Open Banking and Competition in Banks and Fintech : Evidence from Mobile Apps*

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Abstract

This paper examines the impact of open banking adoption on competition and innovation in financial services sector. I construct a novel dataset by combining official open banking authorization records with historical Android app source code to track the integration of open banking among finance apps in the UK and EU. Linking this with high-frequency app performance data, and exploiting cross-country variation in authorization status within the same app, I provide causal evidence that access to consumer banking data boosts app performance. These effects are especially strong during the COVID-19 pandemic, particularly among lending and investment apps and fintech startups. I also find that banks experiencing greater competition from fintech apps, as measured by the similarity of their digital services, face declines in loan issuance, although their profitability remains stable. Overall, the results show that open banking intensifies competitive pressure and reshapes market dynamics in the mobile finance ecosystem.

Keywords: Open Banking, Mobile Apps, Fintech, Competition

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1 Introduction

The past decade has witnessed a dramatic transformation in the delivery of financial services, driven by rapid advances in digital technology and regulatory reforms designed to expand access to financial data. Among these initiatives, open banking has emerged as a potentially disruptive policy, allowing consumers to grant third-party providers secure access to their banking data through standardized APIs. Proponents argue that open banking fosters competition and innovation by lowering barriers for fintech entrants and challenging the dominance of traditional banks. However, others caution that open banking may instead create new competitive distortions, as only authorized providers can participate within a tightly regulated "walled garden," potentially reinforcing the advantages of well-connected or better-resourced players. For traditional banks, the competitive implications are equally uncertain: open banking could erode their market share by empowering fintech rivals, or alternatively, it may push banks to adapt by innovating, specializing in certain services, or improving their understanding of customer needs to defend their position. Despite the growing global adoption of open banking, there is limited empirical evidence on its actual effects on competition and market dynamics.

This paper provides the first large-scale empirical analysis of open banking adoption and its implications for competition and innovation—both in the mobile finance app ecosystem and among traditional banks. A distinctive feature of this study is the construction of a novel dataset that traces the adoption and integration of open banking in financial mobile applications. I begin with official authorization records maintained by national competent authorities—such as the UK's Financial Conduct Authority (FCA) and the European Banking Authority (EBA)—which provide a comprehensive list of all authorized open banking providers over time. I then assemble historical Android source code packages (APKs) for tens of thousands of finance apps, systematically decompile them, and detect their integration with these authorized providers. This approach enables me to identify not only whether an app adopts open banking but also the precise timing of adoption, even among unauthorized apps. In addition, this collection of APKs allows for a detailed examination of traditional banks' apps alongside fintech competitors, offering unique insight into how different types of financial service providers participate in the open banking ecosystem. I merge these adoption records with a comprehensive monthly panel of app performance metrics—including downloads, user engagement, and revenue—sourced from a leading app intelligence platform. These app-level data provide rare, standardized, high-frequency measures of market performance for a broad set of financial service providers, most of which are private firms with limited public disclosure.

Using this dataset, I show that open banking adoption significantly boosts fintech app performance. Apps integrating open banking experience substantial gains in downloads, user activity, and revenue, with effects particularly strong for smaller, non-authorized fintechs relative to larger incumbents. To identify causal effects, I exploit cross-country variation in open banking authorization for the same app: many apps operate across multiple European markets, but authorization status varies by country, enabling within-app comparisons. This design effectively controls for time-varying app-level shocks, such as version updates, marketing campaigns, or platform changes, isolating the effect of open banking access. I further examine the COVID-19 pandemic as an exogenous shock that heightened demand for digital financial services. The pandemic's abrupt lockdowns restricted in-person banking, while rising financial strain increased demand for accessible, low-cost solutions. I find that during this period, apps with open banking capabilities saw pronounced surges in downloads and user engagement, especially among lending and investment platforms. Notably, fintech startups benefited most, showing stronger post-pandemic growth than both incumbent fintechs and traditional financial institutions. These younger entrants were more agile in adapting to the shifting environment and faced fewer barriers to user onboarding, allowing them to quickly scale and serve previously underserved market segments. These findings highlight open banking's role as a flexible infrastructure that fills critical service gaps in times of crisis, particularly through mobile platforms.

Beyond app-level dynamics, I explore whether open banking reshapes market structure by increasing competitive pressure and stimulating innovation. I construct a dynamic competitor network that evolves over time and across countries, based on textual similarity in app store descriptions. Using natural language processing, I extract key terms from app descriptions and compute monthly pairwise similarity scores to map competitive relationships among apps. This approach allows me to track changes in competitive intensity over time. I find that, following open banking adoption, apps become more central in the competitor network and face heightened competitive pressure. Concurrently, they increase the frequency and substantive nature of their product updates. These patterns suggest that open banking fosters a more dynamic and innovative ecosystem, encouraging providers to differentiate through faster iteration and more user-centric development, particularly in the fast-evolving mobile finance sector.

Importantly, this surge in fintech activity also has significant implications for traditional banks. I examine how banks are affected by the intensified competitive environment enabled by open banking by constructing a novel measure of fintech pressure for each bank, based on the textual similarity between the bank's app and those of authorized open banking providers. This measure, derived using natural language processing on app descriptions, captures the degree of overlap in service offerings and target markets. Linking this fintech pressure measure with detailed bank-level data on balance sheets and profitability, I find that banks facing higher fintech pressure experience a significant decline in loan issuance, while their deposit-taking and profitability remain largely unaffected. These results suggest that banks are particularly vulnerable to fintech competition in the lending market, potentially losing borrowers to more agile digital competitors. Supporting this interpretation, I further document from the Global Findex individual-level survey that borrowing from traditional financial institutions declines in countries with open banking, while borrowing from informal providers rises relative to countries without open banking. Together, these findings point to a shifting credit landscape in which open banking intensifies competition in lending markets, reducing banks' lending activity as consumers increasingly seek alternatives outside the traditional banking sector.

Taken together, the findings position open banking as a key driver of consumer-facing financial innovation and market restructuring. By enabling new entrants to challenge incumbents and enhancing the responsiveness of fintech apps to user needs, open banking has intensified competition in the financial sector—particularly in lending markets, where traditional banks face growing pressure. While banks' overall profitability remains stable, their lending activity declines in markets with stronger fintech competition, highlighting the disruptive potential of open banking for traditional credit channels.

Related literature

This paper contributes to several strands of the literature. First, it adds to the expanding body of research on open banking. While open banking is widely regarded as a catalyst for innovation and increased competition (Awrey and Macey (2023)), theoretical work highlights potential unintended consequences. For example, He et al. (2023) shows that it can either foster or hinder competition, depending on whether data sharing levels the playing field or disproportionately benefits fintechs. Goldstein et al. (2022) finds that open banking can prevent banks from shifting risks to creditors and enhance borrower welfare, though it may also lead to inefficient resource allocation. Empirical studies largely document its benefits. Nam (2023) use data from a German fintech loan platform to show that data sharing improves inference about borrower credit quality, enhances credit allocation, and reduces adverse selection. Babina et al. (2024) document the global rise of open banking and its positive impact on consumer access to financial advice, credit, and small business lending. Their model highlights welfare gains from increased market entry and product innovation. Similarly, Yu (2024) exploits a discontinuity in UK firm eligibility and finds that open banking improves small business lending by easing information frictions and collateral constraints.

Alok et al. (2024), using data from India's open banking infrastructure, shows that credit supply expands for both fintechs and traditional banks through multiple channels. Building on this literature, this paper provides the first empirical evidence from the perspective of mobile applications and offers new insights into how open banking addresses unmet demand during times of stress and supports innovation and competition in digital financial services.

Second, this paper contributes to the growing literature on data economy and ownership, which conceptualizes data as a production input or a resource that enhances predictive accuracy. In foundational work, Jones and Tonetti (2020) argue that the nonrivalrous nature of data leads to increasing returns, suggesting that assigning data property rights to consumers could generate welfare gains. Veldkamp et al. (2019) emphasize data as an intangible asset that enables data-savvy firms to compete with traditional incumbents. The value of data has also been studied in various contexts, including its influence on information acquisition and trading strategies (Farboodi and Veldkamp, 2020), firm growth trajectories (Farboodi et al., 2022), market power and firm risk (Eeckhout and Veldkamp, 2022), borrowing and lending decisions (He et al., 2023), and liquidity transformation (Goldstein et al., 2022), among others. Empirical research increasingly supports the view that access to data affects firm behavior and performance. For instance, Demirer et al. (2024) find that data availability influences firms' production efficiency. Babina et al. (2024) show that larger firms disproportionately benefit from investments in data and artificial intelligence. Nonetheless, empirical evidence on the economic role of data remains limited. This paper contributes to this empirical literature by providing new evidence that enhanced access to consumer financial data through open banking enables innovation and intensifies competition among fintechs.

Lastly, this paper contributes to the growing literature on the interaction between finance and technology adoption. The relationship between technological innovation and financial services has been extensively studied. Philippon (2019) documents the declining cost of financial intermediation driven by technological progress. Howell et al. (2024) shows that process automation can reduce racial disparities in credit access by facilitating small loans, extending banks' geographic reach, and minimizing human bias in decision-making. De Roure et al. (2022) finds that fintech lenders, such as peer-to-peer platforms, serve broader and more vulnerable populations, particularly in regions with limited traditional bank presence. Similarly, Erel and Liebersohn (2022) shows that banks do not easily substitute fintech services in underserved areas, highlighting a complementary relationship between fintech and traditional financial institutions. Fuster et al. (2019) demonstrates that algorithmic lending accelerates loan processing without increasing default risk, and responds more flexibly to demand shocks. Babina et al. (2024) emphasizes the role of AI adoption in driving firm innovation and growth. Building on this literature, this paper offers a new perspective on the interaction between finance and technology by examining mobile applications and open banking APIs. It highlights how technological infrastructure in digital finance, particularly through mobile app ecosystems, shapes competition and access, especially during periods of elevated demand.

The remainder of the paper is organized as follows. section 2 outlines the institutional background. section 3 describes the data sources and sample characteristics. section 4 examines consumer demand responses to open banking and their implications for fintech. section 5 analyzes the impact on bank performance and strategic responses. Finally, section 6 concludes.

2 Institutional Background

2.1 Open Banking

Open banking is a financial framework that enables customers to share their banking data with third-party financial service providers through secure and regulated Application Programming Interfaces (APIs), contingent upon their explicit consent. Traditionally, banks have been the sole custodians of customer financial data; however, open banking facilitates broader access to this information by allowing authorized third-party providers (TPPs) to use this asset. The primary objectives of open banking include enhancing competition, reducing barriers to entry, and fostering financial innovation by expanding consumer choice and improving access to financial products and services. Potential benefits include the development of personalized financial management tools, streamlined lending processes, and more efficient payment mechanisms. As financial regulators worldwide recognize its implications, open banking has gained increasing global adoption, with jurisdictions implementing regulatory frameworks to guide its development.

The United Kingdom (UK) has been an early adopter of open banking, establishing a regulatory-driven framework aimed at standardizing financial data sharing across institutions. The UK's initiative was set in motion by the Competition and Markets Authority (CMA), which, in 2016, mandated the country's nine largest banks to develop and maintain open APIs for account information services (AIS) and payment initiation services (PIS). The UK's open banking framework was officially launched in January 2018, aligning with the implementation of the European Union's revised Payment Services Directive (PSD2). However, while PSD2 provided a legal foundation for open banking across the EU, the UK adopted a more structured regulatory approach by creating the Open Banking Implementation Entity (OBIE). The OBIE was tasked with establishing technical API standards, ensuring regulatory compliance, and facilitating adoption among financial institutions and third-party providers. Open banking-related statistics maintained by the OBIE are presented in Figure IA.1 and Figure IA.2. This structured approach has contributed to the rapid expansion of open banking in the UK, with a growing ecosystem of fintech firms leveraging API-based access to financial data to develop automated savings platforms, alternative lending solutions, and personalized financial tools.

