The Digital Banking Differential: A Regional Analysis of Technology Adoption in Europe

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Abstract

This paper examines the relevance of the Technological Acceptance Model (TAM), as proposed by Davis (1989), in explaining regional variation in digital banking adoption. As best as we are aware, this model has only previously been applied with survey-level data. We use relevant regional indicators and Principle Component Analysis (PCA) to construct two justifiable proxies for the deterministic channels described in the model —Perceived Usefulness (PU) and Perceived Ease of Use (PEoU). We use data at the NUTS-2 level for 237 regions, 27 EU member states, and 10 years between 2013-2022 compiled from public repositories by the MOBI-TWIN Project (2022). In the first part of the paper we motivate our question by exploiting the staggered implementation of the European Payment Services Directive 2 (PSD2), as a proxy for a direct positive shock to the Perceived Usefulness of digital banking. Our results suggest that digital banking adoption may increase in response to increased Perceived Usefulness as predicted —though violations of pretreatment trends restrict us from making a causal claim. This justifies our more narrowed analysis to study whether this channel is deterministic, using panel regressions and Instrumental Variables (IV) techniques. We instrument a lagged density variable as an exogenous source of variation, conditional on ample controls such as: intuitional quality, socio-economic indicators, and digital connectivity. Our results support the hypothesis that regional differences in Perceived Usefulness determine digital banking adoption as the model suggests. Though despite yielding positive results from first- and second-stage tests —and subsequent confirmation from Wooldridge (2010) Control Function Approach (CFA)— robustness checks of our estimation leads us to be skeptical of making a formal causal claim. Our findings motivate further research on broader applications of the Technological Acceptance Model and are of use to policymakers by illustrating how regional context influences aggregate adoption behaviors of essential digital services.

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1   Introduction

The turn of the twenty-first century marked the beginning of a profound digital transformation across Europe. Over the past decade in particular, the integration of internet-based services into daily life has accelerated rapidly. In 2014, roughly 80 percent of households in the European Union had internet access; by 2024, that number had surpassed 94 percent according to Eurostat (2025). This growth signals not only expanded connectivity, but a shift in how essential services are delivered and accessed. As highlighted in the World Bank Group (2016) Digital Dividends report, digital technologies have the potential to improve decision-making, increase access to information, support employment matching, and streamline public and private service delivery. What began as voluntary adoption has now become structural: interacting with the state, securing employment, and managing personal finances increasingly requires infrastructure and digital literacy.

This transition has not been evenly distributed. Despite widespread internet penetration, significant gaps have persisted in digital access, usage, and skills —referred to as the digital divide— acting barriers to full digital inclusion according to Lythreatis et al. (2022). These disparities are often linked to structural barriers such as limited infrastructure, lower education levels, and differences in digital literacy. Policymakers have expressed concern about the exclusion of specific groups —rural populations, lower-income households, and older adults— from the benefits of digital transformation. As such, in 2020 the European Commission launched the Digital Decade initiative, which established ambitious targets for connectivity, skills development, public service digitization, and business transformation, all with the aim of achieving an inclusive digital society —Commission (2021). With shocks from the pandemic and innovations in Artificial Intelligence changing the digital landscape, these goals are becoming more relevant than ever. However, understanding what drives or inhibits adoption requires looking beyond surface-level infrastructure and demographic characteristics, toward the mechanisms through which individuals and regions evaluate and internalize digital technologies. One particularly illustrative domain is the banking sector. Over the past decade, digital platforms have rapidly replaced in-person financial services. Digital banking now offers continuous access to financial management, enables better tracking of expenditures, and encourages competitive pricing and innovation among institutions —Omarini (2022). Despite these advantages and near-universal availability of internet access, adoption of digital banking remains uneven across the EU. While over 90 percent of individuals report internet use, only around 64 percent use digital banking as according to Eurostat (2025). This gap raises an important question: Why do so many individuals with internet access choose not to adopt digital banking?

This paper examines this gap by analyzing regional heterogeneity in digital banking adoption. Our analysis further examines the ability of the Technology Acceptance Model (TAM) to explain variation in adoption behavior across regions, focusing on the roles of its latent constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEoU). While the TAM has traditionally been applied at the individual level, we implement the framework at the regional level to assess how context —social, institutional, and infrastructural— influences regional heterogeneity in digital banking adoption. In addition, we also examine the Payment Services Directive 2 (PSD2) as a potential policy shock that may have increased PU by improving

digital security and standardizing consumer protections across the EU. Given its staggered implementation across countries, PSD2 offers a quasi-experimental setting in which to investigate whether PU contributed to subsequent shifts in digital banking behavior. Overall, our results seem to support the relevance of using TAM constructs, suggesting effectiveness in explaining regional heterogeneity in digital banking adoption.

The remainder of this paper is structured as follows; Section 2 reviews the literature on TAM and its relevance to digital banking adoption. Section 3 presents the empirical strategy and discussion of variables. Section 4 examines PSD2 as an institutional intervention that may influence perceptions of usefulness. Section 5 uses panel models and an Instrumental Variables (IV) approach to assess the deterministic relationship between PU and PEoU. Sections 6 concludes with discussion of findings, implications, and limitations.

2 Theoretical Background

In this section we review key theoretical and empirical foundations relevant to the digital banking adoption and digital inequality. We first review the fundamentals of the Technological Acceptance Model by Davis (1989) —discussing past applications ability to explain the adoption of digital banking and e-services. We then draw on regional approaches to help bridge the individual-regional gap. This review will offer the necessary context for applying the TAM at the regional level, motivate our hypotheses, and identify the gap in the literature that we aim to address.

2.1 Technological Acceptance Model

The TAM as introduced by Davis (1989) —and re-evaluated in Venkatesh and Davis (1996)— is one of the most popular frameworks for explaining the decision making process through which individuals adopt new technologies. The TAM was built on the Theory of Reasoned Action (TRA) attributed to Fishbein and Ajzen (1977), who decomposed individual perceptions into broader psychological determinants of behavior intention —literally the intention to act in some way. The TAM was developed for technological contexts, originally under contract with IBM to analyze adoption potential of computer applications by its employees —Venkatesh and Davis (1996). Much like the TRA, the TAM models individual decision making as a function of attitudes about the product itself, and offers a framework to quantify these latent constructs using surveys which draw perception indicators from participants. Davis (1989) necessarily refined the Fishbein and Ajzen (1977) logic on deterministic channels for technological contexts, as adoption decisions in technology are uniquely influenced by an environment of rapid development and continuous innovation. At its core, the TAM posits, are two fundamental deterministic channels through which an individuals behavior intention (to adopt) is decided: PU & PEoU. According to Davis (1989), PU is "the degree to which a person believes that using a particular system would enhance their [performance]", While PEoU is "the degree to which a person believes that using the system would be free of effort". Figure 1 illustrates the sequential deterministic chain of the TAM, notably separated into three parts: (1) the External Stimulus, (2) the Cognitive Responses, and (3) Behavioral Intention & usage.
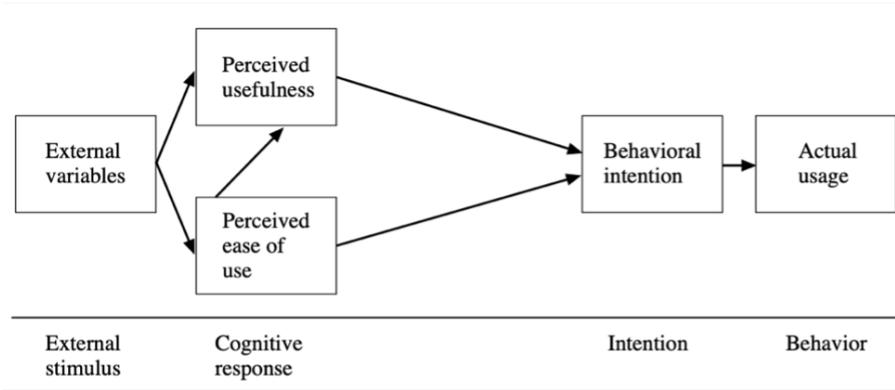
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Figure 1: TAM by Davis (1989)

External Stimuli (1) are characteristics of the environment that influence an individuals perceptions. In the original model these refer to socioeconomic conditions, institutional contexts, and other demographic variables that could influence Cognitive Responses (2): the fundamental variables of interest the TAM was proposed to quantify —PU & PEoU. Regarding these determinants there has been abundant analysis on the independent, joint, and pair-wise influence of PEoU and PU. This is why in Figure 1, there is a added pathway from PEoU to PU, reflecting the partial mediating role of PEoU on PU. Empirically, Behavioral Intention (3) and actual system usage has been found to be mostly driven by an individual's perception of a technology's usefulness —PU. A meta-analysis conducted by King and He (2006) on a range of published applications of the TAM found that PEoU coefficients were less consistent across empirical studies than PU, and more than a third of PEoU coefficients resulted in insignificant (though positive) coefficients. They also find that generally, the effect from PEoU is primarily through its effect on PU. Though PEoU takes a lesser roll empirically, users often view a system as more useful when it is also easier to use —Venkatesh and Davis (1996). The intuition is straight-forward: If a user finds a technology easy to navigate, they are more likely to recognize the benefit of its function (PU). On the other hand, if a system is perceived as too complex, its utility may be undercut, even if it is technically powerful. These relationships illustrate rational-agent foundations of the TAM, where individuals weigh perceived benefits (PU) against cognitive effort (PEoU) in their adoption decisions.

2.2 TAM and Digital Banking

The previous section introduced TAM foundations. Now we review the literature to find the role of the TAM, PU, and PEoU in determining individual digital banking adoption decisions. We will use this discussion to create expectations for our regional application and to form Hypotheses 1 & 2.

Davis (1989) references the underlying "Cost-benefit Paradigm" —originally discussed in Beach and Mitchell (1978)— which lays the foundation for how an individuals perceived expected value of a system decides their adoption decisions. This tells us that how an individual forms a valuation of a technology will be essential for understanding the influence of regional heterogeneity on adoption. Following this logic —an agent who does not adopt must then per-

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ceive the expected value of the technology to be below threshold. This further tells us that there are latent costs or benefit suppression that is keeping potential users from adopting. Elhajjar and Ouaida (2020) utilizes the TAM framework to examine this resistance to digital banking in the Lebanese context; The authors find from 320 survey participants that it is specifically negative perceptions of digital platforms that are impacting usage decisions —where propensity to adopt decreases in negative shocks to PU and PEoU such as: resistance to change, perceived risk, and lagging digital skills. Similar studies in different locational contexts echo these results. In a Saudi Arabian study where only %51 percent of respondents reported use of digital banking, Alnemer (2022) applies the TAM and finds that low PU and PEoU of digital banking impacted adoption decisions negatively. In South-Korea, Gu et al. (2009) reaffirmed that increasing PU and PEoU leads to higher rates of adoption. In addition, they found that TAM constructs were effective in explaining about %72 of the variance in the behavior intention to digitally bank, showcasing the predictive power of the model. In developing contexts such as Cambodia, Ly and Ly (2022) find impacts aligned with TAM and previous conclusions, as payment platforms became more widespread, PU was increasing and significant in determining digital banking adoption —they found PEoU was not as significant in this determination. The vast majority of applications of TAM use Structural Equation Modeling to quantify the latent constructs PU and PEoU —using multiple survey items and scales with Confirmatory Factor Analysis to construct these variables. Ali (2023) offers broader methods on the TAM including Chi-squared tests and descriptive analysis —still mainly using survey data and hierarchical models. The results from this author agree with the significant impact of PU and the lesser impact of PEoU on digital banking adoption. This tells us that not only is the TAM consistent and effective empirically in predicting adoption behavior, but in the context of digital banking, positive and negative forces like; trust, digital skills, and context have significant impact PU and PEoU .

Continuing our discussion of PU and PEoU dynamics, we seek to explore more of the major influences of these latent TAM constructs in the context of digital banking. Benefits of digitization include those from our discussion in Section 1, though more specific ones relating to digital banking are: financial efficacy, convenience, transparency, rewards, and access to financial tools. We also see some indication of how locational context may mediate these benefits in the literature —a central focus of this paper. Perception of costs on the other hand as we will see may be more multidimensional. The broader TAM posits that adoption of a technology decreases with effort costs, though we offer a more nuanced analysis on other avenues specifically impacting digital banking.

At its core, the use of banking services requires a degree of trust in institutions to protect ones sensitive personal information and financial assets —fundamental to the very use-function of a bank (PU). As the digital transition allows individuals to conduct banking on digital platforms, financial institutions contend with the risks inherent to them. Digitally risk-averse customers weigh the perceived risks of scams, hacking, identity fraud, data breaches, financial loss, and other losses of personal assets. In accordance with the literature on Perceived Risk Theory, described as far back as Bauer (1960), the role of perceived risk is an important determinant of consumer decisions. The perceived risk of digital banking is usually associated with the the

platform itself, and there is substantial literature on the relevance of platform trust and adoption using the TAM. Ben Mansour (2016) finds that perceived trust in the platform impacts the TAM construct PU significantly in the context of digital banking, and determines a significant portion of behavior intention. This effect is not just local to digital banking, but reflects a broader hesitance to intersecting personal finance and digital platforms. Gefen et al. (2003) study the roll of platform trust in the adoption of e-commerce —yielding similar results that support the idea of a platforms inherent risk. Featherman and Pavlou (2003) also found that distrust negatively impact adoption decisions. To this end, we exploit this direct association between perceived risk and PU, where in Section 4 we use it to test the basis of PU on impacting digital banking adoption. Over all, hesitance associated with digital banking will help interpret our results later on.

