Digital Diffusion in a Competitive Landscape: A Study of Online Banking Adoption

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Abstract

This study investigates into firm's reaction to rival precedence in technology adoption by exploring U.S. banking firms' online banking adoption practices in the early 2000s. It finds that banks operating in markets with rival precedence were more likely to adopt. Such peer effect was strongest around 2004 - 2006, faded over time, and disappeared eventually, which presents the classic S-curve diffusion pattern.

Keywords: Technology diffusion, bank competition, financial innovation.

JEL Codes: D83, G21, L11, L22, O33.

1 Introduction

The relationship between competition and technological progress has long been a central focus in the economics of innovation. Foundational theories such as Schumpeterian growth models and frameworks of endogenous technological change emphasize that market structure critically shapes firms' incentives to invest in innovation. Seminal empirical work reinforces this perspective, most notably Aghion et al. (2005), who document an inverted-U relationship between product market competition and innovation intensity, building on earlier insights such as Scherer (1967). Bloom et al. (2015) further show that greater competitive pressure improves management practices, highlighting an important mechanism through which competition influences organizational innovation. Although this literature has deepened our understanding of how competition affects innovation at the technological frontier, far

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less is known about how market competition shapes the adoption and diffusion of existing technologies among incumbent firms embedded in local markets. Because economic growth depends not only on invention but also on diffusion, understanding this relationship is central to the broader link between market structure and technological progress.

A separate but related literature on technology diffusion has emphasized the importance of peer effects, organizational constraints, and market dynamics in shaping adoption behavior. Classic studies such as Griliches (1957), who documented the logistic (S-shaped) adoption pattern of new technologies driven by profitability, market density, and dissemination costs, and Mansfield (1968), who analyzed how firm and industry characteristics influence innovation and diffusion rates, provide foundational insights into the timing and determinants of diffusion. More recent work examines emerging technologies such as automation and artificial intelligence, including Acemoglu and Restrepo (2020) and Babina et al. (2023). However, much of this research emphasizes the consequences of technology adoption rather than the competitive processes that drive diffusion decisions. In particular, there remains limited systematic evidence on how competitive environments shape firms' adoption responses to rival behavior. As a result, we lack clear empirical evidence on whether and how market concentration, local growth conditions, and firm size influence the diffusion of new technologies.

This paper addresses this gap by studying the adoption of online banking among U.S. commercial banks and savings institutions between 2003 and 2010. Online banking represents a salient digital financial innovation requiring substantial upfront investment in IT infrastructure, customer interfaces, and back-end security systems. Over this period, adoption increased from near zero to nearly universal levels (Chen and Samaniego, 2025), with substantial variation in timing across institutions and markets. Using a bank-year panel dataset merged with local market characteristics, this paper examines whether banks are more likely to adopt when their local rivals have already done so, and how this responsiveness varies with market concentration, growth conditions, and organizational scale.

The empirical analysis employs Cox proportional hazards models with time-varying covariates to account for the timing of adoption and the evolving influence of explanatory factors. The results show that rival adoption significantly increases the conditional probability that a bank adopts online banking. However, this influence diminishes over time, consistent with the S-shaped diffusion pattern emphasized by Griliches (1957). Moreover, the response to rival adoption is significantly weaker in more concentrated markets, stronger among smaller banks, and more pronounced in slow-growing markets. These findings indicate that competition influences not only incentives to innovate, as emphasized by Aghion et al. (2005), but also the timing and strategic responsiveness of technology adoption.

To guide the empirical analysis, the paper develops a simple two-period Cournot framework in which banks compete in quantities and decide whether to adopt a cost-saving technology. One bank adopts first, lowering its marginal cost and altering market competition. The rival then decides whether to follow. The key insight is that rival adoption changes the follower's profit differential between adopting and not adopting: by remaining at the original cost, the follower loses market share and profits, whereas adoption restores competitiveness and can generate additional efficiency gains due to learning effect. As a result, rival precedence can increase the incentive to adopt rather than merely reduce industry profits. The framework highlights how market conditions and technological parameters shape this response.

The diffusion of online banking provides a suitable setting to study these dynamics. Financial development plays a central role in long-run growth (King and Levine, 1993; Rajan and Zingales, 1998), and online banking represented a major operational innovation with substantial fixed costs and lower marginal servicing costs. Its gradual and uneven rollout across banks and local markets generates variation in exposure to prior adopters. This setting allows examination of whether banks respond to rival adoption by accelerating their own technology adoption decisions.

The empirical analysis uses bank-level Call Report data merged with local market characteristics between 2003 and 2010. The dependent variable is a bank-level indicator for online banking adoption. The central explanatory variable is rival precedence, captured by a dummy equal to one once at least one local competitor has adopted online banking. As an alternative specification, rival precedence is measured as the share of competitors that have already adopted. Main controls include deposit-based measures of market concentration and changes in local market size and economic activity. The empirical strategy exploits within-market, over-time variation in rival precedence to identify how prior adoption by competitors affects a bank's own adoption decision.

Cox proportional hazard models with time-varying covariates are used to model the timing of adoption. This approach accommodates staggered adoption and allows the influence of rival precedence and market characteristics to evolve throughout the diffusion process. Interaction terms between rival precedence and market concentration, growth conditions, and bank size test for systematic heterogeneity in responses. The results are robust to alternative specifications of competition measures, alternative market definitions, and additional controls.

These results provide new evidence on how competitive interactions shape the diffusion of operational technologies. In particular, they show that prior adoption by competitors — rival precedence — significantly affects the timing of a bank's own adoption decision, and

that this effect varies systematically with market structure, local growth conditions, and organizational scale.

The findings contribute to several strands of literature. First, the paper contributes to the literature on competition and innovation by shifting attention from frontier R&D investment to the strategic diffusion of existing technologies. While Aghion et al. (2005) focus on how competition shapes innovation intensity, this paper shows that market structure also conditions the timing and responsiveness of adoption decisions, highlighting that competition influences not only who innovates, but also who adopts and when.

Second, the paper contributes to the technology diffusion literature by documenting how adoption responses to rival precedence vary across markets and firms. Classical diffusion models such as Griliches (1957) emphasize profitability and information spillovers but abstract from competitive structure. By quantifying how rival adoption affects banks differently depending on market concentration, growth conditions, and firm size, the paper provides new stylized facts on when and where diffusion accelerates or slows. The inclusion of time-varying covariates further shows how the influence of prior adoption evolves throughout the diffusion process.

Third, the paper contributes to industrial organization by embedding adoption timing within a dynamic competitive framework. The evidence that responses to rival precedence are weaker in concentrated markets suggests that dominant firms face different strategic incentives than firms in fragmented markets. Documented heterogeneity across firm size highlights how organizational scale shapes strategic adjustment to competitive threats.

More broadly, these results provide empirical evidence on how competition and rival behavior jointly drive digital transformation within a regulated industry. By examining not only whether banks adopt but also when and under what competitive conditions they do so, the paper connects insights from innovation, diffusion, and industrial organization. The findings underscore that technological diffusion is fundamentally shaped by strategic interaction within markets, offering a framework relevant for understanding digital adoption in other sectors.

The remainder of the paper is organized as follows. Section 2 formalizes firm competition and technology adoption in the presence of rival precedence under Cournot competition. Section 3 describes the data in detail and outlines the empirical strategy. Section 4 presents the main empirical findings. Section 5 concludes with a summary and directions for future research.

2 Conceptual Framework

This section presents a two-period Cournot competition framework in which two banks provide homogeneous financial services in a local market.

2.1 Technology and Cost Structure

There are two banking firms, indexed by $i \in \{1, 2\}$, each produces a homogeneous financial service and faces a constant marginal cost of c_i. The cost function is:

$$C_i(q_i) = c_i C(q_i)$$

where $C_i(q_i)$ is assumed to be linear in output, i.e. $C(q_i) = q_i$. Hence, total cost is $c_i q_i$.

A cost-saving technology, such as online banking, becomes available between periods. Adoption of this technology reduces marginal cost by a constant proportion. Specifically, if bank i adopts, its cost becomes:

$$c_i' = \eta \cdot c_i, \quad \text{where } \eta \in (0, 1)$$

The parameter η depends on the adoption order:

- If bank i adopts **early** (as the leader): $c_i' = \eta_e \cdot c_i$
- If bank i adopts **later** (as the follower): $c_i' = \eta_f \cdot c_i$

  where $0 < \eta_f < \eta_e < 1$, indicating that the follower benefits from learning and thus incurs an even lower marginal cost because of adoption.

Assume only bank 1 has adopted the technology prior to period 2. Bank 2 decides whether to adopt based on a privately observed cost draw.

2.2 Two-Period Cournot Competition with Technology Adoption

Period 1: Baseline Cournot Competition

In the first period, both banks simultaneously choose output quantities. The market inverse demand function is:

$$P(Q^{(1)}) = a - bQ^{(1)}, \quad \text{where } Q^{(1)} = q_1^{(1)} + q_2^{(1)}$$

Each bank produces at cost c_i, and earns profits:

$$\pi_i^{(1)} = \left(a - b\left(q_1^{(1)} + q_2^{(1)}\right)\right) q_i^{(1)} - c_i q_i^{(1)}$$

A non-cooperative Nash equilibrium occurs when each bank chooses a quantity that maximizes its own profit given the quantity choices of the other firm. The equilibrium quantities and profits in this period reflect the banks' baseline competitive positions and define their relative market sizes.

