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Stuck in the Adoption Funnel: The Effect of Delays in the Adoption Process on Ultimate Adoption

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Online applications and services automate communications and transactions between firms and consumers, promising large efficiency gains. However, consumers have been slow to use these online technologies intensively, despite widespread adoption of the internet. Customers frequently undergo a staggered adoption process that may involve sign-up, experimentation, trial, and substantial usage until they fully embrace internet services. We ask whether delays in moving through the initial stages of this adoption process contribute to consumers ultimately not using the service intensively. Such behavior would be consistent with laboratory findings on consumer memory. We explore this question using data from a German retail bank where only 24% of the customers who sign up for the bank's online banking service use it substantially. We use exogenous variation in delays in the adoption process, caused by vacations and public holidays in different German states, to identify this effect. We find that delays in the early stages of adoption significantly reduce a customer's probability of moving to substantial usage: A 10-day delay of a customer's first online login reduces the likelihood that she will ever use the technology substantially, by 33%. This effect is more severe for demographic groups with less online experience.

Key words: Technology Adoption, Adoption Process, Online Services, Banking

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1. Introduction

Diffusion of innovations lies at the heart of economic growth (Griliches (1957)), but the diffusion of new technologies and the associated welfare gains may happen only decades after invention (David (1990)). One important area where there is recent evidence of unrealized productivity gains from diffusion is the internet (Baily and Lawrence (2001)). The internet promises cost savings and efficiency gains from the automation of relationships between customers and firms. However, outside of a few narrow sectors, there is little evidence that online applications and services have lived up to their productivity promises (Gordon (2000)). This is surprising because the internet has been very widely adopted (Goldfarb and Prince (2007)). In this paper, we ask whether in the light of a recent behavioral literature on consumer memory loss, delays in the staggered adoption process for these technologies can explain slow diffusion and lack of substantial usage.

We use data on online banking to investigate the empirical relationship between the time spent in different stages of the adoption process for internet services and whether a customer ultimately embraces a technology. Online banking is one of many online technologies that promise to reduce transaction costs and increase efficiency between customers and firms. We have detailed customer-level data on the timing of sign-up for the service, log-ins into the service and transactions. These data allow us to follow customers through the adoption process and evaluate how interruptions in progressing through the stages of the adoption process affect the timing of progress and the eventual adoption outcome.

We characterize a customer's adoption process as an "adoption funnel." The image of the funnel reflects the extent of customer attrition at four stages in the adoption process: sign-up, evaluation, trial, and substantial usage. In our data, which come from a large German retail bank, only 73% of customers who signed up for online banking ever logged in. 63% of customers ever completed an online transaction, and only 24% ever made more transactions online than offline.[1] Many customers take a long time to move to the next stage in the adoption funnel. The transition from sign-up to

[1] This corresponds to findings by Wuebker and Hardock (2002) that about one-third of German online banking customers regularly use their online accounts.

first login takes on average 37 days, and the subsequent transition from first login to the first online transaction takes roughly 21 days. Laboratory evidence from psychology suggests that progress in later stages of adoption may be linked to how fast customers move through earlier stages. For example, the ability to recall information improves for those participants who were asked to recall the information on a previous occasion (Bjork and Bjork (1992), Richardson-Klavehn (1988), Bjork and Geiselman (1978)). Similarly, when consumers learn to use a new technology, an interruption of the learning process may lead to forgetting and the loss of knowledge, which slows or stops adoption, as suggested by Speier et al. (1999a) and Speier et al. (1999b). We explore empirically whether the knock-on effects of early delays, possibly caused by memory loss, slow customer adoption and explain the empirically observed gap between sign-up and usage.

It is difficult empirically to identify the effect of delays in the initial stages of the adoption process on ultimate adoption. A customer's slow progress through all four stages could merely reflect that particular customer's technological aptitude, rather than being a causal relationship between how long a customer took to first log in and her subsequent progress in the technology adoption process. Ideally, we would randomly delay some customers' progress in the initial stages of the adoption funnel and then measure how this affects ultimate adoption. Instead, we exploit a natural experiment that results from variation in the number of school vacation days and public holidays across months and across German states. These vacations and public holidays affect how easily a customer can get online and move to the next stage in the online banking adoption process. We find a strong negative effect: A delay in an early stage of the adoption process reduces a customer's probability of substantially using the new technology. For example, a 10-day delay of a customer's first online login reduces her likelihood of using the technology substantially, by 33%, while a similar increase in the time between login and trying the technology reduces her likelihood by 60%.

We also find that the effect of interruption on ultimate adoption is largest among demographic segments that use the internet less frequently. Since these groups have more to learn and retain about internet services, these findings are in line with the explanation that memory loss may cause the knock-on effect of delays.

The paper is organized as follows. In section 2 we set our findings in the context of the previous literature, before presenting our data in section 3. We record the extent of customer attrition along the adoption funnel for this technology in section 4. Section 5 contains the results of our instrumental variable estimation and the stratification of the results along demographic groups. Section 6 investigates the efficiency implications of delays in the adoption process. We conclude in section 7 with a summary of our results and discuss their applicability to other technologies.

2. Literature Review

We ask whether delays in the staggered adoption process for online technologies can explain slow diffusion. Our work draws upon three streams of research.

First, we build upon substantial research in economics, such as Griliches (1957) and Mansfield (1961), that has highlighted the importance of understanding micro-level heterogeneity as driving the speed with which technologies diffuse. The subsequent empirical literature on diffusion has modeled adoption as a binary decision. In this paper, we incorporate insights from the management literature that underline that adoption in many settings should be thought of as a process, rather than a one-off decision (Rogers (2003), Kalish (1985), and Van Den Bulte and Lilien (2007)). Recognizing that adoption for many technologies is a process, rather than a discrete decision, may help explain why some technologies are slow to diffuse. We explore this by drawing on a second recent stream of behavioral research on the role of delays and interruptions in consumer behavior (Greenleaf and Lehmann (1995)).

Imperfect memory may lead to excess inertia (Hirshleifer and Welch (2002)). Laboratory evidence illustrates that the ability to recall previously acquired information - such as an understanding of the intricacies of the online banking interface - declines in the time that has passed since information acquisition. Bahrick (1979) provides early experimental evidence on the importance to knowledge maintenance of successive exposures to information and on the role of the length of time between exposures for forgetting, suggesting that a sequence of closely-spaced exposures followed by a long-delayed exposure impairs knowledge acquisition relative to alternative sequences. In a set of studies by Bjork and Bjork (1992) and Richardson-Klavehn (1988) on individuals' capacity for memorization, subjects were asked to memorize two lists of items. Recall of the information was tested on the same day and again 24 hours later. The participants who were most successful at recalling the information by the end of the experiment were those who had to recall the same list of items on both days (84% recall rate), relative to participants who did not have to recall any information after memorizing it, but only on the day after (63% recall rate) or those who had to recall different lists of items on the consecutive days (49% recall rate). Similarly, Bjork and Geiselman (1978) find that an initial recall facilitates final recall of the same information, but also impairs the final recall of other previously acquired information. Soman (2003) points to behavioral side-effects of forgetting, suggesting that a long delay after the initial exposure to an experience may lead to a negative retrospective evaluation of the experience. Related to these findings is work by Speier et al. (1999a) and Speier et al. (1999b), who suggest that an interruption of the learning process may lead to forgetting and the loss of knowledge. Dhar et al. (2007) find evidence that momentum drives subsequent consumer behavior in the context of shopping trips: the likelihood to purchase a particular product is higher for those shoppers who previously purchased another, unrelated product. These findings on memory and momentum relate to our work, in that they suggest that an interruption of the learning process for a new technology may lead consumers to forget what they previously learned. The lack of information recall in the interim may then slow down or stop the adoption process.

Last, our findings add to a considerable body of research that examines why some technologies are not used significantly after initial adoption. The majority of this research has focused on corporate settings, where the employer makes the initial adoption decision to sign up for a service or install a new technology, but the employees make the decision to use the product or service (see Forman and Goldfarb (2006) for a survey of this work). A significant gap between installation and ultimate usage by employees has been documented for technologies as diverse as client/server computing, electronic mail, and videoconferencing (see among others Bresnahan and Greenstein (1996), Astebro (Astebro), and Tucker (2007)). The implications for firm productivity and profitability are possibly severe. Brynjolfsson and Hitt (2003) and Bresnahan et al. (2002) point to low usage of IT as a possible explanation for the apparent small productivity gains attributable to firms' IT investments. Devaraj and Kohli (2003) find actual usage to be a critical factor in an IT profitability analysis.

The focus on corporate settings, however, means that the explanations for slow diffusion in this research lie in coordination difficulties among employees and firms. Such explanations are less useful in understanding similar gaps between adoption and usage behavior in situations where a single economic actor controls all stages of the adoption process. Recent research has provided some evidence of the prevalence of such a usage gap between the initial sign-up, trial, and actual usage for a number of consumer technologies. For example, in internet retailing, Goettler and Clay (2006) report that approximately 40% of customers of an online grocer never place an order with the service. Goldfarb and Prince (2007) show that for the internet, there is not necessarily an association between adoption propensity and eventual usage. Meuter et al. (2005) show similar patterns and point to self-reported "consumer readiness" or ability as one differentiating factor between users and non-users of self-service technologies in their sample. In focus groups, Sarel and Marmorstein (2003) observe a gap between sign-up for online banking and actual usage. Encouraging usage benefits firms: both Hitt and Frei (2002) and Lambrecht (2005) find that customers who signed up for PC banking or use online banking actively are more profitable and more easily retained.