2.3   Bridging the Individual-Regional Gap

Previous sections reviewed the literature of TAM constructs in determining digital banking adoption —revealing a consistent significant and positive relationship between PEoU & PU on adoption behavior— at the individual level. One of the primary challenges of this study lies in the lack of access to survey data as the model intends, which necessitates the novel approach this paper proposes by using aggregate indicators to proxy latent TAM constructs for a more macro-level analysis. Specifically, we employ a shift-of-unit analysis to examine regions as agents with idiosyncratic levels of PU and PEoU towards digital banking. This study contributes to the literature by attributing latent TAM constructs to regions —characterizing them by varying levels of PU and PEoU. We then examine how these region-specific determinants influence different intensities of digital platform utilization. This approach broadens the scope of TAM and offers new perspective into the dynamics between the individual and the context in which they make decisions. To the best of our knowledge, the closest and most recent contribution to the literature bridging the individual–regional gap on adoption of digital banking is de Ibarreta et al. (2025). The Authors conduct a regional analysis in Spain on the individual determinants of digital banking adoption and the regional impact of banking location closures. They utilize a logit estimation with random effects —using banking adoption as the outcome. Their analysis reaffirms the significance of commonly cited individual-level predictors—such as age, education, and digital skills—while also identifying physical branch closures as a key regional-level push factor driving digital adoption; specifically areas with lower densities see higher propensities to adopt. These findings offer suggestive evidence in support of this study's underlying hypothesis: that regional context can play a critical role in shaping digital banking adoption behavior. The Theory of Diffusion of Innovation by Rogers (1995), can help us draw this bridge even farther and contextualize what shifting analytical units from individual to region would entail. Where the TAM model emphasizes individual-level evaluation and decision making, Rogers' framework stresses the roles of social systems, institutions, and communication channels that may mediate the potential adopters decisions. We use this logic to illustrate how constructing PU and PEoU at the regional level can reflect aggregate perceptions and regional context as a single unit, that then influences adoption behavior —offering valuable analytical dimension to the TAM framework and literature.

Distribution of DBD Across regions
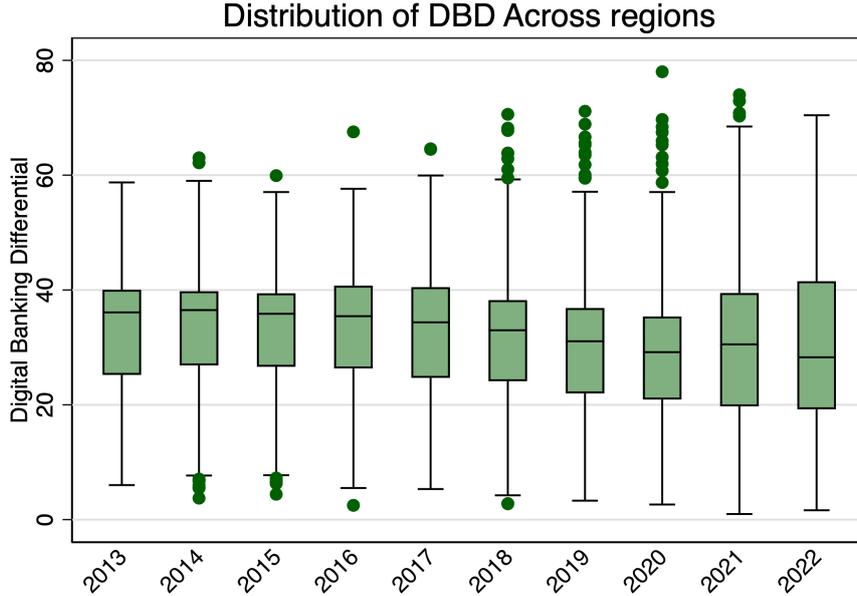
Figure 2: Distribution of the Digital Banking Differential for All Regions, Over Time

Our review of the literature confirms that the TAM is a robust framework for estimating behavioral intention at the level of the individual. Existing research at the regional level highlights the importance of contextual determinants on adoption patterns like: demographics, institutions, and infrastructural access, in shaping digital banking behavior. In Section 3, we describe how we will do this empirically and construct our variables of interest.

3   Methodology

$$\text{DBD}_{it} = \text{Internet Use (private)}_{it} - \text{Internet Banking Use}_{it} \tag{1}$$

We define our outcome variable —the Digital Banking Differential (DBD)— as the difference between the proportion of individuals in a region who use the internet for private purposes and those in a region who also use it to digitally bank —as can be seen in Equation (1). This differences out the real levels of either indicator individually, capturing the decision margin by focusing on internet users who abstain from digital banking despite having access —for reasons we intend to examine. This captures the latent behavioral dimension of adoption choice vital to TAM analysis, and as discussed in Section 2. As the TAM is intended to model adoption decisions, if we were to only use the raw proportion of digital banking users we would capture overall popularity rather than variation in adoption behavior. Figure 2 shows that while the mean DBD across the EU has declined over time, the range of observed values has risen. Some regions exhibit levels as high as 80% of internet users abstaining from digital banking, underscoring the relevance of this study in understanding persistent regional disparities in adoption.

In order to understand to what extent regional differences in the latent constructs of the TAM explains differing adoption behavior, our analysis takes a two-step approach: First, (1)

We conduct an analysis of a policy proxying a positive shock to PU of digital banking —which tells us if there is empirical basis to believe PU can impact the DBD (Section 4). The results will then motivate step (2), applying the TAM framework at the regional level using panel and IV techniques to address the question: Are latent TAM constructs relevant in explaining the DBD at the regional level? We hypothesize for steps (1) and (2):

Hypothesis 1. *The Payment Services Directive 2 (PSD2), proxying a positive shock to PU, will significantly decrease the DBD —DBD is impacted by PU.*

Hypothesis 2. *Regional-level constructs of TAM —PU and PEoU— are significant in predicting the DBD. Specifically, higher regional PU and PEoU determines higher rates of adoption digital banking by internet users, shrinking DBD.*

we will introduce our data and variables in the next subsection and justify the construction of our TAM variables. In Section 4, We will analyze the Payment Services Directive 2 (PSD2) to address Hypothesis 1, and in Section 5 we will conduct our main panel analysis to address Hypothesis 2.

3.1 Data

Our dataset is nearly balanced, with only a small number of missing values —fewer than 0.2% of total observations. We considered imputation methods to achieve a fully balanced panel, though the small number of lost observations in our data is unlikely to bias our analysis. We have data for all variables for 237 NUTS-2 level regions, from the 27 EU member-states, representing 10 years (2013-2022). All indicators come from public repositories and are collected by the Horizon Europe MOBI-TWIN Project (2022). The full list of variables, correlations with DBD, and their descriptions can be found in Appendix Table A13 —further correlations can be found in Appendix Figure A12.

The variables collected cover major structural and non-structural dimensions, quantifying digital behaviors and regional context including: environmental factors, institutional quality, economy, population structures, education, and sector shares. As our unit of analysis is the NUTS-2 level, most variables are aggregates presented as proportions (%) of individuals or households in a given region.

3.2 Constructing Variables of Interest: DBD, PU, PEoU

Our outcome variable, DBD, is constructed according to Equation 1 for every time and region, Using `int_priv`—the percentage individuals that report using the internet for private purposes in the past 12 months— and `int_bank`— the percentage of individuals reporting internet banking usage. This transformation results in a value, DBD_{it}, for every time and region indicating the portion of internet users not digitally banking.

3.2.1 Principal Component Analysis: PU & PEoU

Unlike TAM methodology which uses surveys to directly assess individuals PU and PEoU, our analysis requires constructing credible proxies for these latent constructs using regional level

data. To do so we implement Principle Component Analysis (PCA) to synthesize both PU and PEoU, while paying careful attention to what the common underlying variation of the components reflect, and how it communicates implicitly the underlying concepts and spirit that TAM survey questions address —referencing Venkatesh and Davis (1996) and Venkatesh et al. (2012) as a guide to the curation of component candidates. PU and PEoU as we construct them should then be necessarily interpreted as characteristic of the region itself, rather than solely of the individuals within the region. That is, we conceptualize each region as an agent with idiosyncratic and aggregate contextual readiness towards digital banking adoption. PU and PEoU thus reflect regional-level conditions that shape outcomes of adoption, not specifically any individuals beliefs or capabilities. It is important to acknowledge the possible pitfalls this methodology —as analyzing the region as the sum of its parts can dismiss the nuance within— and we have taken careful consideration in creating our proxies to reflect the latent concepts of the TAM model and invite critical interpretations accordingly.

3.2.2 Perceived Usefulness

We identify three variables that share underlying variance and, when combined, offer a theoretically consistent proxy for PU. In line with TAM, we expect these constructs to reflect the model's core prediction: higher levels of PU are associated with increased adoption of digital banking:

The first candidate is (1) the percentage of individuals that have reported using the internet for interaction with public authorities in the last 12 months —[int_admin]. The considerations that shape individuals' decision to adopt digital platforms for interacting with public authorities are closely aligned with those influencing the adoption of digital banking. Essentially both require that (a) people find it useful for conducting important tasks such as interaction with authority, and (b) they have to be comfortable with sharing sensitive personal information on the platform — comparable perceived risk. In sum, Those that find internet administration useful should also find digital banking useful. From Appendix Table A13, we observe a strong negative correlation (-0.800) with the DBD, indicating that an increase in the portion of individuals utilizing internet for contact with authorities is associated with a decrease in DBD.

The second candidate is (2) the share of agricultural activity by Gross Value Added in a given region [agric_sh]. Because agriculture may have a higher dependency on traditional practices, coupled with its less intensive digital requirements, we see this component as having a positive relationship with the DBD. A preliminary look at the correlation given in Appendix Table A13 (0.343) indicates that this is the case. The final candidate is (3) the percentage of individuals that work in the high-technology sector [hightech], which helps communicate the receptiveness of a population to the digital transformation and its usefulness in employment. There is a moderate significant relationship with the DBD (-0.281) lending credence to this notion. Together, we argue, the shared underlying variation reflects a region's institutional and behavioral orientation toward digital technologies and in part the insensitivity of its use, proxying PU. Regions with higher digital engagement with public services, high-tech employment, and lower agricultural dependence are typically more integrated into the digital economy

and more capable of recognizing and leveraging the usefulness of digital systems such as online banking.

Table 1: Principal Component Analysis: Eigenvalues and Explained Variance for PU Variables

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.8596	1.1726	0.6199	0.6199
Comp2	0.6870	0.2337	0.2290	0.8489
Comp3	0.4533	–	0.1511	1.0000

Table 2: Principal Component Loadings of PU Variables

Variable	Comp1	Comp2	Comp3	Unexplained
int_admin	**0.5170**	**0.8550**	0.0417	0
agric_sh	**-0.6085**	0.3328	**0.7204**	0
hightech	**0.6020**	-0.3978	**0.6923**	0

Table 1 and Table 2 summarize the principal component analysis for the PU variables. We select Component 1 as our proxy for PU, as it has an eigenvalue above one and explains approximately 62% of the total variance. The component loadings are strong and consistent with theoretical expectations—positive for int_admin and hightech, and negative for agric_sh—which supports the interpretation of this component as a valid latent construct aligned with the TAM framework.

3.2.3 Perceived Ease of Use

As we have covered in the theoretical background, PEoU has largely been found to mediate PU, with inconsistent coefficient results across TAM estimations. The literature has also pointed out that PEoU is largely associated with education and digital skills. Though with the data available, we are not able to measure digital skills directly —what is publicly available is not at the NUTS-2 level and lacks necessary time periods. Instead, we use the share of tertiary-educated individuals 16-74 [tert_stud_pc], median age [med_age], and its square [medage2] —in the case of a non-linear relationship with the DBD. We selected these candidates based on their relevance to digital literacy, cognitive accessibility, and generational familiarity with digital platforms which are key influences of PEoU in the TAM. Because of the more minor role in the coming panel analysis, the the PCA loadings and eigen values can be found in the Appendix Tables A13 & A14, where we also select component one for our PEoU index.

Table 3 present the descriptives for our variables of interest. Furthermore, Our dependent variable DBD and the synthetic PU are strongly negatively correlated (–0.587), as expected. The DBD shares a moderate positive correlation with the PEoU (0.271), this is an interesting result and due to effect of age being the strongest influence in the synthetic variable. We should better interpret PEoU as the contrary, in which age increases difficulty of use of the technology. In addition, PU and PEoU are negatively correlated (–0.366), suggesting the same thing. As the literature highlights the lesser mediating role in the TAM model relative to PU, we will

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Table 3: Summary Statistics for Key Variables: DBD, PU, EOU

Variable	Mean	Std. Dev.	Min	Max	N
DBD	31.37	13.34	0.98	78.00	2370
PU	0.00	1.36	-3.68	4.38	2370
EOU	0.00	1.46	-4.29	4.00	2332

continue cautiously interpreting the parameter and focus on the greater parameter of interest —PU. Appendix Figure A8 shows a visual of the relationship between between our synthetic PU and PEoU with regional averages.

4 Payment Services Directive 2

The previous section established the scope and construction of our key variables. We now turn to an initial empirical motivation for the analysis in Section 5 by examining the policy impact of the Revised Payment Services Directive (PSD2). This allows us to assess whether a relationship exists between PU and the DBD at a broad level, as predicted in Hypothesis 1. Our approach is inspired by Polasik et al. (2020), who identify a positive supply-side effect of PSD2 on the entry of new financial-technology firms. In contrast, we investigate its potential demand-side influence on digital banking adoption.

4.1 Background

The revised PSD2 was adopted by European Parliament the 25th of November 2015, to repeal and to amend the original Payment Services Directive (PSD) from 2007 —EUR-Lex (2019). Motivated by the growing inertia of the digital transition —leading to rapid innovation and growing adoption of Fin-tech platforms— regulators addressed growing fears stemming of consumers from questionable digital payment security. The revised PSD2's purported 4 main objectives intended to safeguard consumers and regulate markets according to EU (2018) documents: (a) Bolster integration of digital payment systems across the EU, (b) introduce greater competition into fin-tech (c) To increase safety and security of payment systems (d) To enhance European consumer and business protections. These protections included implementation of regulatory technical standards, available on EUR-Lex (2019): Strong Customer Authentication (SCA) mandating multi-factor authentication for online financial transactions, mandatory incident reporting by financial institutions, and enhanced refund protections.