Solving the system of best response functions yields the unique Cournot equilibrium:

$$q_1^{(1)*} = \frac{a - 2c_1 + c_2}{3b}, \quad q_2^{(1)*} = \frac{a - 2c_2 + c_1}{3b}$$

The corresponding profits are:

$$\pi_1^{(1)} = \frac{(a - 2c_1 + c_2)^2}{9b}, \quad \pi_2^{(1)} = \frac{(a - 2c_2 + c_1)^2}{9b}$$

Period 2: Technology Adoption and Re-Competition.

At the start of period 2, bank 1 is assumed to have adopted the technology, reducing its marginal cost to $c_1' = \eta_e c_1$. Bank 2 draws a private adoption cost $\kappa \sim F$, where $F(\cdot)$ is a continuous, strictly increasing distribution, and it chooses whether to adopt the technology before competing in the market. If bank 2 adopts, its marginal cost becomes $c_2' = \eta_f c_2$; otherwise, it continues to operate at cost c_2.

After the adoption decision, banks engage in Cournot competition as in period 1. The market inverse demand function remains:

$$P(Q^{(2)}) = a - bQ^{(2)}, \quad \text{where } Q^{(2)} = q_1^{(2)} + q_2^{(2)}$$

But the equilibrium quantities and profits in period 2 depend on the cost structure, which reflects the outcome of the banks' adoption decisions. Let π_2^{adopt} and $\pi_2^{\text{no-adopt}}$ denote bank 2's profit under adoption and non-adoption, respectively. The analysis below considers both cases in turn to examine how bank 2's profitability is affected by the adoption decision.

Case 1: Bank 2 Does Not Adopt

With cost parameters $(c_1', c_2) = (\eta_e c_1, c_2)$, the equilibrium quantities are:

$$q_1^{(2)*} = \frac{a - 2\eta_e c_1 + c_2}{3b}, \quad q_2^{(2)*} = \frac{a - 2c_2 + \eta_e c_1}{3b}$$

Profits are:

$$\pi_1^{(2)} = \frac{(a - 2\eta_e c_1 + c_2)^2}{9b}, \quad \pi_2^{\text{no-adopt}} = \frac{(a - 2c_2 + \eta_e c_1)^2}{9b}$$

Case 2: Bank 2 Adopts

If bank 2 adopts, both banks have cost parameters $(\eta_e c_1, \eta_f c_2)$ The equilibrium quantities are:

$$q_1^{(2)*} = \frac{a - 2\eta_e c_1 + \eta_f c_2}{3b}, \quad q_2^{(2)*} = \frac{a - 2\eta_f c_2 + \eta_e c_1}{3b}$$

Profits are:

$$\pi_1^{(2)} = \frac{(a - 2\eta_e c_1 + \eta_f c_2)^2}{9b}, \quad \pi_2^{\text{adopt}} = \frac{(a - 2\eta_f c_2 + \eta_e c_1)^2}{9b}$$

The equilibrium outcomes under the two scenarios—adoption and non-adoption by bank 2—highlight how technology adoption reshapes the competitive landscape through its impact on cost structures and market shares. With these foundational outcomes established, the next section turns to a deeper analysis of the mechanisms and strategic incentives driving adoption, focusing on how rival behavior and market conditions shape banks' adoption decisions.

2.3 Mechanisms and Incentives for Technology Adoption

Proposition 1 (Rival Precedence Encourages Adoption)**.** *The follower bank is more likely to adopt the technology when its rival has already adopted, provided that market demand is sufficiently strong, marginal cost is moderate, and the follower benefits from greater cost savings due to learning.*

To formalize this, consider bank 2—the follower bank—and its gain from adoption under two scenarios. For clarity and tractability in analyzing the effects of rival precedence, both banks are assumed to face identical marginal costs c (i.e., $c_1 = c_2 = c$), which simplifies the comparative evaluation.

When the rival has already adopted (rival precedence), the profitability gain to bank 2 is

$$\Delta\pi_2(\text{Adopt}_2 \mid \text{Adopt}_1 = 1) = \frac{1}{9b}\big[(a - 2c\eta_f + c\eta_e)^2 - (a - 2c + c\eta_e)^2\big].$$

When the rival has not adopted (no rival precedence), the profitability gain to bank 2 is

$$\Delta\pi_2(\text{Adopt}_2 \mid \text{Adopt}_1 = 0) = \frac{1}{9b}\big[(a - 2c\eta_e + c)^2 - (a - 2c + c)^2\big].$$

Define the *incremental gain* to bank 2 from adopting the technology when its rival (bank 1) has already adopted as

$$\text{Gain}_2^{\text{RP}} \equiv \Delta\pi_2(\text{Adopt}_2 \mid \text{Adopt}_1 = 1) - \Delta\pi_2(\text{Adopt}_2 \mid \text{Adopt}_1 = 0),$$

which simplifies to

$$\text{Gain}_2^{\text{RP}} = \frac{4c}{9b}[(\eta_e - \eta_f)(a - c\eta_f) - c(1 - \eta_e)^2].$$

The incremental gain $Gain_2^{\text{RP}}$ to bank 2 from adopting is positive—meaning adoption becomes more profitable when its rival (Bank 1) has already adopted—if and only if

$$(\eta_e - \eta_f)(a - c\eta_f) > c(1 - \eta_e)^2,$$

suggesting that rival adoption amplifies bank 2's incentive to adopt the technology by altering the competitive and cost-saving landscape.

This condition is more likely to be satisfied when:

- **Market demand is sufficiently high** (a is large); in other words, the market has a high willingness to pay. For the follower, this higher willingness to pay translates into greater potential revenue from adopting the technology, making adoption profitable even after the leader has done so.
- **Marginal cost is moderate** (c is in an intermediate range), which allows the cost savings from adoption to play a more decisive role: it lets the first-mover efficiency gains be meaningful, making adoption profitable for the leader, and ensures that the learning spillover provides a significant financial incentive for the follower to adopt.
- **Bank 2 benefits from stronger learning effects** (i.e., $|\eta_e - \eta_f|$ is large), meaning the follower bank can reduce its marginal cost by learning from the early adopter. As a result, bank 2 enjoys greater efficiency gains than its rival did, improving its competitiveness and potential profitability.

Taken together, this result illustrates that a rival's prior adoption can meaningfully influence a bank's incentive to adopt. When market demand is sufficiently strong and the

follower experiences greater cost savings through learning, the strategic environment created by rival adoption enhances the profitability of adoption. This theoretical insight highlights the importance of competitive dynamics in shaping the diffusion path of new technologies and motivates the empirical analysis that follows, where I examine whether banks are indeed more likely to adopt after their rivals have done so.

Proposition 2 (Drivers of Adoption Profitability Gain)**.** *The profitability gain of adoption for the follower bank increases with marginal cost and with the extent of cost reduction achieved through the technology, provided that market demand is strong, marginal cost is moderate, and the follower benefits from greater learning.*

Let $\Delta\pi_2 \equiv \pi_2^{\text{adopt}} - \pi_2^{\text{no-adopt}}$ denote bank 2's net gain from adopting the technology when its rival (bank 1) has already adopted. This captures the profitability difference between adoption and non-adoption, holding fixed the rival's adoption decision. For tractability, both banks are assumed to face the same marginal cost, $c_1 = c_2 = c$. Based on the equilibrium profit expressions derived in Section 2.3, the resulting net gain is derived as:

$$\Delta\pi_2 = \frac{4c}{9b}\left[(1-\eta_f)\left(ac - c^2\left[1-(\eta_e-\eta_f)\right]\right)\right].$$

Taking the partial derivative of $\Delta\pi_2$ with respect to the marginal cost c yields:

$$\frac{\partial\Delta\pi_2}{\partial c} = \frac{4}{9b}\left[(1-\eta_f)\left(a - 2c\left[1-(\eta_e-\eta_f)\right]\right)\right].$$

The sign of this derivative depends on the level of a and c, as well as the interplay between the parameters η_e and η_f. Under conditions analogous to those established in Proposition 1—namely, sufficiently strong market demand, moderate marginal cost, and substantial learning benefits for the follower bank—this partial derivative is positive. This implies that the profitability gain from adoption increases as marginal cost rises.

Intuitively, higher marginal costs raise the expense of not adopting the technology, thereby reducing competitiveness for Bank 2 if it delays adoption. This means that a higher marginal cost implies a larger $\Delta\pi_2$, enhancing the incentive to adopt. In competitive markets characterized by strong demand and moderate costs, follower banks with higher marginal costs have a greater propensity to adopt the technology, and this incentive intensifies as their costs increase.

Taking the partial derivative of $\Delta\pi_2$ with respect to the cost efficiency factor η_f yields:

$$\frac{\partial\Delta\pi_2}{\partial\eta_f} = -\frac{4c}{9b}\left[a + c(\eta_e - 2\eta_f)\right].$$

Under conditions similar to those in Proposition 1 and the earlier part of Proposition 2—namely, strong market demand (a large), moderate marginal costs, and a meaningful gap between η_f and η_e—the expression inside the brackets remains positive. As a result, the derivative is negative, indicating that $\Delta\pi_2$ decreases with an increase in η_f. In other words, the profitability gain from adoption rises as the cost reduction from adoption becomes more substantial (i.e., as η_f decreases). This highlights that greater cost efficiency associated with adoption strengthens the incentive to adopt, particularly for follower banks facing competitive pressure. This confirms that adoption becomes more profitable as cost efficiency improves.