Our work builds on all three research streams: We focus on a consumer's technology adoption, and frame this adoption as a multi-stage process. To explain the documented usage gap, we introduce an additional dimension of a consumer's adoption process: the timing of successive stages. Empirically, our detailed usage data allow us to document a customer's transition between the multiple adoption stages and to explore the effect of delays on ultimate adoption. We draw on research on memory and momentum in consumer behavior to explain why such knock-on effects may arise.

3. Data and the Online Banking Industry

Our data come from a confidential, customer-level data set from a major German retail bank over a 23-month period from September 2001 to July 2003. The bank introduced online banking in 1997. The bank's online service allowed not only monitoring of checking, brokerage, and credit card accounts, but also the ability to initiate domestic and foreign wire transfers; to purchase or sell brokerage account holdings; and to set up recurring payments. This spread of services suggests that the potential for customers to benefit from online banking is high as it takes less time to initiate a transaction online than in a branch. The ability to initiate transactions online also promises cost savings to the bank: in Germany, the cost of processing a paper-based wire transfer, which are significantly more popular in Europe than check-based transactions, is estimated at €1, but an online-initiated wire transfer costs only €0.01 (Wuebker and Hardock (2002)).

For each of 55,513 customers, the data include the date of sign-up for online banking, the monthly number of log-ins, the monthly number of online transactions broken down by type, and the monthly number of off-line transactions. Off-line transactions are not available by type, but include cash withdrawals (common in Germany) and check transactions (uncommon in Germany). In addition, any recurring transactions that were set up off-line or online are counted as such a transaction in perpetuity, independently of whether the majority of the customer's transactions still follows the same pattern. The lack of detailed information on offline usage entails some difficulties in defining usage intensities of online and offline services, which we address in greater detail below. In addition, we observe the age and gender of the primary account holder and the zip code of each customer's branch, which we take as her zip code of residence. 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 in such instances.

Of the 55,513 customers, 3,200 had signed up for online banking prior to our data period. We focus on the 3,592 customers who signed up for the service during the two-year span of the data. Since these customers were adopting the service four or more years after its initial introduction, it seems reasonable to characterize them as representative of an early majority rather than as innovators (Rogers (2003)). Any interpretation of our coefficients, therefore, should be conditioned on the fact that we have data on a subset of customers who ultimately use or would adopt online banking. We have up to 24 observations per customer, depending on when they signed up for online banking. Our initial panel dataset has 45,236 monthly observations.

Our demographic data gives a snapshot picture of these customers. The average customer is 35.8 years old. 52% of customers are male. 30.6% of customers have a brokerage account with the bank in addition to their checking account. The customers are located in all the 16 German states, with North-Rhine/Westphalia having the highest number of customers and Saarland the lowest. The distribution of customers across states is strongly correlated with the states' population.

To control for diverging time trends across and within states, we integrate our primary data set with aggregate data on zip-code level demographics obtained from Acxiom Deutschland GmbH. Of the various demographic variables, only median per-capita income is significantly related to online banking decisions, so we focus on this in our regressions. We also use annual information from Hoppenstedt Firmeninformationen GmbH on the number of the bank's physical branches in the local zip code. We use variation in branch availability across zip codes, together with changes in the number of local branches over time, to identify the effect that the number of branches has on the adoption process. Over the sample period, the bank decreased its branch network by on net 106, or 5.59% of, branches. If these branch closures and openings represent unobservable time trends in the profitability of that location, then interpreting the effect of network density on adoption as causal will be problematic. However, we tried correlating the number of bank branches or the changes therein with demographic variables at the zip code level. The ability of income and population levels or, alternatively, their growth rates, to explain variation in branch closures is extremely limited. Since the zip-code itself is not necessarily the market area of the particular branch, this may reflect that branch closure decisions are based on the profitability of a neighborhood that is larger than the branch's immediate zip-code area for most branches.

4. The Adoption Funnel

4.1. The Four Stages of the Adoption Funnel

Adoption frequently refers to the consumer'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, however, since the consumer undergoes a staggered adoption process. In the case of online banking, the consumer goes through four stages until ultimate adoption or the point where the bank realizes cost savings. We call this adoption process the adoption funnel. It typically requires a customer to first sign up for a service. When she signs up, she becomes identifiable to the firm, allowing it to track her subsequent usage behavior. The customer can then evaluate and explore the service and its offerings. Depending on the outcome of the evaluation stage, the customer may move to the next stage and try the service. Only customers who move to the final stage and use the service regularly generate revenue or reduce cost for the firm. In summary, the adoption process involves four successive and incremental stages:

1. Sign-up: A customer signs up for a self-service technology.
2. Evaluation: A customer evaluates the new service.
3. Trial: A customer first tries the service.
4. Substantial usage: A customer substantially uses the service.

In our data we observe the first stage when a customer signs up for online banking. This involves submitting a paper form to a bank branch indicating the wish to use online banking. Upon receiving the application form, the bank returns a letter detailing log-in identification. The creation of the log-in details is automated and takes between one and two working days, so that the customer is ready to log into the platform within five to seven working days after the bank's receipt of her application.

In the second stage, the customer logs into the web site, sees her account details online, and investigates the functionality of the new service. Our interpretation of this first log-in is that a customer evaluates the service and uses it for informational purposes. While some customers primarily use online banking to monitor their account activity regularly and have arguably completed the adoption process in this second stage, we treat it as incomplete since this stage does not entail direct cost savings to the bank. We measure the third stage, trial, as the first online transaction the customer initiates. In our context, a variety of definitions of the fourth stage, substantial usage, are possible to capture high usage intensity of the online channel. As discussed above, our data contain only overall information on the number of offline transactions, including cash withdrawals per month. As a result, it is not possible for us to discern wire transfers, brokerage transactions and newly set recurring transactions from such other transactions to construct a clean measure for offline and consequently total usage. We therefore approximate substantial usage by requiring that the customer conducts 50% of all recorded transactions online and investigate the sensitivity of our results to this measure by testing different alternative definitions. A second limitation of our data is the aggregation of login and transaction activities to the monthly level, which introduces measurement error into measures of the time spent in different stages of the funnel.

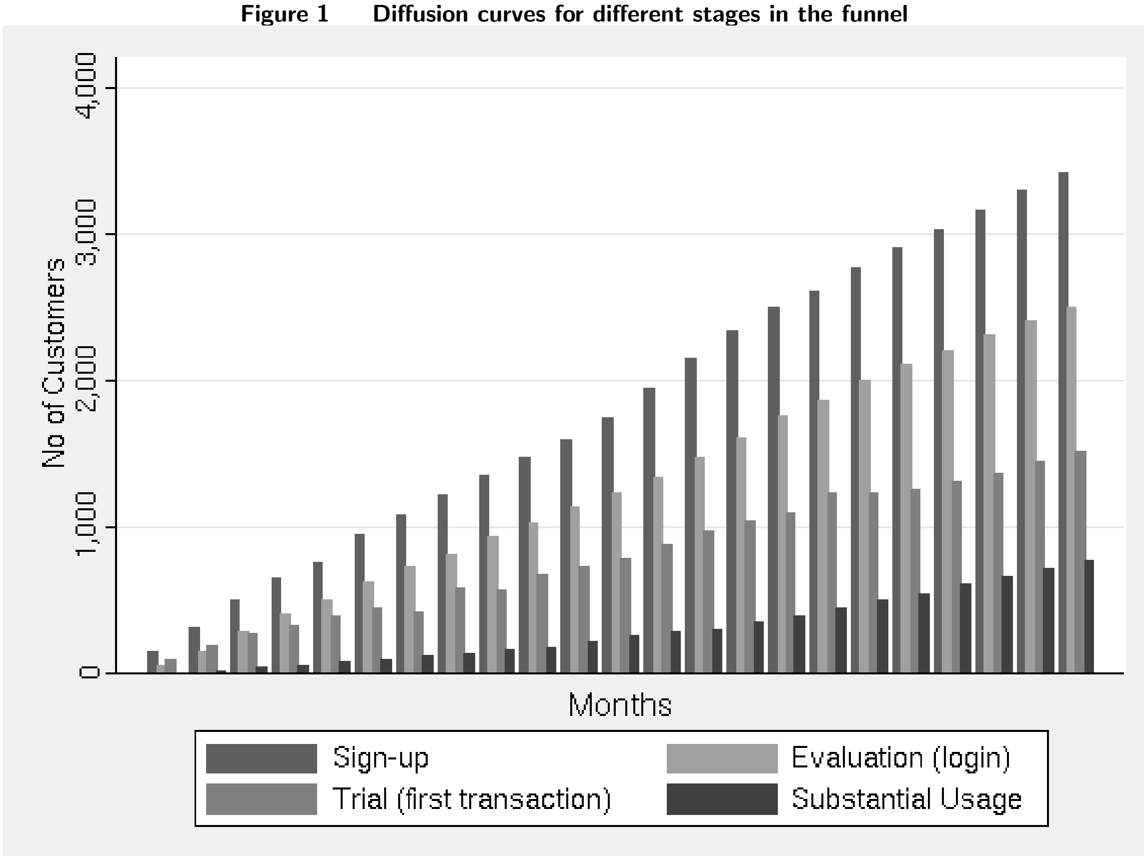
While we develop the adoption funnel in the context of online banking, the general framework applies to other customer self-service technologies. Depending on the service, the exact sequence of stages may differ or the stages may be more nuanced. For example, it is possible that a customer first evaluates the service and is only required to log-in at the trial stage.

