Stuck in the Adoption Funnel: The Effect of Interruptions in the Adoption Process on Usage*

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Abstract

Many firms have introduced internet-based customer self-service applications, such as online payments or brokerage services. Despite high initial signup rates, not all customers actually shift their dealings online. We investigate whether the multi-stage nature of the adoption process (an 'adoption funnel') for such technologies can explain this low take-up. We use exogenous variation in events that possibly interrupt adoption, in the form of vacations and public holidays in different German states, to identify the effect on regular usage of being interrupted earlier in the adoption process. We find that interruptions in the early stages of the adoption process reduce a customer's probability of using the technology regularly. Our results suggest significant cost-saving opportunities from eliminating interruptions in the adoption funnel.

Keywords: Online Banking, Technology Adoption, Adoption Process, Online Security, Self-Service Technology.

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1 Introduction

Firms in many industries, including banking, education and healthcare, allow customers to access and manage their accounts online. Online self-service applications can save money and time for both firms and customers compared to traditional call centers or face-to-face interaction. They also allow firms to improve customer service, target new customers, and cross-sell.

Prior research suggests, however, that online applications have not fully lived up to their productivity promises (Gordon, 2000). This is in part because despite widespread Internet diffusion, customers often fail to use these services consistently (Goldfarb and Prince, 2008). For example, only 20-25% of Italian and French online banking customers transferred money or paid bills online during three months of empirical study (Ensor, 2008; Ensor and Hesse, 2008). Sparse usage of the services' full capabilities, such as online transactions, reduces profits, since active users of online banking generate higher revenues for the bank even after controlling for selection effects (Hitt and Frei, 2002; Lambrecht, 2005).

One notable feature of these technologies is that they require users to navigate a multi-stage adoption process. In online banking, customers often need to first sign up and then log into the service before they can complete a transaction and ultimately become regular users. In this paper, we explore whether the multi-stage nature of the adoption process and the possibility of interruptions in this process can explain why customers often do not use online self-service technologies consistently. We use detailed data on individual users' completion of different stages of the adoption process of an online banking service. Our customer-level data from a German retail bank contain information on the customer's timing of signup for and initial login into the bank's online banking service, as well as information on subsequent usage of the platform. The setting is ideal for studying a multi-stage adoption process, because German banks have to comply with a complex series of security requirements that has led to a clear separation of different stages of adoption.

The presence of multiple stages to adoption allows for interruptions to the adoption process that persistently affect whether regular usage ever occurs. One possible mechanism for this effect is that learning to use and becoming familiar with the technology are costly (Johnson et al., 2003). Customers need to recall this information and behavior to move to the next stage, but if they forget, they have to re-learn how to use the technology. This would explain the lack of regular usage that we observe, providing a separate explanation for the usage gap from those currently proposed in the literature, which emphasize the degree of a technology's 'usefulness' (Davis, 1989).

Interruptions in moving through the stages of the adoption process are common: 37% of users do not log into the service in the same month they signed up, and 29% do not conduct an online transaction in the same month they first log in. The adoption process resembles an 'adoption funnel' due both to these multiple stages and the level of attrition by the end of the adoption process. Only 28% of customers who have experimented with making an online transaction continue to make at least one online transaction per month after their first transaction. If interruptions significantly affect the desired outcome, regular usage, it is crucial for a firm to manage interruptions by ensuring that customers move swiftly through the adoption funnel.

It is difficult to identify empirically a causal effect of interruptions in the initial stages of the adoption process on later regular usage. A positive relationship between customers being interrupted in the completion of the early stages of adoption and a lack of regular usage may not represent a causal relationship, but instead merely customer heterogeneity such as differences in technological aptitude. Both the timely completion of the initial stages of adoption and the customer's usage decisions may therefore reflect customer characteristics that are only partially observable to the researcher.

We address this endogeneity concern by exploiting exogenous sources of interruptions to a customer's adoption process. We use variation in the number of school vacation days and public holidays across months and German states as a shifter of a customer's ability to progress through subsequent adoption stages that is unrelated to the individual customer's propensity to adopt. Vacations and public holidays affect whether customers are able to receive the initial mailing from the bank with login details promptly after signup, allowing them to complete the initial login to the website. Public holidays may at the same time counter later interruptions in the adoption process by providing customers with the option to conduct banking transactions online at a time when branch banking is not available.

We estimate a discrete choice model of the customer's decision to conduct an online transaction once he has completed the signup and login stages of the online banking adoption process. We allow the propensity of conducting online transactions to vary with the incidence of interruptions to the earlier stages of adoption. Instrumenting for interruptions with vacations and public holidays yields, as in Heckman (1978), a simultaneous-equations model with endogenous dummy variables. We find a strong negative effect of early-stage interruptions on usage: An interruption of the adoption process between signup and initial login, or between initial login and the completion of an initial transaction, reduces a customer's probability of using the technology in subsequent months by 16 and 28 percentage points, respectively. This slow-down effect of interruptions on a customer's usage behavior declines with time spent in the adoption stage, providing additional evidence that we identify the causal effect of an interruption rather than underlying customer-level heterogeneity. We use the parameter estimates in rough back-of-the-envelope calculations of the magnitude of savings to the bank from being able to eradicate interruptions. These imply additional cost savings to the bank from the introduction of online banking of 6.4% if customers conduct at least one transaction through the online instead of the offline channel. This highlights the importance to firms of actively managing the customer adoption processes to ensure there are no interruptions.

2 Related Literature

Our work draws upon two literatures: Research on diffusion and adoption of new technologies, in particular where adoption involves multiple stages; and work from the psychology and consumer behavior literature on memory, learning, and momentum.

Much of the literature on technology adoption recognizes that adoption frequently involves the completion of several distinct stages (see e.g., Rogers, 2003), but lacks data to estimate the process with sufficient accuracy. Instead, research into the adoption of new technologies such as Tellis et al. (2003) and Van Den Bulte and Stremersch (2004) typically treats the outcome of the individual adoption decision as a single discrete choice. Other approaches include work by Kalish (1985) who distinguishes between awareness and adoption of innovations in his theoretical model, but employs only the adoption part of the model in estimation since he does not observe whether individuals are aware of an innovation. Similarly, Van Den Bulte and Lilien (2007) build a model of an adoption process to derive the implicit relationship between the observed final adoption outcome and factors that affect behavior in the unobserved interim stages and exploit this theoretical relationship in estimation. Beal et al. (1957) circumvent the unavailability of outcome data at different stages of the adoption process by collecting *ex post* survey data on reported behavior in these stages.