These theoretical results underscore the role of operating costs and cost-saving potential in shaping the profitability of technology adoption. This relationship will be examined in the empirical analysis that follows.

3 Data and Estimation Strategy

This section outlines the data and estimation methodology. Drawing on the conceptual framework, I begin by identifying the key determinants of adoption and then describe how each is operationalized for empirical analysis, including the data sources and variable construction. I then explain how these measures are incorporated into the empirical strategy and detail the implementation of the estimation procedure.

3.1 Determinants of Adoption

The empirical study builds on a conceptual framework that models strategic competition between firms, where each firm chooses whether to adopt the technology as a leader or a follower. The framework identifies a set of key variables, such as market structure, rival behavior, firm-specific and market related characteristics, that shape these adoption decisions. Guided by this theoretical foundation, the empirical analysis examines how these determinants shape observed firm behavior, with a particular focus on estimating the effect of rival precedence and specific bank or market characteristics on a firm's likelihood of adoption. In the following discussion, I explain the role of observable firm and market characteristics in shaping the adoption decision.

Rival Precedence Rival precedence influences firm decisions by reducing uncertainty, increasing competitive pressure, and altering the strategic environment. Its effect can be

positive or negative, depending on market structure, firm capabilities, and the nature of the innovation. Rival precedence can shape adoption decisions by signaling the viability of a technology or increasing competitive pressure to follow. While in theory firms may either accelerate adoption to avoid falling behind or delay to free-ride on information, the conceptual framework developed in the previous section suggests that rival adoption is more likely to encourage adoption. This reflects a setting where competitive pressure and informational spillovers outweigh strategic delay motives. Ultimately, however, the extent to which rival precedence drives adoption is an empirical question, shaped by market dynamics, firm strategy, and the balance of first- and second-mover advantages.

In empirical analysis, rival precedence can be operationalized as a binary or continuous measure and included as a determinant in hazard model. In the baseline model, I use the rival precedence dummy to represent whether a bank is a 'follower' in the market, where $Rival\ Precedence\ Dummy_t = 1$ indicates that for year t there's at least one other bank in the same local market that had already introduced online banking by year $t-1$. In addition, I also measure rival precedence in proportion: the degree to which a bank has been preceded in the market at year t, $Rival\ Precedence\ Ratio_t$, is defined as the proportion of banks in the local market that had adopted online banking by year $t-1$.

To illustrate the substantial spatial heterogeneity in this primary independent variable, Figure 1 presents the geographic distribution of the *Rival Precedence Ratio* across U.S. counties for the year 2003. The map reveals a highly staggered pattern of diffusion; while several urban and competitive clusters exhibit high adoption intensity where rivals moved first (represented by darker regions), significant portions of the country show zero or near-zero rival precedence at this stage. This "rich variation" across markets—both in terms of timing and intensity—provides the necessary empirical foundation for the hazard model estimations in the following section.

Bank Size Given that relative profitability and relative risk of adopting online banking can be different for large and small banks, firm size affects its decision. Bank size is expected to affect adoption decisions because it reflects a bank's capacity to absorb costs, manage risk, therefore implement new technologies. Larger banks typically have more financial and organizational resources, enabling them to adopt innovations earlier and more easily. However, they may also face greater organizational inertia or weaker competitive pressure, leading to delayed action. Conversely, smaller banks may delay adoption due to resource constraints or risk aversion. As such, the relationship between size and adoption is theoretically ambiguous and calls for empirical validation.

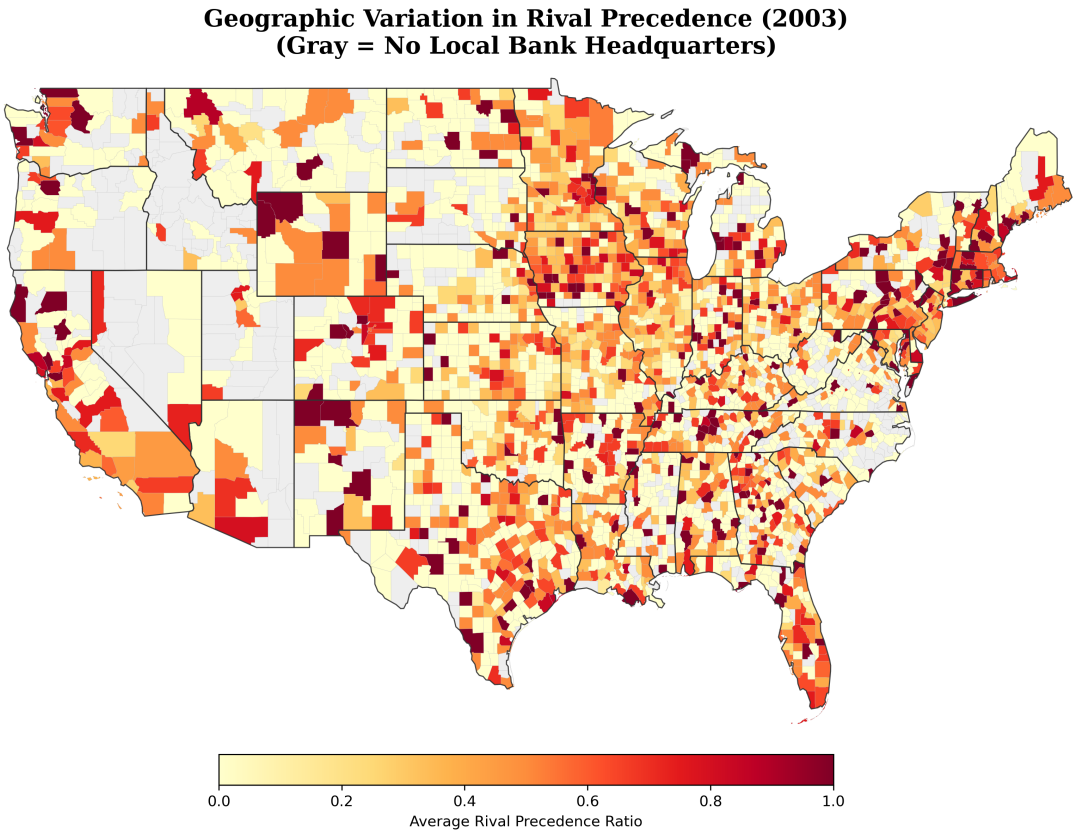


Figure 1: Geographic Variation in Local Rival Precedence (2003)

Notes: This map displays the *Rival Precedence Ratio* across U.S. counties for the year 2003. Darker regions indicate higher peer adoption intensity within the local market. Gray areas indicate counties with no bank headquarters present in the sample.

Bank Holding Company Affiliation with a bank holding company (BHC) can influence adoption decisions, but its impact is context-dependent. On one hand, BHCs may facilitate adoption by providing shared infrastructure, technical support, and strategic coordination across affiliated banks. On the other hand, centralized decision-making or internal complexity within BHCs may delay responsiveness to local market conditions. Thus, the effect of BHC affiliation on adoption is uncertain in theory and requires evidence from data.

Market Concentration Market concentration may influence adoption incentives, but its effect is theoretically unclear. In highly concentrated markets, dominant firms may face stronger incentives to adopt early to preserve market leadership or shape industry standards; on the other hand, with fewer rivals, the competitive pressure to innovate may be weaker, reducing the urgency to adopt. In contrast, in more competitive markets, firms may adopt sooner to avoid being outpaced, though profit margins may be thinner. Thus, the relationship between market concentration and adoption depends on the balance of these forces and must be determined empirically.

Market Wage Rate Higher local wage rates may increase the cost of traditional labor-intensive operations, encouraging firms to adopt labor-saving technologies such as digital services. In markets where labor is relatively costly, adopting automation or digital services becomes more attractive as a way to improve efficiency and reduce operating costs. Thus, wage levels serve as a proxy for the economic pressure to adopt labor-saving innovations, and a positive relationship with adoption is theoretically well-founded.

Market Growth Rate Market growth can influence adoption incentives in opposing ways. Firms in fast-growing markets may adopt earlier to capture emerging demand and scale advantages. On the other hand, rapid growth can strain resources or create uncertainty, prompting firms to delay until the market stabilizes. In slow-growing or saturated markets, adoption may be used as a differentiation strategy. As such, the effect of market growth on adoption timing is theoretically mixed, pointing to the need for empirical investigation.

3.2 Data and Measurement

The two key variables for the empirical analysis are bank's *online banking adoption* status and the *rival precedence measure*, either dummy or ratio, of the market the bank is operating in. In addition, covariates include both market-level[1] factors—such as market structure,

[1]This study adopts county-based definitions of banking markets.

growth rates, and local wage levels—and bank-specific characteristics, including size and affiliation with a bank holding company (BHC).

Online Banking Adoption Annual data[2] from 2003 to 2010 for each bank i at year t: $OB_{i,t} = 1$, if bank i adopted at year t, $OB_{i,t} = 0$ otherwise.

Rival Precedence Dummy For each commercial bank and savings institution at each year from 2003 to 2010, I check whether it operates in a market where at least one other bank headquartered[3] in the same market had introduced online banking prior to year t.