In the European Union (EU), open banking was formally introduced through PSD2, which came into effect in January 2018. Unlike the UK's regulatory-driven framework, PSD2 established broad principles for open banking but allowed national regulators and industry-driven initiatives to shape its implementation. This decentralized approach has led to variability in adoption across EU member states and differences in the technical standards for API integration. While some countries have implemented robust frameworks, others have seen slower adoption due to regulatory fragmentation and differing interpretations of PSD2 guidelines. To address these inconsistencies, initiatives such as the Berlin Group's NextGenPSD2 API standard have emerged, aiming to create a more uniform technical standard across EU financial institutions. Despite these challenges, PSD2 has played a key role in expanding access to financial data, allowing for greater innovation in financial services while maintaining data security and consumer protection standards.

Open banking frameworks developed in the UK and EU have influenced policy discussions in other jurisdictions, with several countries adopting either a regulatory-driven or market-led approach to facilitate financial data sharing. Countries such as Australia, Canada, and Japan have introduced open banking regulations tailored to their financial markets, often incorporating elements from both the UK's centralized model and the EU's decentralized approach. In the United States, efforts to formalize open banking regulations have accelerated in recent years. In October 2024, the Consumer Financial Protection Bureau (CFPB) issued final rules governing Personal Financial Data Rights under Section 1033 of the Dodd-Frank Act, marking a significant step toward regulatory oversight of open banking in the US. While the US has historically relied on market-driven data-sharing agreements, the introduction of formal regulations reflects a shift toward greater consumer data protection and standardized financial data access. Globally, open banking initiatives continue to expand. According to Babina et al. (2024), who compiled a comprehensive database of open banking policies across 168 countries, as of October 2021, 80 countries had at least a nascent open banking initiative, while 49 had adopted key open banking policies. These figures highlight the growing importance of open banking as a global financial infrastructure, with governments and regulatory bodies working to balance innovation, competition, and data security in financial markets.

2.2 Authorized Providers and Non-authorized Providers

Open banking service providers can be broadly classified into authorized and non-authorized entities based on their regulatory status and operational scope. Authorized providers are firms that have obtained formal regulatory approval from financial authorities such as the Financial Conduct Authority (FCA) in the UK or national regulators in EU member states, allowing them to offer account information services (AIS) and payment initiation services (PIS) directly. These firms must comply with capital requirements, operational risk management, and customer protection standards. Upon authorization, they are listed in regulatory registers such as the FCA's Financial Services Register or the European Banking Authority (EBA) Payment Institutions Register, ensuring transparency and oversight. Among authorized providers, two key categories exist: Account Information Providers (AIPs) and Payment Initiation Providers (PIPs). AIPs are entities authorized to access and aggregate financial data from customer accounts, provided they have obtained the customer's explicit consent. They do not execute transactions but instead offer services such as personal financial management tools, credit risk assessment, and financial analytics platforms that help users track spending, manage budgets, or receive tailored financial product recommendations. PIPs, in contrast, are authorized to initiate payments on behalf of customers by directly connecting to their bank accounts. Instead of relying on traditional card networks or manual bank transfers, PIPs facilitate direct account-to-account transactions, often reducing processing costs and improving payment efficiency. This has led to the emergence of alternative payment solutions that offer faster, more secure, and lower-cost payment mechanisms for consumers and businesses[1].

In contrast, non-authorized providers operate within the open banking ecosystem without direct regulatory approval but can still offer services by partnering with authorized firms[2]. One common approach is the agent model, in which a non-authorized firm acts as an agent

[1] Detailed TPP outcome areas and its distribution can be seen in Table IA.1 and Figure IA.4

[2] See FCA guidance: https://www.fca.org.uk/firms/agency-models-under-psd2

of an authorized Payment Service Provider (PSP) and offers open banking services under the principal firm's authorization. In this arrangement, the authorized provider retains full legal responsibility for compliance and consumer protection, while the agent delivers services under the authorized firm's regulatory umbrella. A second category of non-authorized providers includes Technical Service Providers (TSPs), which support open banking infrastructure without directly engaging in payment initiation or account information services. These firms provide services such as API aggregation, fraud prevention, and authentication solutions but do not handle customer funds or process transactions. Because they operate purely as intermediaries, they are not required to obtain direct authorization under PSD2. Last, non-authorized firms may also participate in open banking through white-label or outsourcing arrangements, in which an authorized provider licenses its infrastructure and regulatory status to another entity. In such cases, the non-authorized firm manages the customer interface, while financial transactions and compliance remain under the control of the authorized institution.

The coexistence of authorized and non-authorized providers highlights the diverse ways in which firms participate in open banking—either by obtaining direct regulatory approval or by leveraging partnerships with authorized institutions. While authorized providers are subject to greater regulatory scrutiny, non-authorized models offer a more flexible route for fintech firms to engage in open banking while relying on authorized institutions for compliance.

3 Data and Sample

3.1 Data

Open banking authorization To systematically identify entities authorized to provide open banking services, I rely on official regulatory registers from the Financial Conduct Authority (FCA) for the UK and the European Banking Authority (EBA) for the European Union. For the UK sample, I retrieve information on account information service providers

(AISP) and payment initiation service providers (PISP) from the FCA's online register[3]. To ensure accuracy and completeness, I cross-reference these entities with the Open Banking Implementation Entity (OBIE) register[4], supplementing this with archived records from the Wayback Machine to account for entities that have been removed or whose authorization has lapsed. For each identified provider, further details—such as regulatory status, authorization scope, and firm-specific information—are available on the FCA's official website. For example, the FCA register page for Truelayer Limited[5] provides firm-specific regulatory details. For the EU sample, I extract structured data from the EBA's official JSON dataset[6], which consolidates payment institution authorizations across EU member states. To ensure consistency in the sample, I filter the dataset to retain only entities explicitly authorized to provide payment initiation and account information services. The EBA register includes critical metadata, such as the authorization date, country of registration, and passporting details, which indicates additional jurisdictions where the entity is permitted to operate. If an entity obtains multiple authorizations at different times, only the earliest authorization date is considered. Panel A of Figure 1 presents a heatmap of cumulative domestic and passporting authorizations in the UK and EU over time, while Figure IA.3 displays the volume and direction of passporting flows.

Sampling criteria This study focuses on widely used and high-traffic finance apps. Although millions of mobile apps are available, only a small fraction of top-ranked ones capture the majority of downloads and revenue[7]. To compile a comprehensive list of leading finance apps, I use monthly app download data from Apptopia, a firm that aggregates information on millions of mobile apps and publishers across 58 countries. Apptopia estimates app downloads and revenue by combining actual data from partner apps with publicly available app

[3] `https://register.fca.org.uk/s/search?predefined=AIPISP`

[4] `https://www.openbanking.org.uk/regulated-providers/`

[5] `https://register.fca.org.uk/s/firm?id=001b0000042fMZyAAM`

[6] `https://euclid.eba.europa.eu/register/pir/search`

[7] Bian et al. (2021) shows that top 0.3% of the apps (those among top 10,000) in US accounts for 80% of downloads and 90% of revenue.

store metrics, such as rankings, categories, and user reviews.

Based on monthly download rankings from the Apple App Store for the UK and each EU country, I select the top 1,000 apps for which Apptopia provides reliable coverage between January 2018 to July 2021.[8] Each app entry includes a unique identifier specific to the Apple App Store (iOS) or Google Play (Android). This identifier remains constant across app updates, ensuring consistent tracking over time. For instance, the Facebook app is identified as *284882215* on the Apple App Store and *com.facebook.katana* on Google Play. I use this identifier to construct the URL of the official app page in the Apple App Store, enabling the extraction of app-specific information. Additionally, this identifier facilitates linkage with app source code data, as discussed below. Specifically, matching the Android identifier to package names in the source code archive enables integration between app metadata and technical characteristics. Another crucial identifier is the unified app identifier, which links the iOS and Android versions of the same app. These identifiers serve as key tools for tracking apps across platforms and linking multiple updates of an app on a single platform.

App downloads and revenue App downloads and revenue, along with other key metrics, serve as real-time performance indicators for private firms, particularly those whose financial statements are not publicly available. To track app activity in the finance category, I collect detailed app-level characteristics along with a time series of weekly revenue and download estimates from Apptopia, a leading provider of mobile app intelligence. Apptopia derives key performance metrics such as weekly downloads, revenue, monthly active users (MAU), daily active users (DAU), average revenue per user (ARPU), and engagement by leveraging publicly available app ranking history alongside its proprietary data sources. Additionally, Apptopia aggregates and curates metadata from app store listings on both the Apple App Store and Google Play, including app categories, developer information, content ratings, and update history. For the empirical analysis, I focus on several key app characteristics, which

[8] The complete list of the 19 EU countries in the sample: Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Germany, Finland, France, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Portugal, Romania, Spain, and Sweden.

are summarized in Table 1. To further enrich the dataset with historical versioning details, I supplement Apptopia's records with web-scraped data from publicly accessible sources such as Wayback Machine, Appfigure, F-Droid, and Apkmirror. This additional data enables me to track version updates timing, description, update log, and other app changes over time, offering deeper insights into app evolution. For this research, I aggregate all performance metrics at the monthly level to facilitate empirical analysis.

Android app source code An APK (Android Package) is the standard file format used for distributing and installing applications on Android devices. It is essentially a compressed archive that contains all the necessary components required for an app to function, including the compiled application code (DEX files), resources (images, layouts, and XML files), manifest file (AndroidManifest.xml), and digital signatures for verification. APK files follow a structure similar to ZIP archives and can be extracted or modified using specialized tools. When a user downloads and installs an APK, the Android operating system unpacks the package, verifies its integrity, and installs the app in the device's system. While most users install APKs through the Google Play Store, APKs can also be sideloaded from third-party sources, allowing for manual installation of apps that are not available on official app stores. Developers often use APK packages for testing before deploying apps to public distribution platforms, and advanced users may extract APKs to analyze an app's structure, permissions, or embedded libraries.

I obtain historical Android application packages (APKs) from the AndroZoo Archive Allix et al. (2016), a large-scale repository of Android APK files maintained for research purposes. AndroZoo collects millions of APKs from various sources, including Google Play, third-party app stores, and alternative APK hosting platforms. The dataset is continuously updated, granting researchers access to both current and historical versions of Android applications. As of now, AndroZoo contains over 25 million APKs, primarily used for malware detection and security research. Additionally, for a subset of APKs, AndroZoo provides metadata and static information, such as download counts, review numbers, and rating distributions at the time of collection.

To construct my dataset, I first sample the top 1,000 finance apps per country per month and retrieve all available APK versions for each of these apps. I then analyze these APKs using two primary tools: Android Asset Packaging Tool (AAPT) and JADX-GUI, which allow me to decompile and inspect the source code package. Specifically, I scan for commonly used class names, URLs, and functions that reference APIs provided by authorized third-party providers. For instance, I identify the "TrueLayerOpenbankingProvider" class—a reference to the authorized open banking provider, TrueLayer—within the DEX (Dalvik Executable) files of the Freetrade APK, a non-authorized app. See Figure 2 for details. By systematically analyzing different versions of each app, I detect the earliest instance where a given app adopts a third-party provider's technology[9]. A heatmap presenting the number of apps within the top 1,000 finance apps that have adopted open banking APIs is presented in Panel B of Figure 1. Beyond detecting third-party API usage, AAPT extracts additional metadata from each APK, including version information, target and minimum SDK versions, and requested permissions. I then integrate this extracted information with app metadata, scraped data, and historical app performance metrics, aggregating all components into a monthly panel dataset, which serves as the foundation for my empirical analysis.

3.2 Constructing competitor network

To analyze the competitive landscape of mobile apps, I construct a competitor network for each country on a monthly basis across my sample of UK and EU countries. This network is derived using historical app descriptions, following the text-based industry classification methodology developed in Hoberg and Phillips (2016). Specifically, I extract a bag-of-words representation from app descriptions for each cross-section of the dataset, capturing key textual features that define an app's functionality and market positioning. To quantify

[9]Some third-party APIs or functions may not necessarily serve open banking purposes (e.g., the American Express API). In such cases, I classify them as non-open banking APIs and exclude those apps from the open banking API adopter sample.

similarity between apps, I compute Term Frequency-Inverse Document Frequency (TF-IDF) scores and use these weighted term representations to construct cosine similarity measures for each app pair within a given country and month[10]. To refine the text data, I retain only nouns and proper nouns, as these words are most informative in describing an app's purpose. Additionally, I filter out high-frequency words that appear in more than 20% of apps, ensuring that the most distinguishing terms drive the similarity calculations. The distribution of the number of valid words can be seen in Figure 3

I then classify competitor relationships by applying different similarity thresholds, allowing for a flexible definition of competition intensity. The competitor network is dynamic, reflecting changes in market structure over time, as different sets of apps enter the top 1,000 rankings in each country across different months. This approach captures the evolution of competitive dynamics in the mobile app ecosystem. Using the constructed network, I compute key centrality measures to assess an app's competitive position. Current measures include: degree centrality, betweenness centrality, and clustering coefficients.