4.2. Conversion along the Funnel

We begin with an analysis of attrition as customers move through the funnel. Figure 1 documents that the diffusion process differs considerably for the four stages in the funnel: significantly fewer customers get to the stage of substantial usage than sign up for online banking. Table 1 provides more detail on conversion rates along the funnel. Of all customers who signed up for the service, 73% logged in at least once and 63% completed at least one transaction online. For only 24% do we find substantial usage of online banking.

We now turn to the time spent in different stages of the adoption funnel. On average, customers spend 37 days between sign-up and log-in, 21 days between log-in and the first transaction, and

Figure 1 Diffusion curves for different stages in the funnel



88 days between the first transaction and substantial usage. These estimates are lower than the real time taken because we only observe how long a particular stage took if a customer reached the subsequent stage in the two years of our panel. To account for this downward bias and the resulting censoring of the hazard rate, we use a discrete time hazard specification in our estimation in section 5.

The bank collects two pieces of demographic information about their customers at the individual level; age and gender. We exploit this information to stratify our results by customer characteristic. We divide our sample by whether the primary account holders are male or female (52 vs. 48% of sample customers) and whether they are under or over 40 years of age (68 vs. 32% of sample customers). Our stratification is meant to proxy for the customer's likely exposure to the internet. Market research suggests that by 2002, in age groups below 40, an average of 74.3% of Germans use the internet, compared to an average of 30.3% for the population above 40, with a decline in

Table 1 Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: All Customers (N=3592)				
Share ever evaluate	0.730	0.444	0	1
Share ever try	0.625	0.484	0	1
Share ever use substantially	0.237	0.426	0	1
Time between Sign-up & log-in (N=2622)	37.071	68.717	0	699
Time between log-in & First Transaction (N=2244)	20.877	56.852	0	607
Time between First Transaction & Substantial Use (N=853)	88.070	128.125	0	668
Panel B: Customers under age 40 (N=2523)				
Share ever evaluate	0.746*	0.435	0	1
Share ever try	0.655*	0.475	0	1
Share ever use substantially	0.240	0.427	0	1
Time between Sign-up & log-in (N=1881)	37.845*	70.307	0	699
Time between log-in & First Transaction (N=1650)	19.358*	51.445	0	607
Time between First Transaction & Substantial Use (N=599)	92.195*	129.405	0	668
Panel C: Customers over age 40 (N=1069)				
Share ever evaluate	0.696*	0.460	0	1
Share ever try	0.560*	0.497	0	1
Share ever use substantially	0.232	0.422	0	1
Time between Sign-up & log-in (N=741)	35.311*	64.968	0	638
Time between log-in & First Transaction (N=594)	24.650*	68.361	0	607
Time between First Transaction & Substantial Use (N=254)	79.019*	125.033	0	668
Panel D: Female customers (N=1558)				
Share ever evaluate	0.730	0.444	0	1
Share ever try	0.623	0.485	0	1
Share ever use substantially	0.214*	0.410	0	1
Time between Sign-up & log-in (N=1132)	37.571*	65.457	0	607
Time between log-in & First Transaction (N=963)	16.258*	46.819	0	549
Time between First Transaction & Substantial Use (N=335)	95.100*	134.029	0	668
Panel E: Male customers (N=1856)				
Share ever evaluate	0.733	0.443	0	1
Share ever try	0.630	0.483	0	1
Share ever use substantially	0.255*	0.436	0	1
Time between Sign-up & log-in (N=1354)	35.503*	69.369	0	699
Time Between log-in & First Transaction (N=1163)	24.533*	63.601	0	607
Time Between First Transaction & Substantial Use (N=482)	82.600*	123.875	0	638

* indicates a statistically significant difference in means at the 99% confidence level in comparing panels B and C and panels D and E, respectively.

the share of internet users by 17.8 percentage points in moving from 30-to-39 year olds to 40-to-49 year olds. Similarly, men have internet usage rates of 53% compared to women with 36%.[2]

Table 1 shows that while female customers are equally likely to evaluate or try online banking

[2] Van Eimeren, Birgit, Heinz Gerhard and Beate Frees, "ARD/ZDF-Online-Studie 2004: Internetverbreitung in Deutschland: Potential vorerst ausgeschoepft?", Media Perspektiven, 8, 2004, 350-370.

as their male counterparts, they are statistically significantly less likely to adopt fully by using the service substantially. Younger customers, in contrast, are significantly more likely than customers over the age of 40 to both evaluate and try the service.

5. Results

The conversion rates presented above suggest that customers' progress along the adoption funnel is subject to delays and to substantial attrition. These delays may possibly lead consumers to forget what they previously learned about the use of online banking and, thus, cause attrition. In this section, we explore the extent to which such delays in the early stages of the funnel can explain why customers stop short of completing the adoption funnel. To empirically investigate this question, a regression of attrition on the length of time spent in an earlier stage may not be sufficient: a correlation between time spent and attrition may simply result from customer heterogeneity. For example, a positive correlation could merely reflect the fact that some customers are faster at adopting technology than others. Instead, we want to explore the causal effect that a customer spending a long time between sign-up and log-in, and between log-in and the first transaction, has on the likelihood of ultimate adoption.

We therefore need a variable that shifts independently from other such factors how long an individual spends in a given stage, for example, between log-in and sign-up. We exploit the fact that Germany uses a staggered system of school vacations across states, leading to wide variation in the timing of states' school vacations for different customers in our data set. We begin with an overview of the German vacation system and show evidence that the amount of vacation available affects the time a customer spends in the initial stages of the adoption funnel. We then turn to our main empirical results regarding momentum along the adoption funnel.

5.1. The Effect of Vacations on Delays

While educational policy is a responsibility of the individual German states, the federal government coordinates a system of staggered school vacations across states. This government policy, together with limitations on truck usage of the highway system,[3] aims to reduce traffic congestion during the summer months by ensuring that not everyone goes on vacation at the same time.

At these state specified times, many Germans leave their homes to travel. Even with the staggered vacation periods, this results, for example, in heavy congestions of the highways at the start and end of the different states' vacations.[4] Germans, on average, take 26 vacation days a year (out of the average 5-6 week allowance), compared to the 11 days taken by Americans,[5] and go on roughly 1.6 vacation trips per year.[6] This vacation is often booked up to one year in advance. Figure 2 displays the extensive variation in vacations and public holidays both across states and within states over time.

Vacation days affect a customer's ability to engage in the adoption process because they usually separate a customer from her computer. This exogenous variation in computer usage has also been exploited by Oberholzer-Gee and Strumpf (2007) who study the effect of music downloads on record sales. They show that German school vacation affects downloads and uploads to P2P sites and use vacations to instrument for US record sales. In the context of online banking, a customer who leaves her home for vacation is unlikely either to receive the mailing of her online banking details, such as pre-assigned transaction-specific authorization numbers, or to carry these with her. In addition, consumers are warned against using online banking on public computers at their vacation destination for security reasons.[7] Since recurring transactions, such as utility payments, are typically processed via direct debit, there is limited need for online banking to keep up with regular bill payments on vacation.

[3] Bundesministerium für Verkehr, Bau und Stadtentwicklung, "Lkw-Fahrverbot in der Ferienreisezeit", `http://www.bmvbs.de/-,302.2221/Lkw-Fahrverbot-in-der-Ferienre.htm` (accessed August 16, 2007).

