| | (0.76) | (-1.75) | (1.77) | (1.28) | (-0.66) | (-0.68) |
| *Employee*$_t$ | -0.284 | -0.445** | 0.019*** | 0.180*** | -0.101*** | -0.209 |
| | (-0.93) | (-1.98) | (6.29) | (4.99) | (-3.08) | (-0.96) |
| $IMR_t$ | | -0.080 | -0.007*** | -0.078*** | -0.017 | 0.125 |
| | | (-0.50) | (-3.24) | (-3.03) | (-0.73) | (0.81) |
| Constant | -4.923*** | 2.364 | 1.120*** | 2.362*** | 0.921*** | -2.024 |
| | (-5.58) | (1.53) | (52.68) | (9.55) | (4.10) | (-1.34) |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Observations | 5,020 | 5,100 | 5,100 | 5,133 | 5,133 | 5,100 |
| R-squared | 0.3635 | 0.961 | 0.755 | 0.680 | 0.895 | 0.895 |

**Table 5. Propensity Scores Matching Results**

This table reports the regression results from Equation (3) based on the matched sample using propensity scores matching (PSM). The covariate balance checks are presented in Panel A. We balance the treated and control banks using firm-level controls, namely, *Bank Size*, *Firm age*, *Capital Intensity*, *Leverage*, and *Cost of Capital*. The regression results based on matched samples are shown here and OLS regression coefficients and t-statistics in parentheses. We use the dependent variables on market-based performance ( $MRKTV$ , *Market-Book* and *Tobin's Q* in columns (1)-(3)), earning-based performance ($IB$ and $EPS$ in columns (4)-(5) respectively). $API\_Adopt_{t-1}$ is a dummy variable representing whether bank $i$ adopted APIs in or before year $t-1$. Variables are defined in Table 1. The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Panel A. Results of covariate balance checks* | | | | |
|---|---|---|---|---|
| | Treatment group | Control group | Difference | t-stat |
| | Banks with APIs | Banks without APIs | | |
| *VARIABLES* | Mean | Mean | | |
| *Bank size* | 11.157 | 11.310 | -0.153 | -0.27 |
| *Firm age* | 3.229 | 3.270 | -0.041 | -0.21 |
| *Capital Intensity* | 0.094 | 0.098 | -0.004 | -0.5 |
| *Leverage* | 1.515 | 1.950 | -0.435 | -0.83 |
| *Cost of capital* | 1.129 | 0.332 | 0.797 | 1.49 |

| *Panel B. Regression results using PSM procedure* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | $MRKTV_t$ | $Tobin's\ Q_t$ | $Market\text{-}Book_t$ | $IB_t$ | $EPS_t$ |
| $API\_Adopt_{t-1}$ | 2.521*** | 0.013* | 0.190** | 0.714*** | 2.441** |
| | (3.06) | (1.69) | (2.25) | (4.80) | (2.21) |
| *Control Variables$_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 541 | 541 | 541 | 541 | 541 |
| R-squared | 0.972 | 0.749 | 0.763 | 0.867 | 0.951 |

**Table 6. Entropy Balancing Results**

This table tests the effect of API on adopting banks based on the baseline that employs weightings based on entropy balancing to improve covariate balance between the treatment group (API bank=1) and the control group (API bank=0) by weighing observations so that the moments of the post-weighing distributions (mean, variance and skewness) for the treatment and control samples are equal on each matching dimension. We match covariates of various bank financial characteristics to match all control variables used in the baseline regression model as well as controls for the year. We report regression results based on matched samples (regression coefficients and t-statistics in parentheses). We use the dependent variables on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earning-based performance (*IB* and *EPS* in columns (4)-(5) respectively). $API\_Adopt_{t-1}$ is a dummy variable representing whether bank $i$ adopted APIs in and before year $t-1$. Variables are defined in Table 1. The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *VARIABLES* | $MRKTV_t$ | $Tobin's\ Q_t$ | $Market\text{-}Book_t$ | $IB_t$ | $EPS_t$ |
| $API\_Adopt_{t-1}$ | 16.452*** | 0.039*** | 0.523*** | 1.266*** | -1.837 |
| | (6.30) | (6.86) | (7.07) | (4.55) | (-0.97) |
| *Control Variables$_t$* | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 5,166 | 5,166 | 5,199 | 5,199 | 5,166 |
| R-squared | 0.836 | 0.433 | 0.497 | 0.734 | 0.114 |