EU member states had until the 13th January 2018 to transpose the PSD2 into national law, beginning from the time the directive passed in European Parliament in 2015. The staggered implementation of PSD2 by the EU member-states offers the opportunity to test Hypothesis 1 —the impact of PU on the DBD. We reiterate the link to TAM constructs between this policy shock and PU of digital banking: At its core, a bank exists to secure finances of individuals and institutions. In this sense, security is synonymous with a financial institutions PU. If a bank cannot guarantee the safety of a deposit, PU decreases by definition. If it as TAM posits, and PU is a key driver of the adoption of digital banking, then we should expect the implementation of PSD2 should lead to an increase in the adoption of digital banking by internet users, shrinking

the DBD —Hypothesis 1. This will reflect a convergence of lagging attitudes towards digital banking and internet usage.

4.2 Empirical Strategy

Since transposition into national law was required by European Parliament under threat of fines and economic exclusion, all 27 EU member-states implemented the PSD2 at some point between 2015 and 2020. Because of this, we are not able to rely on a simple Difference-in-Difference (DID) methodology as it relies on a counterfactual of a never-treated group. Instead we look to an extension of the DID method —a Staggered DID (CSDID) by Callaway and Sant'Anna (2021)— which offers a framework to use not-yet-treated regions as comparison groups. This approach will help us in estimating the Average Treatment Effect on the Treated (ATT) for the PSD2 under the rigorous assumption of comparable Pretreatment Trends (PT). A significant and negative coefficient coupled with evidence of PT will tell us that the PSD2 was effective in decreasing the DBD, and confirm Hypothesis 1.

To retrieve the year of implementation we consult publicly available data on EUR-Lex (2019), where there are posted listings of each member-state in reference to PSD2. We utilize the year in which the first instance of PSD2 legislation was referenced by name —(2015/2366). We are then able to identify four main groups of adopters; those who adopted in 2017, 2018, 2019, and, 2020.

Table 4: PSD2 Implementation by Year: Country & Regional Observations

Year	Countries	% of Countries	Regions	% of Regions
2017	3	11.11%	65	27.43%
2018	20	74.07%	143	60.34%
2019	3	11.11%	21	8.86%
2020	1	3.70%	8	3.38%
Total	27	100.00%	237	100.00%

Table 4 presents the distribution of adoption times among the 27 EU member states and 237 regions. We can see that there were three were "early" adopters in 2017, followed by twenty in 2018, three again in 2019, and one in 2020. Columns-3 & -4 reflect the distribution of observations of 237 NUTS-2 level regions. The majority of observations are in 2018, in which 74% of countries and 60% of the regional observations had PSD2 transposed into national law.

We get our first suggestion of a policy "bite" on the DBD through a preliminary visual exploration —Appendix A10 has plots for all countries. We find visual suggestion for a majority of the EU member-states that there was a decrease in the DBD after implementation of the PSD2 directive. Examples of countries helping to form this conclusion in Figure 3.

This preliminary visual exploration corroborates our initial predictions from Hypothesis 1, though it is not reflective of a causal linkage, nor informs us of the magnitude or validity of the ATT. The continuing decline in DBD post-implementation leads us to expect an increasing dynamic policy effect as time from implementation increases.
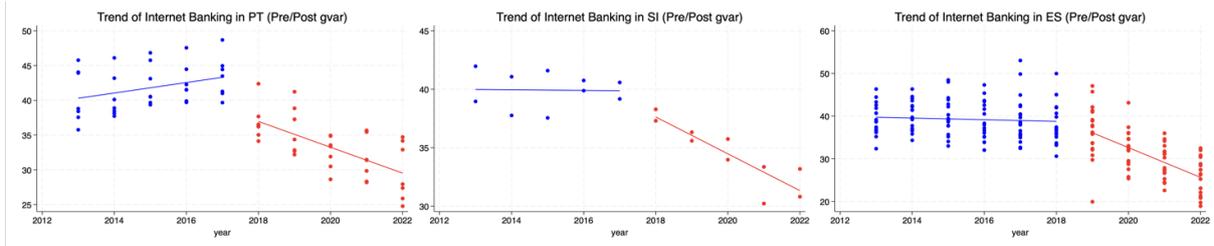
Figure 3: Payment Services Directive 2 on Digital Banking Divide —(PT-2018, SI-2018,ES-2019)

4.3 Pre-Treatment Trends (PT)

Providing evidence of parallel, Pre-treatment Trends is paramount when testing causal inference using any DID approach. Evidence towards PT establishes the credibility of the counterfactual, and since we will be comparing not-yet treated groups, the assumption is more fragile. A preliminary event study allows us to examine whether the pre-implementation coefficients are statistically indistinguishable from the baseline year (t–1).
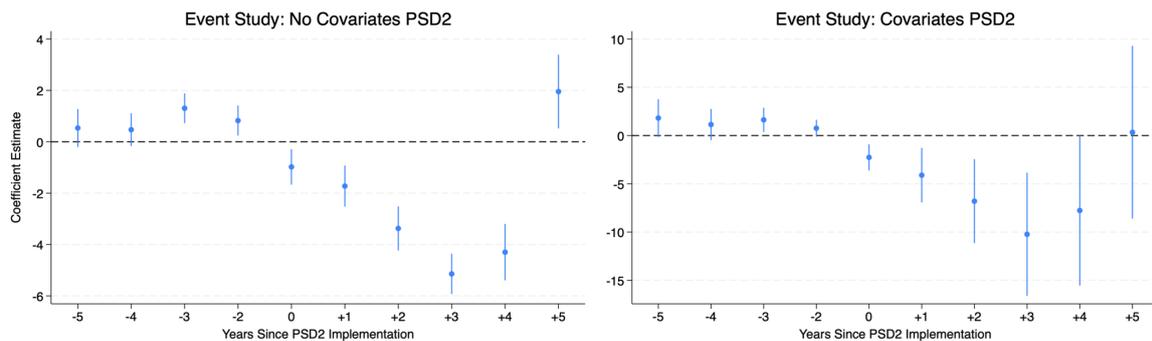
Figure 4: Event Study: Coefficients Since Implementation (base year t-1)

Each year before and after implementation is estimated as a separate indicator relative to the year of implementation. Coefficients are obtained using panel regressions, both with and without covariates, while clustering standard errors at the regional level to account for intra-region correlation. As shown in Figure 4, the results suggest significant violations of the parallel trends assumption. In Column-1 of Appendix Table A18, relative to the base year, there is a statistically-significant deviation of pretreatment coefficients. It should be noted that these pre-implementation coefficients did not differ substantially from zero in the pre-treatment —but were positive and significant— and only became negative starting the year of implementation. This tells us of a possible violation of the No Anticipation assumption (NA). Furthermore the evidence calls into question the credibility of the PT assumption as a whole —and with that the credibility of our counterfactual. Once we add covariates (Column-2 in Appendix Table A18), for, `lgdp`, `lpop`, `eqi`, and unit/time fixed effects, the coefficients pretreatment become mostly insignificant except for the third year before treatment ($p < 0.10$). Including these covariates allows us to control for changes in the economic and social environment (e.g., GDP, population) as well as institutional quality (EQI). The addition of fixed effects helps isolate the policy's

impact from common shocks affecting all regions and region-specific disturbances. Still, we must acknowledge an important violation of the fragile PT assumption and its impact on the causal interpretation of the ATT.

As for post-treatment observations, coefficient changes become more dramatic overtime as we observed previously. They are negative and significant post-treatment indicating that there may have been a dynamic policy effect that strengthened over time. This growing treatment effect makes intuitive sense as public knowledge on implementation may not have disseminated instantly of course, and the impact on individuals adoption choices would only be impacted when they heard of it.

Now having called into question the NA and PT assumptions, before our main estimation it is important to touch on the The Stable Unit Treatment Value Assumption (SUTVA). SUTVA is considered to hold in our setting if (a) each unit experiences the same treatment "dosage," and (b) there are no spillover effects between units—here, NUTS 2 regions. While implementation capacity may vary across countries, the PSD2 directive imposes a uniform set of technical standards and regulatory requirements that all EU member states were mandated to adopt. Given that these standards are coordinated at the EU level and legally binding, the core treatment, i.e., the institutional shift in the digital banking framework is consistent across treated units. To account for minor differences in the enforcement or institutional capacity, we include the EQI index from Charron et al. (2024) as a control, which is used to proxy for the effectiveness of EU policy implementation. This helps mitigate concerns about heterogeneous treatment intensity and supports the plausibility of assumption (a). Regarding (b) the absence of spillovers, it is reasonable to believe that digital banking infrastructure and regulatory compliance are largely bounded by national borders, especially during the initial roll-out of PSD2. Although multinational firms operate across countries, the actual regulatory enforcement mechanisms and consumer protection guarantees tied to PSD2 are only legally binding in the implementing country. Over all, we have found evidence of PT & NA assumption violations and should continue to our estimation cautiously.

4.4 Estimation

In a DiD framework with heterogeneous or dynamic treatment effects, units can be classified into three groups: never-treated, not-yet-treated, and already-treated. Since every EU-27 member state has at some point implemented the PSD2 within a short time-frame, we do not have a never-treated group for the counterfactual comparison. Even non-EU European countries have implemented aspects of the technical principles of PSD2 making them unsuitable for comparison, leading us to forgo their usage in the estimation. We first opt for a simple Two Way Fixed Effects (TWFE) estimation. TWFE is essentially a weighted average of every two-by-two comparison across our adoption groups. We created the dummy variable `treat` that indicates "1" every year past implementation of the policy including the year of implementation, and "0" otherwise. The coefficient β in Equation 2, tells us the difference in the DBD after treatment relative to the before —and whether its significant. the coefficients γ capture the partial effects of time-varying covariates $\mathbf{X}_{it}$. The fixed effects α_i and λ_t control for unobserved, time-invariant regional heterogeneity and common shocks across time, respectively.

$$DBD_{it} = \alpha_i + \lambda_t + \beta \cdot \texttt{Treat}_{it} + \mathbf{X}'_{it}\gamma + \varepsilon_{it} \qquad (2)$$

Table 5 reflects the estimated treatment effect of the policy by TWFE. We find robust negative and significant coefficients at the one-percent level for all estimations ($p < 0.01$). The estimated coefficient remains relatively stable across specifications, even as additional covariates are included. In Column-6, the coefficient for PU suggests that PSD2 led to an average reduction of approximately 2.5 percentage points in the DBD across all regions. This finding supports Hypothesis 1, indicating that a positive shock to PU as predicted by the TAM is associated with a widespread decline in the DBD.

Table 5: TWFE Estimations of PSD2 impact on DBD

	(1)	(2)	(3)	(4)	(5)
treat	-3.437***	-3.362***	-2.368***	-2.551***	-2.480***
	(0.344)	(0.358)	(0.407)	(0.460)	(0.444)
eqi		-4.157***	-3.871***	3.167**	2.981**
		(0.674)	(0.791)	(1.432)	(1.438)
lgdp			0.746	4.462	8.495
			(2.073)	(2.962)	(5.243)
lpop			0.141	-37.94***	-37.36***
			(0.719)	(11.94)	(12.98)
broadaccess			-0.112**	-0.141***	-0.156***
			(0.0466)	(0.0369)	(0.0502)
Region Fixed Effects	No	No	No	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes
R-squared				0.175	0.195
Observations	2370	2370	2370	2370	2370

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

While a traditional TWFE estimator provides valuable information, it assumes homogeneous treatment effects and uses already-treated units as controls, for both of which we have evidence against the credibility of in our event study estimation. Given the heterogeneous effect and staggered adoption of PSD2, for robustness we implement the Callaway and Sant'Anna (2021) DID estimator for hope of discerning the ATT.