We build further on behavioral research that has explored, in other consumer-choice contexts, how delays and interruptions affect behavior. We draw on laboratory evidence from psychology on learning and memory loss that suggests that interruptions early in a given process damage recall and hinder the successful completion of tasks (Bjork and Bjork, 1992; Richardson-Klavehn, 1988; Bjork and Geiselman, 1978; Speier et al., 1999, 2003). In our setting, it is critical for customers to remember the banking website they need to navigate, its features and their login details and password.

The psychology literature also points to a number of reasons for such interruptions to increase the cognitive costs of completing a new task, here the subsequent stage in the adoption process, making it less likely for customers to engage in regular usage of the technology even if they do not abandon the service altogether. First, Bahrick (1979) suggests that due to the lack of repeated recall early in the process, people remember less of the information and behavior relevant for the transition to regular usage, making the incremental adoption decision more costly. Second, Schwarz (1998) finds that the perceived quality of an experience declines in the difficulty of the task, so these cognitive costs may be evaluated as particularly high if memory loss has previously led to a more difficult usage experience. Last, research points to the importance of customers having adopted an 'implementational' mindset in completing a sequence of tasks, which can be lost through interruptions (Gollwitzer et al., 1990; Gollwitzer, 1990, 1993; Gollwitzer and Brandstatter, 1997). In other words, an interruption between signup and evaluation or between evaluation and trial may lead customers to lose sight of their goal of conducting more transactions online. Returning to that implementational mindset may require an additional, persistent cognitive cost. In summary, we expect that in settings where adoption spans multiple stages and interruptions are common, early interruptions affect the adoption outcome because they depreciate accumulated knowledge.

3 Data and the Online Banking Industry

3.1 Overview of Industry and Data

Our data come from confidential customer records from a major German retail bank over 23 months from September 2001 to July 2003. The bank introduced online banking in 1997. Its online service allows customers not only to monitor their checking, brokerage, and credit card accounts online, but also to initiate domestic and foreign credit and wire transfers, to purchase or sell brokerage account holdings, and to set up recurring payments. Customers benefit from online banking because it is quicker to initiate a transaction online than in a branch. There are also cost savings for the bank. In Germany, the non-cash payments system is dominated by credit and wire transfers, which accounted for 49.8% of the total number of non-cash payment transactions in 2001, and direct debits, which accounted for another 36.4% (CPSS, 2003).[1] German estimates put the savings from processing such an online-initiated transfer at €0.50 - 1.00 relative to the cost of a paper-based transaction (Wuebker and Hardock, 2002, and conversations with the bank).

We use data on the 2,130 customers who signed up for the service during the 23-month span of the data and went on to make at least one online transaction during the sample period.[2] For each customer, the data include the date of signup for online banking, the monthly number of logins, and the monthly number of online transactions. This means that we have data on the precise date for signup, but only data on the *month* that customers log in for the first time or conduct their first online transaction. We do not have data on other drivers of customer signup for online banking, such as bank-level marketing activities.

The data further include information on the number of offline transactions that a customer conducts each month. This includes automated transactions, such as direct debits, as well as ATM withdrawals. As a result, a customer makes approximately 17 offline transactions in the average month.[3] The available information on offline activity is therefore more likely a proxy for the customer's overall banking needs rather than representing the actual number of user-initiated offline transactions.

Lastly, the data include several customer attributes, such as the age and gender of the primary account holder,[4] and whether a customer has a brokerage account in addition to a checking account. The data also cover the zip code of the customers' branches, which we take

[1] This is unlike the situation in the US, where checks represent only 2.3% of total payments.

[2] In the Online Appendix, we demonstrate the robustness of our results to this selection criterion by finding similar patterns for customers who never made a transaction during our sample period.

[3] The median number of transactions (14) is slightly lower than the mean, reflecting the 0.79% of customers who conducted more than 75 offline transactions on average each month. We conducted robustness checks to make sure that such customers did not bias our results and found that the exclusion of such outlying customers did not change the results significantly.

[4] We do not observe whether the account is a joint account, but assume instead that the primary account holder manages the household's banking activities.

Table 1: Summary Statistics

	Mean	Std Dev	Min	Max
Interruption bef. Login	0.37	0.48	0	1
Interruption bef. Transaction	0.29	0.46	0	1
Months between signup and login	1.05	1.85	0	21
Months between login and first online transaction	0.67	1.82	0	21
Age	35.60	11.40	15	96
Age squared / 1000	1.40	0.97	0.22	9.22
Male	0.51	0.50	0	1
Brokerage account	0.27	0.45	0	1
Branches in Zip	0.94	0.23	0	1

Cross-sectional descriptive data for 2,130 customers who made at least one online transaction during the 23-month sample period.

	Mean	Std Dev	Min	Max
Make online transaction in given month	0.59	0.49	0	1
No. online transactions / month	2.57	4.03	0	75
No. logins / month	6.15	10.60	0	301
No. offline transactions / month	17.20	17.40	0	250
Vacation Days in month	5.59	7.90	0	31
Public Holidays in month	0.85	0.93	0	4

Panel data for 2,130 customers who made at least one online transaction during the 23-month sample period. Monthly observations covering months subsequent to the customer's first month with at least one online transaction. 27,946 monthly observations.

as their zip code of residence. We use information from Hoppenstedt Firmeninformationen GmbH on the bank's number of physical branches in the local zip code.

Using official state historic records, we collect data on state-level public holidays and school vacations, which we use as instrumental variables. We calculate the length of each vacation period including weekends, as we are interested in identifying periods when people are away from home, rather than merely being off work.

Table 1 provides summary statistics for customer characteristics, banking usage, and vacations. The average customer is 35.6 years old. 51% of customers are male. Customers are located in all 16 German states. 27% of customers have a brokerage as well as a checking account with the bank.