**Table 7. Instrumental Variables**

This table shows the results of the instrumental variable regressions. We used a two-stage least squares (2sls) method to match all control, year, and firm fixed effects models used in the baseline regression model. The instrumental variable is a continuous variable from 0 to 1 measuring the adoption process of privacy legislation by state in the United States in which the bank is headquartered. The dependent variable for the first stage regression is the broadband adoption in the state on the number of APIs owned by bank $i$ in year $t$ shown in Model (0). In the second stage, we use the dependent variables on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earing-based performance (*IB* and *EPS* in columns (4)-(5) respectively). The variables are defined in Table 1). We report regression results (regression coefficients and t-statistics in parentheses). The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| | | | | | | |
|---|---|---|---|---|---|---|
| *Panel A: Regression of API Adoption on bank performance with Instrumental Variable* | | | | | | |
| | (0) | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | $API_t$ | $MRKTV_t$ | *Tobin's* $Q_t$ | *Market-Book*$_t$ | $IB_t$ | $EPS_t$ |
| $Privacy_t$ | 0.008*** | | | | | |
| | (5.45) | | | | | |
| $API\_Adopt_{t-1}$ | | 8.423* | -0.091 | 0.714 | -0.754 | 17.743** |
| | | (1.78) | (-1.36) | (0.94) | (-0.95) | (2.37) |
| *Control Variables*$_t$ | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Observations | 6,020 | 6,021 | 6,022 | 6,023 | 6,024 | 6,025 |
| R-squared | 0.0877 | 0.036 | -0.033 | -0.007 | -0.056 | -0.054 |
| *Panel B: Regression of API Intensity on bank performance with Instrumental Variable* | | | | | | |
| | (0) | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | $API_t$ | $MRKTV_t$ | *Tobin's* $Q_t$ | *Market-Book*$_t$ | $IB_t$ | $EPS_t$ |
| $Privacy_t$ | 0.045*** | | | | | |
| | (5.69) | | | | | |
| $API\_Intensity_{t-1}$ | | 7.614 | -0.024 | 1.781** | -1.177 | 10.873* |
| | | (1.47) | (-0.35) | (2.08) | (-1.27) | (1.81) |
| *Control Variables*$_t$ | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Observations | 6,020 | 6,020 | 6,020 | 6,020 | 6,020 | 6,020 |
| R-squared | 0.0879 | 0.046 | 0.020 | -0.129 | -0.125 | 0.016 |

**Table 8. API Category and Bank Performance**

The table reports regression coefficients and t-statistics (in parentheses) using the Heckman test to examine the difference between the Read-only API and Read-Write API in promoting bank performance.

$$Perf_{i,t} = \alpha_{i,t} + \beta API\ ratio_{i,t-1} + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \quad (4)$$

The regression model is shown in Equation (3). We use the dependent variables on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earing-based performance (*IB* and *EPS* in columns (4)-(5) respectively). We use *R/W_Ratio* and *R_Ratio* to measure the ratio of different APIs in Panel A and B. The *R/W ratio* and *R ratio* are continuous variables representing the proportion of this type of API in the total number of APIs bank $i$ had in year $t$. The control variables are defined in Table 1. All models control for year and firm fixed effects. The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Panel A: Read and Write APIs effect on bank performance* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *MRKTV$_t$* | *Tobin's Q$_t$* | *Market-Book$_t$* | *IB$_t$* | *EPS$_t$* |
| *R/W_Ratio$_{t-1}$* | 2.018** | 0.014 | 0.160* | 0.404** | 3.178** |
| | (2.09) | (1.52) | (1.67) | (2.29) | (2.50) |
| *Control Variables$_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 541 | 541 | 547 | 547 | 541 |
| R-squared | 0.972 | 0.763 | 0.775 | 0.906 | 0.952 |
| *Panel B: Read-only APIs effect on bank performance* | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *MRKTV$_t$* | *Tobin's Q$_t$* | *Market-Book$_t$* | *IB$_t$* | *EPS$_t$* |
| *R_Ratio$_{t-1}$* | 5.561*** | 0.047** | 0.595*** | 2.679*** | 1.807 |
| | (2.61) | (2.32) | (2.81) | (7.17) | (0.64) |
| *Control Variables$_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 541 | 541 | 547 | 547 | 541 |
| R-squared | 0.972 | 0.765 | 0.778 | 0.914 | 0.952 |

**Table 9. The Role of Bank Credit Risk (Non-Performing Loans and Loan Loss Provisions)**

$$Perf_{i,t} = \beta API_{i,t-1} + \partial\ API_{i,t-1} \times Credit\ risk_i + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \qquad (5)$$