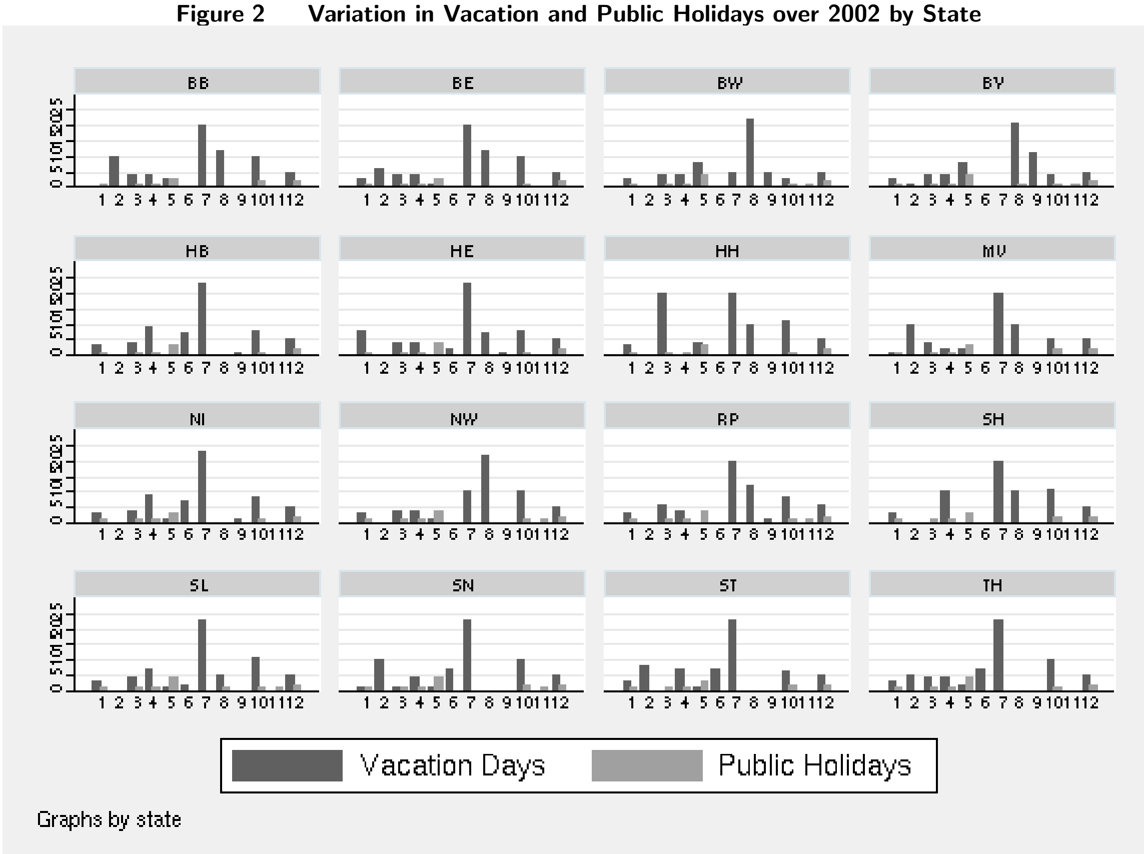
[4] Stroisch, Jörg, "Stau im Urlaub vermeiden", Zeit online, `http://www.zeit.de/reisen/service/stau` (accessed August 16, 2007).

[5] Expedia.com, "2007 International Vacation Deprivation Survey Results", `http://www.expedia.com/vacationdeprivation` (accessed August 16, 2007).

[6] Axel Springer Verlag AG Marketing Anzeigen, "Tourismus 2002", `http://www.mediapilot.de/cda` (accessed August 16, 2007).

[7] The German Federal Office for Security in Information Technology issued a warning against using online banking on vacation: Bundesamt für Sicherheit in der Informationstechnik, "Brennpunkt: IT-Betrueger machen keinen Urlaub", `http://www.bsi-fuer-buerger.de/brennpunkt/urlaub.htm` (accessed August 16, 2007); "Viren, Würmer und Trojaner: Im Urlaub kein Online-Banking", n-tv, July 20, 2006, available at `http://www.n-tv.de/691473.html`.

Figure 2 Variation in Vacation and Public Holidays over 2002 by State



The decreased accessibility of online banking while traveling implies that a customer who signs up for the service in a vacation-heavy month would likely spend longer between signup and log-in than a customer who signs up at another time, for reasons unrelated to unobservable customer tastes for technology. Time off may similarly affect the transition to substantial usage. Similar customers will spend different times between sign-up and log-in, and log-in and their first transaction, merely because they sign up, or log-in, in different months. We use this fact to identify the causal effect of spending longer in the initial stages on the time spent in later stages of the adoption funnel.

There is also variation in the number of state-level public holidays. Traffic patterns suggest that travel is less frequent on these holidays than at the beginning or end of school vacations. The automobile club ADAC, for example, projects no congestion for 20% of 2007 public holidays and holiday weekends and medium to heavy congestion for 60% of the cases, in contrast to projected medium to heavy congestion on 95% of the beginning and ending weekends of states' school vacations.[8]

[8] See `www.adac.de/Verkehr/Staukalender/default.asp` (accessed August 16, 2007).

Spending public holidays at home may award consumers additional time to catch up on chores such as experiment with online banking than during either vacation days or regular working days. The average effect of public holidays on the propensity to use online banking is therefore less clear than the effect of vacations, with travel – albeit less than during vacations – and possible catch-up at home having offsetting effects on online banking usage. More broadly, however, since public holidays alter consumers' availability of time relative to a normal working day, we would expect the monthly transition probabilities of progressing through the funnel to differ across otherwise identical customers with different numbers of public holidays available to them during the month.

For vacations and public holidays to be valid instruments, the presence of public holidays and vacation days has to be independent of other factors that influence a customer's adoption behavior. For example, it would be problematic if the bank changed its marketing campaigns in line with these regionally different holidays. Conversations with the bank assured us, however, that the bank conducted such marketing efforts at a national level only. More importantly, vacations may shift the customers' adoption decisions to specific times or be correlated with customer unobservables. In our data, we do not observe extreme clustering of customer sign-ups for online banking just prior to or immediately after school vacations. Across customers, 22.0% sign up for the service during vacations, 13.9% and 14.1% within 10 days of the closest vacation beginning or end, respectively, and the remaining 50% outside of vacation periods.[9] This suggests that customers are not forward-looking and do not take into account planned vacations and public holidays in deciding when to sign up for online banking. We do not observe customer anticipation, but we could find no statistically significant relationship between various measures of customer adoption and the number of vacations and public holidays in the subsequent month. If customers were anticipating the effect of vacation on their future usage patters, then it is likely that the adoption rates would be influenced by future public holidays and vacations.

To further motivate our choice of instrument, we test whether vacations are correlated with

[9] Across states, schools are closed for vacation approximately 20% of the time and 34% of all days fall within 10 days from either the beginning or the end of a school vacation period.

Table 2 Proximity of sign-up decision to vacations

	N	Age ≤ 40	Age > 40	Men	Women	Brokerage	Checking
Vacation close to sign-up date							
(1) Sign-up in vacation	756	67.6	32.4	52.4	43.7	27.3	72.7
(2) Sign-up < 10 days before vacation	479	69.5	30.5	50.7	43.4	23.2	76.8
(3) Sign-up < 10 days after vacation	487	70.8	29.2	51.1	45.0	30.4	69.6
(4) Sign-up at other times	1721	66.7	33.3	51.3	43.1	28.4	71.6
Difference bw. (1) and (4) significant		no	no	no	no	no	no
Difference bw. (2) and (4) significant		no	no	no	no	**	**
Difference bw. (3) and (4) significant		no	no	no	no	no	no
Days of vacation in sign-up month							
(5) Vacation below median (≤ 3 days)	1847	67.2	32.8	49.9	44.1	27.2	72.8
(6) Vacation above median (> 3 days)	1595	68.7	31.3	53.2	43	28.3	71.7
Difference bw. (5) and (6) significant		no	no	no	no	no	no

customer characteristics. Our assumption that our instrument is a random treatment across customers could be violated if, for example, customers who likely have higher internet usage rates, such as younger people, were concentrated in states that have a higher number of vacation or public holidays. Table 2 compares the share of customers of various attributes who sign-up close to or in a vacation or who have an above-median amount of vacation in their sign-up month to their counterparts. Sign-up behavior does not differ significantly in relation to vacations for different demographic groups, suggesting that vacation in the sign-up month is not correlated with observable customer characteristics, with the possible exception of brokerage account customers who we find to be less likely to sign-up for online banking close to vacations.

We next provide evidence on the explanatory power that our instrument, the number of vacation days in the month of a customer's sign-up, has in predicting the customer's delay between signing up for online banking and first logging into the service. We explain the time a customer spends between signup and login by the vacation days and public holidays in the signup month, as well as controls for the number of branches in the customer's zip code, the median zip-code income, and month-year and state fixed effects.

Both the number of vacation days and public holidays in the sign-up month have statistically significant effects on the average time spent in moving from sign-up to login. We find that additional days of vacation increase the time delay, consistent with customers being away from their home computers, while public holidays decrease the time lags. This is possibly because, as indicated