Rival Precedence Ratio For each commercial bank and savings institution in each year from 2003 to 2010, the extent of rival precedence is measured by calculating the percentage of other banks headquartered in the same local market that had adopted online banking as of year $t-1$. This measure reflects the degree of prior adoption among competitors in the bank's operating environment.

Covariates

- **Bank Holding Company (BHC) Dummy** (BHC_t): An indicator variable equal to 1 if the bank is affiliated with a bank holding company[4] in year t, and 0 otherwise.
- **Bank Size**($Size_t$): Measured by the total assets[5] of the bank, reflecting its scale of operations.
- **Market Concentration** (HHI_t or $CR3_t$): Calculated using the Herfindahl-Hirschman Index (HHI) based on local market deposit shares[6]. As a robustness check, market concentration is also measured by the 3-firm concentration ratio — the share of total market deposits held by the three largest banks.
- **Market Wage Rate** ($Wage_t$): The average wage[7] of bank employees in the local market in year t, capturing labor cost conditions.

[2]Data on each bank's online banking adoption decision can be found in their Consolidation Reports of Condition and Income (Call Reports) submitted to the bank regulatory agencies.

[3]Data on bank headquarters are obtained from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SOD), which provide annual information on the headquarters location (city, county, state, and FIPS code) of all FDIC-insured commercial banks and savings institutions.

[4]Information on banks' affiliations with Bank Holding Companies (BHCs) comes from the FDIC Institution Directory (ID), which records each FDIC-insured institution's charter, headquarters location, and whether it is owned by a BHC, along with the identity of the parent company.

[5]Bank size, measured as total assets, is obtained from the Call Reports filed quarterly by all FDIC-insured institutions.

[6]Bank deposits are obtained from the FDIC SOD, which provides annual deposit data at the branch and bank level, including the geographic location (city, county, state) of each branch. Deposits are aggregated at the bank level within each local banking market to calculate market shares.

[7]Data on county-level employment and payroll for commercial banks and savings institutions are obtained from the U.S. Census Bureau County Business Patterns (CBP) 2003–2010, averaged across commercial banks (NAICS 522110) and savings institutions (NAICS 522120).

- **Market Growth Rate** ($Growth_t$): Defined as the cumulative deposit growth in the local market over the three years preceding year t, serving as an indicator of local market dynamism.

Table 1 provides summary statistics for the key determinants used in the analysis, covering the period from 2003 to 2010. The sample consists of a large-scale panel with 69,163 total observations across 10,162 unique banks. The variables are categorized into bank-level characteristics, such as asset size and BHC affiliation, and market-level factors, including county-level concentration (HHI), wage rates, and deposit growth.

Table 1: Summary Statistics for Key Determinants (2003–2010)

Variable	Mean	Std. Dev.	Min	Max
Bank-level Variables				
Bank Size (Total Assets, $ Millions)	1,340.99	23,351.72	0.52	1,663,998.00
BHC Affiliation (Dummy)	0.20	0.40	0.00	1.00
Market-level Variables				
Market Concentration (HHI)	0.44	0.26	0.00	1.00
Local Wage Rate ($000s)	41.40	13.64	9.52	206.86
Market Growth Rate (%)	3.64	209.03	-1.00	40,639.87
Total Observations		69,163		
Unique Banks		10,162		

Notes: This table presents summary statistics for the full panel of banks. *Bank Size* is expressed in millions of dollars. *Market Growth* represents the three-year cumulative deposit growth in the bank's headquarters county.

3.3 Empirical Strategy

The identification strategy employed here follows the methodology outlined in Hannan and McDowell(1987), which is based on the 'failure time' estimation procedure proposed and used by Lancaster (1979) and Flinn and Heckman (1983). The idea is to apply survival analysis in the story of technology adoption.

Consider the relative hazard rate in a simplified form of a survival model:

$$h_i(t) = \exp\left(X_t'\beta\right) \tag{1}$$

- *Hazard rate* $h_i(t)$: the conditional probability that bank i adopts the innovation at time t, given that it has not adopted by time $t-1$.

- X_t': a vector of explanatory variables relevant to adoption decisions in period t.

- β: a vector of coefficients.
- The model assumes an exponential functional form to ensure that the hazard rate is non-negative.

Then denote $F_i(T)$ the probability that bank i will not have adopted by the end of period T. The probability that bank i will last to the end of the study period T^{2010} without adopting is defined as:

$$F_i(T^{2010}) = \exp\left\{-\int_0^{T^{2010}} h(t)\,dt\right\} \tag{2}$$

The probability that bank i will adopt during some period prior to period T^{2010}, for example T_i is:

$$F_i(T_{i-1}) - F_i(T_i) = \exp\left\{-\int_0^{T_{i-1}} h(t)\,dt\right\} - \exp\left\{-\int_0^{T_i} h(t)\,dt\right\} \tag{3}$$

The likelihood of each bank's adoption experience—either adopting during year T_i or not adopting by the end of T^{2010}—can be expressed as a function of explanatory variables by substituting Equation (1) into Equations (2) and (3).

Given annual bank-level data from 2003 to 2010, the estimation proceeds by maximizing a likelihood function composed of these probabilities. Specifically, the estimator yields values of β that maximize the following likelihood function:

$$L = \prod_{i=1}^{N^1} \{F_i(T_{i-1}) - F_i(T_i)\} \prod_{j=1}^{N^2} F_j(T^{2010}) \tag{4}$$

The estimation procedure can be interpreted as a pooled time-series estimation of Eq. (1) in which each bank is observed each year up to and including the year of adoption or the end of the study period, whichever comes first.

4 Empirical Results

4.1 Main Results

The baseline regression is estimated using the start–stop format[8] with time-varying covariates to account for the fact that key explanatory variables—such as rival adoption,

[8]The start–stop format (also known as episode-splitting) is appropriate for modeling survival-time data with time-varying covariates, such as a bank's exposure to rival adoption or shifting market conditions. This

market conditions, and bank characteristics—evolve over time. This structure allows the hazard rate (i.e., the conditional probability that a bank adopts online banking in a given year, conditional on survival up to that year) to reflect the contemporaneous values of covariates rather than treating them as fixed. In particular, because rival precedence changes dynamically as competing banks adopt, the use of a time-varying specification is essential for accurately capturing its influence on a bank's adoption decision.

Table 2 reports the main results from the baseline regressions. In Column (2), estimates from a Cox proportional hazards model using the start–stop format with time-varying covariates show that rival precedence significantly increases the hazard of adoption: banks exposed to prior adoption by rivals are 28% more likely to adopt online banking at any given time (hazard ratio = 1.28, $p < 0.01$). In addition, market concentration (HHI) and BHC affiliation are positively associated with adoption, with hazard ratios of 1.17 and 1.48, respectively. In contrast, market growth, bank size, and wages do not exhibit statistically significant effects in this specification. These findings emphasize the role of competitive dynamics and organizational structure in driving technology adoption.

Table 2: Determinants of the Conditional Probability of Online Banking Adoption, 2003-2010 (Benchmark)

Dependent: the Hazard of a Bank Adopting Online Banking (estimated with Cox Proportional Hazards Model)				
(1)	(2)	(3)	(4)	(5)
Rival Precedence Dummy	1.2806***	1.3954***		
	(0.0446)	(0.0769)		
Rival Precedence Ratio			1.5408***	1.6349***
			(0.0536)	(0.0856)
Market Concentration	1.1716***	1.1642**	1.1341***	1.1313**
	(0.0630)	(0.0771)	(0.0546)	(0.0565)
Market Growth	0.9999	0.9999**	0.9999	0.9999**
	(0.0002)	(0.0004)	(0.0002)	(0.0001)
BHC Dummy	1.4830***	1.4888***	1.4685***	1.4745***
	(0.0401)	(0.0352)	(0.0398)	(0.0341)
Bank Size	0.9997	1.0696**	0.9999	1.0714**
	(0.0009)	(0.0354)	(0.0008)	(0.0367)
Market Wage Rates	0.9992	1.0041	0.9997	1.0049
	(0.0009)	(0.0036)	(0.0009)	(0.0032)
Rival Precedence × Year Trend		0.9560**		0.9698
		(0.0181)		(0.0202)
Bank Size × Year Trend		0.9353**		0.9338**
		(0.0310)		(0.0320)
Market Wage × Year Trend		0.9985**		0.9984***
		(0.0007)		(0.0006)
No. of Observations	31,489	31,489	31,489	31,489
LR Test Statistics/Wald Chi2	255.86	411.33	357.83	510.39

Note: Figure in parentheses are standard errors, *p<0,1, **p<0.05, ***p<0.01

structure allows the hazard of adoption to be linked to the covariate values relevant to each time period, rather than assuming they remain fixed throughout. For robustness, a single-record specification using baseline or averaged covariates is presented in Section 4.4.

In addition, Column (4) uses a continuous measure of rival precedence—the share of rival banks that have adopted—instead of the binary indicator. The results remain robust: switching to this alternative measure does not materially alter the findings. Rival adoption continues to significantly increase the hazard of adoption, with a larger effect size (hazard ratio = 1.54). This hazard ratio implies that moving from a market environment where none of a bank's rivals have adopted (rival precedence ratio=0%) to one where all rivals have adopted (rival precedence ratio=100%) is associated with a 54.1% higher hazard of adoption. Because the ratio is continuous, the model also allows for the interpretation of smaller marginal shifts; for instance, a 10-percentage-point increase in the proportion of adopted rivals is associated with an approximate 4.4% increase in the hazard of adoption.[9] While the binary measure in Column (1) captures the initial "shock" of any rival adoption, the continuous version reflects the cumulative intensity of competitive pressure, yielding consistent patterns that reinforce the role of rival precedence as a primary driver of the diffusion process.