The tables below show regression results for API, including interaction effects with the level of non-performing loans (NPL). We include the interaction term between the API and dummies for *High_NPL* (for firms with *NPL* above the average bank level, the *High_NPL* dummy equals 1). The cross-sectional analysis results of *High_NPL and API_Adopt* are presented as interactive items in the table. We apply the same dependent variables as in Equation (3) on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earing-based performance (*IB* and *EPS* in columns (4)-(5) respectively). We use $API\_Adoption$ to measure API situation, which is a dummy variable representing whether bank $i$ adopted APIs in and before year $t$. The control variables are defined in Table 1. We report regression results (regression coefficients and t-statistics in parentheses). The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Panel A: The role of Non-Performing Loans on API adoption* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | $MRKTV_t$ | $Tobin's\ Q_t$ | $Market\text{-}Book_t$ | $IB_t$ | $EPS_t$ |
| $API\_Adopt_{t-1}$ | 10.691*** | 0.020* | 0.413*** | 0.967*** | 7.107*** |
| | (13.52) | (1.82) | (3.56) | (9.20) | (9.16) |
| $API\_Adopt_{t-1} \times High\_NPL_t$ | -10.772*** | -0.008 | -0.347** | -0.513*** | -5.993*** |
| | (-10.92) | (-0.58) | (-2.30) | (-3.76) | (-6.19) |
| $Control\ Variables_t$ | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 4,077 | 4,077 | 4,077 | 4,077 | 4,077 |
| R-squared | 0.967 | 0.782 | 0.740 | 0.936 | 0.928 |
| *Panel B: The role of Loan Loss Provisions on API adoption* | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | $MRKTV_t$ | $Tobin's\ Q_t$ | $Market\text{-}Book_t$ | $IB_t$ | $EPS_t$ |
| $API\_Adopt_{t-1}$ | 27.140*** | 0.034 | 0.614*** | 1.943*** | -0.166 |
| | (15.50) | (1.40) | (3.33) | (10.92) | (-0.09) |
| $API\_Adopt_{t-1} \times High\_LLP_t$ | -25.098*** | -0.021 | -0.483** | -1.492*** | 3.700** |
| | (-13.81) | (-0.83) | (-2.43) | (-7.77) | (2.02) |
| $Control\ Variables_t$ | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 4,748 | 4,748 | 4,772 | 4,772 | 4,748 |
| R-squared | 0.960 | 0.760 | 0.702 | 0.888 | 0.899 |

**Table 10. The Role of Bank Competition (Product Similarity and Fluidity)**

$$Perf_{i,t} = \beta API_{i,t-1} + \partial\, API_{i,t-1} \times Competition_i + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \qquad (5)$$

The table below shows regression results for API on bank performance, including interaction effects with the level of bank product similarity and product fluidity. We include the interaction term between the API and dummies for similarity (for firms with similarity above the average bank level, the similarity dummy equals 1) and dummies for product fluidity (for firms with fluidity above the average bank level, the fluidity dummy equals 1). The cross-sectional analysis results of *High_Similarity and API_Adopt* are presented as interactive items on Panel A, while the cross-sectional analysis results of *High_Fluidity and API_Adopt* are presented are presented as interactive items on Panel B. We apply the same dependent variables as in Equation (3) on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earing-based performance (*IB* and *EPS* in columns (4)-(5) respectively). We use $API\_Adoption$ to measure API situation in both Panel A and Panel B, which is a dummy variable representing whether bank $i$ adopted APIs in and before year $t$. The control variables are defined in Table 1. We report regression results (regression coefficients and t-statistics in parentheses). The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Panel A: The role of product similarity for API adoption* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$API\_Adopt_{t-1}$* | 6.311*** | 0.033*** | 0.424*** | 1.161*** | 3.803*** |
| | (10.13) | (3.83) | (4.51) | (13.73) | (6.25) |
| *$API\_Adopt_{t-1}$ × $High\_Similarity_t$* | -6.141*** | -0.044*** | -0.576*** | -1.329*** | -1.273 |
| | (-6.33) | (-3.31) | (-3.78) | (-9.70) | (-1.34) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 4,077 | 4,077 | 4,077 | 4,077 | 4,077 |
| R-squared | 0.967 | 0.783 | 0.741 | 0.938 | 0.927 |
| *Panel B: The role of product fluidity for API adoption* | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$API\_Adopt_{t-1}$* | 4.590*** | 0.017** | 0.251*** | 0.772*** | 3.027*** |
| | (8.28) | (2.28) | (2.97) | (10.06) | (5.61) |
| *$API\_Adopt_{t-1}$ × $High\_Fluidity_t$* | -3.215*** | -0.010 | -0.191 | -0.487*** | 1.098 |
| | (-2.86) | (-0.66) | (-1.07) | (-3.00) | (1.00) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 4,077 | 4,077 | 4,077 | 4,077 | 4,077 |
| R-squared | 0.967 | 0.782 | 0.74 | 0.936 | 0.926 |

**Online Appendix**

**“The effects of voluntary open banking adoption”**

In this online appendix, we provide additional discussions and robustness tests that supplement the empirical analysis in the main body of the manuscript.