3.2 The Adoption Funnel

'Adoption' frequently refers to the customer's decision to purchase or begin using a product or service. For customer self-service technologies, it is difficult to identify one discrete decision that indicates adoption. In the case of online banking, the customer goes through four successive stages before the bank realizes cost savings. Our empirical measures are developed in the specific context of online banking, but the general framework applies to other self-service technologies. We call this adoption process the 'Adoption Funnel.' The different stages of the adoption funnel are:

a) Signup: A customer signs up for a new internet service.

b) Evaluation: A customer logs into the service for the first time.

c) Trial: A customer processes the first transaction using the service.

d) Regular usage: A customer regularly uses the service to process transactions.

Signup occurs when a customer submits a paper form to a bank branch indicating the wish to use online banking. The bank sends back a letter detailing the login ID. This system allows the bank to verify the user's identity and to transmit the login details securely. Creating the login details is automated and takes between one and two working days.

At signup the customer learns three types of information: the features of the service (types of transactions that can be done online), the benefits of the service (time savings and 24/7 accessibility compared to branch services) and the actual steps involved in using the service. The customer needs to recall this information to transition to all later stages.

Evaluation occurs after a customer received the login details that were sent by the bank following the signup stage. At evaluation, the customer logs into the web site and is able to check account details online and to investigate what the new service can do. In the evaluation stage, the customer learns new behavior. First, customers need to log into the online banking web site. This requires remembering to use the login ID and where they stored it. Second, customers learn how to navigate the banking web site (Johnson et al., 2003), a potentially difficult task for an inexperienced user.

Trial occurs when customers initiate their first online transaction. Though evaluation (first login) and trial (first transaction) are often used synonymously, in our setting they are separated both functionally and empirically. First, a customer can log in at any time but requires a specific need for a transaction to try the service. Second, the separation is due to security practices that are mandated for German banks. In a mailing separate from (but simultaneous to) the mailing of the login details, the customer receives a list of 6-digit transaction authorization numbers (TAN). An online transaction can only be executed if it is verified with a TAN. Trial therefore requires the customer to jump through an extra security hoop, making the customer's interaction with the online banking site more complex than at evaluation. Learning involves understanding web site navigation for transactional purposes, filling out the online transaction form and authorizing transactions. The customers need to further remember where they stored their TANs (Wuebker and Hardock, 2002).

Regular usage occurs when the customer uses the technology to conduct transactions in each month. We evaluate this by studying whether, in the months after initial trial, the customer uses the technology to make transactions. Only when a customer attains regular usage, can the customer and the bank fully benefit from the service.

3.3 Interruptions in the Adoption Funnel

In moving to regular usage, customer learning of the online platform can be facilitated by a speedy transition through the adoption process, thereby reinforcing the memorization of newly learned information and behavior through repeated recall (Bjork and Bjork, 1992; Richardson-Klavehn, 1988; Bjork and Geiselman, 1978). At the same time, the fact that adoption is not a single one-time event opens the possibility for exogenous interruptions to the process. An interruption slows movement through the adoption funnel by causing customers to forget the knowledge they previously accumulated (Speier et al., 1999, 2003). If a vacation, for example, interrupts the adoption process after the initial signup, a customer may not remember the service's features, benefits or steps required for usage upon return. A similar interruption later on in the adoption process after trial may result in forgetting how to log in or navigate the banking web site.

Empirically, we consider a customer's adoption process to be interrupted between signup and evaluation if a customer fails to log in during the month of signup. The only exception to this is if signup was in the week prior to the end of the month (meaning that the observed delay in logging into the website could plausibly be explained by the time it took the bank to mail the envelope). We similarly consider customers to be interrupted between evaluation and trial if they fail to conduct their first online transaction in the month of their first login. By this definition, a significant share of customers experience interruptions of different lengths during the adoption process: As reported in Table 1, 37% of customers do not log in during the month of their signup, and on average customers take 1.05 months to complete their move from signup to evaluation. 29% of customers do not conduct their first transaction in the month of their first log in, taking on average 0.57 months to move from evaluation to trial. After customers make their first online transaction, they conduct another online transaction in only 59% of subsequent months. We explore the impact of these interruptions on regular usage of online banking.

3.4 Exogenous Sources of Interruptions

We want to infer a causal relationship between interruptions in initial stages of the adoption funnel and subsequent usage. The challenge is that a positive relationship between a customer being interrupted in the completion of an early stage of adoption and a lack of regular usage may merely be the result of customer heterogeneity along a variety of dimensions, including technological aptitude, cost of time, or the availability of internet access.

To identify the causal relationship, we need a plausibly exogenous source of interruptions in the earlier adoption stages that is not correlated with the customer's unobserved attributes that lead to regular usage. We exploit the unusually regimented system of school vacation and public holidays in Germany that vary across the 16 German states. This provides an exogenous source of events that shift an individual customer's propensity to interrupt the adoption process and to move to the next stage of the adoption funnel, but are unrelated to their unobserved characteristics.

Vacation days affect a customer's ability to receive the mailing containing the online banking details and to initially log into online banking, since they usually separate customers from their computer and their mail. This exogenous variation in computer usage caused by vacations has also been exploited by Oberholzer-Gee and Strumpf (2007). It implies that customers who sign up for the service in a vacation-heavy month would be more likely to interrupt their adoption process and delay their first login than customers who sign up in another month, for reasons unrelated to unobservable customer tastes for technology. Therefore, similar customers have different likelihoods of interrupting the adoption process between signup and evaluation, merely because they sign up in different months.

Public holidays represent an additional source of exogenous variation in whether a customer interrupts the adoption process. Similar to vacation days, they cause a delay in the customer's receipt of login details, an obvious deciding factor for whether a customer interrupts the adoption process after signup and hence delays their first login. However, once a customer has received both the login details and the TANs, there needs to be a specific reason why that customer decides to make an online transaction. One reason independent of customer-specific drivers of transaction behavior may be that, as is the case on public holidays, bank branches are closed and consequently there are no other ways of making a transaction on the particular day. Also, customers may use public holidays to catch up with chores such as paying bills. This logic suggests that customers are more likely to make a transaction if they experience a larger number of public holidays and that otherwise identical customers move through the adoption funnel at different speeds if they face different numbers of public holidays in a month.[5]

Table 1 illustrates the extent of variation in public holidays and vacations days across customers and months. There are up to four public holidays and up to 31 school vacation days in a month, with an average of one holiday and six vacation days.[6] This reflects the fact that public holidays are largely set at the state level, with German states setting between nine to twelve public holidays each year, and that the federal government coordinates the timing of school vacations to minimize overlap across states.