One important consideration when interpreting the baseline Cox regression results is the validity of the proportional hazards (PH) assumption, which requires that the effect of each covariate on the hazard remains constant over time. If this assumption is violated, the estimated hazard ratios may misrepresent how the effect of a covariate evolves throughout the observation window. To assess this, a test based on Schoenfeld residuals is conducted (see Table A.1 in Appendix for test results). The global test rejects the null of proportional hazards across all covariates ($p < 0.001$), indicating that the effect of at least one covariate likely changes over time. At the individual level, violations are indicated for rival precedence ($p = 0.034$), bank size ($p = 0.034$), and wage rates ($p < 0.001$), while the remaining covariates appear consistent with the assumption. To account for these potential time-varying effects, the following analysis allows the influence of selected covariates to evolve over time, providing a more flexible specification that captures dynamic adoption behavior more accurately.

Specifically, time-varying covariates are introduced by interacting rival precedence, bank size, and wage rates with a continuous time variable, enabling their effects on the hazard of adoption to change gradually over the observation window.[10] Results of the time-varying covariate specification are shown in Columns (3) and (5), using the rival precedence dummy and continuous ratio measures, respectively. In Column (3), the main effect of rival precedence remains positive and significant (hazard ratio = 1.40, $p < 0.01$), indicating that banks exposed to prior rival adoption are initially more likely to adopt online banking. However,

[9] For a continuous variable in a Cox Proportional Hazards model, the effect of a marginal change Δx is calculated as $HR^{\Delta x}$. Here, $1.5408^{0.10} \approx 1.044$, or a 4.4% increase.

[10] This is implemented in Stata using the `tvc()` and `texp()` options, which create interactions between specified covariates and a chosen time function (e.g., linear time trend).

the interaction with time yields a hazard ratio of 0.956, implying that this effect shrinks by approximately 4.4% per year (1 – 0.956), suggesting diminishing influence over time. Similar time-varying patterns are observed for bank size and wage rates. The main effect of bank size is positive and significant (HR = 1.07), but its time interaction (HR = 0.935) indicates that the influence of size weakens over time. For wages, the interaction term (HR = 0.9985) suggests a slight annual decline in its effect. Overall, these results highlight that the baseline impacts of competitive exposure and institutional characteristics are strongest early on but gradually attenuate as the adoption process evolves. Standard errors are clustered at the county level to account for spatial correlation in unobserved factors affecting adoption.

Column (5) uses the continuous rival precedence ratio instead of the binary indicator. While the time interaction term is not statistically significant, its negative impact remains consistent with the result in Column (3), suggesting a possible decline in the effect over time. Importantly, the main effect of rival adoption remains strong, and the time-varying patterns for bank size and wage rates are robust across both specifications. This consistency reinforces the overall conclusion that the influence of competitive and institutional factors tends to diminish as adoption diffuses.

4.2 Time Varying Effect of Rival Precedence

Given the previous findings that the effect of rival precedence on adoption weakens over time, it is important to directly examine how this influence evolves across the study period. Understanding the temporal pattern of this effect can offer insight into whether competitive pressure is primarily an early-stage driver of adoption or if it continues to matter as online banking becomes more widespread. This analysis not only helps contextualize the earlier results but also speaks to whether the diffusion process follows the expected S-shaped pattern, in which peer effects are strongest during the early to middle stages of adoption and taper off as saturation approaches.

To examine how the influence of rival precedence evolves over time, the model in Table 2 includes year-specific interactions of the rival precedence dummy with indicators for each year from 2004 to 2010. This flexible specification allows the effect of rival adoption to vary non-parametrically across time rather than assuming a constant or linear trend. Column (2) reports the time-varying effect of rival precedence based on the baseline model, while Column (3) incorporates time-varying covariates.[11] With 2003 set as the reference year, the estimated coefficients capture how the effect of rival precedence in each subsequent year

[11]Following evidence from the Schoenfeld residual test that bank size and wage rates violate the proportional hazards (PH) assumption, both variables are included with time-varying effects through interactions with a linear time trend.

compares to its impact in that baseline year. The results show that the effect of rival precedence is strongest and statistically significant in the early years—particularly 2004 to 2006—when hazard ratios range from 1.31 to 1.38, indicating that exposure to prior rival adoption substantially increased the likelihood of adoption—by 31% to 38% relative to 2003—during this period. The estimated effects decline thereafter, becoming statistically insignificant from 2008 onward, and even fall below one by 2010 (HR = 0.74, p = 0.13). This trend supports the earlier finding of a diminishing influence of rival adoption over time, consistent with an S-shaped diffusion pattern, where peer effects are strongest in the early and middle stages of adoption but fade as the technology becomes more widespread.

Figure 2 visually synthesizes the relationship between individual competitive response and macro-level technology diffusion. The S-shaped curve tracks the cumulative adoption rate, which shows a sharp acceleration between 2004 and 2006. This period of rapid growth corresponds precisely with the peak in rival precedence intensity, where the estimated hazard ratios are at their highest and most statistically significant. As the market nears saturation from 2008 onward—indicated by the flattening of the cumulative curve—the influence of rival adoption begins to "fade." The confidence intervals for the hazard ratios widen and eventually overlap the 1.0 threshold, visually confirming that the pressure to follow a rival's lead diminishes once the technology has become a industry standard. This dual-axis representation reinforces the interpretation that while rival precedence is a critical engine during the "takeoff" phase of technology diffusion, its marginal impact is exhausted as the pool of non-adopters shrinks.

The time-varying components of bank size (HR = 0.94, p = 0.043) and wage rates (HR = 0.998, p = 0.028) are both statistically significant and less than one, confirming that their influence on adoptiond diminishes over time. The effect of bank size declines by approximately 6.5% per year (1 – 0.935), suggesting that while larger banks were more likely to adopt early, this advantage fades as adoption becomes more widespread. Similarly, the effect of local wage levels shows a small but significant downward trend, possibly reflecting the diminishing marginal influence of labor market conditions on technology adoption. These patterns imply that early adopters tend to be larger banks or those in high-wage areas, but as the diffusion progresses, smaller institutions and banks in lower-wage regions catch up, reducing the gap in adoption timing. These results reinforce the interpretation that institutional and economic factors initially play a prominent role in adoption decisions but gradually lose influence as market conditions evolve and adoption nears saturation.

Parallel specifications based on the continuous rival precedence ratio are reported in columns (4) and (5). The results remain robust, exhibiting consistent patterns in both the strength and temporal variation of rival effects compared to the dummy-based models.

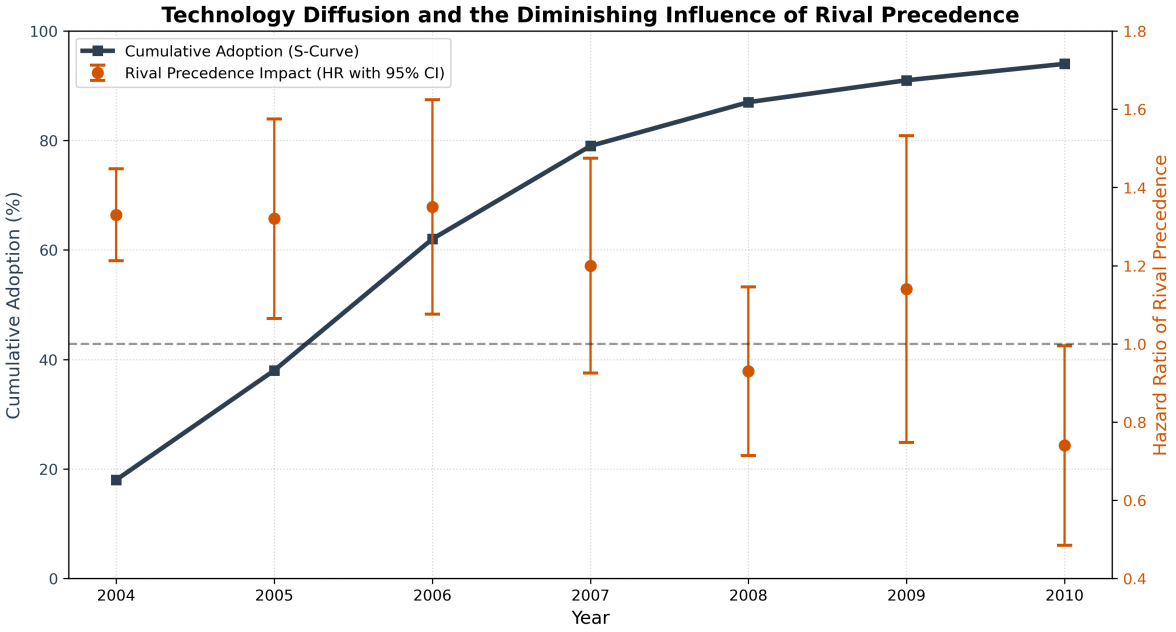


Figure 2: Technology Diffusion and the Diminishing Influence of Rival Precedence

Notes: The primary axis (left) tracks the cumulative percentage of unique banks adopting online banking ($N = 10,162$), illustrating the S-shaped diffusion curve. The secondary axis (right) displays the Hazard Ratios for the Rival Precedence dummy with 95% confidence intervals, relative to the 2003 baseline.