**Table A1. Correlation matrices of the key variables**

We calculated the correlation coefficient for each pair of key variables and demonstrated its significance. We have included independent and dependent variables and interaction variables in our analysis. (1)-(3) respectively represent the bank's ownership of the API; (4)-(8) represent the market value and profitability of banks. Among the key variables of our cross-sectional analysis are (9)-(13). All variables are defined in Table 1. The continuous variables are winsorized at their first and 99th percentiles. * indicates statistical significance at the 1% levels.

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | *API_Adopt* | 1 | | | | | | | | | | | | |
| (2) | *API_Intensity* | 0.5777* | 1 | | | | | | | | | | | |
| (3) | *API_bank* | 0.4842* | 0.2820* | 1 | | | | | | | | | | |
| (4) | *MRKTV* | 0.4410* | 0.3912* | 0.5305* | 1 | | | | | | | | | |
| (5) | *Tobin's Q* | 0.0508* | 0.0119 | 0.0633* | 0.1549* | 1 | | | | | | | | |
| (6) | *Market-Book* | 0.0812* | 0.0223* | 0.1142* | 0.1383* | 0.7816* | 1 | | | | | | | |
| (7) | *IB* | 0.3886* | 0.3461* | 0.4702* | 0.9370* | 0.1231* | 0.1129* | 1 | | | | | | |
| (8) | *EPS* | 0.0944* | 0.0617* | 0.1190* | 0.1342* | 0.1666* | 0.1837* | 0.1628* | 1 | | | | | |
| (9) | *NPL* | -0.0283* | -0.0164 | -0.0330* | 0.0160 | -0.1375* | -0.1677* | -0.0382* | -0.2437* | 1 | | | | |
| (10) | *LLP* | -0.0218* | -0.0172 | -0.00420 | 0.0290* | -0.1949* | -0.2306* | -0.00310 | -0.2588* | 0.3936* | 1 | | | |
| (11) | *Z-score* | -0.0125 | -0.00970 | -0.0258* | -0.0131 | 0.0279* | 0.0282* | -0.0140 | 0.0503* | -0.1121* | -0.1296* | 1 | | |
| (12) | *Similarity* | -0.0747* | -0.0539* | -0.1202* | -0.1775* | -0.2734* | -0.2374* | -0.2032* | -0.2683* | 0.1833* | 0.0786* | -0.0165 | 1 | |
| (13) | *Fluidity* | -0.0569* | -0.0475* | -0.0728* | -0.1291* | -0.2546* | -0.3248* | -0.1375* | -0.2305* | 0.1488* | 0.1781* | -0.0622* | 0.5191* | 1 |

**Table A2. Propensity Scores Matching**

The Propensity score matching indicates that all univariate differences in bank characteristics are statistically insignificant, suggesting that any differences in bank performance between the treatment and control groups should be driven by the presence or absence of an API rather than observable bank characteristics. The means of the five measures of bank performance for the treated banks: $MRKTV$, *Market-Book,* and *Tobin's Q*, *IB*, and *EPS* are significantly higher than those of the control banks, which are consistent with our main results. In addition, we also show by visualization in Appendix Figure 1 that there are no significant differences between the means of the variables before and after matching (minor deviations from the mean, small t-values are not significant), i.e., the matched data pass the balance test.

| *VARIABLES* | Treatment group (Banks with APIs) Mean | Control group (Banks without APIs) Mean | Difference | t-stat |
|---|---|---|---|---|
| *MRKTV* | 22.0619 | 11.7311 | 10.3308*** | 6.71 |
| *Market-Book* | 1.4668 | 1.3384 | 0.1284* | 1.52 |
| *Tobin's Q* | 1.0455 | 1.0265 | 0.0189*** | 4.30 |
| *IB* | 1.5572 | 1.1846 | 0.3725*** | 3.17 |
| *EPS* | 9.9683 | 8.4640 | 1.1485* | 1.31 |

**Table A3. Entropy Balancing Matching**

The entropy balancing matching indicates that all univariate differences in bank characteristics are statistically insignificant, suggesting that any differences in bank performance between the treatment and control groups should be driven by the presence or absence of an API rather than observable bank characteristics. After weighting, the difference in bank characteristics between the treatment and control groups is tiny.