Table 3 Determinants of Time between Signup and log-in

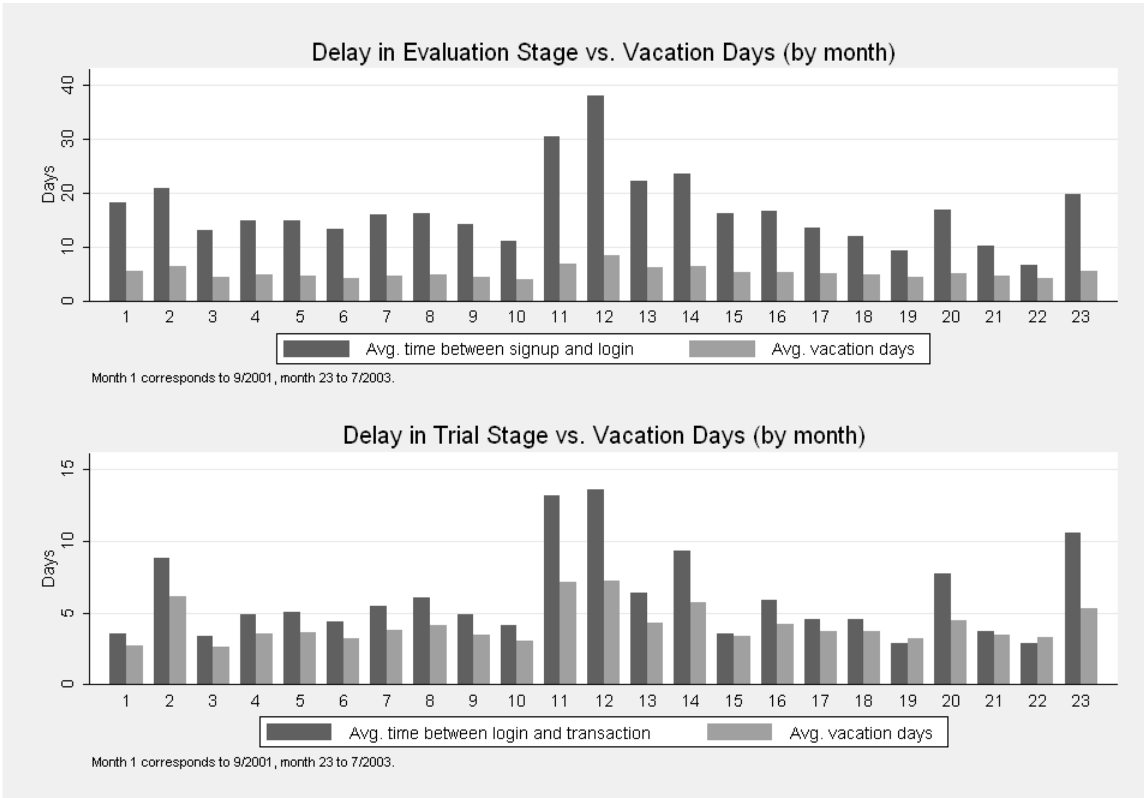
	Coefficient		Robust Std. Error
VacationDays Signup Month	3.3616	***	0.3821
PublicHols Signup Month	-21.5539	***	2.7267
Branches in Zip	33.6380	***	4.8357
Income	5.0572	***	1.0945
Month-Year Dummies	Yes		
State Dummies	Yes		
Observations	5691		

Dependent Variable: Days between signup and first login. Sample: Customers who have logged in but not yet performed an online transaction.
* $p<0.10$,** $p<0.05$,***$p<0.01$.

above, people use the extra time to catch up with chores such as banking. Vacations and public holidays also have economically significant effects on the delay between sign-up and login. Increasing the number of vacation days in the customer's sign-up month by one standard deviation of 6.21 days increases the average delay between sign-up and login by 20.87 days, while a one-standard deviation increase in the number of public holidays, or 0.90 days, yields a decrease of a similar magnitude of 19.43 days. We conclude this discussion with a graphical display of the relationship between the residual time spent in the first two stages of the adoption funnel, after removing the effect of the other explanatory variables in table 3, and the number of vacation days in the signup or log-in month, respectively. Figure 3 illustrates the co-movement in delays and vacation times, suggesting that vacation time at the time of earlier decisions indeed shifts the time spent transitioning to a later stage of the adoption process.

Lastly, we test whether different stages of a customer's adoption process are interrelated. We find that a customer's probability to transition to the next stage is affected by the number of vacation and public holidays at the time she completed her previous transition: Vacation days in the sign-up month decrease and public holidays increase a customer's probability to log-in for the first time (-0.009, p-value <0.001 for vacation; 0.085, p-value <0.001 for public holidays), controlling for income, branch density, and state and month dummies. We find similar results for a customer's probability to transition from her first log-in to her first online transaction.

Figure 3 Relationship between residual time between sign-up and log-in or between log-in and online transaction and vacation days



5.2. The Effect of Delays on Incremental Adoption

The adoption process is a typical latent variable setting where we can observe a series of discrete choices in each month about whether to move to the next stage of the funnel but not the underlying benefits. It is difficult to control for the endogeneity of an explanatory variable in a typical hazard model (Bijwaard (2007)). Instead as discussed by Allison (1982), we exploit the fact that discrete-time hazard models can be estimated using standard binary discrete choice models such as a binary probit, if all the data are organized into a panel and all post-adoption observations are deleted. The advantage of this procedure is that it allows us to retain the attractive hazard model properties, which control for censoring and entry and exit of observations, while still gaining the specification flexibility of a binary choice model.[10]

In our setting we estimate the probability to transition to a later stage of the adoption funnel,

[10] See Van Den Bulte and Lilien (2007) for a previous application of this empirical method.

i.e. trial and substantial usage, conditional on having reached an earlier stage, i.e. signup and evaluation. We use an instrumental variable probit specification to look at the effect of the time spent in early stages on the probability of moving to the later stages of the adoption funnel. The number of vacation days and public holidays at the time of reaching the earlier stage in the funnel serve as instruments to control for the possible endogeneity of the variable measuring time spent in the early stage. We include the results of the first-stage regressions and, where appropriate, Durbin-Wu-Hausman tests to support the statistical validity of our instruments. We consider the decision to initiate the first online transaction first and the decision to transition to substantial usage next.

Transition to Trial We measure the effect of the number of days between sign-up and log-in on a customer's propensity to complete her first online transaction. We perform our empirical analysis on the subset of 7,573 monthly observations of customers who have already logged in to the service, but have not yet completed an online transaction. In this specification, as in all of the remaining specifications, we control for differences in propensities to conduct online activity, here transactions, across time and states by using a full set of dummies for each month and each state in our regressions. We further include controls for the number of bank branches in the customer's zip code and the zip code's median income, both of which change over time and across zip-codes. Last, we include variables for the number of vacation days and holidays in each potential transition month.

Table 4 displays the results for this initial specification. The first-stage regressions for the endogenous variable *Time between Sign-up and Log-in*, included for reference, yield similar results to the ones in Table 3. They differ from the above specification by the inclusion of vacation days and public holidays in the possible transition month to the trial stage. As above, we find that vacation days increase the time lag, while public holidays decrease the time lag.

Our instrumental variable probit estimate for the effect of time between signup and log-in on trial is -0.0082. This translates to a monthly marginal effect of approximately -0.0027, implying that every extra day spent between sign-up and log-in reduces the probability of doing an online transaction by 0.0027 in a given month. Therefore, a 10-day delay would reduce the probability of trial in that month by approximately 0.027. Such a delay would reduce the average monthly propensity of 0.29 of trying the technology by 9%.

The control variables $VacationDays$ and $PublicHols$ have an effect on the timing of the first transaction that is directionally consistent with our instruments' effect on sign-up, though not significant at conventional levels. The point estimates suggest that vacation days reduce the likelihood of doing an online transaction, while public holidays increase the likelihood of doing an online transaction.

We also find a consistent, significant effect of changes in branch density on trial. An increase in the number of bank branches is associated with a higher likelihood that a customer will do an online transaction. This could suggest that branch banking complements online banking or that an increase in branch density promotes online activity, through e.g. more intense exposure to advertising.

The first column of table 4 displays results from a regular probit estimation. A comparison of the estimates for the effect of time between sign-up and log-in across columns one and two shows that the IV probit regression results in a substantially more negative effect than the regular probit. To the extent that transition speeds are correlated with a customer's technological aptitude, we would expect the uninstrumented results to overstate the effect of delays. Instead, we find an implied upward bias in the coefficient, which makes it unlikely that biases caused by technological aptitude dominate the results. Generally, this result suggests that there are additional, and possibly offsetting, confounding factors that drive the uninstrumented effects. Our instrumental variable results capture the effect of delays that can be predicted by variation in vacations and public holidays. This is, strictly speaking, a "local average treatment effect"[11] whereby the measured coefficient for the instrumental variable results only measures the mediated effect of vacation and

[11] See Imbens and Angrist (1994) for a detailed description of limitations of local average treatment effects.

public holidays on the adoption process, but not necessarily the effect on the adoption process of other events that may spark a delay or an acceleration in adoption.

We conduct several robustness checks of our results. The third column of table 4 displays standard errors that are clustered at the state level, to account for within-state correlations in behavior. We take the most conservative approach and cluster at the state level even though there is additional variation over time. Unsurprisingly, the clustering leads to a slight loss of significance compared to the robust standard errors in column two. The fact that we retain significance at the 5% level for the effect of time between sign-up and log-in supports our general results. We also verified our results using a linear probability model, leading to similar coefficients. The Durbin-Wu-Hausman test for endogeneity allows us to reject the exogeneity of the variable *Time between Sign-up and Log-in* at the 1% level for all specification of the linear probability model. Last, we estimated a Cox proportional hazards model, not controlling for the endogeneity of *Time between Sign-up and Log-in*. The relative size of the estimates resembles that of the regular probit. Including the instruments directly in the main model resulted in the same sign for the effect of these variables as in the IV probit models.

Table 4 How Time between Sign-up and log-in affects move from log-in to first Online Transaction

	Probit	**Probit IV**	
Standard Errors	Robust	Robust	Clustered State
Time between Sign-up & log-in	-0.0005**	-0.0082***	-0.0082**
	(0.0003)	(0.0016)	(0.0034)
Branches in Zip	0.2528***	0.1836***	0.1836
	(0.0673)	(0.0635)	(0.1434)
Income	0.0057	0.0087	0.0087
	(0.0084)	(0.0080)	(0.0225)
VacationDays	-0.0053	-0.0064	-0.0064*
	(0.0042)	(0.0041)	(0.0033)
PublicHols	0.0070	0.0035	0.0035
	(0.0653)	(0.0613)	(0.0669)
		First Stage Regressions for ‘Time between Sign-up & log-in’	
VacationDays Signup Month		1.0335***	1.0335**
		(0.1593)	(0.4811)
PublicHols Signup Month		-4.7521***	-4.7521***
		(0.7175)	(1.7547)
Branches in Zip		-5.3939**	-5.3939
		(2.7380)	(6.2024)
Income		0.4104	0.4104
		(0.4205)	(0.7502)
VacationDays		-0.3192	-0.3192***
		(0.2222)	(0.1131)
PublicHols		0.4323	0.4323
		(2.9060)	(2.1795)
Adoption month Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Observations	7573	7573	7573

Dependent Variable: Indicator for when a customer first does an online transaction. Sample: Customers who have logged in but not yet performed an online transaction.
* p<0.10,** p<0.05,***p<0.01.