Table 3: The Time-Varying Effect of Rival Precedence relative to 2003, 2004-2010

Dependent: the Hazard of a Bank Adopting Online Banking (estimated with Cox Proportional Hazards Model)				
(1)	(2) RP Dummy	(3) RP Dummy	(4) RP Ratio	(5) RP Ratio
Rival Precedence_2004	1.3328***	1.3074***	1.5468***	1.5307***
	(0.0597)	(0.0597)	(0.0628)	(0.0642)
Rival Precedence_2005	1.3204***	1.3310***	1.7890***	1.8059***
	(0.1267)	(0.1281)	(0.1921)	(0.1943)
Rival Precedence_2006	1.3454***	1.3809***	1.6451***	1.6601***
	(0.1411)	(0.1453)	(0.1897)	(0.1885)
Rival Precedence_2007	1.2032	1.2507**	1.5440***	1.5516***
	(0.1361)	(0.1410)	(0.1954)	(0.1925)
Rival Precedence_2008	0.9338	0.9882	1.1820	1.1990
	(0.1122)	(0.1188)	(0.1641)	(0.1611)
Rival Precedence_2009	1.1424	1.2392	1.5582**	1.5626**
	(0.1987)	(0.2160)	(0.3077)	(0.2944)
Rival Precedence_2010	0.6644	0.7377	0.9377	0.9611
	(0.1329)	(0.1481)	(0.2363)	(0.2291)
Market Concentration	1.1610**	1.1642**	1.1288**	1.1289**
	(0.0772)	(0.0770)	(0.0568)	(0.0563)
Market Growth	0.9999**	0.9999**	0.9999**	0.9999**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
BHC Dummy	1.4819***	1.4888***	1.4682***	1.4758***
	(0.0357)	(0.0353)	(0.0347)	(0.0342)
Bank Size	0.9997	1.0698**	0.9999	1.0716**
	(0.0008)	(0.0355)	(0.0007)	(0.0368)
Market Wage Rates	0.9992	1.0041	0.9997	1.0050
	(0.0023)	(0.0036)	(0.0020)	(0.0032)
Bank Size × Year Trend		0.9351**		0.9336**
		(0.0310)		(0.0321)
Market Wage × Year Trend		0.9985**		0.9984***
		(0.0007)		(0.0006)
No. of Observations	31,489	31,489	31,489	31,489
LR Test Statistics/Wald Chi2	360.46	418.58	477.00	519.04

In addition to the time-varying effects, the results also highlight the role of market structure and institutional characteristics. The coefficient on market concentration (HHI) is positive and statistically significant (hazard ratio = 1.16, p = 0.023), suggesting that banks in more concentrated markets are more likely to adopt online banking. This may reflect greater ability to invest in new technologies or stronger incentives to differentiate in less competitive environments. These patterns raise an important question: Do the effects of rival adoption differ depending on a bank's market environment or organizational capacity? The next section explores this by introducing interactions between rival precedence and both market concentration and bank size, allowing for heterogeneous responses to competitive pressure.

4.3 Adding Interaction Terms

Building on the baseline and time-varying specifications, this section explores whether the effect of rival adoption differs systematically across banks and market environments. In particular, the analysis focuses on interactions between rival precedence and three key factors: local market competition, local market growth, and bank size. These dimensions capture important sources of heterogeneity in how banks may perceive and respond to competitive pressure. For example, highly concentrated markets may either amplify peer effects, as dominant banks respond strategically to rival moves, or dampen them if limited competition reduces the need to react. Growing markets could heighten the urgency to adopt due to emerging opportunities and increased rivalry, but may also lead to adoption delays if rapid expansion strains implementation capacity. Similarly, larger banks may be more responsive due to greater resources and technical capacity, yet could also face organizational inertia that slows their reaction to competitive pressures. Examining these interactions offers insight into which types of banks or markets are most influenced by rival adoption, and whether competitive spillovers are conditioned by structural and strategic factors.

4.3.1 Market Concentration

Columns (2) and (3) of Table 4[12] present results from a specification that interacts the rival precedence dummy with market concentration (HHI) to assess how peer effects vary across competitive environments. The results reveal a strong and statistically significant interaction between rival precedence and market concentration, with a hazard ratio of 0.44 ($p < 0.01$). Since this value is well below 1, it indicates that the positive effect of rival adoption on a bank's adoption hazard declines sharply as market concentration increases.

[12]To assess robustness, all specifications in Table 3 are re-estimated using the continuous rival precedence ratio in place of the dummy. Results are presented in Appendix Table A.2 and confirm the main findings.

Given that HHI ranges from 0 to 1, this suggests that banks in more concentrated (i.e., less competitive) markets are less responsive to peer behavior, consistent with reduced strategic pressure in such environments. This reflects a classic moderation effect: peer influence tends to be stronger in competitive markets, where firms closely monitor one another and peer behavior serves as a credible signal. In contrast, in concentrated markets, dominant banks may not view peer behavior as threatening or strategically relevant. Moreover, innovation tends to function as a competitive differentiator only when meaningful competition exists.

In concentrated markets, dominant banks may also have more resources and strategic incentives to adopt early without waiting for peers, using adoption as a means to signal leadership or maintain their position. With less need to coordinate and minimal fear of fast followers, these banks may pursue adoption based on internal capabilities or long-term positioning—not peer behavior. Conversely, in more competitive markets, firms may delay adoption until others move first, using peer behavior as validation in a risk-averse environment. This dynamic reinforces the finding that peer effects are conditional on market structure—they are amplified by competitive pressure, but muted where dominance reduces the relevance of external signals.

Compared to Column (2), which excludes time-varying controls, Column (3) also shows that market growth and bank size,[13] which were previously insignificant, become statistically significant when allowed to vary with time—highlighting the importance of accounting for changing institutional and economic conditions. Overall, the findings suggest that peer effects are strongest where competition is more intense, and that responses to rival adoption are shaped not only by timing but also by market structure.

4.3.2 Market Growth

Column (5) of Table 4 examines whether the effect of rival adoption varies with local market growth, including an interaction between the rival precedence dummy and market growth, alongside time-varying controls for bank size and wage. The estimated hazard ratio on the interaction term is 1.0011 ($p = 0.078$), which is statistically significant at the 10% level. This suggests that the peer effect intensifies modestly in faster-growing markets, indicating that banks may be more likely to respond to rival adoption when operating in expanding local economies. While the magnitude of the effect is small, its direction and significance highlight meaningful heterogeneity in how banks incorporate competitive signals into adoption decisions across different growth contexts.

[13] Column (2) includes only time-invariant controls, while Column (3) adds time-varying covariates for bank size and wage, following the earlier PH assumption tests indicating that their effects are not constant over time.

Table 4: Interaction Effect of Market Concentration, Market Growth and Bank Size, 2003-2010

Dependent: the Hazard of a Bank Adopting Online Banking (estimated with Cox Proportional Hazards Model)								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rival Precedence Dummy	2.0892***	2.0442***	1.2801***	1.2779***	1.2938***	1.3001***	1.2971***	1.4695***
	(0.1741)	(0.1981)	(0.0450)	(0.0522)	(0.0454)	(0.0532)	(0.0457)	(0.0850)
Market Concentration	2.0875***	2.0681***	1.2187***	1.2369***	1.215***	1.2266***	1.2208***	1.2817**
	(0.2060)	(0.2120)	(0.0671)	(0.0778)	(0.0669)	(0.0774)	(0.0672)	(0.0780)
Rival Precedence × Market Concentration	0.4527***	0.4686***						
	(0.0542)	(0.0621)						
Market Growth	0.9999	0.9999**	0.9999	0.9999**	0.9999	0.9999**	0.9999	0.9999**
	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Rival Precedence × Market Growth			1.0010	1.0010*				
			(0.0010)	(0.0006)				
BHC Dummy	1.4825***	1.4909***	1.4855***	1.4941***	1.4849***	1.4906***	1.4863***	1.4932***
	(0.0401)	(0.0345)	(0.0402)	(0.0347)	(0.0402)	(0.0347)	(0.0402)	(0.0347)
Bank Size	0.9999	1.0715**	0.9997	1.0747**	1.0403**	1.1648***	0.9997	1.0787**
	(0.0008)	(0.0365)	(0.0009)	(0.0379)	(0.0163)	(0.0513)	(0.0009)	(0.0376)
Rival Precedence × Bank Size					0.9609**	0.9232***		
					(0.0150)	(0.0237)		
Market Size	1.0008**	1.0013*	1.0011***	1.0016***	1.0010***	1.0016***	1.0155**	1.0962***
	(0.0003)	(0.0006)	(0.0003)	(0.0006)	(0.0003)	(0.0006)	(0.0060)	(0.0296)
Rival Precedence × Market Size							0.9859**	0.9139***
							(0.0059)	(0.0247)
Rival_Market_Interaction × Year Trend								1.0167***
								(0.0049)
Market Wage Rates	0.9983	1.0038	0.9983	1.0041	0.982*	1.0040	0.9982*	1.0044
	(0.0009)	(0.0035)	(0.0009)	(0.0037)	(0.0009)	(0.0036)	(0.0009)	(0.0036)
Bank Size × Year Trend		0.9310*		0.9308**		0.9303**		0.9317**
		(0.0330)		(0.0328)		(0.0331)		(0.0326)
Market Wage × Year Trend		0.9981**		0.9979**		0.9980**		0.9982**
		(0.0008)		(0.0008)		(0.0008)		(0.0008)
No. of Observations	31,489	31,489	31,489	31,489	31,489	31,489	31,489	31,489
LR Test Statistics/Wald Chi2	311.65	470.61	267.94	459.31	271.41	469.00	271.46	496.08