The CSDID estimator uses "not-yet-treated" works as follows: for each adoption-group g, units that are not yet treated in period t (i.e., those with $G_i > t$) are used as "valid" controls — Equation 3. This design avoids the problems from our of standard TWFE, such as bias from treatment effect heterogeneity or contamination from already-treated units.

$$\widehat{\text{ATT}}_{g,t} = E[Y_{it}(1) - Y_{it}(0) \mid G_i = g, t \geq g] \approx E[Y_{it} \mid G_i = g, t \geq g] - E[Y_{it} \mid G_i > t] \qquad (3)$$

Callaway and Sant'Anna (2021) offer a compelling framework for causal inference in staggered adoption settings that lack a never-treated group. By creating a way to aggregate group-

time average treatment effects (ATT_g,t), their approach is more robust for the estimation of dynamic policy effects. They also highlight Inverse Probability Weighting (IPW) as a credible method of estimation of DID with covariates and not-yet-treated units. Our main findings using this approach are presented in Figure 5 — with detailed estimates broken down by year in Appendix Table A19. For those interested in results without covariates, see Appendix Figure A11.
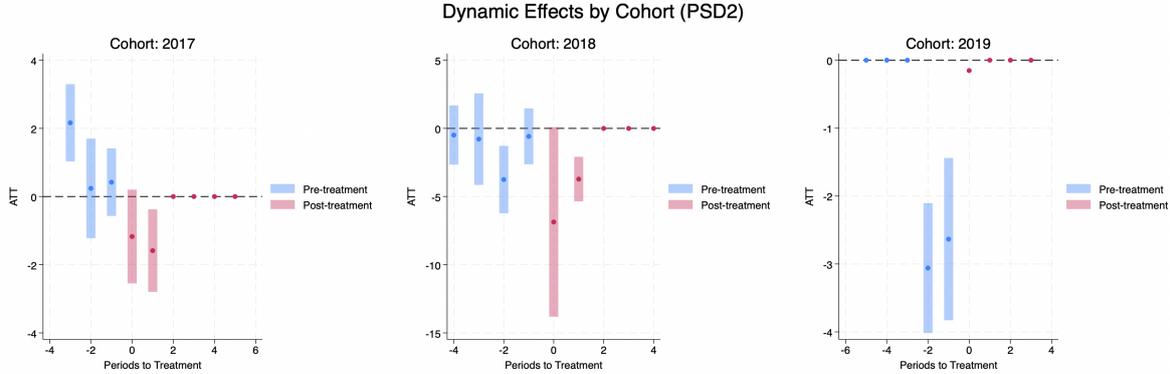
Figure 5: Callaway and Sant'Anna conditional DID using not-yet-treated group & IPW estimation method: PSD2 on DBD

Table 6: Simple & Group ATT Estimates for PSD2

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]
Simple ATT	-4.070***	1.367	-2.98	0.003	[-6.749, -1.390]
G2017	-1.380***	0.467	-2.96	0.003	[-2.294, -0.465]
G2018	-5.293***	1.947	-2.72	0.007	[-9.108, -1.477]

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

From inspection of both Figure 5 and the coefficients in the simple & group-wise ATT in Table 6, we can gather a few important pieces of information to guide our conclusions on the impact of the policy. First, the 2018 cohort with the majority of observations suggests clearly that there was some sort of treatment effect, though as discussed earlier, PT violations lead us to be critical about interpreting the causal effect of the PSD2 —supported by a significant chi-squared pretend test (chi(9): 118.6027, p = 0.000). The interpretation of the simple ATT coefficient from Table 6 is as follows: Overall, those regions in member-states that transposed PSD2 into law saw a decreased DBD —or in other words increased adoption of digital banking by potential users— by 4.01%. Even though there were significant violations of PT as we found, the signs and magnitude consistent through out our estimations gives us confidence that Hypothesis 1 has some validity. For the purposes of our investigation, this is enough evidence to keep exploring the impact of TAM constructs on digital banking adoption behavior.

4.5 Robustness checks

Though our main estimation was able to suggest a negative relationship between the PSD2 and the DBD, the environment that this policy was implemented in makes it highly susceptible to violations of the NA assumption and could skew our understanding of the results. To correct

for this, we do our TWFE estimation again, adding lags and leads to the relative year of implementation.

Table 7: TWFE Treatment Effects on DBD by Lag Specification

	(1) Lag 2	(2) Lag 1	(3) No Lag	(4) Lead 1	(5) Lead 2
Treatment Effect	-0.316	-0.844^{***}	-2.480^{***}	-2.698^{***}	-3.644^{***}
Std. Error	(0.463)	(0.303)	(0.444)	(0.639)	(0.705)

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

The results in Table 7 support observance of a violation of the NA assumption as there is a significant ($p < 0.01$) and negative treatment effects when we lag implementation by one year—though it is notably smaller in magnitude. There is also clear support for the presence of dynamic treatment effects, as we observe that coefficient magnitudes increase with time. The fact that the second lag is not significant reassures us that any anticipatory behavior was likely limited to just one year before the PSD2 transposition. For the complete regression results, see Appendix Table A20. The significance of the one-year lag is plausible for a few reasons: Banks and firms were likely aware of the incoming regulation shift and may have started adapting their systems, products, or customer outreach strategies preemptively. Similarly, consumers might have responded to the evolving environment around digital security and open banking before the official enforcement date. A quick event study to further explore the first lag of implementation reveals that the results are more ambiguous than can be inferred from the TWFE coefficient —Table 8:

Table 8: Dynamic Effects for Implementation Lag of One Year

	Coefficient	Std. Err.	z	P>$|z|$	[95% Conf. Interval]
Pre_avg	-0.954	0.851	-1.12	0.262	[-2.621, 0.713]
Post_avg	-1.533***	0.438	-3.50	0.000	[-2.391, -0.674]
Tm3	-0.490	1.107	-0.44	0.658	[-2.661, 1.680]
Tm2	0.136	1.206	0.11	0.910	[-2.227, 2.500]
Tm1	-2.507***	0.904	-2.77	0.006	[-4.280, -0.735]
Tp0	-0.292	0.736	-0.40	0.691	[-1.734, 1.149]
Tp1	-2.773***	0.361	-7.68	0.000	[-3.480, -2.065]

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

Overall, the sporadic significance of treatment effects across pre- and post-treatment periods suggests that our initial specification –without modeling anticipation effects– is likely more reflective of the "true" impact of the policy. The consistent signs and magnitudes observed in our first estimation lend further credibility to this assumption. Taking this suggestive evidence in favor of Hypothesis 1 seriously, we now proceed to our main analysis, which builds on our results from this section.

5 TAM at the Regional Level

5.1 Empirical Approach

To further examine whether regional heterogeneity in the latent TAM constructs determine DBD outcomes as predicted — we will be implementing panel techniques and IV methodologies to address sources of bias. We specifically aim to test Hypothesis 2 by studying how the significance of our variables of interest evolve as we shut off potential back-doors. Afterwards we then introduce and interrogate our chosen instrument for PU —the lagged (natural log) of density— to extract the unbiased parameter with an IV approach. We deliberately choose not to instrument for PEoU, as our primary objective is to directly examine the relationship between this core theoretical determinant and digital banking adoption. Instrumenting would risk obscuring the conceptual link we aim to highlight. We will then employ the Wooldridge (2010) Control Function Approach (CFA) to extract endogeneity from our estimation and discuss the nature of the bias.

$$\text{DBD}_{it} = \alpha + \beta_1 \text{PU}_{it} + \beta_2 \text{PEoU}_{it} + \mathbf{X}'_{it}\boldsymbol{\gamma} + \varepsilon_{it} \tag{4}$$

Equation (4) sets out the core TAM estimation as Davis (1989) originally presented. Where DBD_{it} is the Digital Banking Differential for region i in time t. PU_{it} and $PEoU_{it}$ are our synthetic variables proxying the latent TAM constructs that we constructed in Section 3.2.1. $\mathbf{X}'_{it}$ is a vector of relevant covariates for the confounding channels between our variables of interest and the the DBD —controlling for "external stimulus". Finally, ϵ_{it} is the idiosyncratic error term, which we assume also contains a structure of time invariant heterogeneity specific to each region (μ_i), as well as shocks commonly experienced by all regions in each time (λ_t) — motivating use of unit and time fixed effects respectively - illustrated in Equation (5).

$$\varepsilon_{it} = \mu_i + \lambda_t + u_{it} \tag{5}$$

If TAM constructs at the regional level significantly explain differences in the DBD, We expect to see the coefficient associated with PU (β_1) to be negative and significant —as a region increases in the PU of digital banking, we should observe a decrease in the percentage of potential system users not using it. As for PEoU (β_2), we expect a positive coefficient, as its construction flipped the sign we were expecting. PEoU may or may not be significantly different from zero as literature suggests.

We introduce controls into our estimation in three phases —signs next to variable names are how we predict they will influence the DBD: First, (1) region and time fixed effects. These control for unobservable, time-invariant regional characteristics—such as culture, geography, or historical banking infrastructure —also common shocks across all regions in a given year, such as EU-wide campaigns or macroeconomic fluctuations. (2) Institutions and economy: `eqi`(-), `lgdp`(-), `erate2064`(-) —The quality of institutions and the wealth of a region can influence the DBD directly, as the quality of institutions and a region's level of economic development can shape both the availability of digital infrastructure and public integration in digital systems. Regions with higher institutional quality and stronger economic performance are more likely

to support effective policy implementation, foster digital innovation, and reduce perceived risks associated with online financial services —thus contributing to lower DBD values. In phase (3) we implement covariates that capture the level of development in the digital environment —through broadband penetration, `broadaccess`(-)— as well as the physical environment with our index that captures pollution and climate comfortability— `envir`(+)[1], as these sorts of conditions may influence business locations and employment decisions. Together, these covariates help isolate the effect of our key explanatory variables from confounding spatial and temporal influences. We also make sure to cluster all estimations at the regional level for added robustness. Collectively these covariates control for regional disparities in digital infrastructure, wealth, amenities, technological maturity, labor market conditions and other environmental factors that may confound in our estimation. Without their inclusion our PU and PEoU coefficients may not truly reflect that of the region and capture the effects of other channels. Signs and correlations can be found in Appendix Figure A12, which are largely consistent with our predictions on their respective effects on the DBD.
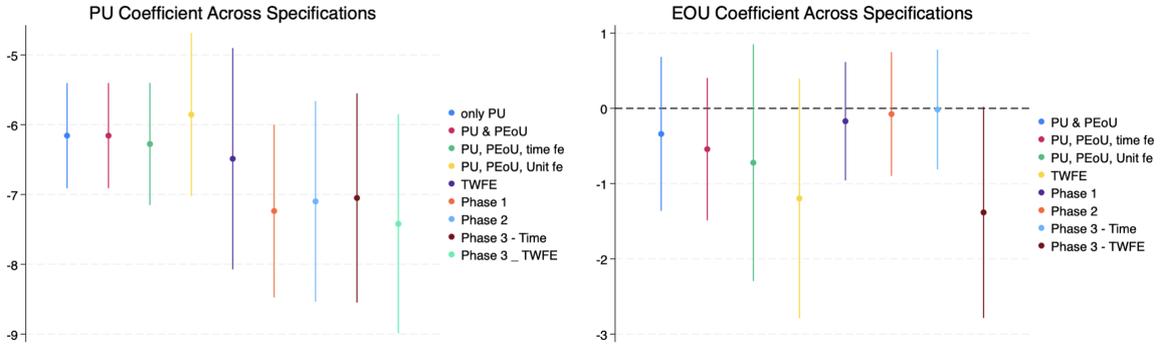
Figure 6: Evolution of Perceived Usefulness & PEoU coefficients with covariates and Fixed effects

In Figure 6, we visualize the evolution of our key coefficients as covariates are progressively introduced. Tables A22 and A23 in the Appendix present these results in table form. This preliminary visualization reveals two insights: First, the coefficient on PU becomes increasingly negative as more covariates are added. This suggests that part of the effect of PU on the DBD may have been masked by omitted variables that positively influence the outcome —a point we return to. Second, PEoU remains statistically insignificant across all specifications except the fully specified model. Table 9 shows the progression of estimations to the final specification —with all covariates and TWFE. We find that both PU and PEoU are negatively signed and statistically significant, indicating that regions with higher PU and PEoU are associated with lower differentials (DBD). PU remains highly significant ($p < 0.01$), while PEoU reaches significance at the 10 percent level ($p < 0.10$). This pattern is not unusual; as discussed in Section 2, PEoU is often less predictable in empirical TAM studies. Whether this reflects the real-world relevance of PEoU or limitations in our proxy construction remains open. Since PU and PEoU are principal component constructs, the coefficients should be interpreted as the effect of one

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[1]`envir` is also a PCA construction using variables: air quality (ug/m3 of air pollutant PM2.5, weighted average), heating & cooling days (energy demand) - correlations, loadings and such are available in Appendix Tables A15, A16, A17

standard deviation change in each: a one-unit increase in PU corresponds to a 7.42% decrease in the DBD, while a one-unit increase in PEoU corresponds to a 1.4% decrease. These results align with Hypothesis 1, indicating a strong association between PU and the DBD. However, to draw robust conclusions about the TAM's explanatory power at the regional level, we must first address potential endogeneity in the relationship between PU and DBD.

Table 9: Panel Estimations of DBD: Naive to Full Specification

	(1)	(2)	(3)	(4)	(5)	(6)
PU	-6.157***	-6.039***	-6.277***	-5.856***	-7.357***	-7.421***
	(0.385)	(0.356)	(0.447)	(0.565)	(0.800)	(0.796)
EOU		-0.340	-0.542	-0.722	-1.051	-1.383*
		(0.522)	(0.483)	(0.762)	(0.664)	(0.713)
eqi					1.917	1.948
					(1.216)	(1.231)
lgdp					24.38***	23.94***
					(5.737)	(5.474)
erate2064					-0.502***	-0.526***
					(0.0972)	(0.104)
broadaccess						0.0489
						(0.0585)
envir						-0.289
						(0.500)
Constant	31.37***	31.40***	30.15***	31.40***	-181.8***	-179.5***
	(0.654)	(0.659)	(0.644)	(0.00843)	(55.27)	(53.60)
R-squared				0.194	0.300	0.301
Observations	2370	2332	2332	2332	2332	2332
FE: Unit / Time	No / No	No / No	No /Yes	Yes / No	Yes / Yes	Yes / Yes

5.2 Endogeneity and Instrumental Variables (IV)

In the interest of maintaining a focused analysis on the core of the TAM, the coming estimations will focus primarily on analyzing PU —this is primarily due to the relative influence that PU has in the model, and the largely secondary influence of PEoU found both in the literature and in our estimations sofar. In addition, there is some plausibility that PEoU as we have constructed may be exogenous. PEoU is constructed from demographic and educational characteristics, specifically: median age, its square, and tertiary students —that are unlikely to respond to changes in digital banking behavior. It's difficult to imagine the DBD influencing a region's age structure or education levels in the short run. These variables proxy cognitive and generational ease with technology, and are better thought of as upstream determinants of digital banking adoption, not outcomes of it. For PU, Though all panel estimations exhibit a significant negative relationship inline with Hypothesis 2, we must address the possibility of endogeneity between the DBD and PU, in the form of simultaneity bias and reverse causality. A plausible channel of endogeneity is that regions with already high digital banking usage may exhibit a greater PU towards it. In addition, at the regional level, there may be latent variables that influence both the DBD and PU that we are not able to directly account for. With this hurdle between us and

Hypothesis 2; addressing the endogeneity bias in our estimation is the main focus for the rest of the study.