| *Panel A: Without weighting* | | | | | | |
|---|---|---|---|---|---|---|
| | Treatment Group | | | Control Group | | |
| *VARIABLES* | Mean | Variance | Skewness | Mean | Variance | Skewness |
| *Bank Size* | 11.18 | 5.343 | -0.2245 | 7.518 | 2.365 | 1.004 |
| *Firm Age* | 3.236 | 0.7743 | -1.313 | 2.425 | 0.7548 | -0.8664 |
| *Cap Intensity* | 0.1044 | 0.0006 | 0.9581 | 0.1108 | 0.0044 | 5.625 |
| *Leverage* | 1.477 | 1.276 | 1.784 | 1.308 | 2.383 | 3.946 |
| *Cost of Capital* | 0.9487 | 38.64 | 13.75 | 7.716 | 40855 | 49.96 |
| *Cash Holding* | 0.1005 | 0.0090 | 1.384 | 0.0574 | 0.0032 | 3.368 |
| *Panel B: With weighting* | | | | | | |
| | Treatment Group | | | Control Group | | |
| *VARIABLES* | Mean | Variance | Skewness | Mean | Variance | Skewness |
| *Bank Size* | 11.18 | 5.343 | -0.2245 | 11.18 | 5.694 | -0.060 |
| *Firm Age* | 3.236 | 0.7743 | -1.313 | 3.236 | 0.6519 | -1.779 |
| *Cap Intensity* | 0.1044 | 0.0006 | 0.9581 | 0.1044 | 0.01295 | 3.715 |
| *Leverage* | 1.477 | 1.276 | 1.784 | 1.477 | 6.805 | 3.217 |
| *Cost of Capital* | 0.9487 | 38.64 | 13.75 | 0.9506 | 42.85 | 41.28 |
| *Cash Holding* | 0.1005 | 0.0090 | 1.384 | 0.1005 | 0.01372 | 1.788 |

**Table A4. Alternative measurement of API on bank performance**

The table reports baseline regression coefficients and t-statistics (in parentheses) using the Heckman test as well as alternative propensity score matched and entropy balanced samples. Panel A, Panel B, and Panel C show the effects of API intensity on the bank performance. In Panel A, the column (0) shows the Heckman first-stage regression, which calculates the probability that the API will be adopted and produces the variable IMR. We conclude the IMR into the control variables for the following Heckman second-stage regressions. In Panel B, we use a caliper width of 0. 5% (no replacement) to match all control variables used in the baseline regression model and controls for the year. In Panel C, we test the effect of API on adopting banks based on the baseline that employs weightings based on entropy balancing to improve covariate balance between the treatment group (API bank=1) and the control group (API bank=0) by weighing observations so that the moments of the post-weighing distributions (mean, variance and skewness) for the treatment and control samples are equal on each matching dimension.

In Panel A, Panel B, and Panel C, *API_Intensity* is used as an alternative measure of the API situation, which is a continuous variable representing the number of APIs bank $i$ had in year $t$. We use the same dependent variables on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earing-based performance (*IB* and *EPS* in columns (4)-(5) respectively). The control variables are defined in Table 1. All models control for year and firm fixed effects. The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Panel A: Baseline regression of API Intensity on bank performance* | | | | | | |
|---|---|---|---|---|---|---|
| | (0) | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$API_t$* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$Broadband_t$* | 0.545 | | | | | |
| | (0.63) | | | | | |
| *$API\_Intensity_{t-1}$* | | 0.153*** | 0.000 | 0.010 | 0.037*** | 0.120** |
| | | (3.07) | (0.48) | (1.22) | (5.11) | (2.48) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Observations | 5,020 | 5,100 | 5,100 | 5,133 | 5,133 | 5,100 |
| R-squared | 0.3635 | 0.960 | 0.755 | 0.680 | 0.893 | 0.894 |

| *Panel B: Propensity Score Matched Sample of bank performance on API Intensity* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$API\_Intensity_{t-1}$* | 0.303** | 0.003** | 0.053*** | 0.177*** | 0.073 |
| | (2.05) | (2.45) | (3.56) | (6.85) | (0.37) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 541 | 541 | 541 | 541 | 541 |
| R-squared | 0.972 | 0.750 | 0.767 | 0.874 | 0.950 |

| *Panel C: Entropy balancing regression of bank performance on API Intensity* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$API\_Intensity_{t-1}$* | 1.480*** | 0.002** | 0.023*** | 0.147*** | -0.266 |
| | (4.32) | (2.35) | (2.69) | (3.25) | (-1.62) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 5,166 | 5,166 | 5,199 | 5,199 | 5,166 |
| R-squared | 0.824 | 0.388 | 0.455 | 0.731 | 0.115 |

**Table A5. Number of API Category on Bank Performance**

The table reports regression coefficients and t-statistics (in parentheses) to examine the difference between the Read-only API and Read-Write API in promoting bank performance.