Transition to Substantial Usage Now, we turn to the next stage of the adoption funnel and explore whether delays in earlier stages drive a customer's probability to transition to substantial usage, i.e. the eventual adoption outcome. We measure both the effect of the number of days a customer spends between sign-up and log-in and the effect of the number of days between log-in and their first online transaction on progressing to substantial usage. Table 5 explores the results for these regressions. We again find that delays in the earlier adoption stages have a negative effect on substantial usage. Our IV-probit estimate of -0.0106 for the effect of time between sign-up and log-in on substantial usage implies that each day of delay between sign-up and log-in has roughly a -0.001 marginal effect on the likelihood of adoption. This marginal effect should be compared to an average propensity to substantially use the technology in each month of 0.042. A 10-day delay between sign-up and log-in therefore reduces adoption propensities by roughly 0.014 percentage points, an effect of 33% on the baseline. Again, a comparison with the straight probit results in column 1 of table 5 suggests that the local average treatment effect of delays predicted by state-sanctioned time off is more negative than the raw correlation in the data.

We then analyze the effect of time spent between log-in and first online transaction on transition to substantial usage (fourth column of table 5). The probit estimate of -0.0291 has a roughly -0.003 marginal effect on the likelihood to adopt. A 10-day delay results in an effect on the average adoption propensity of 0.025, which is high compared to the average propensity of substantial usage of 0.042, an effect of 60%. As before, we find that the effect of delays predicted by our IV specification is more negative than in the regular probit.

In the last column of table 5, we compare the effect of time between sign-up and log-in and time between log-in and the first online transaction on a customer's probability to substantially use online banking. With these two endogenous variables, we do not achieve convergence under maximum likelihood; instead we use Newey's two-step minimum chi-squared estimator for a probit model with endogenous regressors (Newey (1987), eq. 5.6). In the combined regression, each day between sign-up and log-in has a statistically insignificant marginal effect of only -0.00002. Each day between log-in and first online transaction in contrast has a marginal effect of -0.0026 on whether a customer adopts substantial usage. This suggests that the most immediate delays in the funnel matter the most for lack of progress in the later stages. Earlier delays matter mainly because they have knock-on effects throughout the adoption process.

Our other control variables switch in both signs and significance, echoing the heterogeneity that previous researchers have found in the factors influencing different stages of the adoption process (Goldfarb and Prince (2007)). The effect of changes in the number of bank branches is now statistically insignificant, possibly because the presence of branches matters less in driving a customer to online banking once she is more acquainted with the online interface. The negative effect of income on full adoption, consistent with previous findings on internet usage (Goldfarb and

Table 5 How Time between Sign-up and log-in and Time between log-in and First Online Transaction affect Progress from First Online Transaction to Substantial Usage

	Probit	Probit IV			
Standard Errors	Robust	Robust	Clustered State	Standard	Standard
Time between Sign-up & log-in	0.0008**	-0.0106***	-0.0106**		-0.0002
	(0.0003)	(0.0027)	(0.0043)		(0.0027)
Time Between log-in & First Transaction	.0003			-0.0291*	-0.0301**
	(0.0003)			(0.0156)	(0.0139)
Branches in Zip	0.0308	0.0213	0.0213	0.0339	0.0324
	(0.0714)	(0.0625)	(0.0909)	(0.0832)	(0.0840)
Income	-.01529	-0.0042	-0.0042	-0.0195*	-0.0197*
	(0.0094)	(0.0089)	(0.0122)	(0.0112)	(0.0116)
VacationDays	-0.0095**	-0.0085**	-0.0085***	-0.0098**	-0.0099**
	(0.0042)	(0.0038)	(0.0031)	(0.0048)	(0.0049)
PublicHols	-0.1345**	-0.1015*	-0.1015**	-0.1243	-0.1235
	(0.0687)	(0.0614)	(0.0412)	(0.0804)	(0.0811)
		First Stage Regressions for endogenous variables Time between Sign-up & log-in, log-in & Trans			
VacationDays Sign-up Month		0.5372***	0.5372***		1.047***
		(0.0759)	(0.1574)		(0.0632)
PublicHols Sign-up Month		-3.2201***	-3.2201***		-5.344***
		(0.3223)	(0.8578)		(0.4200)
VacationDays log-in Month				-0.0422	-0.992***
				(0.0607)	(0.0685)
PublicHols log-in Month				-1.324***	4.829
				(.379)	(0.4153)
Branches in Zip		-0.2215	-0.2215	0.137	-.6417
		(1.2798)	(4.4059)	(1.4434)	(1.4385
Income		0.8474***	0.8474**	-0.178	0.8538***
		(0.1738)	(0.3661)	(0.186)	(0.1857)
VacationDays		-0.0429	-0.0429*	-0.0086	-0.0011
		(0.0899)	(0.0249)	(0.865)	(0.8625)
PublicHols		1.2452	1.2452*	0.415	0.9593
		(1.3970)	(0.7491)	(1.3929)	(1.3882)
Adoption month Dummies	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes
Observations	19742	19742	19742	19742	19742

Dependent Variable: Indicator for when a customer first conducts 50 % of transactions by online banking. Sample: Customers who did an online transaction in previous month but have not yet switched 50 % of their activity to online banking.
* p<0.10,** p<0.05,***p<0.01.

Prince (2007)), may reflect that the discount the bank grants for transactions conducted online is not sufficiently large to induce higher income customers to shift usage online. Public holidays in the potential transition month consistently have a negative point estimate for their effect on substantial usage, in contrast to their effect on the transition to trial, suggesting heterogeneity in customers' willingness to use additional time off for these different types of activity.

In the above analysis we define substantial usage as the point at which a customer switches 50% of their transaction activity to online banking. To check that the results are not an artifact of a particular boundary, we also tried several alternative definitions of substantial usage. These different definitions led to results of the same sign and significance. The point estimates were smaller, however, for less restrictive (or smaller) definitions of substantial usage. The relative magnitudes for the stratification results that we discuss below remain the same.

Our results suggest that delays in initial stages of the adoption process are crucial for understanding attrition in later stages of the adoption process. One explanation for this could simply be that a delay means that the optimal time for using the technology has passed. However, this seems unlikely for online banking where there is a recurring need for the service. An alternative explanation could be that delays negatively affect a customer's ability to learn how to use a new self-service technology. For example, Wuebker and Hardock (2002) report that customers need to complete 10 to 20 online transactions to become fully accustomed to the new channel. When this learning process is interrupted, customers possibly forget their prior knowledge, preventing them from progressing to substantial usage. Such an explanation is also consistent with laboratory findings on memory, interruptions and momentum: When individuals are not prompted to recall information in the intermediate, they are more likely to forget. Interruptions increase the cost of adoption and therefore decrease the customer's value of substantial usage, causing delayed or ceased full adoption.

In the next section, we stratify our results by customer demographics associated with online experience. If the effects of delays are more substantial for customers who have less online experience, this would provide anecdotal support for the role of memory and learning in causing our results.

5.3. Stratification

We exploit the bank's demographic information regarding age and gender of its customers, as well as information on the customers' product types to investigate whether delays affect the different demographic groups differentially. Product type denotes the type(s) of account(s) the customer holds with the bank, including checking, saving, or brokerage accounts. The raw probit estimates in table 6 suggest that delays between sign-up and log-in have a larger negative effect on the likelihood of completing an online transaction for those who are over 40, female, or have a brokerage account. Note that brokerage account holders are on average significantly older than checking account only holders (38.9 years compared to 34.5 years), so that the age and product type stratifications may be picking up similar sources of consumer heterogeneity. While in the previous section we estimate an average effect across all customer groups, this supports that different customers are heterogeneous in how they are affected by the treatment. The results fit with anecdotal evidence about lack of confidence with new technologies amongst these segments, especially among older women,[12] and support the interpretation that delays in the funnel have a more profound effect when customers have less familiarity with online transactions and likely have a greater need for learning the new technology. This is consistent with the previously cited laboratory findings on the impact of consumer memory on subsequent actions.

We find similar results for transition to substantial usage (table 7). Again, the effect of delays in the time between sign-up and log-in are greater for customers age 40 and older. However, the effects for women and brokerage account holders are now statistically insignificant, while the effects for men and checking account holders remain negative and significant. One interpretation is that the effect of a delay at different stages of the funnel is heterogeneous, even for otherwise similar customers.