The key to addressing an endogenous regressor is selecting a credible instrument to act as an exogenous source of variation that isolates a portion of the variation within the endogenous regressor we can plausibly be considered causal. This means that an instrument should meet the rigorous assumptions discussed in the seminal work from Angrist et al. (1996). Instruments should be: (1) Relevant, meaning it is strongly correlated with PU in our estimation. At the same time, it must satisfy the (2) exclusion restriction —that the only effect of the instrument on the DBD is through PU. It should also be (3) exogenous, meaning that the instrument should not be correlated with the error term. Additionally, the instrument's effect on PU should be consistent in direction across observational units —(4) monotonicity. Finally, an instrument should be (5) intuitive and theoretically justified; otherwise, it becomes vulnerable to criticism and undermines the credibility of the identification strategy.

We propose using the natural log of density —lagged two periods— as a plausible instrument to derive the direct effect of PU on the DBD. Though at first this may seem unlikely, we argue that our instrument is intuitive and satisfies the five conditions key for causal inference — conditional on controlling channels of influence in which density might indirectly impact our outcome.

We first offer intuition for the instruments most rigorous condition —-the exclusion restriction. The validity of our instrument lays within the construction the DBD variable itself. Initially, there is an argument that density may impact both the level private internet use and the level of digital banking in a region —both the components that make up our variable. Though as discussed in Section 3, DBD really quantifies neither of these indicators. In conducting the transformation from Equation (1), the real levels of these two variables are differenced out, and our outcome (DBD) only reflects the latent exclusion of potential users of digital banking. This differential is the cause of some sort of behavioral, institutional, and contextual variables that make people decide to adopt or not —which is the aim of our study to quantify. For example, areas with low density (rural) and low internet penetration can still have a high proportion of their internet users digitally banking, resulting in a low DBD for the region. On the other hand, a region with extremely high internet penetration and a lower proportion adopting digital banking would result in a high DBD —perhaps due to the informal markets. Essentially our outcome then is not driven by density directly, but by how density shapes the regional environment that influences the expected value of adoption —what the TAM and our study posits is only through the PU. Appendix Figure A13 supports the plausibility of this logic with internet banking rates and internet penetration rates plotted seperatley against our instrument, what results is high amounts of variation in internet penetration and digital banking usage at different density levels —and necessarily— low correlation.

To further justify the exclusion restriction quantitatively, a preliminary correlation between DBD, PU, and our instrument reveal the fundamental dynamics that support the use of our instrument (Appendix Table A24). We observe a strong positive correlation between PU and our instrument, almost 50% (0.498), enough to justify the relevance assumption of our instrument. The correlation between `ldens` and the outcome DBD, shows a small, negative relationship of

about 5% (-0.047) —the magnitude difference supporting our relevance and exclusion claims respectively. Once we account for the channels through which density impacts can have an impact on DBD: Socio-economic, institutional, and demographic back doors that influence the adoption environment —our instrument should not have any correlation with the error term of our estimation —satisfying the exogeneity restriction. Formally, our identification strategy relies on the component of density that is orthogonal to these controls and operates only through its effect on PU, not through other channels.
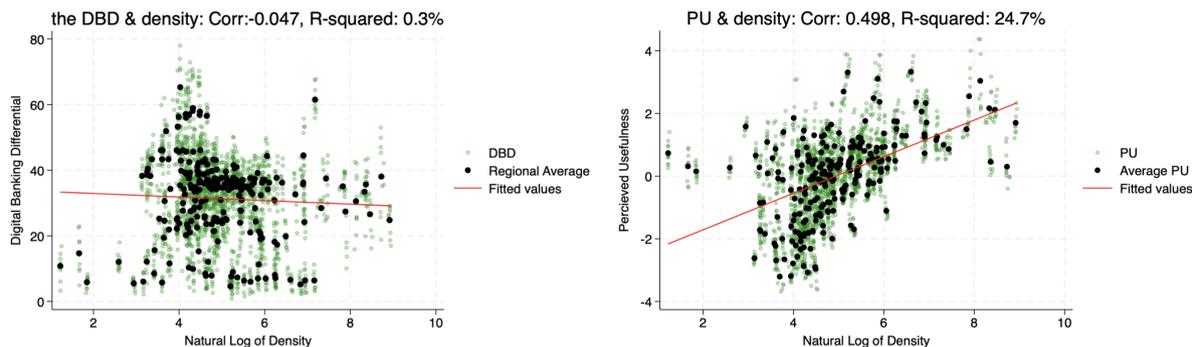
Figure 7: Exclusion and Relevance Scatter: Natural Log of Density, Digital Banking Differential, and Perceived Usefulness —By Region

In order to further avoid simultaneity bias and use a more clearly pre-determined instrument in our estimation, we look to use the lag of density. This is intuitive as lagged density can influence digital infrastructure today that in turn influences contemporary PU for a region, it is harder to connect past density effecting adoption attitudes behavior directly. From Appendix Table A25, we choose the most distant lag level that minimizes observation losses in our estimation —as we only have a decade of data. We use the second lag of population density as our instrument which fulfills our needs, showing a low correlation with the DBD at –0.06, and a strong positive correlation with PU at 0.498. From this point forward, the term density refers to the second lag of the natural logarithm of population density, unless otherwise specified.

Figure 7 provides visual support for both the relevance (right) and exclusion conditions (left). While there is a clear positive correlation between density and PU, no discernible pattern emerges between density and the DBD, reinforcing the assumption that density affects the outcome only through the endogenous regressor. The nature of density in the sample is important to note: it is a relatively slow-moving variable with a sample mean of 4.947 with low within-region variation over time (SD = 0.017) and much higher between-region variation (SD = 1.157).

This dynamic strengthens the case for not only the exclusion restriction but the exogeneity condition too, as small temporal fluctuations in density are unlikely to directly influence changes in the adoption of internet banking among internet users during the study period. Instead, density primarily captures structural, cross-sectional differences that operate through contextual factors such as PU. Though on the surface the apparent lack of within variation may sound

Table 10: IV Estimation Progression

	(1)	(2)	(3)	(4)	(5)	(6)
			Dependent variable: DBD			
PU	-1.120	0.916	1.114	-11.17***	-29.22***	-28.13***
	(1.317)	(1.754)	(1.811)	(1.883)	(6.699)	(5.799)
PEoU		3.115***	3.393***	0.324	-5.937***	-6.551***
		(0.779)	(0.834)	(1.452)	(1.283)	(1.617)
eqi					-0.714	-0.620
					(1.862)	(1.752)
lgdp					45.78***	43.55***
					(8.572)	(7.757)
erate2064					-0.156	-0.234
					(0.208)	(0.180)
broadaccess						0.108
						(0.0915)
envir						-1.261
						(0.779)
Constant	31.04***	30.60***	34.12***	31.03***	-418.9***	-398.1***
	(0.823)	(0.922)	(0.850)	(2.445)	(93.45)	(84.83)
R-squared	0.121	-0.0054	0.0058	0.911	0.843	0.853
Observations	1870	1870	1870	1870	1870	1870
FE: Time / Unit	No / No	No / No	Yes / No	No / Yes	Yes / Yes	Yes / Yes

Standard errors in parentheses

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

concerning: as it would blend into structural characteristics for a region overtime —disappearing with fixed effects in our estimation— if we take first differences of our instrument, we actually find there is ample variation within regional units overtime (Appendix Figure A14, Appendix Table A27). Combined with a reasonably large amount of observations for 230-plus regions, we should see that it is enough for a reliable within variation to extract a valid IV estimate in that dimension even considering fixed effects.

The monotonicity assumption requires that the direction of the effect of the instrument on the endogenous variable is consistent across observational units. In our setting, this implies that an increase in population density (ldens) should not reduce PU in any region. This assumption is plausible given that higher-density regions tend to exhibit greater exposure to digital services, more integrated infrastructure, and stronger incentives to adopt efficient digital tools — all of which are likely to uniformly increase PU or leave it unaffected. There is little theoretical or empirical basis to expect that higher population density would lead to lower perceptions of usefulness, supporting the credibility of the monotonicity assumption in our application.

5.2.1 Instrument Variables & Control Function Approach

Now having introduced the instrument and discussed its validity, we are able to turn to the IV estimations for examination. Table 10 present our main results:

Our PU variable evolves drastically with the addition of covariates and fixed effects; specifi-

cally noting the leap in magnitude from our final OLS specification in Column-6 of Table 9 —to our final IV specification in Column-6 of Table 10, almost a four-fold increase in effect. Our IV estimation tells us that an increase in regional PU by one-unit leads to a decrease in the DBD by more that 28% ($p < 0.01$). This implies that for some regions if they find a way to increase PU by one standard deviation, they could completely close the DBD gap. Even for PEoU, the negative and significant ($p < 0.01$) coefficient indicates that a increase in PEoU results in a decrease in the DBD by around 6.6%. According to the output, our model explains around 85% of the variance in the DBD —consistent with expectations given the inclusion of region and year fixed effects, along with structural predictors of digital behavior. We argue that the high R^2 reflects strong explanatory power rather than overfitting and that these results suggest that TAM holds relevance at the regional level as Hypothesis 2 predicts. However, studying the strength of our instrument is key to determining how much confidence we can place in the estimations coefficients.

Table 11: Instrument Diagnostic Tests

Test	Statistic	p-value
First Stage		
F-test (excluded instruments)	16.24	0.0001
Sanderson-Windmeijer F	16.24	0.0001
Sanderson-Windmeijer Chi-sq	18.79	0.0000
Second Stage		
Kleibergen-Paap LM stat (Under-ID)	16.87	0.0000
Cragg-Donald Wald F	55.74	–
Kleibergen-Paap Wald F	16.24	–
Stock-Yogo Critical Values (K=1, L=1)		
10% maximal IV size	16.38	
15% maximal IV size	8.96	
20% maximal IV size	6.66	
25% maximal IV size	5.53	
Robust Inference		
Anderson-Rubin Wald F	21.84	0.0000
Anderson-Rubin Chi-sq	25.27	0.0000

In Table 11, we present the diagnostic tests for both stages of our IV estimation. The first-stage F-test for excluded instruments yields a value of 16.24 — comfortably above the conventional threshold of 10 — suggesting that our instrument is relevant. This is reinforced by both the Sanderson-Windmeijer F & Chi-squared tests. The Kleibergen-Paap LM test rejects under-identification at the 1% level, further supporting the strength of the instrument. While the Kleibergen-Paap Wald F-statistic (16.24) falls just short of the Stock-Yogo 10% critical value (16.38), the gap is negligible. Even with the previous result, the Anderson-Rubin Wald F & Chi-squared tests strongly reject the null (P = 0.000), showing that our second-stage esti-

mates remain valid even under weak instrument conditions. By most standards, our instrument is both strong and well-identified. Finally, by adding an arbitrary instrument to the estimation —our density variable squared— we get an insignificant Hansen J statistic ($p = 0.989$) leading us to not reject the null hypothesis of valid instruments.

Table 12: Control Function Approach - IV Comparison

	(1) OLS-DBD	(2) CFA-first	(3) CFA-second	(4) IV
PU	-7.421***		-28.13***	-28.13***
	(0.796)		(4.924)	(5.799)
PUresid			21.02***	
			(4.872)	
L2.ldens		2.694***		
		(0.625)		
EOU	-1.383*	-0.0532	-6.551***	-6.551***
	(0.713)	(0.0454)	(1.215)	(1.617)
eqi	1.948	-0.0438	-0.620	-0.620
	(1.231)	(0.0750)	(1.257)	(1.752)
lgdp	23.94***	0.994***	43.55***	43.55***
	(5.474)	(0.248)	(6.754)	(7.757)
erate2064	-0.526***	0.0146**	-0.234**	-0.234
	(0.104)	(0.00584)	(0.108)	(0.180)
broadaccess	0.0489	0.0101***	0.108	0.108
	(0.0585)	(0.00265)	(0.0765)	(0.0915)
envir	-0.289	0.0185	-1.261**	-1.261
	(0.500)	(0.0290)	(0.592)	(0.779)
Constant	-179.5***	-25.37***	-406.1***	-398.1***
	(53.60)	(4.370)	(75.11)	(84.83)
R-squared	0.301	0.621	0.385	0.853
Observations	2332	1870	1870	1870
Unit / Time FE	yes / yes	yes / yes	yes / yes	yes / yes

Standard errors in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

We will now utilize Wooldridge (2010) CFA as it allows us to extract and examine the endogeneity from our estimation, and gives us the unbiased parameter for PU. The CFA works similarly to a two-stage least squares (2SLS) estimation method: In the first-stage the dependent variable is the main variable of interest —PU in our case— and the explanatory variables are the instrument (lagged density) and controls including unit and time fixed effects. Instead of getting the predicted values of PU to use as the independent variable in the second-stage — Wooldridge (2010) recommends predicting the residuals from the first-stage and inserting them into the second-stage as its own variable. The residuals from the first-stage regression reflect the portion of the endogenous variable (PU) that is not explained by the instrument nor included covariates. As such, the residuals capture any remaining endogeneity or omitted factors that

influence PU, and when inserted in the second stage, the result should un-bias the coefficient of interest and present a coefficient for the residuals in the exact amount of the bias of the estimation.