In estimation, we use the number of vacation days and public holidays in the 14-day window after each customer signs up for online banking as instruments for whether or not a customer's adoption process is interrupted between signup and first login. For example, if a customer signs up for online banking on August 14, we use vacations and public holidays that occur from August 15 to August 28. Since we only have monthly data on the timing of login and transactions, we use the number of vacation days and public holidays in the month following the first login as an instrument for an interruption between the initial login and the initial online transaction. The monthly data are less precise, but we were able to use the exact signup date to improve the precision of the instrument for an interruption before a first transaction. In cases where the first login falls into the same month as sign-up, we use only the public holidays in the 30-day window beginning one week after the signup date as an instrument for an interruption between first login and first transaction.

[5]School vacations do not affect whether or not a bank branch is open. As shown in Table 3, the effect of vacations on interruptions between first login and first transaction is not statistically significant, and we do not use vacations as instruments in that stage.

[6]The Online Appendix illustrates that this variation stems from variation across states in the timing and length of vacations and public holidays over the course of the year. It also provides evidence that Germans make extensive use of such vacations to travel.

Table 2: Median Splits for Instrumental Variable

	Below Median	Above Median	Diff.
Public Holidays in Signup Month			
Interruption bef. Login	0.55	0.62	-0.078***
Vacation Days in Signup Month			
Interruption bef. Login	0.53	0.59	-0.062***
Public Holidays in Login Month			
Interruption bef. Transaction	0.40	0.15	0.250***

The table compares the percentage of customers who were interrupted before their first login or first transaction among customers with holidays or vacation days below vs. above the median number of vacation days or holidays in the sample. *** indicates significant at the 0.001 level.
Sample: 2130 customers who made at least one online transaction during the 23-month period.

Table 3: Linear Probability Models of the Incidence of Interruptions

	Interruption bef. Login		Interruption bef. Transaction	
	(1)		(2)	
Public Holidays Signup Month	0.120	0.023***		
Vacation Days Signup Month	0.007	0.003***		
Public Holidays Login Month			−0.086	0.018***
Vacation Days Login Month			−1.3E-04	−0.002
Age	−0.006	−0.005	−0.002	−0.004
Age squared	0.059	−0.053	0.026	−0.049
Male	−0.050	0.021**	0.079	0.019***
Brokerage	0.019	−0.023	−0.015	−0.022
Bank Branches	0.061	−0.044	0.065	−0.041
Month Controls	Yes		Yes	
Observations	2,130		2,130	

* p <0.10, ** p <0.05, *** p <0.01. OLS specifications for the likelihood of interruptions.
Sample: 2130 customers who made at least one online transaction during the 23-month sample period.

As shown by the median splits in Table 2, vacation days and public holidays are strong predictors of interruptions. Customers with an above-median number of vacation days or public holidays in the signup month have a significantly higher incidence of interruptions between signup and login than customers with a below-median number of vacation days and public holidays. Customers with an above-median number of public holidays are also significantly less likely to interrupt the adoption process between first login and first transaction.

Table 3 reports the estimates of a linear probability model of the incidence of an interruption. Column (1) in Table 3 displays the results of an OLS regression of whether or not a customer experienced an interruption in the transition to login (evaluation stage) on customer characteristics, public holidays, and vacation days following signup. The results suggest that public holidays and vacation days in the signup month are positively and significantly associated with interruptions, controlling for seasonality, customer demographics and customer bank attributes. Column (2) similarly displays the results of an OLS regression of the incidence of interruptions in the transition to the first transaction (trial stage) on customer characteristics, public holidays and vacation days in the login month. Vacation days are not significant here, so we did not use them as instruments in our main specification.

Our ability to use the number of vacation and public holidays as instrumental variables depends on their satisfying the exclusion restriction. This requires that the instrument affects the outcome variable only through the single known causal channel. In our context, this causal channel is that prior public holidays and vacation days affect regular usage only through earlier interruptions, and not through other means. Though there are no formal statistical tests to support the exclusion of the instrumental variables from our main modeling equation of regular usage, it is important to ensure as far as possible that previous occurrences of public holidays and vacation days are independent of other factors that influence a customer's adoption behavior in later stages of adoption. For example, it would be problematic if the bank changed its marketing campaigns to match vacations or state public holidays. Conversations with the bank assured us, however, that the bank conducted such marketing efforts at a national level only. In our estimation, we also control for possible month- or state-specific factors by including seasonal and state fixed effects.

We also checked whether customers who sign up before a vacation or public holiday differ in observable attributes from the remaining customers. Our assumption that our instruments are a random treatment across customers could be violated if there are proportionally fewer customers who sign up in these periods or if the customers who do are less likely to use the internet or are older. There are, however, no statistically significant differences in the shares of customers or in the demographic features of the customers who sign up before a vacation or public holiday compared to other times.

4 Modeling a Multistage Adoption Process

In this section, we outline our empirical approach to estimating the determinants of a customer's decision to use online banking and how the customer's experience earlier in the adoption funnel affects this decision. We focus on the customer's decision to make at least one online transaction in a given month following the initial trial. We assume that a banking customer i who has completed the initial stages of adoption of the service uses the online banking service in month t, $t = 1, ..., T_i$, provided that they derive positive utility from using the service. In the data, we observe only whether the customer uses the online banking service, U_{it}, but not the underlying latent utility from doing so, U^*_{it}.

We capture the benefits of using the service by a vector of customer attributes, $X_{it}\beta$. These include the number of bank branches near the customers and whether they hold a brokerage account, to proxy for the likely value of a physical branch location; the customer's age and gender, to reflect possible differences in cost of time across these demographic groups; and their overall demand for banking services, which we approximate by the number of offline transactions the customer makes in that month. We further include seasonal and state controls, and the number of public holidays and vacation days in a month, to allow for systematic differences in the attractiveness of online banking in different months or in different locations within Germany.