3.3 Descriptive statistics

My empirical analyses rely on two distinct app samples. The main sample consists of the top 1,000 finance apps, as previously defined, and is referred to as the top 1,000 UK and EU sample. The second sample includes all UK finance apps tracked by Apptopia, which I refer to as the UK sample.

Table 1 presents descriptive statistics on key app performance metrics. Several observations are noteworthy. First, the finance mobile app market exhibits a highly skewed distribution. The top 1% of finance apps receive over 10,000 downloads per month per country, whereas the median app records just over 100 downloads per month per country. This stark contrast underscores the intense competition within the mobile finance app ecosystem. Second, more than 95% of finance apps are free to download, and the revenue figures reported

[10] Currently, if an app is not available in an English-language version, it is excluded from the competitor network.

in the dataset likely underestimate actual earnings from downloads and in-app purchases. Many freemium (free to download with paid upgrade options) finance apps operate their own websites, allowing them to bypass app store transactions and avoid commissions of 15% to 30% charged by platforms such as the Apple App Store and Google Play Store. Third, unlike gaming and shopping apps, which rely heavily on in-app advertising, a relatively small proportion of finance apps integrate ads or connect to ad networks. This suggests that finance apps predominantly generate revenue through alternative monetization strategies, such as subscriptions, transaction fees, and premium services. Finally, the median version age of apps in the sample is approximately 1.6 months, reflecting frequent updates and continuous development. This further highlights the dynamic and competitive nature of the mobile finance app market, where regular updates may be necessary to maintain security, regulatory compliance, and user engagement.

3.4 Determinants of Participation of Open Banking

To better understand the key factors that drive open banking adoption among finance mobile apps, I examine the relationship between app characteristics and the likelihood of adopting open banking services. This analysis includes both authorized providers and non-authorized apps that integrate an authorized provider's API.

To ensure a comprehensive assessment of adoption decisions while avoiding duplicate observations, I focus on the UK sample for the regression analysis. For each year, I define a binary adoption variable, indicating whether an app adopts open banking in that year. Apps that adopted open banking in previous years are excluded from the sample in subsequent years, ensuring that in each year, the sample consists only of new adopters and non-adopters. I then regress the adoption indicator on various app characteristics to identify significant predictors. Additionally, I examine early adoption (adopted open banking in 2018) and late adoption (adopted open banking after 2020) by constructing separate binary outcome variables and running the same regression.

The results, presented in Table 2, reveal several patterns. Each regression is estimated both with year fixed effects (even-numbered columns) and without year fixed effects (odd-numbered columns) to control for time-specific factors. The findings indicate that apps adopting open banking tend to be younger, operate across a broader audience, and demonstrate strong past performance. Specifically, apps that support multiple languages and operate across multiple platforms are significantly more likely to adopt open banking, as evidenced by the positive and significant coefficients on these indicators. The results for early adopters follow a similar pattern. In contrast, late adopters do not exhibit strong past performance, suggesting that their adoption may be driven by strategic response to intensified competition. Overall, these findings suggest that relatively young, competitive apps with a strong recent performance history are more likely to adopt open banking—particularly at an early stage of its implementation. This aligns with the idea that more innovative and growth-oriented firms are the first movers in adopting new financial technologies.

4 Consumers' Reaction to Open Banking Adoption

To understand how consumers respond to open banking, I begin by examining the demand-side effects when a financial service provider adopts open banking—either through obtaining direct authorization or by integrating with an already authorized third-party provider. This section presents two empirical strategies to assess consumer response. First, I conduct an event study to capture the dynamic effects around the time of adoption. Second, I leverage cross-country variation in authorization status to strengthen causal identification.

4.1 Event Study

I implement a standard event-study framework to trace the temporal pattern of consumer response before and after a provider becomes involved in open banking. The specification is as follows:

$$Demand_{ict} = \sum_{\tau \neq 0} \beta_\tau OBEvent_{ic\tau} + X'_{it}\gamma + \delta_{ic} + \delta_t + \varepsilon_{it} \tag{1}$$

where i indexes apps, c countries, and t months. The dependent variable $Demand_{ict}$ is the log-transformed monthly download volume, specifically using the transformation $\log(1 + y)$ to accommodate the highly skewed distribution of downloads and the presence of zeros. The event variable $OBEvent_{ic\tau}$ is a set of month-relative-to-event indicators, excluding the month of adoption ($\tau = 0$). For authorized open banking providers, the event is defined as the month of receiving authorization. For non-authorized providers that integrate with an authorized API provider, the event is defined as the month in which the integration first occurs. The coefficients β_τ thus capture the dynamic treatment effects on consumer demand surrounding open banking involvement. To control for confounding factors, I include app-country fixed effects (δ_{ic}) to absorb time-invariant app-specific characteristics, and month fixed effects (δ_t) to account for aggregate shocks and seasonal trends. In addition, I include time-varying control variables X_{it} to capture evolving app features that may influence demand.

Authorized Open Banking Provider The estimated event-time coefficients for authorized open banking providers are plotted in Panel A of Figure 4. The results suggest a gradual increase in consumer demand following authorization. The effect becomes statistically significant within a year, with an estimated increase of approximately 20%. This pattern indicates that the benefits of open banking authorization unfold progressively rather than through an immediate spike. One plausible explanation for the gradual impact is limited consumer awareness or understanding of open banking, which may delay behavioral responses. Moreover, authorized providers are typically larger and more established—even well-known financial institutions such as Barclays or NatWest—whose growth trajectories tend to be more stable and incremental. The wide confidence intervals further underscore the substantial heterogeneity in post-authorization outcomes, suggesting that the effectiveness of open banking adoption varies significantly across providers.

Non-Authorized Open Banking Providers The event study coefficients for non-authorized open banking providers are displayed in Panel B of Figure 4. In contrast to authorized providers, these apps experience a more immediate and noticeable improvement in consumer demand after integrating with an authorized API provider. The increase is approximately 5%, smaller in magnitude but more abrupt. This pattern may reflect the more agile nature of smaller fintech firms, which can more quickly leverage newly gained data access to deliver consumer-facing improvements. However, the smaller overall effect size may also point to limitations in scalability. While non-authorized providers can rapidly capture early gains, sustaining growth over time may be more challenging without the institutional reach or infrastructure of authorized players.

4.2 Identification Using Cross-country Heterogeneity

To strengthen the causal interpretation of the impact of open banking, I exploit cross-country heterogeneity in authorization status to compare outcomes for the *same* app across countries with and without authorization. This approach builds on the logic of Khwaja and Mian (2008), who compare within-firm borrowing behavior across markets with different credit supply shocks. Analogously, I compare within-app consumer demand where the supply-side conditions—namely, access to customer bank data via open banking—differ across countries. The key identifying assumption is that differences in authorization status across countries for the same app are exogenous to unobserved, time-varying app-level factors. That is, any differential performance must stem from variation in the treatment (authorization), rather than from confounding changes in the app itself. The following Difference-in-Differences specification is estimated:

$$Demand_{ict} = \beta_1 OBAuth_{ic} \times Post_{ict} + \beta_2 OBAuth_{ic} + \beta_3 Post_{ict} + \delta_{ic} + \delta_{it} + \varepsilon_{ict} \quad (2)$$

where $Demand_{ict}$ is the log-transformed measure of monthly downloads, revenue, monthly active users (MAU), daily active users (DAU), user engagement, or average revenue per user (ARPU) for app i in country c and month t. The transformation $\log(1 + y)$ is used to handle skewed distributions and zero values. The variable $OBAuth_{ic}$ is a binary indicator for whether app i is authorized as an open banking provider in country c, and $Post_{ict}$ is an indicator equal to 1 in all months following the authorization date in that country. The interaction term $OBAuth_{ic} \times Post_{ict}$ captures the causal effect of open banking authorization on app performance. To ensure that the comparison is within the same app across different countries, I include app-month fixed effects (δ_{it}), which absorb any time-varying app-specific shocks (e.g., version updates). I also control for app-country fixed effects (δ_{ic}), which capture persistent differences in app usage levels across countries—such as apps that are primarily used in the UK but not widely adopted in other EU countries. Standard errors are clustered at the country and month levels to allow for arbitrary correlation within these dimensions.

The regression results are reported in Table 3. Column 1 shows that, following authorization to access bank data, providers experience a 19.8% increase in downloads in countries where authorization is granted, relative to countries where it is not. Columns 2 through 6 reveal similarly strong effects on other performance outcomes, with DAU, MAU, and revenue increasing by over 20%. While engagement and ARPU also improve, the magnitudes are smaller. Importantly, all performance metrics exhibit statistically significant gains. Because this identification strategy compares the same app across markets where only the authorization status differs—while holding constant all app-specific shocks—the findings provide causal evidence that open banking authorization drives improvements in app performance.

4.3 COVID-19 as a Catalyst for Open Banking

In this section, I use COVID-19 as an exogenous and unexpected shock to consumer behavior in financial services, examining how it influenced the adoption trajectories of open banking and non-open banking apps. There are two key reasons for focusing on the COVID-19 pandemic. First, it represents a significant demand shock. The pandemic triggered lockdowns and social distancing measures, forcing consumers to transition toward mobile and online financial solutions as physical access to banks and financial institutions became restricted. At the same time, widespread job losses and income reductions intensified financial strain, increasing the need for more accessible and cost-effective financial services. Second, COVID-19 serves as a saliency shock that heightened consumer awareness of digital financial services, including open banking. During crises, the importance of efficient, secure, and integrated financial management tools becomes more apparent, potentially accelerating the adoption of open banking solutions. As individuals sought more seamless ways to track their finances, access credit, or make transactions remotely, open banking apps may have gained greater visibility and adoption.

Given these dynamics, I compare the adoption patterns of open banking apps versus non-open banking apps, using data as of the end of 2019, just before the onset of COVID-19. This allows for a clearer identification of the differential effects of the pandemic on the adoption of apps with open banking capabilities compared to those without.

4.3.1 Baseline Result

Authorized Open Banking Providers To examine the impact of COVID-19 on the demand for open banking financial services, I employ a difference-in-differences (DiD) approach, estimating the following regression specification:

$$Demand_{ict} = \beta_1 OBAuth_{ic} \times PostLockdown_t + X'_{ict}\gamma + \delta_{ic} + \delta_{it} + \epsilon_{ict} \tag{3}$$

in which the subscript i, c, and t denote app, country, and month respectively. The COVID-19 lockdown indicator, $PostLockdown_t$ equals one for all months following the first lockdown in the UK and EU, which began in March 2020[11]. The key treatment variable, $OBAuth_{ic}$, equals one (zero) if the observation corresponds to an authorized (non-authorized) app. The outcome variable, $Demand_{ict}$ is the logarithm of the monthly downloads, revenue, monthly active users (MAU), daily active users (DAU), or the level of engagement and ARPU of app i in country c in month t. I scale the outcome variables using $log(1+y)$ transformation as the distribution of downloads and revenue numbers are highly skewed, as shown in Table 1.

[11] All EU countries in the sample, as well as the UK, implemented initial lockdown measures in mid-to-late March 2020.

To account for time-invariant differences in app demand across countries, I add app-country fixed effects δ_{ic}. Additionally, year-month fixed effects δ_t are included to control for seasonality and common macroeconomic shocks affecting all finance apps in the UK and EU. If COVID-19 affected all finance apps similarly, its general impact would be absorbed by these time fixed effects. Standard errors are double-clustered at the country and year-month levels to ensure robustness against correlated shocks. The key variable of interest is $PostLockdown_t \times OBAuth_{ic}$, and its coefficient ($\beta_1$) captures the differential effect of COVID-19 on the demand for authorized third-party providers (TPPs) relative to non-authorized providers. A positive β_1 suggests a greater increase in demand for authorized open banking apps compared to their non-authorized counterparts following the lockdowns.