Table 12 presents the results from the control function approach (CFA) with Column-1 reproducing baseline OLS estimates from Column-6 of Table 9, which we expect to be biased due to endogeneity. The key idea in the CFA is to separate the variation in PU that is explained by our instrument (lagged population density) from the residual variation in PU that is unexplained. The coefficient on density in the first-stage regression (Column-2) is positive and significant (2.694; $p < 0.01$), meaning that increases in density are associated with higher PU. This makes intuitive sense: denser (urban) regions are more likely to benefit from agglomeration effects such as peer learning, digital familiarity, and accessibility of services. However, this only tells us one side of the story. The second-stage (Column-3) residual coefficient captures the portion of PU not explained by density that impacts the DBD. Interestingly, the residual coefficient is not only significant ($p < 0.01$) —an indication that endogeneity was a problem— but also presents a positive bias (21.02), meaning there is a tendency in our PU coefficient to zero. This brings us back to our instrument, as fundamentally, the IV only used the part of the variance in PU that could be explained by density. Meaning we captured channel that encourages the increased PU of a region, decreasing DBD. On the other hand the positive bias presumably captures the hesitance to digital bank, a proverbial "dead goose" that could include institutional distrust, low digital readiness, or other structural barriers —concepts that individual level TAM applications have found to be significantly and negatively impacting adoption decisions. Our study supports this literature in saying that choosing not to adopt digital banking may not be exclusively due to the technology being un-useful —but the stigmas associated with the platform usage itself. If the interpretation of the residual parameter truly holds, then Hypothesis 2 holds more credibility—by showing that regional-level PU —as driven by density— is indeed associated with increased adoption among potential digital banking users. At the same time, it suggests that the remaining, density-unrelated variation in PU may reflect regional-level hesitancy factors, such as perceived risk or lack of trust, which appear to inhibit adoption. In any-case, a final observation supports our conclusion: by comparing the Column-3 and Column-4, the identical coefficients tell us that our instrument was effective in removing the endogeneity from the estimation, further supporting our instrument and results accordingly. In sum, both of these channels reinforce the relevance of using latent TAM constructs at the regional level in explaining the DBD —concluding our main analysis.

5.3   Robustness checks

The first robustness check that we apply, is checking the exclusion restriction of our instrument with a balance test against other covariates. The findings suggest that our covariates are significant in determining our instrument, this could reflect avenues that density impacts the DBD other than through our PU variable. On the other hand, many of the values are near zero (e.g. broadband access — -0.000698; ($p < 0.01$)), indicating that if there is a violation, the bias from it would be extremely small — Table A28. We also run a lead-lag test of the outcome, DBD, which full output can be found in Appendix Table A29. We find that the

first lead is significant (–29.00; $p < 0.01$), while the second is not (–85.35; $p > 0.10$). Though significance of one lead is concerning, the second not being is of some support to our estimation. We observe the lags to be all negative, significant ($p < 0.01$), and decrease in magnitude further from the present, indicating there is some dynamic relationship, though not enough to raise concern. The last robustness test that we implement is by changing the lags for our instrument —Appendix A30: This robustness check confirms that the negative and significant effect of PU on the DBD holds across a variety of lagged instrument specifications. While the magnitude of the PU coefficient decreases with more recent lags, the overall direction and significance remain stable. This consistency suggests that the relationship is not sensitive to the choice of lag, reinforcing the credibility of the instrumental variable strategy. Taken together, these checks provide confidence in the credibility of our identification strategy. While the exclusion restriction may not be perfectly airtight as our lead-lag test showed, any potential violations appear to be minimal. finally, the stability of our IV estimates across alternative lags strongly supports the robustness of our main finding: that regional PU has a meaningful and consistent effect in reducing the DBD and furthermore that latent TAM constructs are relevant in explaining adoption behavior at the regional level.

6 Conclusions

The Technological Acceptance Model as originally posited by Davis (1989) is a popular framework for analyzing the latent constructs that determine the adoption of a new technology. While it has been utilized extensively at the individual level with survey data, the goal of this paper was to test whether regional heterogeneity in the latent constructs of the model —Perceived Usefulness and Perceived Ease of Use— determined digital banking adoption by potential users in the European Union. We split this paper into two parts: First, we analyzed the policy effect of the Payment Services Directive 2, utilizing a staggered Difference in Differences approach by Callaway and Sant'Anna (2021). Though violations of Pretreatment Trends kept us from making any causal claims, we found suggestion that an increase Perceived Usefulness may be associated with a lower Digital Banking Differential. These findings motivated our main panel analysis, where we instrumented a lagged density variable to get an unbiased parameter gain insight into whether regional heterogeneity in Perceived Usefulness determined the digital banking differential. Our findings of robust and negative coefficients suggested so. We then implemented a Control Function Approach by Wooldridge (2010), which revealed that our instrument was effective in revealing a channel that encouraged adoption of digital banking, and that the positive coefficient on the residuals likely reflected the hesitancy factors that could plausibly be associated with perceived risk. This supported our hypothesis, as both our bias and coefficient aligns with Technological Acceptance Model latent constructs, and the benefit-cost paradigm. We concluded with robustness tests that showed some indication of violation of the exclusion restriction. out of an abundance of caution we hesitate to make a full causal claim, as the construction of our PU and PEoU variables could influence outcomes of estimations in our favor, though we have found strong suggestion that the Technological Acceptance Model is relevant in explaining adoption behavior at the regional level. Policy makers should take interest with

these findings, as they communicate how behavior is a function of the individual, and the context in which they make their decision. Researchers can also benefit from this insight, as it broadens the scope of the analysis that can be conducted with the technological acceptance model framework.

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APPENDIX

Table A13: Descriptive statistics with indicator descriptions

Variable	Description	Level	Mean	Std. Dev.	Min	Max	Observations	Corr. with DBD
Digital Banking Differential (DBD)								
DBD	Digital	Overall	31.37	13.34	0.98	78.01	N = 2370	1.00
	Banking	Between		12.51	4.65	65.30	n = 237	
	Differential (DBD)	Within		4.70	12.23	49.19	T = 10	
int_priv	(%) Individuals using	Overall	82.59	11.23	41.33	99.44	N = 2370	-0.61
	internet for	Between		9.40	57.72	97.98	n = 237	
	private purposes	Within		6.17	52.96	103.93	T = 10	
int_bank	(%) Individuals	Overall	51.22	22.06	1.37	96.49	N = 2370	-0.92
	using internet	Between		20.44	4.73	92.73	n = 237	
	for banking	Within		8.40	24.45	85.42	T = 10	
Perceived Usefulness (PU)								
int_admin	Internet use	Overall	52.21	20.10	2.61	94.35	N = 2370	-0.80
	for admin.	Between		18.72	7.74	91.39	n = 237	
	purposes (%)	Within		7.41	23.08	90.50	T = 10	
agric_sh	Share of	Overall	3.07	2.73	0.00	13.58	N = 2370	0.35
	GVA in agricultural	Between		2.70	0.01	11.92	n = 237	
		Within		0.44	-0.29	6.88		
hightech	Share of	Overall	3.69	2.14	0.39	13.60	N = 2370	0.35
	high-tech employment	Between		2.06	0.69	10.62	n = 237	
		Within		0.58	1.07	6.88		
Perceived Ease of Use (PEoU)								
med_age	Median age	Overall	43.57	3.10	33.40	52.10	N = 2332	0.16
	of population	Between		2.97	34.32	51.31	n = 234	
		Within		0.91	40.05	46.70	T-bar = 9.97	
tert_stud_pc	(%) Population	Overall	29.95	9.61	11.40	62.10	N = 2370	-0.54
	with tertiary	Between		9.23	12.16	56.07	n = 237	
	education (16-74)	Within		2.71	17.10	39.75	T = 10	
Environment and infrastructure								
eqi	European	Overall	0.12	0.98	-2.63	2.82	N = 2370	-0.66
	Quality of	Between		0.98	-1.98	2.40	n = 237	
	Government Index	Within		0.13	-0.54	0.91	T = 10	
envir	Environmental policy	Overall	0.00	1.32	-3.86	5.12	N = 2370	0.49
	performance index	Between		1.30	-3.63	4.60	n = 237	
		Within		0.24	-0.98	1.03	T = 10	
broadaccess	(%) Households with	Overall	82.84	10.11	24.32	100.00	N = 2370	-0.48
	broadband access	Between		7.40	59.52	96.91	n = 237	
		Within		6.90	32.34	102.14	T = 10	
airqua	Air quality	Overall	12.41	4.50	2.80	39.51	N = 2370	0.46
	index (higher = worse)	Between		4.08	3.57	26.17	n = 237	
		Within		1.92	4.87	32.06	T = 10	
cooling	Cooling	Overall	107.24	141.69	0.00	841.72	N = 2370	0.42
	degree days	Between		136.36	0.01	725.39	n = 237	
		Within		39.38	-96.46	315.52	T = 10	
heating	Heating	Overall	2548.22	914.01	92.31	6421.79	N = 2370	-0.38
	degree days	Between		899.96	142.02	6147.90	n = 237	
		Within		169.01	2021.20	3033.45	T = 10	
Economy and Population								
erate2064	Employment	Overall	71.56	8.35	42.10	89.70	N = 2370	-0.44
	rate (20–64 years)	Between		7.88	44.02	86.83	n = 237	
		Within		2.80	60.10	81.43	T = 10	
lgdp	Log of regional	Overall	10.18	0.39	8.92	11.52	N = 2370	-0.45
	GDP per capita	Between		0.38	9.18	11.28	n = 237	
		Within		0.11	9.44	10.73	T = 10	
ldens	Log of	Overall	4.95	1.16	1.22	8.94	N = 2340	-0.05
	population density	Between		1.16	1.23	8.92	n = 235	
		Within		0.02	4.81	5.06	T-bar = 9.96	

t
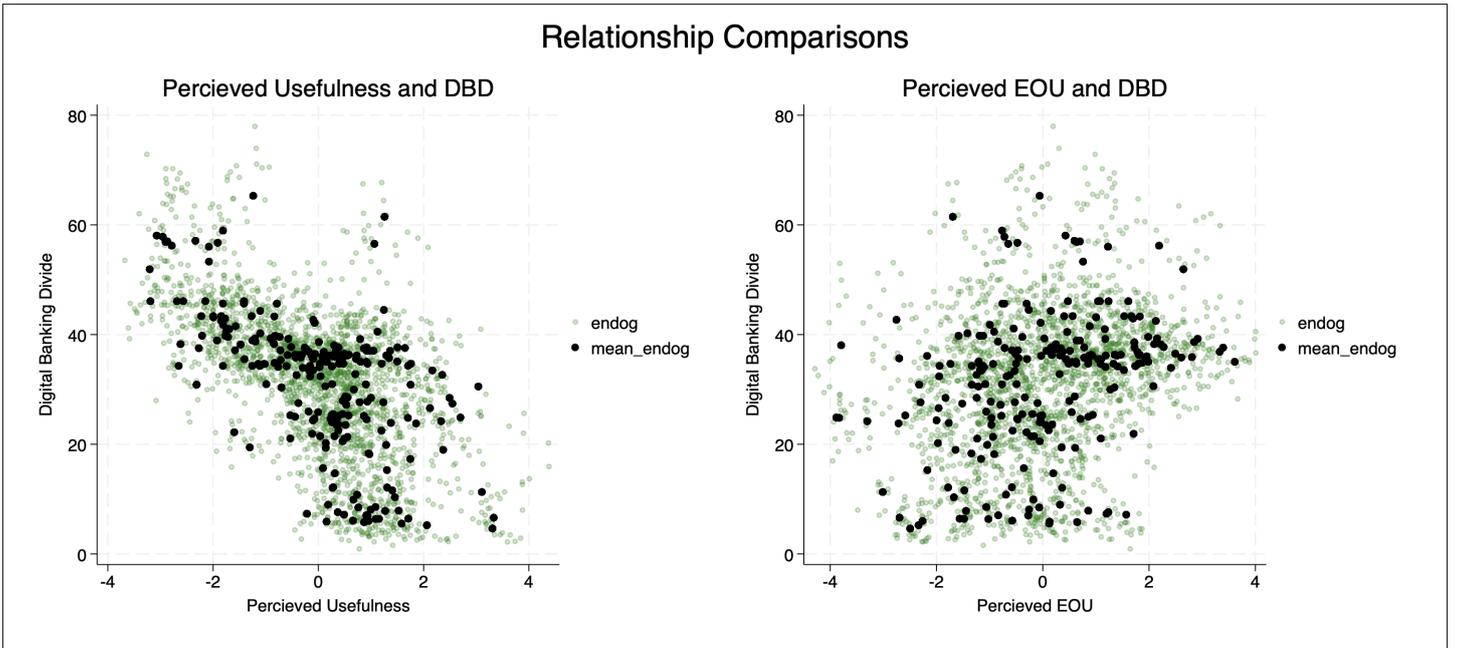
Figure A8: Scatter plots of PCA constructs PU and PEOU

Table A14: Principal Component Analysis for PEOU Variables

Component	Eigenvalue	Difference	Proportion	Cumulative
PC1	2.1429	1.2871	0.7143	0.7143
PC2	0.8558	0.8546	0.2853	0.9996
PC3	0.0012	—	0.0004	1.0000

Variable	PC1	PC2	PC3
tert_stud_pc	−0.3347	0.9423	0.0015
med_age	0.6665	0.2356	0.7073
mage2	0.6662	0.2377	−0.7069

Table A15: Correlation Matrix: Environmental Indicators

	cooling	heating	airqua
cooling	1.0000	−0.7082	0.1554
heating	−0.7082	1.0000	−0.0750
airqua	0.1554	−0.0750	1.0000

Table A16: Principal Component Analysis: Eigenvalues and Explained Variance

Component	Eigenvalue	Difference	Proportion	Cumulative
PC1	1.744	0.775	0.581	0.581
PC2	0.969	0.682	0.323	0.904
PC3	0.287	—	0.096	1.000

Table A17: PCA Loadings for Environmental Index (Unrotated)