$$Perf_{i,t} = \alpha_{i,t} + \beta API\ ratio_{i,t-1} + \gamma Controls_{i,t} + \varphi_i + \omega_t + \epsilon_{i,t} \quad (4)$$

The regression model is shown in Equation (4). We use the dependent variables on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earing-based performance (*IB* and *EPS* in columns (4)-(5) respectively). We use *R/W intensity* and *R intensity* to measure the number of different APIs in Panels A and B. The *R/W_Intensity* and *R_Intensity* are continuous variables representing the number of this type of APIs bank $i$ had in year $t$. The control variables are defined in Table 1. All models control for a year and firm fixed effects. The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Panel A: Number of Read and Write APIs effect on bank performance* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$R/W\_Intensity_{t-1}$* | 2.753*** | 0.013** | 0.190*** | 0.331*** | 3.283*** |
| | (5.51) | (2.00) | (2.71) | (5.58) | (7.25) |
| | YES | YES | YES | YES | YES |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | 4,077 | 4,077 | 4,077 | 4,077 | 4,077 |
| Observations | 0.967 | 0.782 | 0.740 | 0.936 | 0.926 |
| *Panel B: Number of Read only APIs effect on bank performance* | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$R\_Intensity_{t-1}$* | 2.568*** | 0.019** | 0.333*** | 0.463*** | 2.628*** |
| | (3.86) | (2.27) | (3.58) | (5.88) | (4.35) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 4,077 | 4,077 | 4,077 | 4,077 | 4,077 |
| R-squared | 0.967 | 0.782 | 0.741 | 0.936 | 0.926 |

**Table A6. The Role of Bank Credit Risk and Bank Competition**

The tables below show regression results for API, including interaction effects with the level of credit risk and competition. We include the interaction terms between the API and the dummy for *NPL* (for firms with NPL above the average bank level, the NPL dummy is equal to 1), the dummy for product similarity (for firms with similarity above the average bank level, the similarity dummy equals 1) and the dummy for product fluidity (for firms with fluidity above the average of bank level, the fluidity dummy equals 1). The $API\_Intensity$ variable is a continuous variable representing the number of APIs bank $i$ had in year $t$.

The cross-sectional analysis results of *High_NPL and API_Intensity* are presented as interactive items on Panel A, the cross-sectional analysis results of *High_Similarity and API_Intensity* are presented as interactive items on Panel B, and the cross-sectional analysis results of *High_Fluidity and API_Intensity* are presented as interactive items on Panel C. We apply the same dependent variables as in Equation (3) on market-based performance ($MRKTV$, *Market-Book* and *Tobin's Q* in columns (1)-(3)), earing-based performance (*IB* and *EPS* in columns (4)-(5) respectively). The control variables are defined in Table 1. We report regression results (regression coefficients and t-statistics in parentheses). $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

*Panel A: The role of Non-performing Loans (NPL) on API Intensity*

| VARIABLES | (1) $MRKTV_t$ | (2) $Tobin's\ Q_t$ | (3) $Market\text{-}Book_t$ | (4) $IB_t$ | (5) $EPS_t$ |
|---|---|---|---|---|---|
| $API\_Intensity_{t-1}$ | 5.003*** | 0.009* | 0.222*** | 0.224*** | 5.334*** |
| | (13.63) | (1.91) | (4.23) | (5.03) | (16.15) |
| $API\_Intensity_{t-1} \times High\_NPL_t$ | -4.968*** | -0.009* | -0.206*** | -0.211*** | -5.331*** |
| | (-13.44) | (-1.79) | (-3.89) | (-4.72) | (-16.04) |
| $Control\ Variables_t$ | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 4,077 | 4,077 | 4,077 | 4,077 | 4,077 |
| R-squared | 0.968 | 0.782 | 0.741 | 0.936 | 0.930 |

*Panel B: The role of Product Similarity on API Intensity*

| VARIABLES | (1) $MRKTV_t$ | (2) $Tobin's\ Q_t$ | (3) $Market\text{-}Book_t$ | (4) $IB_t$ | (5) $EPS_t$ |
|---|---|---|---|---|---|
| $API\_Intensity_{t-1}$ | 0.114 | 0.004*** | 0.055*** | 0.073*** | 0.202*** |
| | (1.58) | (4.24) | (5.45) | (8.60) | (3.08) |
| $API\_Intensity_{t-1} \times High\_Similarity_t$ | -0.003 | -0.006*** | -0.067*** | -0.108*** | -0.220** |
| | (-0.03) | (-4.87) | (-4.94) | (-9.40) | (-2.48) |
| $Control\ Variables_t$ | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |

*Panel C: The role of Product Fluidity on API Intensity*

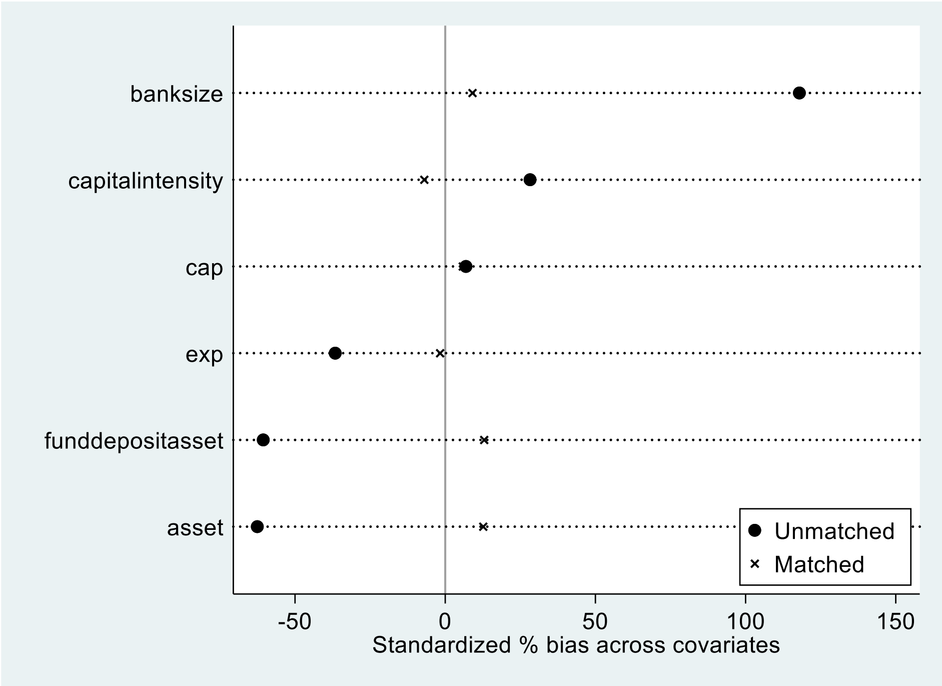
| VARIABLES | (1) $MRKTV_t$ | (2) $Tobin's\ Q_t$ | (3) $Market\text{-}Book_t$ | (4) $IB_t$ | (5) $EPS_t$ |
|---|---|---|---|---|---|
| $API\_Intensity_{t-1}$ | 0.112** | 0.001 | 0.019*** | 0.015*** | 0.080* |
| | (2.22) | (1.07) | (2.74) | (2.59) | (1.75) |
| $API\_Intensity_{t-1} \times High\_Fluidity_t$ | 0.090 | 0.001 | -0.009 | 0.213* | 3.420*** |
| | (0.09) | (0.08) | (-0.06) | (1.82) | (3.83) |
| $Control\ Variables_t$ | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 4,077 | 4,077 | 4,077 | 4,077 | 4,077 |

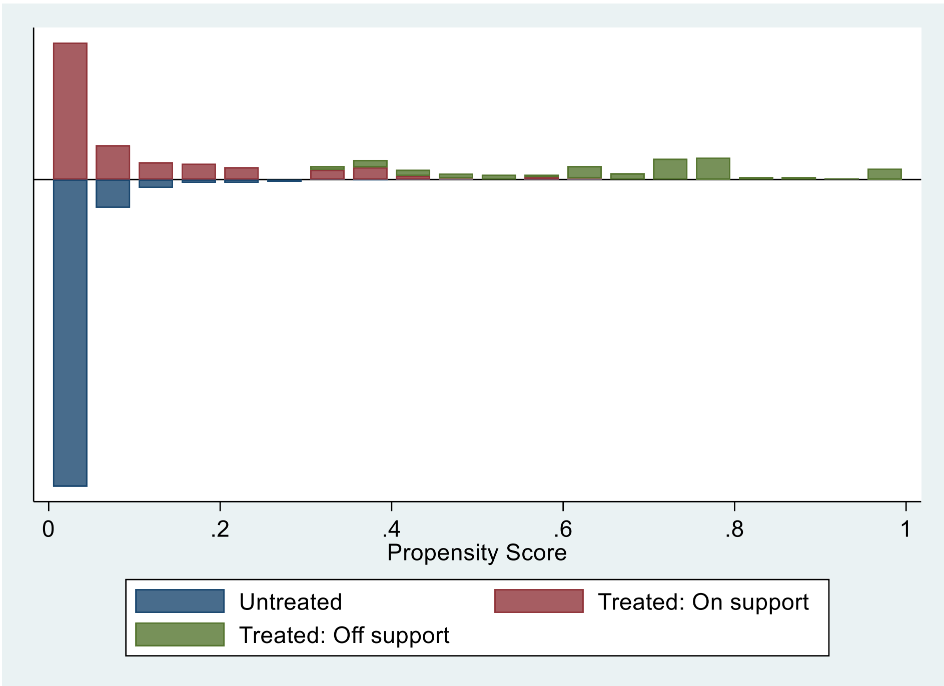
**Table A7. Robustness Test of Exclude Financial Crisis Period**