The costs of using the service reflect the customer's perceived cost of returning to the website that month and reusing the service, which are cognitive costs the customer incurs in the adoption process (Johnson et al., 2003). As we discuss in section 3.3, cognitive costs could span learning how to navigate the banking website, remembering login details, and where they stored and how to use their TANs. Such learning costs likely decline in the customer's experience with the service. Accordingly, we include a vector of indicator variables ζ_{it} that reflects how long the customer has been making transactions using online banking. We include an indicator for whether a customer used the service in the last month, $U_{i,t-1}$, as a separate cost shifter, reflecting the potential for state dependence in cognitive costs. Int_Login_i captures whether that customer experienced an interruption between signup and initial login. Int_Trans_i similarly captures an interruption between initial login and the first online transaction.

Since customers can relearn and reengage in an implementational mindset, the effect of Int_Login_i and Int_Trans_i on utility may not persist forever and instead may be most important in the initial periods where cognitive costs are highest. In our main specification, we represent this potential for the decreasing importance of interruptions flexibly with non-parametric interactions between ζ_{it} and the interruption indicators, Int_Login_i and Int_Trans_i.[7]

We further recognize that the customer's usage decisions reflect individual-specific, unobserved shifters of the customer's utility of usage. We allow for both random customer- and month-specific shocks ν_{it}^3 to the utility from using online banking, such as random fluctuations in the amount of bills that the customer needs to pay in a given month, and persistent individual heterogeneity in the utility of usage, ϵ_i^3, that is possibly correlated with unobserved determinants of the incidence of interruptions. As in the linear probability models in Table 3, we specify the likelihood of being interrupted in adoption as a function of customer attributes and, importantly, exogenous determinants of interruptions. This results in

[7]We also use a specification where we impose a linear functional form on the diminishing impact of interruptions, with similar results. These are reported in the Online Appendix.

a system of three estimating equations:

$$\begin{aligned}
Int_Login_i &= I(\beta_{10} + X_i^1\beta_{11} + Z_i^1\gamma_1 + \epsilon_i^1 > 0) = I(\overline{u}_i^1 + \epsilon_i^1 > 0) \quad (1)\\
Int_Trans_i &= I(\beta_{20} + X_i^2\beta_{21} + \alpha_{21} Int_Login_i + Z_i^2\gamma_2 + \epsilon_i^2 > 0) = I(\overline{u}_i^2 + \epsilon_i^2 > 0)\\
U_{it} &= I(\beta_{30} + X_{it}^3\beta_{31} + \zeta_{it}\alpha_{30} + Int_Login_i(\alpha_{31}^1 + \zeta_{it}\alpha_{32}^1) + Int_Trans_i(\alpha_{31}^2 + \zeta_{it}\alpha_{32}^2)\\
&\quad + \alpha_{33}U_{i,t-1} + \epsilon_i^3 + \nu_{it}^3 > 0) = I(\overline{u}_{it}^3 + \epsilon_i^3 + \nu_{it}^3 > 0)
\end{aligned}$$

The propensities for customer interruptions in Equation (1) include two sets of instruments, Z_i^1 and Z_i^2, that affect a customer's progress through the trial and evaluation stages of the adoption funnel. Z_i^1 contains, as discussed in section 3.4, the number of public holidays and the number of school vacation days in the two-week period following the customer's initial signup for online banking, and Z_i^2 contains the number of public holidays in the month after the customer first logs in. These are exogenous sources of variation in interruptions between signup and the first login or between the first login and first transaction that are excluded from the customer's subsequent usage decisions and are uncorrelated with the unobserved determinants of that decision, ϵ_i^3. The instruments allow us to identify a causal effect of interruptions on the customers' regular usage that abstracts from differences in customers' underlying adoption and usage propensities as captured by the ϵ_i.

We assume that the unobserved customer attributes ϵ_i are freely correlated and follow a mean-zero trivariate normal distribution with variance-covariance matrix $[[1, \rho_{12}, \rho_{13}]; [\rho_{12}, 1, \rho_{23}]; [\rho_{13}, \rho_{23}, \sigma_3^2]]$.[8] The correlations between ϵ_i are the source of endogeneity concerns in identifying the effect of interruptions. Heckman (1978) shows that under weak conditions satisfied here, all parameters of the multiple-equations model are econometrically identified, with the exception of the variances of ϵ_i^1 and ϵ_i^2, which we normalize to one. We estimate

[8] This parameterization is slightly more restrictive than the non-parametric identification strategy suggested by Vytlacil and Yildiz (2007), but it allows us to more easily incorporate discrete explanatory variables X_i.

the standard deviation of the unobserved individual effect in the utility to usage, σ_3, freely. Last, we assume that the random customer- and month-specific shocks to the utility from online banking, ν_{it}^3, are distributed according to a standard normal distribution with mean zero and standard deviation one and are independent across t and of ϵ_i^1, ϵ_i^2, and ϵ_i^3.

In estimation, we extend the approach introduced by Heckman (1978) for dummy endogenous variables in a simultaneous-equations system to panel data. Under our assumptions, the likelihood of observing customer i's stream of interruption and usage outcomes is given by:

$$\begin{aligned} L_i &= \Pr\left(Int\_Login_i = int_i^L, Int\_Trans_i = int_i^T, U_{i1} = u_{i1}, ..., U_{iT_i} = u_{iT_i}\right) \\ &= \int_{-\infty}^{\infty} \Bigg[\int_{-\infty}^{\left(2int_i^T - 1\right)\overline{u}_i^2} \int_{-\infty}^{\left(2int_i^L - 1\right)\overline{u}_i^1} f(\,\epsilon_i^1, \epsilon_i^2 \,|\, \epsilon_i^3) d\epsilon_i^1 d\epsilon_i^2 \\ &\quad \times \prod_{t=1,...T_i} \left(1 - \Phi(\overline{u}_{it}^3 + \epsilon_i^3)\right)^{1-u_{it}} \Phi(\overline{u}_{it}^3 + \epsilon_i^3)^{u_{it}} \Bigg] f(\epsilon_i^3) d\epsilon_i^3. \end{aligned} \quad (2)$$

where int_i^L and int_i^T denote customer i's observed outcomes for $\{Int\_Login_i, Int\_Trans_i\}$ and u_{it} their observed transaction decisions. $f(\,\epsilon_i^1, \epsilon_i^2 \,|\, \epsilon_i^3)$ denotes the conditional bivariate normal distribution of ϵ_i^1 and ϵ_i^2 given a realization for ϵ_i^3 with marginal pdf $f(\epsilon_i^3)$. Conditional on ϵ_i^3, the first part of the likelihood, corresponding to the propensities of a customer experiencing interruptions, is therefore a bivariate probit probability for each of the four possible interruption outcomes, $\{Int\_Login_i, Int\_Trans_i\}$=$(0,0)$, $(0,1)$, $(1,0)$, $(1,1)$. Similarly, the likelihood of observing each transaction decision, conditional on ϵ_i^3, is a univariate probit probability.