Note: Figure in parentheses are standard errors, *p<0.1, **p<0.05, ***p<0.01

Interestingly, market growth itself becomes statistically significant (p = 0.011), with a hazard ratio below one, implying that banks in faster-growing markets are, on average, less likely to adopt online banking. This pattern may reflect a form of expansion-induced delay: in high-growth markets, banks are often focused on scaling their physical presence—through customer acquisition, branch expansion, or deposit growth—and may deprioritize investment in digital innovation in the short term. Adoption of new technologies like online banking may be postponed in favor of managing growth surges. In contrast, in slower-growing or mature markets, where physical expansion opportunities are limited and customer bases are more stable, banks may turn to technology as a means of improving efficiency, retaining customers, and reducing operational costs. In such environments, digital tools serve as a substitute for market growth, enabling banks to enhance competitiveness and manage overhead. Together, these results suggest that while peer influence increases modestly with growth, the strategic value of adoption itself varies systematically with market maturity.

4.3.3 Bank Size

Column (7) of Table 4 investigates whether the effect of rival adoption varies with bank size, including an interaction between the rival precedence dummy and bank size, along with

time-varying controls. The interaction term presents negative and statistically significant impact (hazard ratio = 0.92, p = 0.002), indicating that the peer effect diminishes as banks grow larger. In other words, smaller banks are more responsive to rival adoption, while larger institutions appear less influenced by peer behavior. This result is consistent across specifications, and the interaction becomes more precisely estimated with the inclusion of time-varying covariates.

Several mechanisms help explain why peer effects are stronger for smaller banks. First, smaller banks often face greater uncertainty when evaluating new technologies. Observing peer adoption can provide reassurance that the technology is reliable, effective, or necessary. Second, they may engage in social learning, using the experiences of early adopters to assess practical implementation challenges and customer responses. In contrast, larger banks may already have internal analytics or pilot programs, reducing the value of learning from others. Finally, competitive pressure may play a more direct role: smaller banks may perceive peer adoption as a threat to their customer base, especially if rivals gain a reputational or service advantage. In this context, mimicking adoption becomes a defensive strategy to maintain relevance and avoid falling behind. Together, these dynamics help explain why peer influence is more pronounced among smaller, less autonomous institutions.

Taken together, the interaction results underscore that peer effects in technology adoption are not uniform, but instead vary systematically with market conditions and institutional capacity. Rival adoption has a stronger influence in competitive and slower-growing markets, and among smaller banks, where uncertainty, learning, and competitive pressure heighten responsiveness. In contrast, peer influence weakens in concentrated markets and among larger institutions with greater strategic autonomy. These patterns highlight the importance of considering heterogeneity in peer responsiveness when analyzing technology adoption.

4.3.4 Market Size

Columns (8) and (9) of Table 4 examine how the effect of rival adoption varies with market size, using both baseline and time-varying interaction terms. The main effect of market size is positive and significant at baseline: banks operating in larger deposit markets are approximately 9.6% more likely to adopt (HR = 1.096, $p < 0.01$), suggesting that scale and market potential encourage adoption. This provides empirical support for the conceptual framework results, which predict that in markets with sufficiently strong demand (as measured by deposit levels), rival precedence encourages adoption (see Section 2.3). However, the interaction between rival precedence and market size is less than 1 (HR = 0.914, $p < 0.01$), indicating that the influence of rival adoption is weaker in larger markets.

This suggests that in larger markets, banks rely less on rival behavior

These relationships also evolve over time. The interaction between market size and the time trend is less than 1 (HR = 0.984, $p < 0.01$), indicating that the positive effect of market size on adoption diminishes over time. Thus, the advantage of being in a large market becomes less pronounced in later years. Meanwhile, the three-way interaction between rival precedence, market size, and time (HR = 1.017, $p < 0.01$) suggests that the dampening effect of market size on peer influence fades over time. That is, in later years, rival adoption becomes more influential even in larger markets. This dynamic is consistent with a diffusion process in which early adoption is shaped by market fundamentals and strategic responses to peers, while peer influence becomes stronger across all market sizes as the innovation becomes more established.

Together, these findings indicate that while larger markets promote earlier adoption overall, peer effects are initially more influential in smaller markets but grow in importance across all markets as the diffusion process unfolds.

4.4 Robustness Checks

4.4.1 Estimation Methods

To assess the robustness of the main results, an alternative estimation approach is implemented using the non-split (single-record) format, as a complement to the start–stop (episode-splitting) specification used throughout the core analysis. While the start–stop format is well-suited for incorporating time-varying covariates and capturing annual variation in covariate values, it relies on more complex data restructuring. In contrast, the single-record format simplifies the setup by representing each bank with a single observation, typically using covariates measured at baseline or averaged over time. This approach provides a useful check on whether the key findings—particularly those concerning rival adoption and its interactions—are robust to differences in how survival-time data are structured and modeled. Results from this alternative specification are reported below.

As mentioned above, two versions are estimated: one that uses the first observed year (baseline year) to define all covariates, and another that uses time-averaged values over the at-risk period. Notably, the baseline model includes 5,223 banks, while the average covariate model retains 9,245 banks. The difference in sample size arises from how each approach handles missing data. In the base year approach, all covariates are drawn from a bank's first year in the sample. If any variable is missing in that initial year—due to data limitations, reporting gaps, or variable availability—then that bank is excluded from the estimation. In contrast, the average covariate model aggregates available information over the entire risk

period. As long as a variable is observed in at least one year during this period, the bank is retained in the sample. This more flexible structure substantially reduces attrition due to isolated missing values and yields a larger and more representative sample.

Table 5 presents robustness checks using the single-record specification, where each bank is represented by a single observation and covariates are measured either at baseline (Columns 1–2) or averaged over the risk period (Columns 3–4). Across all specifications, the effect of rival adoption remains positive and statistically significant, reaffirming the core result that banks are more likely to adopt online banking when peers have already done so. The estimated hazard ratios range from 1.11 to 1.91, depending on whether the rival precedence dummy or ratio is used, and whether covariates are baseline or averaged.

Table 5: Determinants of the Conditional Probability of Online Banking Adoption, 2003-2010 (Non-split Approach)

Dependent: the Hazard of a Bank Adopting Online Banking (estimated with Cox Proportional Hazards Model)				
(1)	(2)	(3)	(4)	(5)
Rival Precedence Dummy	1.1104**		1.6030***	
	(0.0510)		(0.1034)	
Rival Precedence Ratio		1.3429***		1.9136***
		(0.0766)		(0.1106)
Market Concentration	1.0687	1.0752	1.3993***	1.2872***
	(0.0916)	(0.0837)	(0.1151)	(0.0911)
Market Growth	1.0000	1.0000	0.9999***	0.9998
	(0.0006)	(0.0006)	(0.0004)	(0.0004)
BHC Dummy	1.3178***	1.3016***	1.6902***	1.6716***
	(0.0678)	(0.0670)	(0.0579)	(0.0573)
Bank Size	0.8302***	0.8119***	1.0003	1.0004
	(0.0356)	(0.0378)	(0.0004)	(0.0004)
Market Wage Rates	0.9893***	0.9891***	1.0039***	1.0053
	(0.0022)	(0.0022)	(0.0011)	(0.0011)
Baseline Covariates	√	√		
Average Covariates			√	√
No. of Observations	5,223	5,223	9,245	9,245
LR Test Statistics/Wald Chi2	117.66	140.37	306.78	378.88

Note: Figure in parentheses are standard errors, *p<0,1, **p<0.05, ***p<0.01

Market concentration continues to have a positive and significant association with adoption in specifications using averaged covariates (Columns 3–4), consistent with prior findings. Market growth becomes statistically significant only in Column (3), where the hazard ratio is just below one, echoing earlier results that faster-growing markets are modestly less likely to adopt. The BHC dummy remains a strong and stable predictor across all models. Notably, the direction of the bank size and wage effects depends on how the covariates are measured. While baseline values suggest that smaller banks and lower-wage markets adopt earlier,

these patterns weaken or reverse when using averaged covariates, reflecting sensitivity to specification and the temporal structure of the covariates.

Overall, the consistency of the rival adoption coefficients—across different measurement strategies and survival data structures—supports the robustness of the main findings and suggests that the influence of peer adoption is not an artifact of model setup.

4.4.2 Market Concentration Measures

To assess the robustness of the baseline results to alternative definitions of market concentration, this section replaces the HHI with the three-firm concentration ratio (CR3), defined as the share of total market deposits held by the largest three banks in each local market.[14]

Table 6 reports the results: across all specifications, the core results remain consistent with the baseline; the rival precedence dummy and the rival precedence ratio continue to be strong, positive, and statistically significant predictors of adoption timing, reinforcing the presence of strategic peer effects in the diffusion of online banking.