Differences in the strength of instruments across different demographics also support a causal interpretation. For example, it seems reasonable that those aged 40 or older are less likely to be affected by vacations because they are much less likely to have school-aged children. In the first stage of the regressions in table 6, we find that for people aged 40 or older, an additional day of vacation in the sign-up month increases the time between sign-up and log-in by a statistically

[12] DePallo, Mildred, "AARP National Survey on Customer Preparedness and E-Commerce: a Survey of Computer Users age 45 and older", 2000, available at `http://www.aarp.org/research/reference/publicopinions/aresearch-import-189.html`.

insignificant 0.22 days, but by a significant 1.38 days for those who are under 40. To confirm this reasoning, we obtained data from the German Statistical Office, `http://www.destatis.de`, on the presence of school-aged children under the age of 17 in households broken down by the age of the head of household. The data suggest that heads of household between the ages of 32 and 45 are most likely to have school-aged children, with the share of households with children exceeding 40% of households for every year age in this range, relative to significantly lower shares for other ages. The results for the subsample of online banking customers between the ages of 32 and 45 strongly support the causal interpretation of our main age stratification: each additional day of vacation increases the average delay between sign-up and login by a statistically significant 1.78 days, with similar results to the ones obtained for the under 40 year olds in the second stage.

Table 6 Stratified: How Time between Signup and log-in Affects Move from log-in to First Online Transaction

	Probit IV					
	Over 40	Under 40	Man	Women	Brokerage	Checking Only
Time between	-0.0137***	-0.0078***	-0.0044*	-0.0117***	-0.0150***	-0.0073***
Sign-up & log-in	(0.0033)	(0.0017)	(0.0024)	(0.0017)	(0.0053)	(0.0017)
Branches in Zip	-0.0880	0.2678***	0.3252***	-0.2065**	-0.4645***	0.1158*
	(0.1266)	(0.0769)	(0.0913)	(0.0917)	(0.1153)	(0.0676)
Income	0.0182	0.0137	0.0044	0.0230*	-0.0112	0.0128
	(0.0123)	(0.0099)	(0.0111)	(0.0126)	(0.0207)	(0.0086)
VacationDays	-0.0081	-0.0059	-0.0045	-0.0059	-0.0086	-0.0054
	(0.0064)	(0.0050)	(0.0058)	(0.0061)	(0.0113)	(0.0045)
PublicHols	-0.0435	0.0264	0.0608	-0.0215	-0.0028	-0.0130
	(0.0972)	(0.0764)	(0.0883)	(0.0898)	(0.1233)	(0.0674)
	First Stage Regressions for endogenous variable 'Time between Sign-up and log-in'					
VacationDays	0.2240	1.3823***	1.3903***	0.8463***	0.1404	1.1694***
Sign-up Month	(0.1648)	(0.2242)	(0.2531)	(0.1861)	(0.3721)	(0.1868)
PublicHols	-3.2914***	-4.3081***	-4.7471***	-3.4105***	-1.8460	-5.4048***
Sign-up Month	(1.1447)	(1.0275)	(1.1167)	(1.0060)	(1.3913)	(0.8014)
Branches in Zip	-15.1131***	-1.2854	-9.6528**	-8.5856*	-23.1767***	-6.1931**
	(3.4728)	(3.8482)	(3.8162)	(4.4133)	(6.5239)	(3.1452)
Income	0.5854	0.7300	0.0219	0.9965	-1.3726**	0.3160
	(0.5207)	(0.5984)	(0.5104)	(0.7914)	(0.5579)	(0.4737)
VacationDays	-0.2747	-0.3915	-0.4269	-0.2935	-0.0760	-0.3522
	(0.2896)	(0.3055)	(0.3178)	(0.3428)	(0.3452)	(0.2565)
PublicHols	2.0358	-0.1975	0.6356	1.1201	3.6702	1.0574
	(4.1273)	(3.8216)	(4.0470)	(4.5698)	(4.9413)	(3.2770)
Ad mo Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2775	4798	4067	3081	2844	6430

Dependent Variable: Indicator for when a customer first conducts an online transaction. Sample: Customers who have logged in but not yet done an online transaction.
* p<0.10,** p<0.05,***p<0.01. Robust Standard Errors.

Table 7 Stratified: How Time between Sign-up and log-in affects move from first Online Transaction to Substantial Usage

	Probit IV					
	Over 40	Under 40	Man	Women	Brokerage	Checking
Time between	-0.0152***	-0.0096***	-0.0134***	0.0032	-0.0081	-0.0101***
Sign-up & log-in	(0.0055)	(0.0029)	(0.0023)	(0.0044)	(0.0055)	(0.0028)
Branches in Zip	-0.3742**	0.1151	0.1623**	-0.0303	-0.2548*	0.0132
	(0.1543)	(0.0793)	(0.0801)	(0.1218)	(0.1442)	(0.0654)
Income	-0.0072	-0.0057	-0.0238**	0.0058	-0.0083	-0.0062
	(0.0150)	(0.0113)	(0.0111)	(0.0150)	(0.0143)	(0.0091)
VacationDays	-0.0099	-0.0083*	-0.0079*	-0.0086	-0.0230***	-0.0090**
	(0.0066)	(0.0046)	(0.0046)	(0.0071)	(0.0079)	(0.0040)
PublicHols	-0.0413	-0.1305*	-0.1007	-0.1224	-0.0015	-0.1031
	(0.1065)	(0.0750)	(0.0759)	(0.1110)	(0.1303)	(0.0644)
	First Stage Regressions for endogenous variable 'Time between Sign-up & log-in'					
VacationDays	0.3222**	0.6377***	0.3939***	0.9357***	0.4605***	0.5544***
Sign-up Month	(0.1401)	(0.0893)	(0.0890)	(0.1199)	(0.1440)	(0.0761)
PublicHols	-3.2727***	-3.2235***	-4.5836***	-0.1820	-3.8539***	-3.0819***
Sign-up Month	(0.6163)	(0.3813)	(0.5160)	(0.5050)	(0.5823)	(0.3408)
Branches in Zip	-22.4561***	7.4817***	4.6829***	-9.6956***	-13.3329***	-1.0510
	(2.8922)	(1.2826)	(1.5965)	(2.1739)	(3.0074)	(1.3385)
Income	0.3147	1.0860***	0.4838**	1.3553***	0.1447	0.7687***
	(0.3014)	(0.2159)	(0.2262)	(0.2682)	(0.2506)	(0.1791)
VacationDays	-0.1298	-0.0195	-0.0086	-0.0677	-0.0477	-0.0461
	(0.1580)	(0.1067)	(0.1282)	(0.1320)	(0.1463)	(0.0935)
PublicHols	1.7636	1.1213	1.0999	1.4131	1.9359	1.2623
	(2.2992)	(1.6820)	(1.9905)	(2.0795)	(2.6533)	(1.4722)
Ad mo Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5274	14468	9545	9072	5884	17947

Dependent Variable: Indicator for when a customer first conducts 50 % of transactions by online banking. Sample: Customers who in previous month had done an online transaction but not yet switched 50 % of their activity to online banking.
* p<0.10,** p<0.05,***p<0.01. Robust standard errors.

6. Implications

Banks invest in online banking to migrate paper-based transactions online and reduce the cost of processing transactions. To get a rough idea of the cost-savings involved we exploit research by Wuebker and Hardock (2002) who suggest that each online transaction reduces a bank's variable costs by approximately €0.50. In our sample, the median customer who reaches substantial usage makes 3.5 online transactions a month, compared to negligible amounts for the remaining customers. This implies that converting a customer to a substantial user generates roughly €1.75 in average monthly savings. This assumes that these online transactions replace paper-based transactions one-for-one; if some online transactions represent increases in overall transactions, as opposed to offline replacement, these cost savings represent an upper bound on the likely cost savings.

This suggests that there are measurable benefits to the bank from customers fully embracing online banking. In our empirical work, we do not model the source of customers' delays or how the bank can influence these. Instead of conducting a full policy counter-factual of alternative sources of delays, we consider how decreases in delays at various stages of the funnel feed through the adoption process to affect the average number of transactions across online customers and the bank's associated cost savings. While this analysis does not shed light on the behavioral foundations for heterogeneity in completing the adoption process, the estimated magnitudes are suggestive of the cost savings to be realized by the bank from even small increases in customers' speed of adoption.