The regression results, presented in Panel A of Table 4, indicate that following the COVID-19 lockdown, the average monthly downloads of authorized open banking providers increased by 15.5% relative to non-authorized providers. The effect remains consistent across key performance metrics, with the exception of user engagement and ARPU, where the impact is less pronounced. These findings suggest that while users significantly increased their downloads of open banking apps, they only marginally increased their frequency of engagement and spending on these platforms. To zoom into the dynamic effects, I replace the $PostLockdown$ dummy with a series of time indicators and report the estimated coefficients of the interaction terms with the OB Authorization indicator in Panel A of Figure 5. For the period between month -5 and month +5, I assign an indicator for each month, and for the period before month -5 and after month +5, I assign one indicator to the whole period $\mathbb{1}(t < -5)$ (or $\mathbb{1}(t > -5)$), respectively. The results reveal a persistent upward trend in demand for authorized open banking apps, with the effect continuing to strengthen several months after the lockdowns began.

Non-authorized Open Banking Providers Next, I extend the difference-in-differences (DiD) analysis to include non-authorized open banking providers among the top 1,000 sample, estimating the following regression specification:

$$Demand_{ict} = \beta_1 OB_{ic} \times PostLockdown_t + X'_{ict}\gamma + \delta_{ic} + \delta_t + \epsilon_{ict} \quad (4)$$

where all variables are defined as in the previous analysis of authorized providers, and the outcome variables remain demand metrics transformed using a $log(1 + y)$ adjustment to account for skewed distributions. The key treatment variable, OB_{ic}, equals one (zero) if the app, as of the time of COVID-19 lockdown, adopts an open banking API provided by an authorized provider, and zero otherwise. I include the same set of year-month fixed effects δ_t and app-country fixed effects δ_{ic} to control for time-invariant differences across countries and common temporal shocks. Standard errors are double-clustered at the country and year-month levels. The key coefficient of interest, β_1, captures the differential effect of COVID-19 lockdown on demand for apps integrating open banking APIs relative to those that do not.

The regression results, presented in Panel B of Table 4, indicate a statistically significant increase in demand for non-authorized open banking-powered apps following the lockdown. On average, these apps experienced a 17% to 18% increase in downloads, monthly active users (MAU), and daily active users (DAU) post-lockdown, with the effect being highly significant. However, revenue growth for these apps was more modest, increasing by only 5.4%, which is lower than the revenue growth observed for authorized providers. This suggests that non-authorized providers face greater challenges in converting user acquisition into revenue generation, possibly due to weaker monetization strategies or greater dependence on external payment processors. Additionally, engagement levels increased by only about 1%, and no significant effect was observed on average revenue per user (ARPU). This suggests that while open banking-powered apps gained higher visibility and user adoption during the pandemic, they still encountered difficulties in sustaining long-term user engagement and monetization. However, these estimates likely represent a lower bound of the true effect, as a significant portion of financial transactions and revenue may occur outside app store-recorded revenue metrics, particularly for apps that process transactions via external payment systems or direct banking integrations.

The dynamic DiD results further reveal an immediate surge in demand following the lockdown. As shown in Panel B of Figure 5, the first month after lockdown saw a 5% increase in downloads, indicating a rapid shift toward digital financial solutions. This early jump suggests that consumers quickly adopted open banking-powered apps in response to mobility restrictions and the need for alternative financial management solutions.

4.3.2 Heterogeneity

Service Type The baseline regression results suggest that consumer demand for open banking services increased following the onset of COVID-19. But what specific types of services did users turn to? To answer this question, I explore whether the increase in demand varies by the type of service provided. I classify apps into five categories based on their app descriptions: payment, lending, investment, insurance, and miscellaneous. For multi-function apps, I assign the most salient or prominently featured service type based on their description. Each service type is represented by a binary indicator, and I add a triple interaction term to Equation Equation 4 and estimate the heterogeneous effects across apps with different service types using the following specification:

$$\begin{aligned} Demand_{ict} =& \beta_1 OB_{ic} \times PostLockdown_t \times Service_i + \beta_2 PostLockdown_t \times Service_i \\ &+ \beta_3 OB_{ic} \times PostLockdown_t + X'_{ict}\gamma + \delta_{ic} + \delta_t + \epsilon_{ict} \end{aligned} \tag{5}$$

The regression results are presented in Table 5. I find that the overall increase in demand is primarily driven by lending and investment apps, which experienced 24.5% and 20.1% greater increases, respectively, compared to other open banking apps. In contrast, payment apps saw a relative decrease of 18.9%. This decline may reflect the overall slowdown in economic activity and a sharp drop in in-person retail transactions during lockdowns. Notably, online purchases (e.g., on Amazon or other e-commerce platforms) are not captured as demand for payment apps in my data, as these transactions often happen outside of the payment apps. For insurance and miscellaneous service categories, I find no statistically significant additional increase in demand. These results underscore the role of open banking—particularly lending apps—as a substitute for traditional credit channels during times of financial stress. While I cannot directly observe the outcomes of the lending (e.g., repayment, default, or financial well-being), the observed surge in demand suggests that consumers faced widespread and unmet borrowing needs during the pandemic. Whether this response enhanced consumer welfare remains an open question, but it clearly reveals the critical role of fintech platforms in filling the gap left by conventional banking institutions during crisis periods. The strong demand in borrowing providers is also supported by individual-level Global Findex survey data, the results are shown in Table 10.

Provider Type To further explore heterogeneity in the demand for open banking services, I divide apps by provider type into three main categories: traditional banks, neo-banks, and fintechs. Among fintech providers, I distinguish between incumbents and startups, where startups are defined as publishers that launched their first app after 2016. The list of neo-banks is compiled from publicly available sources including Neobanks.app[12] and The Financial Brand[13].

Using a regression specification similar to Equation 5, I test for differences in pandemic-driven demand across these provider types. The results in Table 6 indicate that the surge in demand for open banking services is primarily driven by fintech apps, rather than by apps from traditional banks or neo-banks. In fact, downloads for bank and neo-bank apps show little to no increase during the pandemic period. One possible explanation is that traditional banks and neo-banks were already widely adopted before the pandemic, leaving less room for new user acquisition during the crisis. Additionally, traditional banks may have faced operational hurdles in onboarding new customers during the lockdown, such as requirements for in-person identity verification or more cumbersome account setup processes, which fintech platforms are typically better positioned to streamline through digital channels. A

[12]https://neobanks.app/
[13]https://thefinancialbrand.com/list-of-digital-banks

particularly interesting finding is that fintech startups experienced 9.9% higher growth in app downloads relative to fintech incumbents. This suggests that COVID-19 served as a catalyst for emerging fintech players, offering them a unique growth opportunity amid changing consumer needs and preferences. The increase in adoption of startup apps highlights both the agility of newer entrants and the unmet demand for alternative financial services during times of crisis. It underscores the important role fintech startups play in enhancing financial access and innovation when traditional channels fall short.

4.3.3 Impact on Competition and Innovation

The previous sections demonstrate that open banking apps—particularly those developed by fintech firms—played an important role in serving customer needs during the COVID-19 pandemic. A more critical question, however, is whether open banking has broader implications for competition and innovation in the financial app ecosystem. To provide preliminary evidence, I extend the baseline specification in Equation 4, shifting the focus from customer demand to competition. Specifically, I utilize the competitor network centrality measures introduced in subsection 3.2 as proxies for the competitive pressure faced by each app in the top 1,000 sample. The following regression is estimated:

$$Competition_{ict} = \beta_1 OB_{ic} \times PostLockdown_t + X'_{ict}\gamma + \delta_{ic} + \delta_t + \epsilon_{ict} \tag{6}$$

where $Competition_{ict}$ refers to one of three competitor network centrality metrics for app i in country c at month t. I employ both unweighted centrality (reported in odd-numbered columns) and cosine similarity-weighted versions (reported in even-numbered columns). The specification includes app-country and month fixed effects, with standard errors two-way clustered. As shown in Table 7, open banking apps face increased competitive pressure after the pandemic shock across all centrality metrics and specifications, though the effect size is modest. This provides suggestive evidence that open banking fosters greater competition among financial service providers.

To explore innovation, I shift to the publisher level and examine three outcomes: the frequency of version updates, the number of newly launched apps, and the number of discontinued apps. These outcomes are measured across the publisher's entire portfolio, including both finance and non-finance apps.[14] The regression follows the same structure as before:

$$Innovation_{pt} = \beta_1 OB_p \times PostLockdown_t + X'_{pt}\gamma + \delta_p + \delta_t + \epsilon_{pt} \tag{7}$$

where $Innovation_{pt}$ denotes the frequency of version updates, number of new apps, or number of delisted apps for publisher p in month t. Results in Table 8 indicate that open banking publishers are significantly more active in updating their existing apps—both in terms of overall and major updates—following the lockdown. However, there is no evidence of increased app launches among these publishers, whether in finance or other categories. One possible explanation is that maintaining open banking services involves ongoing compliance and API-related costs, prompting firms to focus resources on existing apps rather than new development. Regarding app discontinuation, there is little evidence that open banking apps are more or less likely to be delisted. Nevertheless, the consistently negative coefficients suggest these apps may be more resilient in a competitive market, potentially benefiting from stronger product-market fit or sustained user demand.

5 Banks' Reaction to Open Banking Adoption

This section describes the construction of a measure capturing banks' exposure to open banking and investigates how open banking affects banks' behavior.

5.1 Measuring Banks' Open Banking Exposure

To quantify the textual overlap between banking apps and fintech apps, I compute pairwise similarities based on their app store descriptions. Each app description is first converted into a vector using the Term Frequency-Inverse Document Frequency (TF-IDF) method. TF-IDF is a widely used technique in natural language processing that captures the importance of

[14]Finance app publishers often develop apps in other categories such as productivity, retail, or business.

each word in a document relative to its importance across the entire corpus. Words that are frequent in a particular description but rare across other descriptions receive higher weights, helping to highlight distinctive content.

The construction of TF-IDF involves two components: term frequency (TF) and inverse document frequency (IDF). The TF component captures how frequently a word appears in a specific app description. For any word w in description d, the term frequency is defined as:

$$\mathrm{TF}_{wd} = \frac{f_{wd}}{\sum_{w' \in d} f_{w'd}} \tag{8}$$

where f_{wd} denotes the number of times word w appears in app d, and the denominator sums over all word occurrences in that description. This normalization ensures that TF values are comparable across documents of different lengths.

The IDF component down-weights common terms and up-weights rare ones, helping to distinguish words that are particularly informative. It is computed as:

$$\mathrm{IDF}_{w} = \log\left(\frac{N}{1 + |\{d \in D : w \in d\}|}\right) \tag{9}$$

where N is the total number of app descriptions in the corpus, and $|\{d \in D : w \in d\}|$ is the number of descriptions in which word w appears. The addition of 1 in the denominator prevents division by zero.

The final TF-IDF score for word w in description d is then given by:

$$\text{TF-IDF}_{wd} = \mathrm{TF}_{wd} \times \mathrm{IDF}_{w} \tag{10}$$

With each app description now represented as a TF-IDF vector, I compute the similarity between any two apps using cosine similarity:

$$\mathrm{CosineSimilarity}(A, B) = \frac{\vec{v}_A \cdot \vec{v}_B}{\|\vec{v}_A\| \cdot \|\vec{v}_B\|} \tag{11}$$

where $\vec{v}_A$ and $\vec{v}_B$ denote the TF-IDF vectors of app descriptions A and B, respectively.

Cosine similarity ranges from 0 to 1, where higher values indicate greater textual overlap.

To construct a bank-level measure of open banking exposure, I take the average cosine similarity between each bank's app and all authorized open banking providers' apps. A higher value reflects greater similarity in the services described, indicating that the bank potentially overlaps more with fintech offerings and may face stronger exposure from open banking. Specifically, I construct the exposure measure by comparing the earliest available app descriptions of banks in 2018 with the latest app descriptions of authorized third-party providers in 2023. This timing choice is intentional. By anchoring bank app descriptions in 2018—prior to widespread third-party entry—I avoid capturing banks' potential responses to competitive pressure in the form of strategic changes to their app content. At the same time, using 2023 app descriptions for authorized third parties ensures that the features of fully developed open banking apps are adequately reflected. Notably, in 2018, the number of authorized third-party providers was small and largely limited to the UK, and their app features may not yet have represented the broader open banking ecosystem.