Variable	PC1	PC2	PC3
airqua	0.2146	0.9733	−0.0816
heating	−0.6847	0.2095	0.6981
cooling	0.6966	−0.0939	0.7113
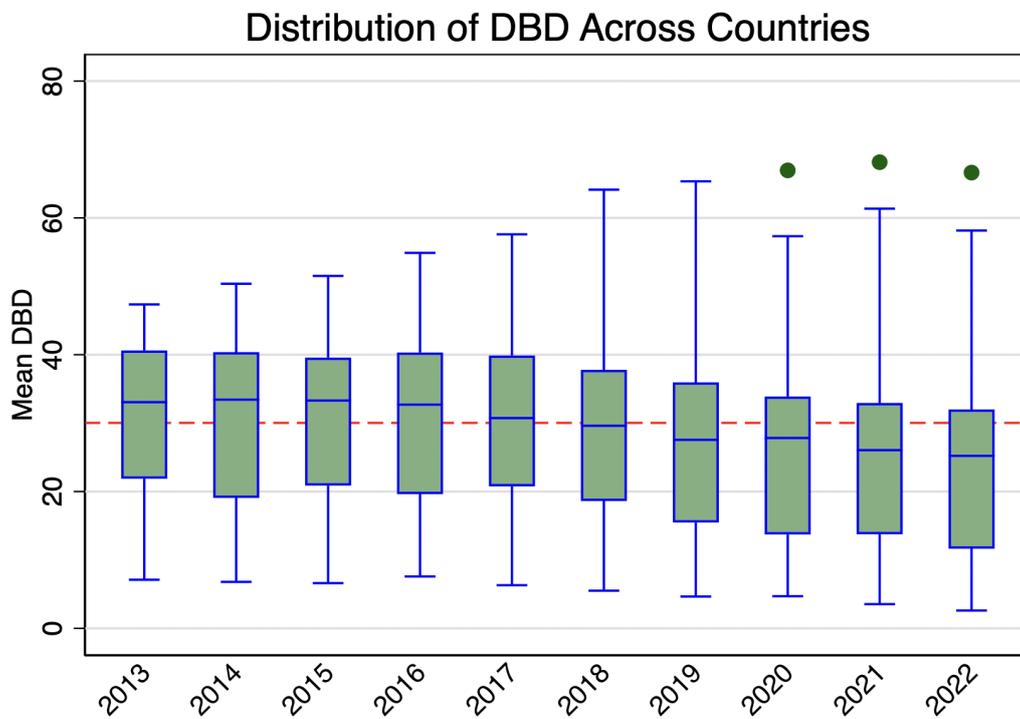
Figure A9: distribution of country averages over time
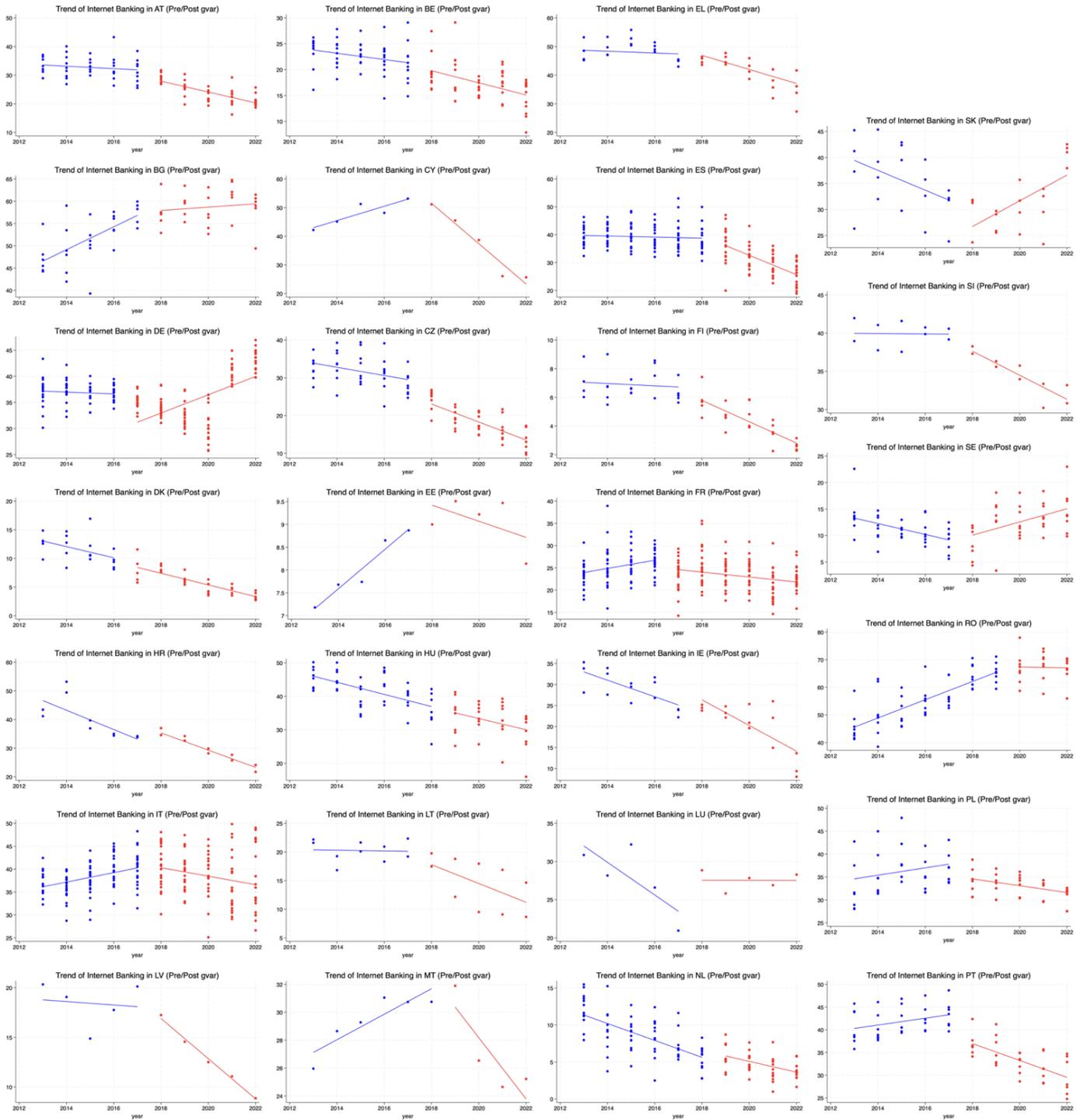
Figure A10: Banking Trends PSD2

Table A18: Estimated Coefficients from Dynamic Panel Regressions

Variable	eq_1	eq_2
Event time coefficients		
pre_5	0.536	1.810
pre_4	0.470	1.141
pre_3	1.305***	1.625*
pre_2	0.826**	0.757
post_0	-0.978**	-2.263**
post_1	-1.725***	-4.109**
post_2	-3.373***	-6.803**
post_3	-5.144***	-10.235**
post_4	-4.298***	-7.767
post_5	1.953**	0.339
Controls		
lgdp		8.964*
lpop		-28.647*
eqi		2.983*

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Equation 2 includes unit and time fixed effects with standard errors clustered at the regional level.

Figure A11: Naive CSDID plot: no covariates

Table A19: Difference-in-Differences Estimates by Cohort

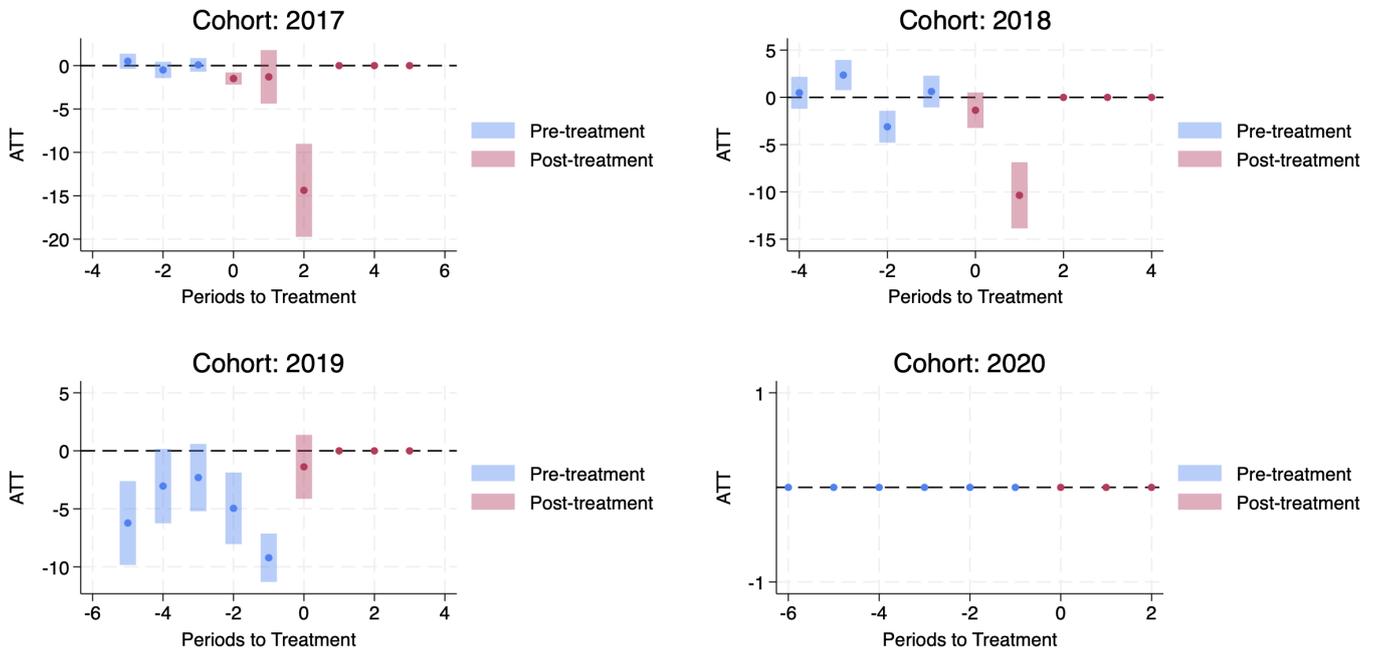| Group	Period	Coef.	Std. Err.	z	P>|z|	[95% CI]
6*g2017	t_2013_2014	2.164	0.578	3.74	0.000	[1.031, 3.298]
	t_2014_2015	0.239	0.745	0.32	0.748	[−1.221, 1.700]
	t_2015_2016	0.422	0.505	0.83	0.404	[−0.569, 1.412]
	t_2016_2017	−1.173	0.702	−1.67	0.095	[−2.549, 0.202]
	t_2016_2018	−1.587**	0.617	−2.57	0.010	[−2.797, −0.377]
	t_2016_2019 to 2022	0 (omitted)	–	–	–	–
6*g2018	t_2013_2014	−0.491	1.107	−0.44	0.658	[−2.661, 1.680]
	t_2014_2015	−0.785	1.715	−0.46	0.647	[−4.147, 2.576]
	t_2015_2016	−3.752***	1.261	−2.98	0.003	[−6.221, −1.282]
	t_2016_2017	−0.585	1.047	−0.56	0.577	[−2.635, 1.466]
	t_2017_2018	−6.864	3.548	−1.94	0.053	[−13.816, 0.089]
	t_2018_2019	−3.722***	0.834	−4.47	0.000	[−5.355, −2.089]
	t_2018_2020 to 2022	0 (omitted)	–	–	–	–
4*g2019	t_2016_2017	−3.060***	0.487	−6.28	0.000	[−4.015, −2.105]
	t_2017_2018	−2.637***	0.611	−4.32	0.000	[−3.828, −1.439]
	t_2018_2019	−0.152	2.73e−13	−5.6e+11	0.000	[−0.153, −0.153]
	t_2019_2020 to 2022	0 (omitted)	–	–	–	–

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

Table A20: TWFE Estimations of DBD, lags Year

	(1) lag 2	(2) lag 1	(3) no lag	(4) for 1	(5) for 2
treat_2	-0.316				
	(0.463)				
treat_1		-0.844***			
		(0.303)			
treat			-2.480***		
			(0.444)		
treat_f				-2.698***	
				(0.639)	
treat_f2					-3.644***
					(0.705)
eqi	2.843*	2.829*	2.981**	2.833*	2.875**
	(1.444)	(1.442)	(1.438)	(1.442)	(1.445)
lgdp	8.795*	8.840	8.495	8.131	7.188
	(5.319)	(5.363)	(5.243)	(5.116)	(4.941)
lpop	-38.03***	-37.78***	-37.36***	-37.55***	-37.38***
	(13.04)	(13.03)	(12.98)	(12.93)	(12.81)
broadaccess	-0.157***	-0.156***	-0.156***	-0.161***	-0.159***
	(0.0506)	(0.0508)	(0.0502)	(0.0503)	(0.0497)
Constant	492.4**	488.3**	485.8**	492.6**	499.5**
	(200.0)	(199.9)	(198.5)	(197.4)	(194.7)
R-squared	0.187	0.188	0.195	0.197	0.204
Observations	2370	2370	2370	2370	2370
Unit FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