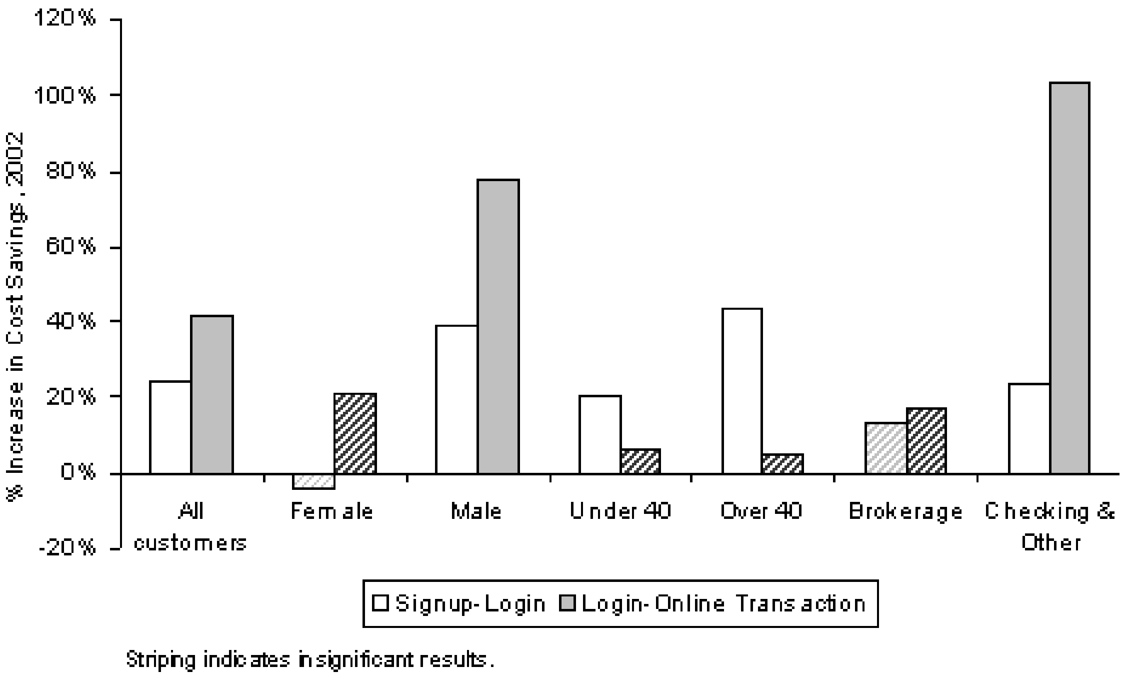
We calculate the incremental savings of reducing delays by 1 day, 10 days, and 30 days. We consider both an acceleration of the first stage of the funnel (sign-up to log-in) and of the second stage of the funnel (log-in to transaction). Based on the expected change in the number of customers with sustained usage from such reductions, we estimate the incremental cost savings to the bank in the month of acceleration. We also compute an aggregate measure of cost savings generated in the year following the acceleration.

In our analysis, we focus on a constant set of customers and trace their progress under alternative delay scenarios. We use the subset of customers as of January 2002 who have previously tried the service by making at least one online transaction and who ultimately complete the transition to substantial usage. On average, these 413 customers have an empirical likelihood of 4.6% of moving from the trial stage of the adoption funnel to full adoption in any given month. We hold this probability constant and compute the share of sustained users out of the 413 customers over time. The advantage of focusing on a fixed set of customers is that we do not need to incorporate into the analysis additional customers who enter the trial stage of the funnel at different points in the future, which might change the monthly transition probability to sustained usage in unpredictable ways. However, a limitation of holding the transition probability constant is that it does not capture selection within the sample of 413 customers, and therefore heterogeneity in the transition probability. For example, customers who ascribe the highest value to online banking are likely to complete the adoption process early. For them, the average transition propensity of the sample is therefore too low, resulting in a predicted transition date that is too late. Since these customers are also likely to have a higher number of online transactions, our approach underestimates cost savings from accelerating their transition through the funnel. On the flip side, we are likely to overstate cost savings from accelerating adoption by marginal customers who are nearly indifferent between full adoption and not progressing further in the adoption funnel.

Figure 4 illustrates the gains in savings if customers spent 10 fewer days between sign-up and evaluation (first log-in) and between evaluation and trial (first online transaction). The calculations use the fact that in the full sample, customers with substantial usage conduct an average of 2.5 additional online transactions per month than customers in the previous stage of the funnel. We scale up these incremental transactions by the above per-transaction savings of €0.50 and compute predicted annual savings for 2002 for the sample of 413 customers who transition to substantial usage over the course of the year. We then compute cost savings under alternative funnel transition times and compare the results to the baseline, the results of which are shown in figure 4.

In the first scenario, we reduce the time between sign-up and log-in by 10 days for all 413 customers. Reducing the time between sign-up and log-in by one day has a marginal effect on the probability of completing the adoption funnel of 0.0014 for the full sample. A 10-day acceleration

Figure 4 Yearly Cost Savings from a 10-day Speed-Up



increases the adoption propensity by roughly 0.014, increasing cost savings from online banking in the first year by 24%, as illustrated in Figure 4. We then consider a more extreme acceleration of transition times by 30 days. The effect of speeding up the transition by 30 days is roughly 67%. Since the effect of delays in the immediately preceding stage of the funnel outweigh any earlier stages, we find greater effects from speeding up the transition to trial (first online transaction): A 10-day acceleration increases cost savings by 42%, and a 30-day faster transition increases cost savings by 106% in the first year. This linear extrapolation of marginal effects may, however, overstate the actual effect on cost savings. Note also that the increases in transactions in going from a trial-stage customer to a substantial-usage customer do not reflect additional increases in the number of transactions conducted by substantial users that may result from speeding up the transition along earlier stages of the funnel. As such, our results represent a conservative estimate of the overall savings potential.

Stratifying our results illustrates the cost implications of the differences in adoption behavior between demographic groups. Accelerating adoption by customers who are male, over 40 years old, and not owners of brokerage accounts promises higher than average cost savings. As indicated by the striped bars in Figure 4, some of our results with respect to other demographic groups are not statistically significant.

In general, our previous estimates suggest that moving customers along the adoption funnel speedily and preventing hold-ups can accelerate adoption. In addition to ensuring technological usefulness, as discussed by Davis (1989) and Davis et al. (1989), this staggered adoption process requires that managers pay particular attention to and manage customers' transition along the funnel. Targeting each specific stage in addition to the initial signup stage has not been a focus in financial institutions to date, but there are relatively easy ways banks could use to speed up their customers' transition through the funnel. For example, by simply setting up computers in their branches, employees could educate customers on how to use online banking. Introducing a more differentiated pricing structure could provide financial incentives to customers to swiftly progress along the adoption funnel.

7. Conclusion

When purchasing a durable good, a consumer typically undergoes an extensive decision process, but then makes a single purchase decision that immediately generates revenues for firms. Similarly, for frequently purchased products ranging from consumer goods to travel services, learning about the fit between a particular product and one's needs is accomplished through repeat purchases, each of which generates firm revenue. By contrast, sign-up for a new customer internet service rarely has immediate profit implications for firms. The firm only reaps cost savings when a customer fully embraces the technology.

In this paper we explore the adoption process for customer online services, and in particular the empirically observed gap between initial sign-up and usage. We use the image of an adoption funnel to highlight attrition at four incremental stages: sign-up, evaluation, trial and substantial usage. We empirically explore the adoption funnel in the context of online banking where there is substantial attrition along the funnel: in our observation period, only 24% of customers that sign up for the service progressed to using it substantially. We explore the extent to which delays in the early stages of the adoption process can explain this attrition. We identify the causal effect of delays on full adoption by using exogenous variation in the number of vacation days and public holidays in different stages. This state-sanctioned time off leads to time delays in the adoption process. These delays in turn reduce a customer's probability to transition to a latter stage and to substantial usage. If a customer's first log-in is delayed by 10 days, this reduces her likelihood of using the technology substantially by 33%. Delaying a customer's first transaction after log-in by 10 days reduces the average probability that she will substantially use online banking by 60%. One interpretation of these results is that a delay leads customers to forget what they have already learned about the technology and consequently makes them more likely to abandon their adoption. Such an interpretation is consistent with findings on consumer memory and learning. In support of this hypothesis, we find evidence that these effects are more severe among demographic groups with less internet experience.

It is in a firm's interest, therefore, to reduce delays that customers experience in the earlier stages of the adoption process. We calculate that speeding up the time between sign-up and initial log-in by 10 days could, for this bank, increase cost savings from online banking by up to 24%. There are multiple ways for firms to speed up their customers' adoption. Firms can, for example, educate their customers, introduce pricing schemes that provide financial incentives for progress along the funnel, or optimize the timing of their promotional activities. Our results also suggest that firms could benefit from designing their IT systems to eliminate stages along the adoption funnel (as Amazon.com did by introducing the 1-click-ordering option to shorten the purchasing process). Alternatively, firms can set deadlines by which customers need to transition to the next stage. Some software companies such as The MathWorks[13] already impose deadlines and require customers to activate the product within a given period after installation. Similarly, e*Trade Financial requires customers to access their account within the first 30 days of sign-up. While consumers use deadlines as commitment devices, externally imposed deadlines are usually more effective than self-imposed

[13] The MathWorks, "Matlab & Simulink Student Version: Frequently Asked Questions", `http://www.mathworks.com/academia/student_version/faq/` (accessed October 9, 2007).

deadlines (Ariely and Wertenbroch (2002)). Research also suggests that shorter time limits are more effective than longer time limits (Amir and Ariely (2004)). Similar to redemption of coupons with expiration dates (Inman and McAlister (1994)), we would expect that such deadlines lead to a peak in adoption shortly before expiration.

Our results apply to many customer self-service technologies. For example, consumers go through similar stages when they sign up, evaluate, try and subsequently transition (or not) to substantial usage of an online grocer. Similarly, consumers may sign up for online account management of reward travel, but never stop receiving paper statements or processing bookings offline. There is also evidence of substantial lack of continued usage in the realm of online entertainment activities such as "Second Life", where only 18% of the registered 9.03 million users as of July 2007 had logged into the website in the last 60 days.[14] We believe that in these settings, firms can also benefit from closer monitoring the adoption funnel and, at crucial gaps in the funnel, encourage customers to transition to the next stage.

[14] Rose, Frank, "How Madison Avenue Is Wasting Millions on a Deserted Second Life," *Wired Magazine 15.08*, July 24, 2007.

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