5.2 Open Banking's Impact on Bank Performances

One natural outcome variable sets are the performance from accounting data issued by banks annually. To causally capture the impact on banks, I employ the following regression

$$Y_{bct} = \alpha + \beta Post_{ct} \times FintechExposure_b + \delta_{ct} + \gamma_b + \varepsilon_{bct} \tag{12}$$

where Y_{bct} denotes the outcome of bank b in country c at time t. $Post_{ct}$ equals 1 for years 2019 and onward. $FintechExposure$ is defined as the average TF-IDF cosine similarity, as described in subsection 5.1, between bank b's app and all authorized third-party apps. Country-year fixed effects and bank fixed effects are included to control for macroeconomic trends and unobserved bank-specific characteristics.

Table 9 presents the results. Panel A focuses on the asset side of banks. Compared to banks that are less similar to fintechs, those with a higher open banking exposure experience a significant decline in loan issuance. Specifically, a one-standard-deviation (0.0156) increase in $FintechExposure$ is associated with a 6.1% decrease in net loan issuance and a 9.7% decrease in gross loan issuance, both statistically significant at the 5% level. These reductions are accompanied by a significant decline in total assets and the number of employees. In contrast, I find no significant effect on deposit levels or total debt, suggesting that open banking fintechs primarily disrupt banks on the lending side. Services such as budgeting tools, financial planning, investment advice, or payment solutions may complement rather than directly compete with banks. However, alternative lending models offered by fintechs—particularly those relying less on traditional credit records—pose a direct threat to banks' core lending activities. Panel B reports results on profitability. I examine growth in net interest income, net fee income, and net income before tax, but none of these proxies show statistically significant effects. The negative sign on net interest income and the positive sign on net fee income may suggest that banks are losing interest revenue from reduced lending activity, while possibly shifting toward fee-based income streams. Measures of overall profitability—including return on equity (ROE), return on assets (ROA), and profit margin—also show no significant changes. Overall, the results suggest that banks are indeed affected by open banking, with the most pronounced impact observed in their lending operations.

I find corroborating evidence using the World Bank's Global Findex database—a triennial, nationally representative survey on how adults save, borrow, make payments, and manage risk. The survey provides harmonized individual-level data across countries and years, making it suitable for cross-country policy evaluation. I use this dataset to examine whether open banking adoption is associated with changes in household financial behavior, particularly in savings and borrowing channels. Specifically, I use the Findex microdata (Development Research Group, Finance and Private Sector Development Unit (2022)) from the 2014, 2017, and 2021 waves to estimate the following regression:

$$Y_{ict} = \alpha + \beta \text{ Open Banking}_c \times \text{Post}_t + \gamma_1 \text{Control}_{it} + \gamma_2 \text{Control}_{ct} + \theta_{Rt} + \delta_c + \lambda_t + \varepsilon_{ict} \quad (13)$$

The dependent variable is a binary indicator constructed from survey responses indicating whether the individual used a specific savings or borrowing channel—either a formal financial institution or an informal provider—in the past 12 months. *Open Banking* is a dummy equal to 1 if the respondent's country had implemented open banking regulation by the end of 2021. *Post* equals 1 for the 2021 wave and 0 for the 2014 and 2017 waves. Individual-level controls include age, gender, income quintile, and education level. Country-level controls, drawn from the World Bank World Development Indicators, include the employment rate, inflation rate, and GDP per capita. All specifications include region-by-year fixed effects (θ_{Rt}), country fixed effects (δ_c), and year fixed effects (λ_t).

Table 10 reports the regression results. The interaction term *Open Banking* $\times$ *Post* is positive and significant at the 1% level for informal borrowing, and negative and significant at the 1% level for borrowing from financial institutions. The difference between these two effects is also statistically significant at the 1% level, indicating a substitution from formal to informal borrowing following open banking adoption. This substitution effect is concentrated among the bottom 60% of the income distribution and increases monotonically as income declines, while higher-income individuals show little change. On the other hand, open banking does not appear to negatively affect savings held at financial institutions. In fact, savings at both financial institutions and informal providers increase in countries that have implemented open banking. These findings suggest that open banking and fintech may improve borrowing access for lower-income groups traditionally underserved by banks.

5.3 Open Banking's Impact on Bank Innovation and Competition

In progress.

6 Conclusion

This paper provides the first empirical evidence on how open banking affects competition in financial services. I show that open banking intensifies competition by boosting the performance of fintech apps, especially smaller and unauthorized providers, and by increasing competitive pressure throughout the market.

For fintechs, open banking adoption leads to meaningful increases in downloads, user activity, and revenue. Authorized providers experience gradual but sustained growth, while non-authorized adopters see faster, more immediate gains. Exploiting cross-country variation in authorization status within the same app, I further provide causal evidence that access to customer financial data via open banking contributes to performance gains across key metrics. These effects intensified during the COVID-19 pandemic, particularly for lending and investment apps, underscoring open banking's role in delivering financial services when traditional channels were disrupted. Fintech startups benefited most, responding quickly to shifting consumer needs. I also find that open banking apps face greater competitive pressure and become more active in updating their products, suggesting accelerated innovation.

For banks, the competitive pressures triggered by open banking have significant spillover effects. Banks facing higher fintech competition reduce their loan issuance, although their deposit-taking and profitability remain largely unaffected. These results highlight the disruptive impact of open banking on credit markets, with traditional banks losing lending share to more agile fintech competitors. Taken together, the findings position open banking as a key driver of financial access, competition, and market restructuring—shaping both fintech growth and traditional banking activities, with broader implications for the future of financial services.

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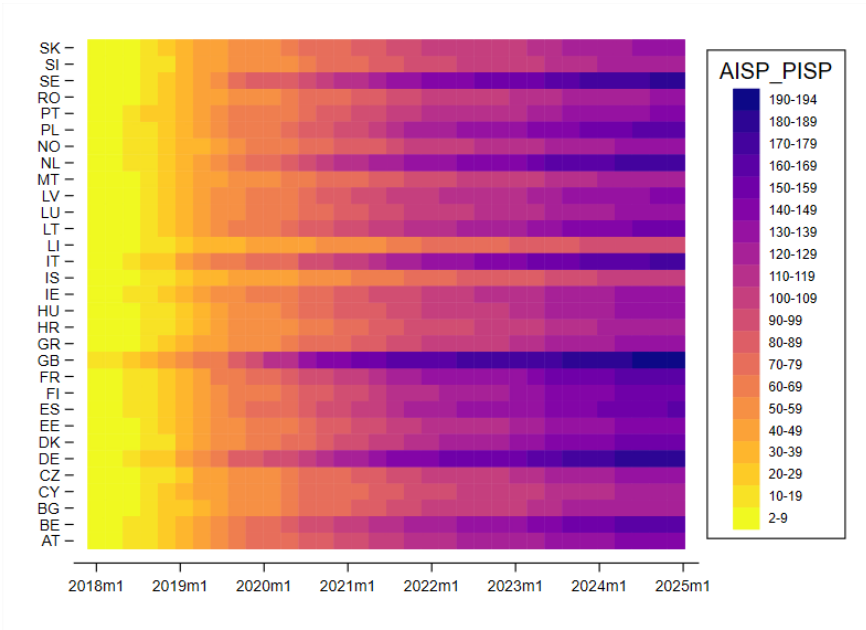
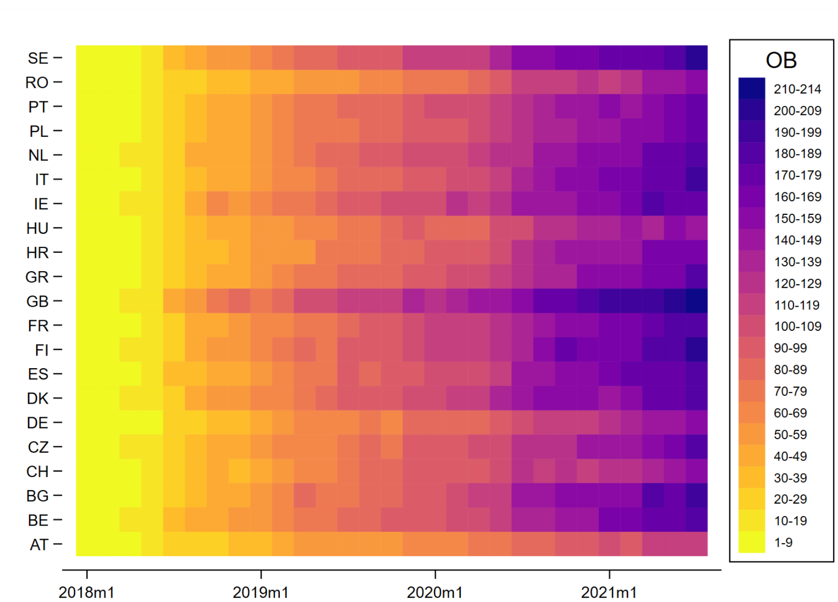
Figure 1: Numbers of Authorized and Non-authorized Providers in UK & EU

(a) Cumulative Authorized Provider

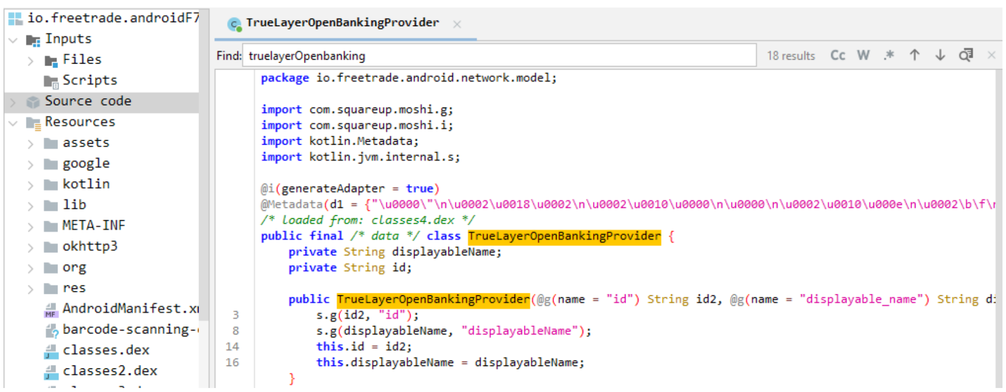


(b) Non-authorized Provider in Top 1,000



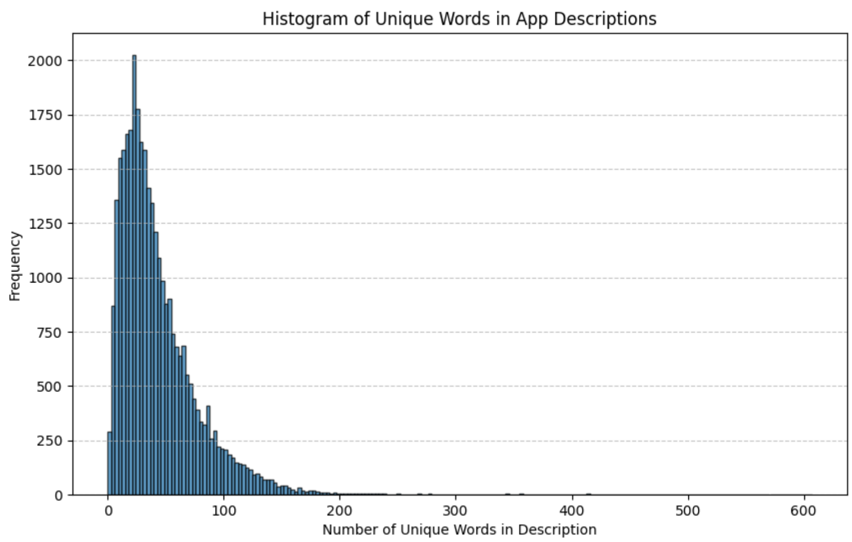
Note.— This figure displays the evolution of authorized and non-authorized open banking providers over time. Panel A plots the cumulative number of authorized providers across all UK and EU countries. Panel B shows the number of top 1,000 finance apps in each country (covered by Apptopia) that have integrated an API from an authorized provider.