We evaluate the 2-dimensional integral over the conditional joint normal distribution of $(\epsilon_i^1, \epsilon_i^2)$ using the GHK simulator and similarly employ Monte-Carlo simulation techniques to integrate over the distribution of ϵ_i^3. We then find parameters that maximize the aggregate log-likelihood across customers. The Online Appendix contains a detailed derivation of the log-likelihood function. It also discusses the difficulty of implementing an alternative modeling approach, a simultaneous-equations-hazard specification for the time a customer spends in each stage of the funnel.

5 Results

Table 4 presents the results of multiple empirical specifications for the customer's regular usage decision. We begin with linear probability models that explore the relationship between regular usage and interruptions. Model (1) presents results from an OLS regression of the customer's usage decision in every month after initial trial on indicators of interruptions earlier in the adoption funnel and customer attributes. Model (2) repeats this specification, instrumenting for the interruption variables with the number of vacation and holidays in the month following signup and the number of holidays in the month following first login in a two-stage least squares estimation. In the systems-of-equations estimates that follow, we allow the effect of such interruptions to vary with the number of months passed since trial. Here, we focus simply on the aggregate effect of interruptions to facilitate the interpretation of standard instrumental variable tests.

The coefficients suggest that interruptions affect customer usage in statistically and economically significant ways. In the OLS specification in column (1), the probability of conducting at least one online transaction in a given month is 10.2 and 15.9 percentage points higher for a customer that does not experience an interruption before the first login or the first transaction, respectively, relative to an otherwise identical customer who is interrupted. The 2SLS specification in column (2) entails a similar effect for an interruption before login on regular usage, suggesting that endogeneity concerns do not generally bias the results downwards. The effect of an interruption before the first online transaction on regular usage increases in absolute terms under 2SLS. This may be because measurement error introduced by our monthly data means that we include some interruptions in moving from the evaluation to the regular usage stage that are only artifacts of someone's adoption spanning the end of one month and the beginning of another month.

The specification in column (1) allows us to obtain conventional instrumental variable test statistics for the endogenous interruption variables. The Anderson canonical correlation likelihood-ratio test for underidentification suggests that we can reject the hypothesis that the first-stage equation is under-identified ($p < 0.0001$). Our instruments are therefore good predictors of interruptions.[9]

The remaining specifications in Table 4 recognize both the discrete nature of our outcome variables, as well as the panel nature of the usage decisions. Model (3) is a random effects probit specification of the probability of regular usage. This specification includes the effect of interruptions on transaction behavior, but as in Model (1) does not treat interruptions as endogenous. Controlling for unobserved customer attributes with the random effects framework yields similar results to the earlier models for the effect of interruptions in significance and direction. Model (6), our main specification, controls for the possible endogeneity of interruptions using the system-of-equations estimator from Equation (1).

As above, the parameter estimates for our main model, Model (6), suggest that both an interruption before the first login and an interruption before the first transaction significantly reduce the probability that a customer moves to regular usage. We calculate marginal effects for each individual by computing the difference in predicted marginal probability of usage if the customer has an interruption and if he does not. Averaging across individuals, this suggests a 15.7 percentage point increase (95% confidence interval 12.3%-19.1%) in the likelihood of a customer conducting an online transaction in the first month after making a transaction from eradicating the interruption between signup and evaluation, and a 28 percentage point increase (95% confidence interval 24.3%-31.7%) from eradicating the inter-

[9]We also checked for overidentification by running a specification similar to those reported in Table 4 but dropping public holidays in the signup month as an instrument in the first stage. This means that our equations were exactly identified. The results were similar.

ruption between evaluation and trial. This compares to 37% and 29% of customers in the sample who experience interruptions between signup and login and between login and first transaction. This indicates that the effect is economically significant.

The interactions with the month dummies suggest that the impact of an interruption before the first login becomes very small roughly three months after the first online transaction. For the more recent interruption before the first online transaction, the impact is more persistent, and the marginal effect implies a 14.8 percentage point decrease in the probability of conducting a transaction even after nine months.[10] Though the marginal effects are similar to the 2SLS coefficients on average, they also suggest significant heterogeneity in the effect of interruptions with time passed.

The control variables indicate that regular usage increases at a decreasing rate in the customer's age and is higher for men relative to women. These variables may proxy for the customer's opportunity cost of time or computer experience. Our results also show that the availability of physical bank branches is correlated with a greater probability of regular usage, possibly reflecting the fact that banks are more likely to be present in regions with a higher need for banking. Similarly, customers with a greater number of offline transactions who are likely to have a greater affinity for banking are more likely to make repeated transactions online.[11]

[10] These marginal effects do not represent the marginal effects of the full interaction variable, but rather the conditional marginal effects of moving from *Int_Login* or $Int\_Trans = 0$ to *Int_Login* or $Int\_Trans = 1$, holding fixed the particular number of months the customer has so far spent in the usage stage. We therefore focus purely on the marginal effect on the usage probability of experiencing an interruption if the customer is in months 0-3 in the usage stage, months 4-6, etc.

[11] We also tried other control variables such as zip-code level data on income, educational attainment, and internet activity. These measures were insignificant in predicting adoption behavior.