[14]The CR3 is log-transformed to reduce scale compression near its upper bound and to better distribute variation across moderately concentrated markets. While the transformation does not eliminate skewness, it improves numerical stability and comparability within the Cox model. It also enables a semi-elastic interpretation, where coefficients reflect the effect of percentage changes in market concentration on the hazard of adoption.

Table 6: Determinants of the Conditional Probability of Online Banking Adoption, 2003-2010 (CR3 as an Alternative Measure of Market Concentration)

Dependent: the Hazard of a Bank Adopting Online Banking (estimated with Cox Proportional Hazards Model)				
(1)	(2)	(3)	(4)	(5)
Rival Precedence Dummy	1.2895**		1.1271***	
	(0.0658)		(0.0375)	
Rival Precedence Ratio		1.4776***		1.3138***
		(0.0561)		(0.0507)
CR3	0.8566***	0.8595***	4.9801***	2.4699***
	(0.0494)	(0.0400)	(2.8583)	(0.3823)
Rival Precedence × CR3			0.1668***	0.2026***
			(0.0966)	(0.0443)
Market Growth	0.9999**	0.9999**	0.9999**	0.9999**
	(0.0001)	(0.0004)	(0.0004)	(0.0001)
BHC Dummy	1.4927***	1.4794***	1.4913***	1.4645***
	(0.0348)	(0.0338)	(0.0347)	(0.0331)
Bank Size	1.0708**	1.0737**	1.0723**	1.0744**
	(0.0359)	(0.0378)	(0.0367)	(0.0388)
Market Wage Rates	1.0037	1.0042	1.0040	1.0041
	(0.0022)	(0.0030)	(0.0033)	(0.0030)
Bank Size × Year Trend	0.9344**	0.9319**	0.9331**	0.9317**
	(0.0314)	(0.0328)	(0.0319)	(0.0337)
Market Wage × Year Trend	0.9984**	0.9984**	0.9983**	0.9984**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
No. of Observations	31,488	31,488	31,488	31,488
LR Test Statistics/Wald Chi2	425.93	502.41	306.78	599.86

Note: Figure in parentheses are standard errors, *p<0,1, **p<0.05, ***p<0.01

The coefficient on CR3, when entered alone, yields hazard ratios below one (columns (1)–(2)), suggesting that banks in highly concentrated markets are less likely to adopt early—consistent with the notion that competitive pressure is weaker when market dominance is concentrated among a few institutions. This stands in contrast to the baseline HHI specifications (Table 2), where market concentration is associated with earlier adoption. The divergence reflects the fact that HHI and CR3 capture different aspects of market structure. HHI incorporates the entire distribution of market shares and can indicate high concentration even when market power is spread across several mid-sized firms, potentially encouraging strategic rivalry and earlier adoption. In contrast, CR3 isolates the dominance of the top three firms and better reflects environments where fringe competitors face limited strategic influence. In markets where the top three firms control, say, 95% of deposits, smaller banks may perceive little room to compete or influence customer behavior, and thus delay adoption. For example, a small bank operating in a market where ten firms each hold around 10% of deposits (high HHI, moderate CR3) might adopt early to maintain parity with peers, whereas that same bank in a market where three firms hold 90% (high CR3) may lack incentive to act independently. This pattern is broadly consistent with the rising portion

of the U-shaped relationship between competition and innovation proposed by Aghion et al. (2005). In this context, high CR3 likely reflects low competitive pressure—akin to the left side of the U-curve—while elevated HHI, when driven by several mid-sized competitors, may correspond to a moderate competition environment that encourages adoption in response to rival behavior.

When CR3 is interacted with rival precedence (columns (4)–(5)), the results shift notably. The main effect of CR3 becomes strongly positive (HRs > 2), and the interaction term is also significantly greater than one. This pattern suggests that in more concentrated markets, banks are especially responsive to peer behavior. In such environments, peer adoption may serve as a credible signal or competitive benchmark, amplifying the marginal effect of rival precedence. These findings align with the interaction effects reported using HHI (Table 4), indicating that peer effects operate more strongly under competitive pressure—regardless of the specific concentration metric used.

Taken together, the Table 6 results support the robustness of the main findings. While the relationship between market concentration and baseline adoption differs depending on the concentration measure, the interaction between concentration and peer behavior consistently reinforces the importance of strategic interdependence in the diffusion of online banking.

5 Conclusion

This paper investigates how market competition and peer behavior jointly influence the adoption of new technology, focusing on the diffusion of online banking among U.S. commercial banks and savings institutions. While much of the existing literature has focused on firms innovating at the technological frontier, this study shifts attention to the adoption of existing technologies—a process shaped by strategic interaction, market structure, and institutional context. Using Cox proportional hazards models with time-varying covariates, the analysis shows that exposure to rival adoption significantly increases the likelihood of adoption, particularly in the earlier stages of diffusion. However, this peer effect is not uniform. It is stronger in more competitive and slower-growing markets and among smaller banks, suggesting that competitive pressure and organizational constraints play a critical role in influencing adoption strategies.

These findings provide new empirical evidence on the strategic diffusion of innovation in a regulated service sector, where adoption decisions are determined not only by market forces but also by the broader institutional environment. By tracing the timing of adoption across heterogeneous firms and markets, the analysis sheds light on the strategic dimension of technology diffusion. It moves beyond binary adoption outcomes to highlight

how competitive pressure and peer behavior contribute to the sequencing of adoption decisions. This approach extends existing work on innovation and diffusion by identifying the importance of market structure and strategic interdependence in influencing firm behavior across diverse industry contexts.

This study offers new perspective on how firms' competitive environments influence both the timing and likelihood of technology adoption. It contributes to diffusion theories by illustrating how peer effects interact with market structure and organizational characteristics. While grounded in the banking sector, the insights are applicable to other industries undergoing digital transformation in contexts defined by institutional constraints, strategic interaction, and evolving market conditions. It also holds relevance for policymakers aiming to accelerate technology diffusion, suggesting that both market incentives and peer dynamics should be considered when designing interventions to promote adoption.

Future research could explore the long-term consequences of adoption timing, such as how early versus late adoption affects firm performance, competitive positioning, or market structure. Additional work may also examine whether similar peer dynamics operate in other industries undergoing digital transformation, including healthcare, education, and logistics. More broadly, the framework developed in this study provides an empirically applicable approach for analyzing how firms respond not only to the arrival of new technologies, but also to the strategic behavior of others within their competitive environment. As digital innovation continues to reshape traditional industries, understanding the mechanisms behind strategic adoption will remain central to both economic research and policy design.

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Appendix

Table A.1: Test of Proportional Hazards Assumption (Schoenfeld Residuals)

Variable	**rho**	**Chi-sq**	**df**	**p-value**
Rival Precedence Dummy	-0.025	4.50	1	0.034
Market Growth	-0.006	0.01	1	0.920
Market Concentration	-0.002	0.02	1	0.884
BHC Dummy	-0.009	0.64	1	0.424
Bank Size	-0.021	4.49	1	0.034
Market Wage Rates	-0.056	18.50	1	0.000
Global test		36.57	6	0.0000

Table A.2: Interaction Effect of Market Concentration, Market Growth and Bank Size, 2003-2010 - Rival Precedence Ratio

Dependent: the Hazard of a Bank Adopting Online Banking (estimated with Cox Proportional Hazards Model)						
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rival Precedence Ratio	3.2829***	3.2236***	1.5349***	1.5288***	1.5470***	1.5371***
	(0.2653)	(0.2685)	(0.0652)	(0.0593)	(0.0440)	(0.0593)
Market Concentration	2.0781***	2.0532***	1.1336***	1.1335**	1.1372***	1.1348**
	(0.1542)	(0.1392)	(0.0546)	(0.0565)	(0.0548)	(0.0566)
Rival Precedence × Market Concentration	0.2515***	0.2584***				
	(0.0333)	(0.0342)				
Market Growth	0.9999	0.9999***	0.9999	0.9999**	0.9999	0.9999**
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Rival Precedence × Market Growth			1.0010	1.0011		
			(0.0013)	(0.0009)		
BHC Dummy	1.4529***	1.4596***	1.4683***	1.4755***	1.4692***	1.4758***
	(0.0394)	(0.0333)	(0.0398)	(0.0341)	(0.0398)	(0.0341)
Bank Size	1.0002	1.0726**	0.9999	1.0720**	1.0030	1.0728**
	(0.0008)	(0.0384)	(0.0008)	(0.0370)	(0.0020)	(0.0370)
Rival Precedence × Bank Size					0.9934	0.9982
					(0.0044)	(0.0011)
Market Wage Rates	0.9998	1.0049*	0.9998	1.0050	0.9997	1.0044
	(0.0009)	(0.0029)	(0.0009)	(0.0032)	(0.0009)	(0.0032)
Bank Size × Year Trend		0.9330*		0.9333**		0.9333**
		(0.0334)		(0.0322)		(0.0323)
Market Wage × Year Trend		0.9984***		0.9983**		0.9984**
		(0.0006)		(0.0007)		(0.0006)
No. of Observations	31,489	31,489	31,489	31,489	31,489	31,489
LR Test Statistics/Wald Chi2	466.71	588.80	358.32	479.35	360.44	467.91

Note: Figure in parentheses are standard errors, *p<0,1, **p<0.05, ***p<0.01