Figure 2: Screenshot for APK Source Code of the Freetrade App



NOTE.— This figure presents the decompiled content of a historical version of the Freetrade app's APK using JADX-GUI. The highlighted section shows the presence of the class "TrueLayerOpenBankingProvider", which provides direct evidence that the app had integrated with the open banking provider TrueLayer, allowing us to infer open banking adoption by the Freetrade app.

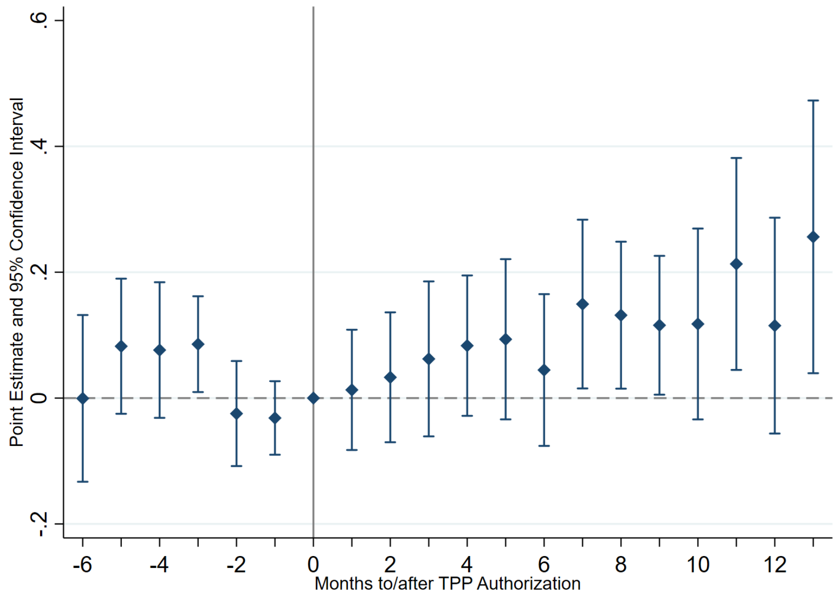
Figure 3: Distribution of Word Frequency in App Descriptions



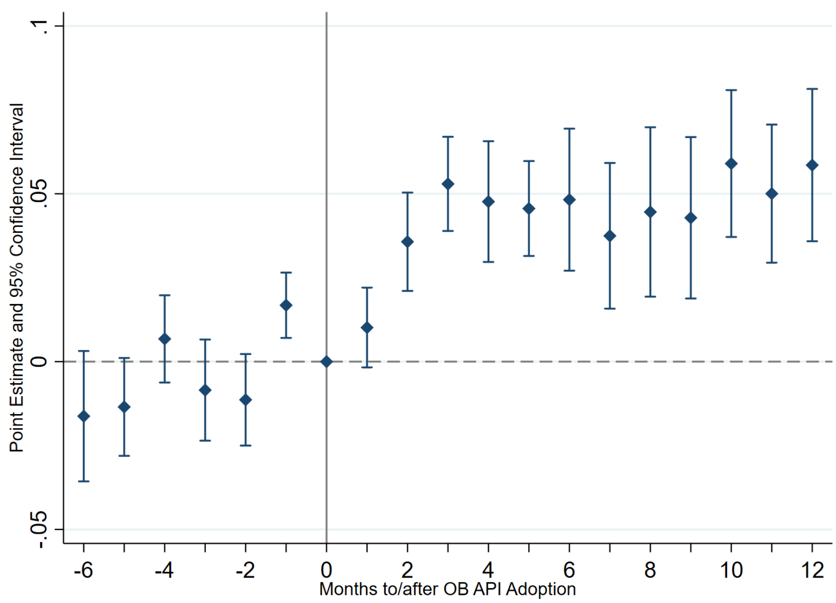
NOTE.— This figure shows the distribution of word counts in app descriptions for the top 1,000 finance apps in the UK and EU sample. Following the methodology of Hoberg and Phillips (2016), I convert each description into a vector of nouns and proper nouns, excluding high-frequency words that appear in more than 20% of apps. The distribution indicates that app descriptions contain a sufficient number of informative words to construct meaningful text vectors for identifying competitors.

Figure 4: Demand Response to Open Banking: Event Study

(a) Authorized Provider



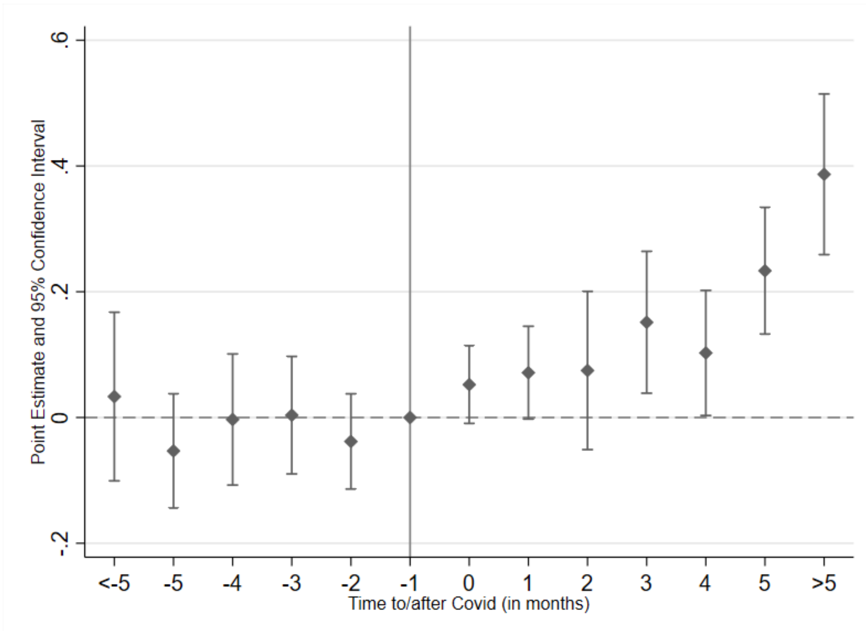
(b) Non-authorized Provider



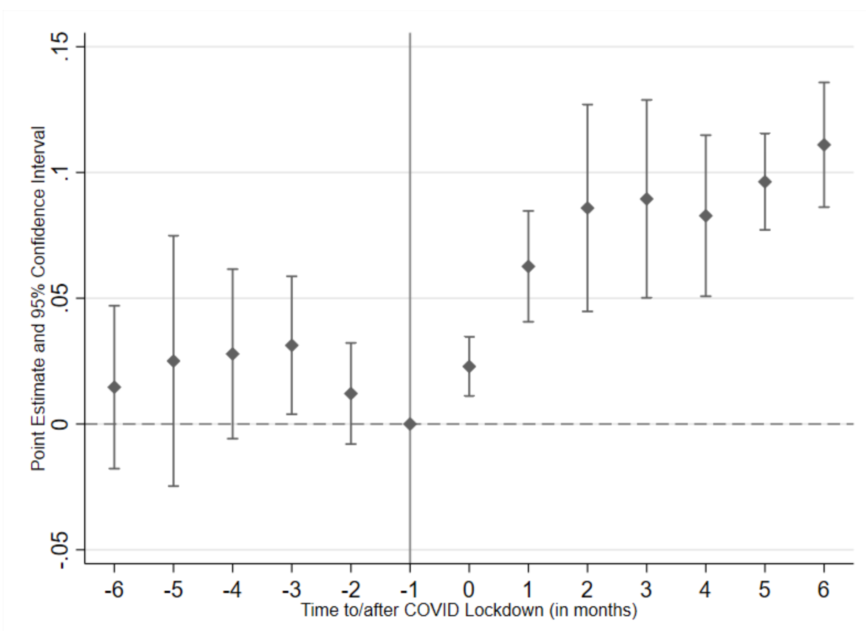
NOTE.— This figure presents event study coefficients in Equation 1 around the adoption of open banking. Panel A plots the coefficients relative to the month when a provider first received authorization, see . Panel B displays the coefficients around the month an app was first detected to integrate an open banking API from an authorized provider.

Figure 5: Dynamic Effects of COVID-19 on Demand for Open Banking Providers

(a) Authorized Provider



(b) Non-authorized Provider



Note.— This figure presents the Difference-in-Differences regression coefficients capturing the impact of COVID-19. Panel A plots the dynamic interaction coefficients from Equation 3, measured relative to the onset of lockdowns in March 2020, for authorized open banking providers. Panel B shows the corresponding dynamic coefficients from Equation 4 for non-authorized apps that integrated with an authorized open banking API.

Table 1: Summary Statistics

	mean	*sd*	*p*1	*p*50	*p*99	*count*
Downloads	725.78	5221.45	1.00	102.00	10872.00	902,893
Revenue	71.30	701.22	0.00	0.00	1182.00	902,893
DAU	927.76	9499.20	0.00	68.87	14599.11	902,893
MAU	2831.29	18919.38	0.00	382.60	43147.68	902,893
ARPU	0.66	4.45	0.00	0.00	9.99	902,893
Engagement	0.18	0.14	0.00	0.17	0.50	902,893
Age (month)	57.50	36.14	2.00	53.00	140.00	902,893
In-App Purchases	0.18	0.38	0.00	0.00	1.00	902,893
In-App Advertising	0.44	0.50	0.00	0.00	1.00	902,893
Same publisher apps	9.37	20.72	1.00	3.00	107.00	902,893
# Past versions	22.02	22.86	0.00	17.00	107.00	902,893
Version age (month)	7.95	14.09	0.00	1.60	65.57	902,893

NOTE.—This table presents summary statistics for the top 1,000 finance apps in the UK and EU on the iOS App Store, covering the period from January 2018 to July 2021. DAU denotes average daily active users, MAU refers to monthly active users, and ARPU represents average revenue per user. Engagement, defined as the ratio of DAU to MAU, serves as a proxy for how frequently the average user opens the app.

Table 2: Determinants of Open Banking Adoption

	Adoption		Early Adoption		Late Adoption	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	−0.004***	−0.004***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	0.000***	0.000***	0.000**	0.000***	0.000***	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
In-app Purchases	0.002	0.001	0.000	0.001	−0.001	−0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multi-language	0.015***	0.014***	0.005***	0.006***	0.004***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multi-platform	0.026***	0.026***	0.010***	0.010***	0.008***	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multi-category	−0.001	−0.001	−0.000	−0.001**	−0.000	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
App portfolio	−0.004***	−0.003**	0.001	−0.001	−0.002***	−0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Past Downloads	0.094***	0.095***	0.047***	0.045***	0.004	0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year FE		Y		Y		Y
Observations	71,316	71,316	71,316	71,316	71,316	71,316
R-sq.	0.015	0.016	0.005	0.012	0.004	0.019

Note.—This table reports the characteristics of open banking adopters. For each year, the sample consists of apps that adopt open banking within that year and those that have not yet adopted, excluding any apps that adopted in previous years. The annual samples are then pooled across years. Early adopters are defined as those who adopted open banking in 2018, while late adopters are those who adopted in 2020 or later.