Table 4: Discrete Choice Models of the Customer's Usage Decision

	Linear Models				Rnd Eff Probit Model		System-of-Equations FIML Models					
	OLS		2SLS				No interruptions		No state dependence		Main model	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
	(1)		(2)		(3)		(4)		(5)		(6)	
Regular Usage												
Interruption bef. Login	−0.102	0.006***	−0.136	0.017***	−0.633	0.046***			−0.670	0.056***	−0.582	0.062***
Interruption bef. Login												
× Months since 1st Transaction												
Months 4-6					0.543	0.056***			0.690	0.058***	0.520	0.066***
Months 7-9					0.439	0.060***			0.608	0.057***	0.416	0.069***
Months 10+					0.495	0.053***			0.641	0.045***	0.472	0.056***
Interruption bef. Transaction	−0.159	0.006***	−0.360	0.044***	−0.701	0.048***			−1.464	0.061***	−0.992	0.064***
Interruption bef. Transaction												
× Months since 1st Transaction												
Months 4-6					0.326	0.058***			0.397	0.061***	0.308	0.070***
Months 7-9					0.410	0.063***			0.478	0.059***	0.397	0.071***
Months 10+					0.496	0.056***			0.606	0.048***	0.467	0.059***
Months 4-6					0.384	0.043***			0.192	0.042***	0.405	0.046***
Months 7-9					0.300	0.048***			0.029	0.044	0.323	0.050***
Months 10+					0.023	0.049			−0.363	0.042***	0.064	0.046
Age	0.016	0.001***	0.015	0.001***	0.041	0.008***	0.044	0.007***	0.054	0.008***	0.048	0.007***
Age Squared	−0.177	0.016***	−0.163	0.016***	−0.462	0.092***	−0.499	0.087***	−0.587	0.090***	−0.523	0.079***
Male	−0.003	0.006	0.009	0.007	−0.003	0.035	−0.037	0.030	0.091	0.032***	0.050	0.029*
Brokerage	0.009	0.006	0.011	0.006*	0.036	0.039	0.023	0.033	0.007	0.037	0.029	0.031
Bank Branches	0.041	0.012***	0.052	0.013***	0.094	0.073	0.117	0.058**	0.262	0.066***	0.170	0.056***
Public Holidays (t)	−0.006	−0.004	−0.006	−0.004	0.005	0.052	−0.004	0.054	−0.002	0.055	2.3E-5	0.053
Vacation Days (t)	−0.001	3.8E-4	−0.001	3.8E-4	−0.004	0.002*	−0.003	0.002*	−0.003	0.002	−0.004	0.002**
No. Offline Transactions	0.004	1.9E-4***	0.004	1.9E-4***	0.014	0.001***	0.012	3.0E-4***	0.015	3.4E-4***	0.012	3.3E-4***
Transaction Decision ($t-1$)					0.881	0.023	0.889	0.015***			0.920	0.017***
Interruption bef. Login												
Age							−0.016	0.013	−0.019	0.013	−0.024	0.013*
Age Squared							0.166	0.152	0.203	0.158	0.254	0.159
Male							−0.125	0.056**	−0.137	0.057**	−0.143	0.058**
Brokerage							0.042	0.063	0.001	0.065	0.019	0.065
Bank Branches							0.157	0.121	0.160	0.127	0.101	0.129
Public Holidays Signup Month							0.290	0.063***	0.327	0.068***	0.321	0.068***
Vacation Days Signup Month							0.017	0.007***	0.018	0.007***	0.017	0.007**
Interruption bef. Transaction												
Age							−0.012	0.013	−0.005	0.013	0.001	0.013
Age Squared							0.151	0.149	0.078	0.157	0.009	0.154
Male							0.184	0.058***	0.251	0.061***	0.227	0.059***
Brokerage							−0.032	0.064	−2.3E-4	0.068	−0.003	0.067
Bank Branches							0.216	0.125*		0.130*	0.081	0.129
Public Holidays Login Month							−0.215	0.055***	−0.270	0.060***	−0.261	0.058***
σ_3					0.635	0.019***	0.712	0.017***	1.005	0.019***	0.637	0.019***
ρ_{21}							0.408	0.041***	0.113	0.049**	0.199	0.056***
ρ_{31}							0.294	0.035***	0.144	0.045***	0.015	0.056
ρ_{32}							0.392	0.034***	−0.415	0.043***	−0.349	0.048***
Log-Likelihood	−18,589		−19,105		−13,449		−16,637		−16,863		−16,064	
Observations	27,946		27,946		27,946		32,206		32,206		32,206	

* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Model (1) is a linear probability model of the customer's decision to conduct an online transaction in each month. Model (2) uses public holidays and vacation days in the signup month as instruments for an interruption before login and public holidays in the login month as an instrument for an interruption before the initial transaction. Model (3) is a random effects Probit estimation of Model (1). Models (4) through (6) instrument for the endogenous interruptions using the FIML estimator based on trivariate normal distributions for the individual unobserved effects.

Sample: 2,130 customers who made at least one online transaction during the 23-month sample period.

Our main specification also allows for state dependence in the customer's usage decision by including an indicator variable for whether the person made a transaction in the prior month. As expected, the coefficient on prior usage is positive, indicating a positive association with transaction behavior over time.

The bottom panels of Table 4 contain the parameter estimates of the remaining ancilliary equations. In line with the median splits presented in Table 2, an interruption before the first login is positively correlated with the presence of both public holidays and vacations after signup. These results suggest that the more school vacation days or public holidays there are after signup, the more likely a person is to get interrupted in moving to initial login for online banking, possibly because of the increased amount of travel at these times. We find a negative and significant effect from public holidays on an interruption occurring before the first online transaction, consistent with either the increased value of online banking in times of when branches are closed or with an increased focus on household tasks on public holidays.

We use the proportional chance criterion (PCC) to examine the fit of our main specification. If we classify a customer as conducting an online transaction in a month provided their predicted adoption probability exceeds 0.5, we correctly predict 64.02% of customers' decisions to make at least one online transaction in a month. This is statistically significantly higher than the PCC of 51.62%.

As robustness checks, Table 4 contains in columns (4) and (5) two alternative specifications of the usage model. Model (4) is a model that jointly estimates the probability of interruptions in the initial stages and the probability of later regular usage, but that does not consider the effect of interruptions on regular usage. A likelihood ratio test (significant at the 1% level) suggests that the model with interruptions better reflects regular usage behavior than the alternative specification that excludes these terms. The incidence of interruptions in early stages is thus important in explaining lack of regular usage.