The table shows the regression coefficients and t-statistics (in parentheses) using the Heckman test. After removing the period of the financial crisis, in case the impact of API on bank performance was affected by the financial crisis, the sample period became 2010-2022. We use the dependent variables on market-based performance ($MRKTV$, *Market-Book* and $Tobin's\ Q$ in columns (1)-(3)), earing-based performance ($IB$ and $EPS$ in columns (4)-(5) respectively). We use $API\_Adoption$ and $API\_Intensity$ to measure API situation in Panel A and Panel B. The $API\_Adoption$ variable is a dummy variable representing whether bank $i$ adopted APIs in and before year $t$, and the $API\_Intensity$ variable is a continuously variable representing the number of APIs bank $i$ had in year $t$. The control variables are defined in Table 1. All models control for year and firm fixed effects. The continuous variables are winsorized at their first and 99th percentiles. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Panel A: Baseline model of bank performance on API Adoption* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$API\_Adopt_{t-1}$* | 1.856*** | 0.015** | 0.215*** | 0.191*** | 3.395*** |
| | (3.61) | (2.30) | (3.17) | (3.56) | (7.48) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 3,659 | 3,659 | 3,659 | 3,659 | 3,659 |
| R-squared | 0.968 | 0.791 | 0.760 | 0.954 | 0.934 |
| *Panel B: Baseline model of bank performance on API Intensity* | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| *VARIABLES* | *$MRKTV_t$* | *Tobin's $Q_t$* | *Market-$Book_t$* | *$IB_t$* | *$EPS_t$* |
| *$API\_Intensity_{t-1}$* | 0.104** | 0.001 | 0.019*** | 0.005 | 0.102** |
| | (2.04) | (1.08) | (2.79) | (0.91) | (2.27) |
| *Control $Variables_t$* | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Observations | 3,660 | 3,660 | 3,660 | 3,660 | 3,660 |
| R-squared | 0.968 | 0.789 | 0.759 | 0.954 | 0.933 |

**Figure A1. Deviations Before and After PSM**



## Online Appendix. API Classification Measures

To classify APIs, we use a broader approach based on the information they process: we cluster APIs by HTTP method combination (Craig et al., 2022; Serbout et al., 2022) , and determine an API can only request data from a specified resource (R) or also send data to a server to create/update a resource (R/W). In our paper, we classify APIs into Read-only (accounting for 51.127% of APIs of US public banks) and Read-Write (which represent 48.87% of APIs of US public banks) types.

Based on the detailed information in banks' developer portals, such as the usage of the API and the detailed description: A Read-only (R) API often includes questions about "Transaction inquiry, Transaction details, Transaction history, Account balance or statements", while a Read-Write (R/W) API often contains descriptive phrases such as "Payment request, Payment transfer, Payment type, and Authorized open access".

More specifically, Read-Write APIs allow the clients to perform both GET and POST operations on some resources handled by the API. For banks, these types of APIs allow to the clients to perform such operations and can be used to realize banking online services, mobile applications, etc. They enable third parties to perform operations involving transferring money and making payments, transferring funds, etc., and allow third-party partners to perform financial transactions without the clients leaving their platforms, which provides more convenience for the bank's users, and Increased user retention for the partner.

While Read-only APIs that only allow the client to read data with no provided operation to edit any resource. For banks, banks can provide Read-only APIs to third-party partners by providing. For banks, providing Read-only APIs allows them to provide third-party partners with access to information such as account balances, transaction history, etc. This helps provide real-time access to customer information, helping third parties to better manage and analyze money flows and provide customized financial advice, while maintaining their security.

As R/W APIs can expand available bank customer information of existing customers and new customers, their credit risk can be assessed more accurately (Butaru et al., 2016), implying a possible reduction in credit risk through the increased availability of information through APIs. Rather than expanding the existing bank customer information, R-only can facilitate data retrieval and easier access to existing bank customer data and provide more in-depth analysis and wider customer data and provide more in-depth analysis and comprehensive services (He et al., 2023), thereby creating a more competitive service offering and retaining existing customers.