Table 3: Demand Response to Open Banking Authorization: Identification

	(1) Download	(2) Engagement	(3) Revenue	(4) MAU	(5) DAU	(6) ARPU
Post	−0.191	−0.022*	−0.088	−0.497	−0.449	−0.012
	(0.23)	(0.01)	(0.07)	(0.36)	(0.29)	(0.01)
OBAuth × Post	0.198**	0.027***	0.406***	0.265*	0.230**	0.053***
	(0.09)	(0.01)	(0.12)	(0.13)	(0.11)	(0.02)
App × Month FE	Y	Y	Y	Y	Y	Y
App × Country FE	Y	Y	Y	Y	Y	Y
Observations	160,751	160,751	160,751	160,751	160,751	160,751
R-sq.	0.890	0.893	0.838	0.915	0.938	0.793

Note.—This table reports the coefficients from estimating Equation 2. The variable *OBAuth* is a binary indicator equal to one if the app is authorized as an open banking provider in a given country. The identification relies on within-app comparisons across countries with and without authorization, holding app-level characteristics constant. Standard errors are clustered by country and year-month, and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Impact of COVID-19 on Open Banking Provider Demand: Baseline

Panel A. Authorized Provider

	(1) Download	(2) Engagement	(3) Revenue	(4) MAU	(5) DAU	(6) ARPU
OBAuth × PostLockdown	0.155***	0.015***	0.274***	0.119***	0.119***	0.039***
	(0.02)	(0.00)	(0.01)	(0.03)	(0.02)	(0.00)
App × Year-Month FE	Y	Y	Y	Y	Y	Y
App × Country FE	Y	Y	Y	Y	Y	Y
Observations	124,119	124,119	124,119	124,119	124,119	124,119
R-sq.	0.879	0.888	0.821	0.918	0.942	0.759

Panel B. Non-authorized Provider

	(1) Download	(2) Engagement	(3) Revenue	(4) MAU	(5) DAU	(6) ARPU
OB × PostLockdown	0.170***	0.008***	0.054***	0.185***	0.183***	−0.000
	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)	(0.00)
Year-Month FE	Y	Y	Y	Y	Y	Y
App × Country FE	Y	Y	Y	Y	Y	Y
Observations	459,056	459,056	459,056	459,056	459,056	459,056
R-sq.	0.887	0.853	0.911	0.900	0.916	0.916

Note.—This table presents the impact of COVID-19 on demand for open banking apps. The variable *OBAuth* is a binary indicator equal to one if an app is authorized as an open banking provider in a given country as of the end of 2019. The variable *OB* is a binary indicator equal to one if an app has integrated the open banking API of an authorized provider by the end of 2019. Panel A reports the coefficients from estimating Equation 3, while Panel B reports the coefficients from Equation 4. Standard errors are clustered by country and year-month, and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Heterogeneity in Service Type

	(1)	(2)	(3)	(4)	(5)
OB × PostLockdown	0.273***	0.124***	0.066***	0.165***	0.150***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
OB × PostLockdown × Payment	−0.189***				
	(0.03)				
OB × PostLockdown × Borrowing		0.245***			
		(0.04)			
OB × PostLockdown × Investment			0.201***		
			(0.03)		
OB × PostLockdown × Insurance				−0.027	
				(0.05)	
OB × PostLockdown × Miscellaneous					−0.027
					(0.03)
Year-Month FE	Y	Y	Y	Y	Y
App × Country FE	Y	Y	Y	Y	Y
Observations	459,056	459,056	459,056	459,056	459,056
R-sq.	0.887	0.887	0.888	0.887	0.887

NOTE.—This table reports the coefficients from a triple difference-in-differences regression based on Equation 5, which extends the baseline specification by interacting open banking adoption with service types. The outcome variable is the logarithm of monthly downloads. Service types are identified based on app descriptions and represented by binary indicators. Standard errors are clustered by country and year-month, and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Heterogeneity in Provider Type

	(1)	(2)	(3)	(4)	(5)
OB × PostLockdown	0.240***	0.163***	0.042**	0.134***	0.128***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
OB × PostLockdown × Bank	−0.275***				
	(0.03)				
OB × PostLockdown × Neobank		−0.154*			
		(0.07)			
OB × PostLockdown × Fintech			0.213***		
			(0.03)		
OB × PostLockdown × Fintech Incumbent				0.072***	
				(0.02)	
OB × PostLockdown × Fintech Startup					0.171***
					(0.03)
Year-Month FE	Y	Y	Y	Y	Y
App × Country FE	Y	Y	Y	Y	Y
Observations	459,056	459,056	459,056	459,056	459,056
R-sq.	0.887	0.887	0.887	0.887	0.888

NOTE.—This table reports the coefficients from a triple difference-in-differences regression based on Equation 4, extended to include interactions with provider types. The outcome variable is the logarithm of monthly downloads. Provider types are classified using app names and descriptions, as detailed in subsubsection 4.3.2. Standard errors are clustered by country and year-month, and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Impact on Competition Among Open Banking Apps

	Degree		Betweeness		Clustering	
	(1) Unweighted	(2) Weighted	(3) Unweighted	(4) Weighted	(5) Unweighted	(6) Weighted
OB × PostLockdown	0.026**	0.026**	0.000***	0.000***	0.007**	0.005***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Year-Month FE	Y	Y	Y	Y	Y	Y
App × Country FE	Y	Y	Y	Y	Y	Y
Observations	459,056	459,056	459,056	459,056	459,056	459,056
R-sq.	0.874	0.874	0.428	0.401	0.608	0.636

NOTE.—This table reports the coefficients from Equation 6. Outcome variables: degree centrality, betweenness centrality, and the clustering coefficient are calculated from the competitor network constructed using the top 1,000 finance apps in the UK and EU, based on textual analysis of app descriptions following the methodology of Hoberg and Phillips (2016). Odd-numbered columns report results using unweighted network measures, while even-numbered columns present results weighted by cosine similarity. Standard errors are clustered by country and year-month, and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Impact on Innovation Among Open Banking Apps

	Updates		**New apps**		**Dead apps**	
	(1) Major Updates	(2) All Updates	(3) Finance	(4) Non-finance	(5) Finance	(6) Non-finance
OB × PostLockdown	0.031***	0.092**	0.002	−0.000	−0.007*	−0.001
	(0.01)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)
Year-Month FE	Y	Y	Y	Y	Y	Y
Publisher FE	Y	Y	Y	Y	Y	Y
Observations	102,649	102,649	150,696	150,696	150,696	150,696
R-sq.	0.465	0.582	0.075	0.138	0.129	0.217

Note.— This table reports the coefficients from Equation 7. Innovation is proxied by the frequency of version updates and the introduction of new apps. âDead appâ refers to the delisting of inactive apps from the app store. New apps and dead apps are measured as binary indicators, while updates are captured as a count variable. Regressions are conducted at the publisher level. Standard errors are clustered by country and year-month, and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Impact of Open Banking on Bank Performances

Panel A. Balance Sheet

	(1) Net Loan	(2) Gross Loan	(3) Total Asset	(4) No. Employee	(5) Gross Loan	(6) Total Deposit
Post × FintechExposure	−3.901**	−6.179**	−7.180*	−5.370***	2.766	−3.403
	(1.67)	(2.31)	(3.74)	(1.38)	(2.14)	(2.37)
Bank FE	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y
Observations	3,286	3,142	3,392	3,001	3,257	3,216
R-sq.	0.910	0.879	0.798	0.905	0.894	0.872

Panel B. Profitability

	(1) Net Interest Income	(2) Net Fee Income	(3) Net Income	(4) ROA	(5) ROE	(6) Profit Margin
Post × FintechExposure	−0.125	0.006	−9.686	0.930	13.828	−11.166
	(1.02)	(1.23)	(8.24)	(5.12)	(19.36)	(46.46)
Bank FE	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y
Observations	2,959	2,907	3,034	3,440	3,417	2,982
R-sq.	0.449	0.259	0.224	0.681	0.585	0.696

Note.—This table presents the estimated impact of open banking on bank performance. The variable *FintechExposure* is defined as the average TF-IDF cosine similarity between each bankâs 2018 app description and the app descriptions of all authorized open banking providers in 2023. Details on the construction of this exposure measure are provided in subsection 5.1. The variable *Post* is a binary indicator equal to one for years 2019 and onward. Panel A reports the coefficients from estimating Equation 12, focusing on balance sheet variables. Panel B presents results from the same specification, focusing on profitability measures. Standard errors are clustered at the year level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Open Banking and Borrowing and Saving Provider Decision

	Borrowing		Saving	
	(1) Financial Institution	(2) Informal Provider	(3) Financial Institution	(4) Informal Provider
Open Banking × Post	−0.029***	0.004***	0.048***	0.024***
	(0.01)	(0.00)	(0.01)	(0.00)
Age	−0.000***	−0.000	−0.000***	−0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Female	−0.008***	−0.002***	−0.008***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
Income (21% - 40%)	0.016***	0.003**	0.040***	0.012***
	(0.00)	(0.00)	(0.00)	(0.00)
Income (41% - 60%)	0.026***	0.006***	0.078***	0.022***
	(0.00)	(0.00)	(0.00)	(0.00)
Income (61% - 80%)	0.034***	0.007***	0.113***	0.027***
	(0.00)	(0.00)	(0.00)	(0.00)
Income (81% - 100%)	0.042***	0.006***	0.171***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)
Education (Secondary)	0.034***	0.003***	0.081***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)
Education (Tertiary)	0.083***	0.002**	0.211***	0.024***
	(0.00)	(0.00)	(0.00)	(0.00)
Employment Rate	−0.025	−0.027*	0.046**	0.063***
	(0.02)	(0.02)	(0.02)	(0.02)
Inflation Rate	0.015	−0.025**	−0.029***	0.067***
	(0.01)	(0.01)	(0.01)	(0.01)
GDP per capita	−0.000	0.000***	0.000	−0.000**
	(0.00)	(0.00)	(0.00)	(0.00)
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Region × Year FE	Y	Y	Y	Y
Observations	307,401	307,401	307,401	307,401
R-sq.	0.046	0.054	0.264	0.109

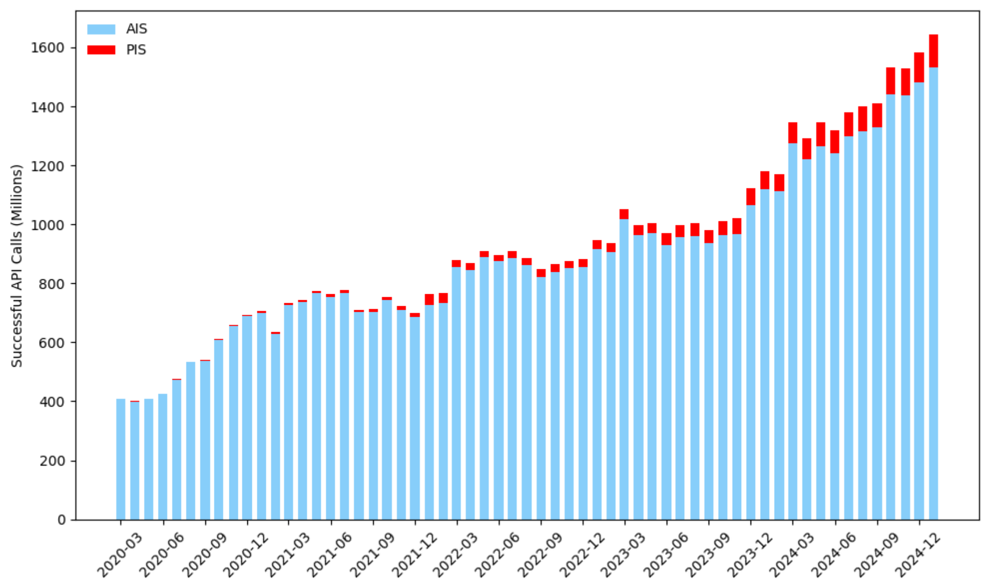
NOTE.—This table presents the results from estimating Equation 13. The outcome variables are binary indicators based on responses to survey questions from the World Bank Global Findex. Standard errors, clustered at the year level, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix to "Open Banking and Fintech Innovation Adoption: Evidence from Mobile Apps"