Model (5) shows results from a specification that omits state-dependence by excluding the previous month's usage decision as an explanatory variable. The results show that if we did not account for state dependence in our main specification, we would overestimate the effect of interruptions on regular usage.

Across specifications, we thus find that interruptions both early and later in the adoption process affect regular usage. At signup, customers learn information that is required for the transition to all subsequent stages. Customers need to know their TANs and the different types of transactions available online in order to move to regular usage. Our results thus suggest that an interruption prior to the first login hurts memorization of relevant information and results in greater cognitive costs of regular usage later on, just as an interruption immediately prior to the stage of regular usage does.

6 Policy Projections

The results in Table 4 suggest that interruptions between earlier stages in the adoption process can affect regular usage. This section provides some rough estimates of the overall effect of these interruptions on firm costs in order to guide firm policy. We calculate how the marginal probability of usage would change if the bank ensured its customers moved smoothly along the adoption funnel and prevented interruptions in the move to the trial or evaluation stages of online banking. Before proceeding, we should note two caveats. First, we simply compare outcomes for a customer that experiences an interruption and an identical customer that does not, rather than varying the underlying source of interruptions. Second, out estimates strictly identify only the average local treatment effect of vacations and holidays. We are therefore making an assumption that they can be considered proxies for other sources of interruptions that the bank has some control over in these estimates.

We use the estimates presented in Model (6) of Table 4. Table 5 describes the results for customers in the first month following their first transaction. It compares the average

Table 5: Projections of change in the likelihood of making a transaction in the first month after first transaction from eradicating different kinds of interruptions

	Mean	Std Dev	Min	Max	Observations
Current usage	0.49	0.22	0.01	0.99	2130
Predicted usage if no interruption	0.64	0.15	0.13	1.00	2130
Predicted usage if no interruption bef. login	0.56	0.21	0.02	0.99	2130
Predicted usage if no interruption bef. transaction	0.58	0.18	0.05	1.00	2130

predicted likelihood of someone using online banking for transactions in that subsequent month if we eradicate the interruption before the first login, the interruption before the first online transaction, or both interruptions. All of these projections are calculated as the mean of each individual's projected difference in marginal propensity. The projections suggest that the share of customers that use online banking in that month would increase by 15 percentage points if all interruptions were eradicated. It also suggests that preventing interruptions between signup and login (a 7 percentage point increase) would have a slightly weaker effect than preventing interruptions before the first online transaction (a 9 percentage point increase).

To get a rough idea of the cost savings involved, we use estimates from Wuebker and Hardock (2002) as well as the bank, that suggest that replacing an offline transaction by its online equivalent reduces a bank's variable costs by approximately €0.50–1.00.[12] We use the €0.50 figure, assuming only one transaction per month, even though the average number of transactions in our sample is 4.3 per month. A retail bank with 1 million new users of online banking, like the user base of the bank we study, could therefore save at least €6 million in the first 12 months if these customers made at least one transaction online. The results in Table 6 suggest that the bank we study could therefore expect to see additional savings of around €384,000 from the increased online transactions due to the prevention of interruptions in the 11 months following the month of first online usage. This represents an

[12]This estimate has the advantage that it is specifically for this time period and country, but it is an aggregate estimate that does not distinguish between different types of transactions.

Table 6: Proportional increase in transactions over first 12 months in usage stage

	Mean	Std Dev
Cost-savings, no interruption	0.064	0.092
Cost-savings, no interruption bef. login	0.016	0.036
Cost-savings, no interruption bef. transaction	0.048	0.085

increase of cost savings by 6.4%.

Our results suggest that moving customers along the adoption funnel faster can increase the likelihood of their using the service in subsequent months. The staggered adoption process requires that managers pay particular attention to preventing interruptions and manage customers' progress along the adoption funnel. There are a number of ways of minimizing interruptions to the adoption process, such as in-branch or online customer education measures on the benefits and usage of the platform, timing promotions to coincide with periods with likely interruptions, or using price incentives or deadlines to complete the adoption process or its stages. Though we do not have access to data that could assess the relative costs and feasibility of these different techniques, our results suggest value to investigating various ways of reducing interruptions in the adoption process.

7 Conclusion

Online services that firms offer customers typically have a multi-stage adoption process. Adoption for such services can be characterized as an 'adoption funnel' where customers have the potential to experience interruptions in four incremental stages: Signup, evaluation, trial, and regular usage. The profitability of such services relies on customers successfully navigating the multiple stages and regularly using the service afterwards.

This adoption funnel is vulnerable to interruptions. An interruption can lead to forgetting of information and behavior previously learned and the loss of an implementational mindset. As a result, reengaging in the adoption process may lead to significantly greater cognitive costs, preventing customers from moving to regular usage. We explore empirically how interruptions in earlier stages of the adoption funnel affect later regular usage. We use variation in interruptions resulting from differences in state-level public holidays and vacations to address endogeneity concerns. Our results demonstrate that exogenous interruptions in early stages significantly lower the probability that a customer will later regularly uses the service. Interruptions can therefore partly explain low regular usage.

Our results also highlight that the extensive regulatory efforts to ensure online data security could potentially have unintended consequences for the diffusion of online services. In the case we study, the bank initiated the multiple-stage signup process in response to pressure by European regulators that required individual authorization for the release of personal data. To satisfy the opaque conditions for 'electronic consent' of directive 95/46/EC, the bank used traditional written means to prove that the customers had consented to their data being made accessible online, and developed the system of access codes or TANs for each online transaction. For similar security concerns, US Federal Financial Institutions Examination Council recommended in 2006 that banks use multi-factor identification for authentication as opposed to the commonly used username/password combination. Measures to address such security concerns are not limited to the banking sector. Increasingly complicated processes to protect the security of customers have also been suggested in many industries[13]. Our research emphasizes that multi-stage authentication processes are more vulnerable to interruptions and may lead to lower levels of adoption.

[13]See for example, 'Idaho Code S 39-1394', which requires written authentication for electronic physician order systems.

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