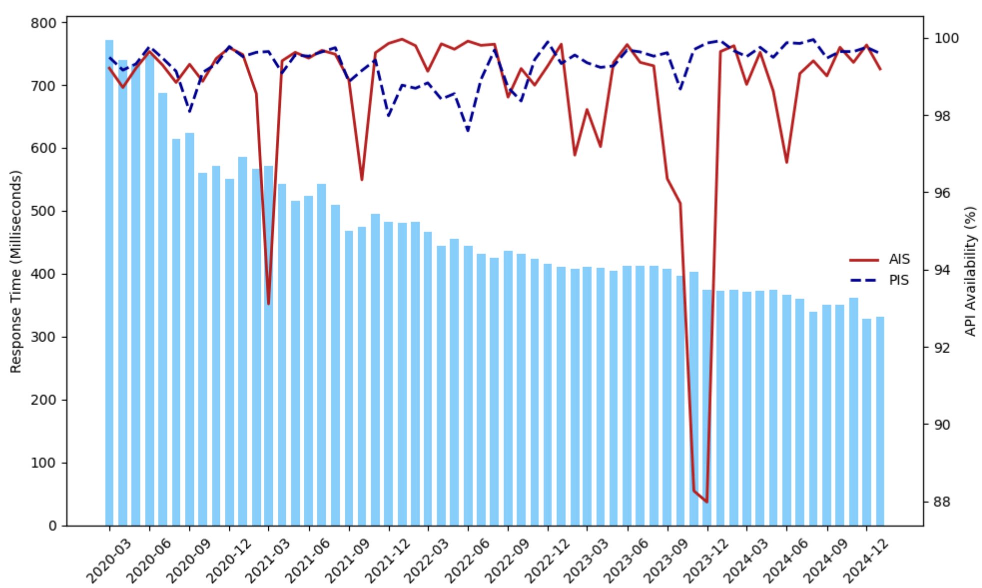
A Additional Figures

Figure IA.1: UK Open Banking API Call Numbers, Availability, and Response Time

(a) Successful API Call Numbers



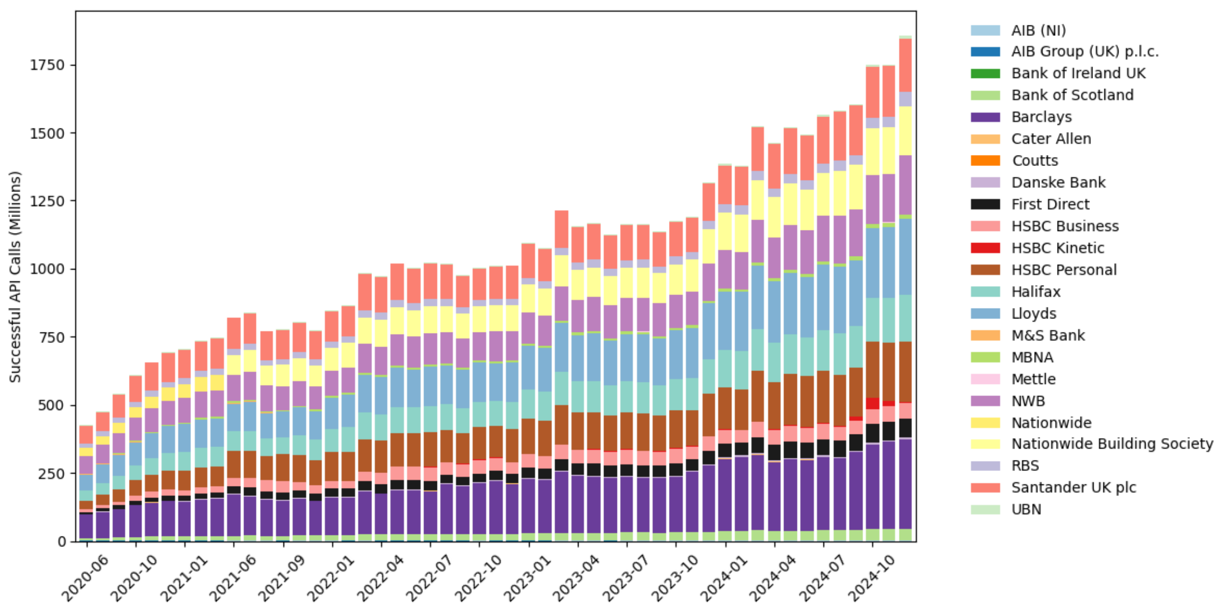
(b) Availability and Response Time



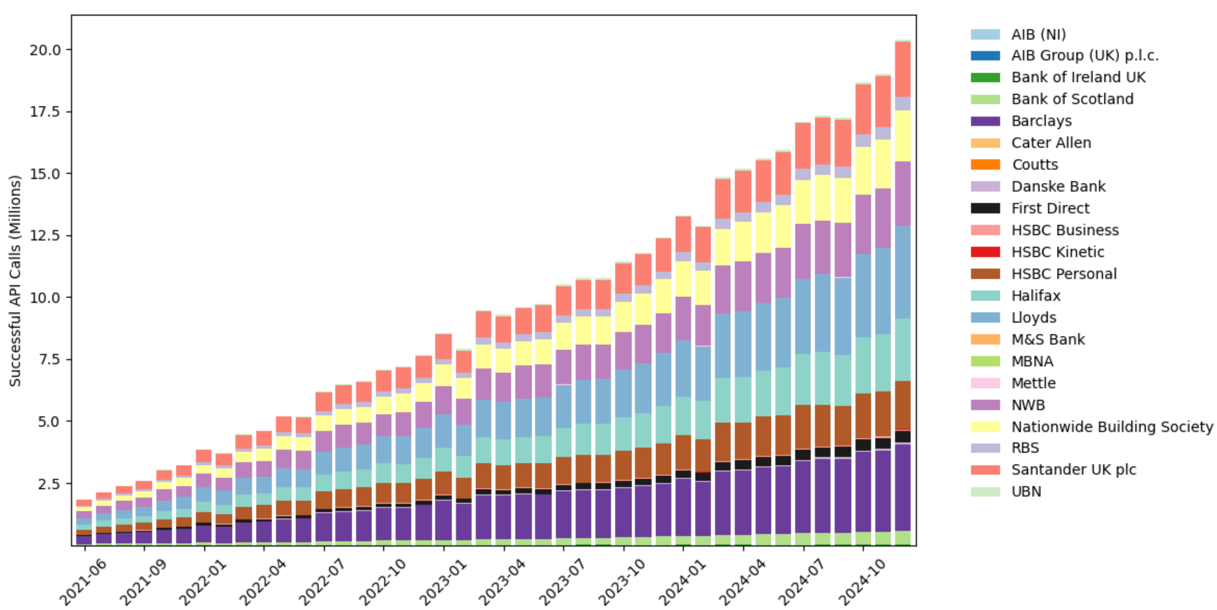
Note.—This figure illustrates the development of open banking APIs in the UK. Panel A presents the monthly aggregate number of successful API calls initiated by authorized third-party providers (TPPs), broken down into Account Information Service (AIS) and Payment Initiation Service (PIS) calls. Panel B shows the trends in average response time and average availability percentage for banksâ open banking APIs over the same period. The data is sourced from UK's Open Banking Implementation Entity (OBIE).

Figure IA.2: UK Open Banking API Calls By Major Banks

(a) Successful API Calls

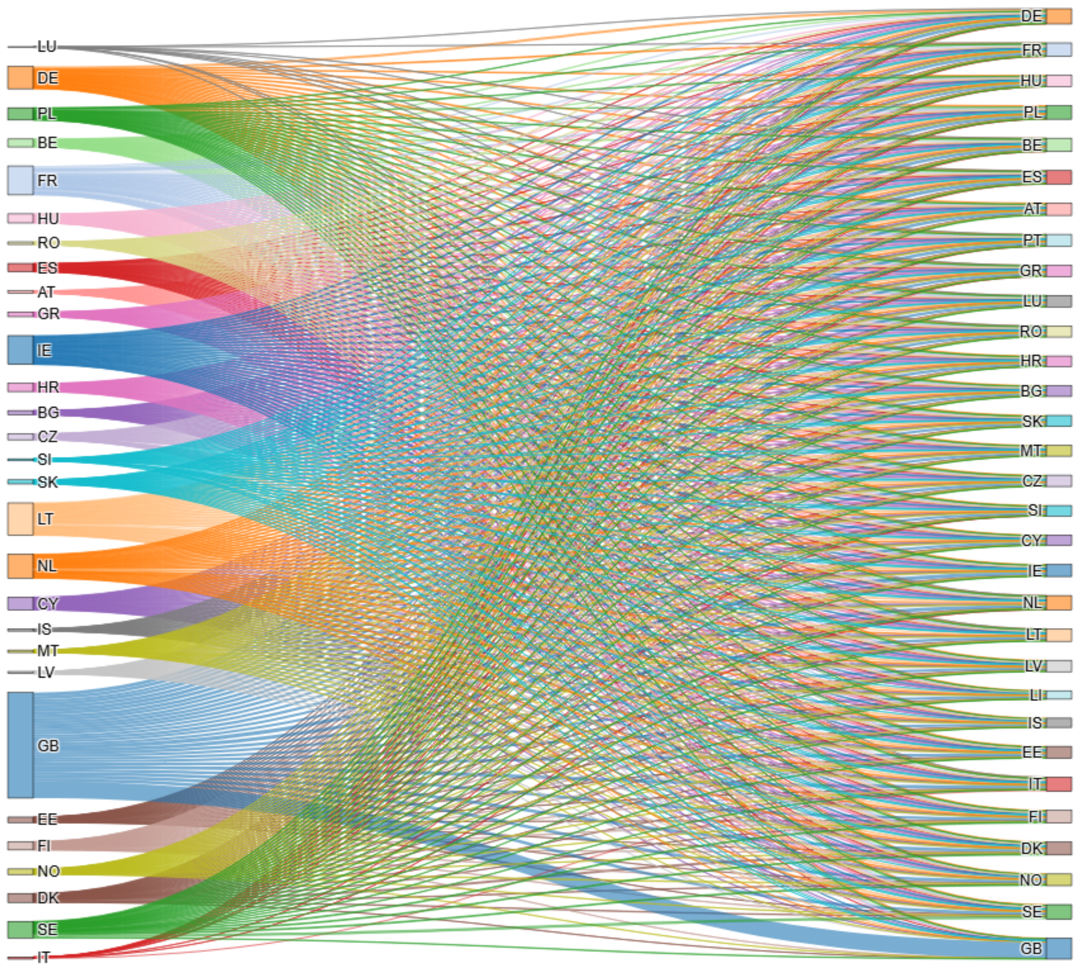


(b) Payment Requests API Calls



NOTE.—This figure presents the breakdown of open banking API calls by UK banks. Panel A displays the total number of successful API calls received by each bank, while Panel B focuses specifically on calls related to payment initiation services. The data is sourced from UK's Open Banking Implementation Entity (OBIE).

Figure IA.3: Sankey Diagram of Open Banking Passporting Flows Between the UK and Europe



Note.— This Sankey diagram illustrates cross-border open banking passporting relationships between countries. The left side represents the country of the service provider (passporting out), while the right side shows the country receiving the service (passporting in). The width of each flow corresponds to the number of passporting arrangements from providers in one country to recipients in another. The data is sourced from the UK Financial Conduct Authority (FCA) and the European Banking Authority (EBA) register.

Figure IA.4: Distribution of UK Third-Party Providers Across Outcome Areas

NOTE.—This graph shows the distribution of UK's TPP outcome areas defined by UK's Open Banking Implementation Entity (OBIE). The figures in the graph are not weighted. Detailed outcome area explanations are in Table IA.1.

B Additional Tables

Table IA.1: OBIE Outcome Areas and Related Open Banking Propositions

Outcome Area	Outcome Area Explanation	Related Propositions
Improved financial decision-making	Individuals and small businesses are actively engaged with their finances and routinely use open banking-enabled account services to review and control their finances seamlessly.	• Personal finance manager • Income and expenditure analysis • Small business financial management
Increased access to advice and guidance	Individuals and small businesses conveniently access timely debt advice, financial advice or help with tax or welfare.	• Legal aid and welfare support services • Income maximisation • IFA services • Roboadvice • Tax advice • Referrals to Money Helper • Cashflow management
Better borrowing	Individuals and small businesses benefit from using open banking-enabled cost-effective credit when they need it and can manage the burden of any debts they have.	• Consumer lending • Invoice financing • Asset financing • Small business finance • Debt advice • Automatic overdraft lending • Affordability analysis • Account sweeping • Affordable credit
Increased saving and investments	Individuals and small businesses are actively engaged in using open banking to help them with saving and asset-building. They put money aside, maximise their balances and/or returns by accessing the most appropriate savings and investment products and tools.	• Micro savings • Non-advised savings and investment • Account sweeping
Expanded payments choice	Individuals and small businesses are using the best open banking-enabled payment solutions meeting their needs for low cost, speed, convenience, control, visibility and security.	• E-Commerce payments • P2P payments • International payments • Card top-ups • Request to pay • Bill payment • Fraud detection • Rewards and loyalty management
Increased switching	Individuals and small businesses are getting better deals by confidently comparing financial services and household bills and subscriptions. They receive reminders and nudges to shop around, as a result of easier and more convenient personalised propositions.	• Subscription management • Financial product comparison services • Bill comparison and switch services • Other product comparison services

NOTE.—This table presents the outcome areas of TPPs defined by Open Banking Implementation Entity.