Table A21: Callaway and Sant'Anna (2021) Difference in Differences with lag

Group	Event Time	Coefficient	Std. Err.	z	[95% Conf. Interval]
5*G2016	t_{2013_2014}	2.164	0.578	3.74	[1.031, 3.298]
	t_{2014_2015}	0.240	0.745	0.32	[-1.221, 1.700]
	t_{2015_2016}	0.421	0.505	0.83	[-0.569, 1.412]
	t_{2015_2017}	-1.781***	0.409	-4.35	[-2.583, -0.979]
	t_{2015_2018} to t_{2015_2022}			(omitted)	
6*G2017	t_{2013_2014}	-0.490	1.107	-0.44	[-2.661, 1.680]
	t_{2014_2015}	-0.785	1.715	-0.46	[-4.146, 2.576]
	t_{2015_2016}	-3.752***	1.260	-2.98	[-6.222, -1.282]
	t_{2016_2017}	-0.584	1.046	-0.56	[-2.635, 1.466]
	t_{2016_2018}	-3.224***	0.482	-6.68	[-4.169, -2.279]
	t_{2016_2019} to t_{2016_2022}			(omitted)	
3*G2018	t_{2016_2017}	-3.060***	0.487	-6.28	[-4.014, -2.105]
	t_{2017_2018}	-2.634***	0.610	-4.32	[-3.828, -1.439]
	t_{2017_2019} to t_{2017_2022}			(omitted)	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
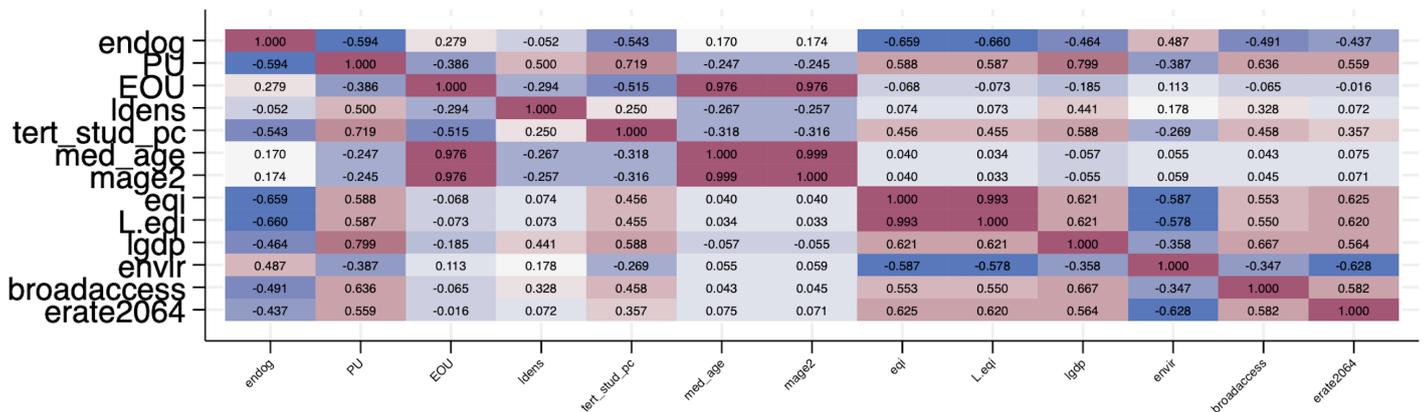
Figure A12: Heat Map of all Variables

Table A22: Effect of Perceived Usefulness (PU) on the Digital Banking Differential (DBD)

	(1) pooled	(2) time fe	(3) unit fe	(4) time & unit fe
Scores for com_1	-5.672***	-5.649***	-6.325***	-6.347***
	(0.164)	(0.167)	(0.279)	(0.449)
Year = 2013		0		0
		(.)		(.)
Year = 2014		1.407		1.510***
		(0.999)		(0.410)
Year = 2015		1.492		1.602***
		(0.999)		(0.411)
Year = 2016		1.822*		1.986***
		(1.000)		(0.418)
Year = 2017		0.716		0.875**
		(1.000)		(0.417)
Year = 2018		0.679		0.928**
		(1.001)		(0.435)
Year = 2019		0.139		0.454
		(1.002)		(0.452)
Year = 2020		-0.467		-0.0387
		(1.004)		(0.490)
Year = 2021		0.926		1.431***
		(1.006)		(0.519)
Year = 2022		0.769		1.342**
		(1.008)		(0.548)
Constant	31.37***	30.62***	31.37***	30.36***
	(0.223)	(0.709)	(0.0914)	(0.332)
R-squared	0.336	0.339	0.900	0.902
Observations	2370	2370	2370	2370

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table A23: Effect of Perceived Usefulness (PU) and Ease of Use (EOU) on the Digital Banking Differential (DBD)

	(1) pooled	(2) time fe	(3) unitfe	(4) time & unit
Scores for com_1 (PU)	-5.589***	-5.522***	-5.856***	-6.488***
	(0.179)	(0.185)	(0.333)	(0.449)
Scores for com_1 (EOU)	0.594***	0.652***	-0.722**	-1.198***
	(0.165)	(0.170)	(0.320)	(0.382)
Year = 2013		0		0
		(.)		(.)
Year = 2014		1.179		1.514***
		(1.011)		(0.414)
Year = 2015		1.347		1.898***
		(1.011)		(0.421)
Year = 2016		1.645		2.423***
		(1.013)		(0.436)
Year = 2017		0.482		1.413***
		(1.014)		(0.445)
Year = 2018		0.350		1.556***
		(1.016)		(0.472)
Year = 2019		-0.241		1.201**
		(1.020)		(0.500)
Year = 2020		-0.872		0.842
		(1.025)		(0.543)
Year = 2021		0.515		2.510***
		(1.030)		(0.586)
Year = 2022		0.288		2.528***
		(1.036)		(0.626)
Constant	31.39***	30.92***	31.40***	29.81***
	(0.224)	(0.728)	(0.0916)	(0.367)
R-squared	0.348	0.351	0.903	0.905
Observations	2332	2332	2332	2332

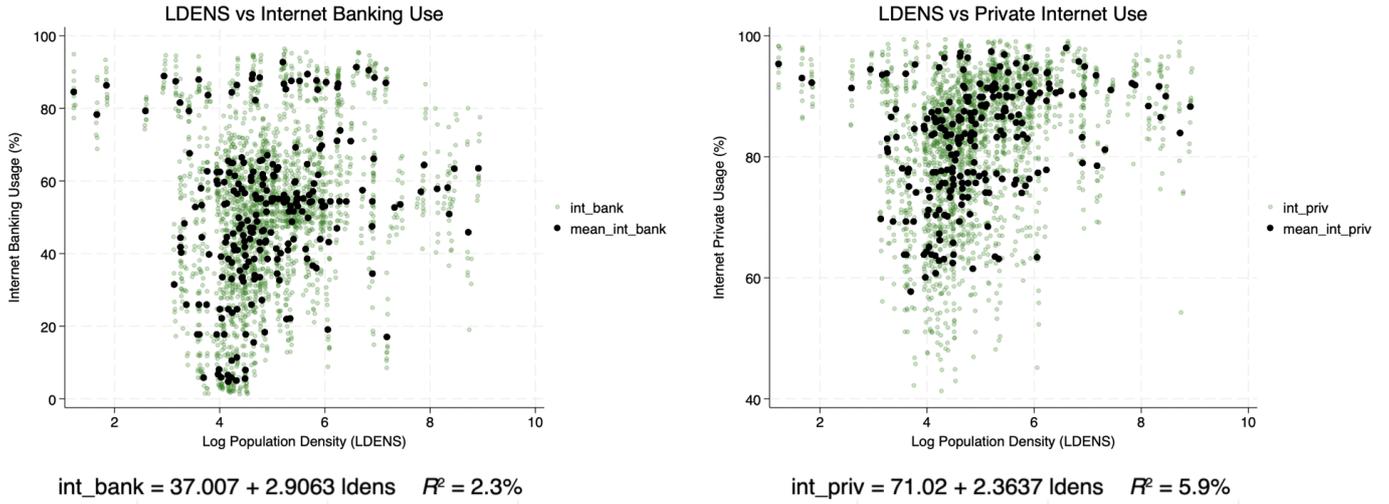*Standard errors in parentheses*

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

Figure A13: DBD variables decomposition and density

Table A24: Correlation Matrix between *DBD*, *PU*, and *ldens*

	DBD	PU	ldens
DBD	1.0000	-0.5797	-0.0469
		(0.0000)	(0.0234)
PU		1.0000	0.4984
			(0.0000)
ldens			1.0000

Table A25: Correlation Matrix with Lagged *ldens* Variables

	DBD	PU	ldens	L1.ldens	L2.ldens	L3.ldens
DBD	1.0000	-0.6103	-0.0652	-0.0622	-0.0602	-0.0584
PU		1.0000	0.5048	0.5013	0.4988	0.4966
ldens			1.0000	0.9999	0.9999	0.9998
L1.ldens				1.0000	1.0000	0.9999
L2.ldens					1.0000	1.0000
L3.ldens						1.0000

Table A26: Summary Statistics for *l2dens*

Variable	Mean	Std. dev.	Min	Max	Observations
l2dens overall	4.9468	1.1550	1.2238	8.9263	$N = 1870$
l2dens between		1.1569	1.2238	8.9124	$n = 234$
l2dens within		0.0172	4.8561	5.0340	$\bar{T} = 7.99$
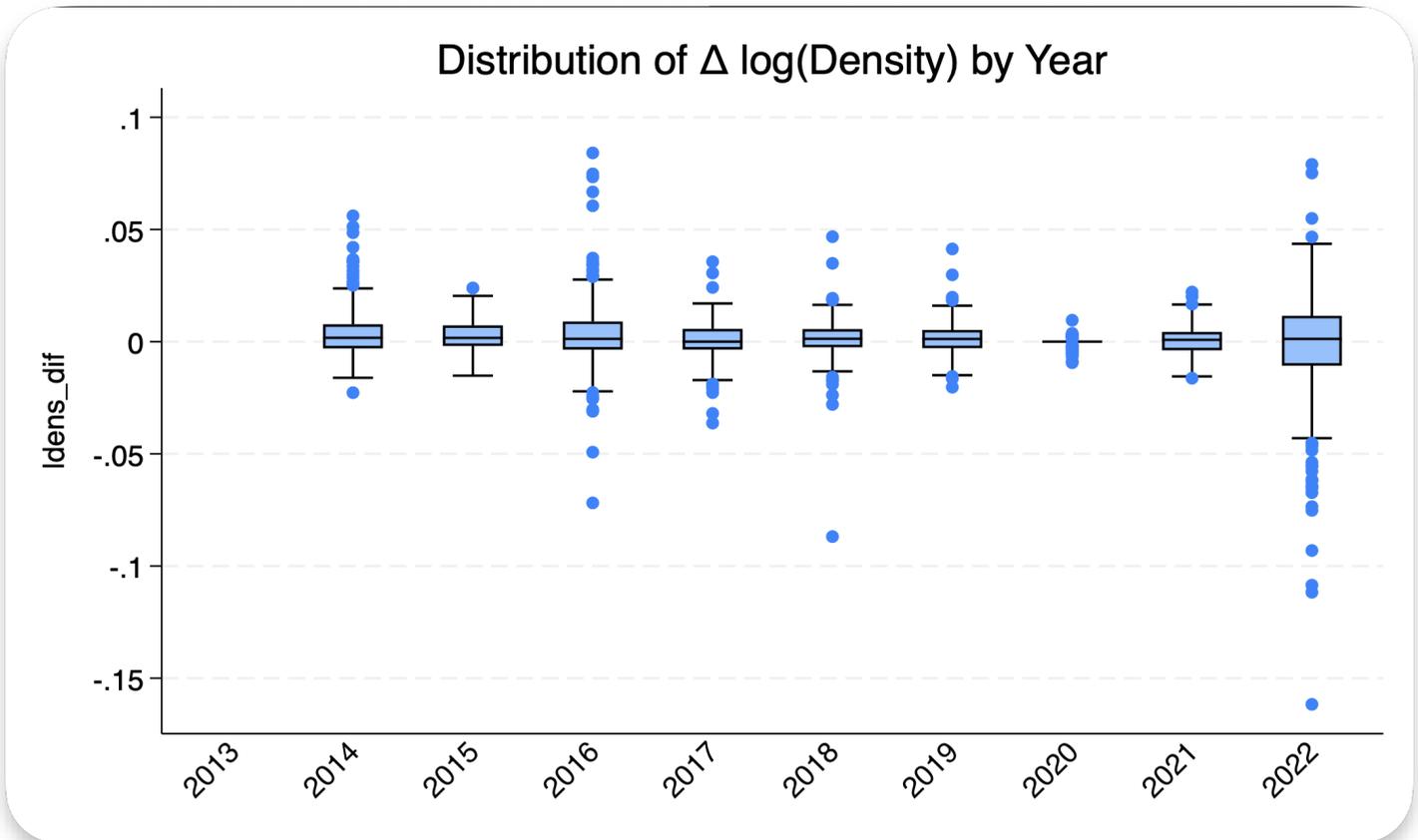
Figure A14: Difference in density overtime - within variance

Table A27: Summary Statistics for First Difference of Log Density ($ldens_dif$)

Variable	Mean	Std. Dev.	Min	Max	Observations
$ldens\_dif$ overall	0.0012	0.0130	-0.1616	0.0841	$N = 2105$
$ldens\_dif$ between		0.0071	-0.0227	0.0256	$n = 235$
$ldens\_dif$ within		0.0110	-0.1598	0.0726	$\bar{T} = 8.96$

Table A28: Balance Tests- Relative to Instrument

	(1) L2.dens	(2) L2.ldens	(3) L2.ldens	(4) L2.ldens	(5) L2.ldens	(6) L2.ldens	(7) L2.ldens	(8) L2.ldens
PU	7.380							0.0123***
	(5.473)							(0.00262)
EOU		-0.0467***						-0.0383***
		(0.00415)						(0.00433)
erate2064			-0.00224***					-0.000214
			(0.000656)					(0.000480)
eqi				-0.0219**				-0.0260***
				(0.00917)				(0.00623)
lgdp					-0.104***			-0.0586***
					(0.0248)			(0.0198)
broadaccess						-0.00197***		-0.000698***
						(0.000251)		(0.000216)
envir							0.00280	-0.000195
							(0.00350)	(0.00294)
Constant	341.5***	4.928***	5.093***	4.941***	5.989***	5.090***	4.937***	5.598***
	(1.714)	(0.00149)	(0.0456)	(0.00180)	(0.251)	(0.0196)	(0.00171)	(0.198)
R-squared	0.0258	0.376	0.106	0.0921	0.144	0.212	0.0762	0.448
Observations	1870	1870	1870	1870	1870	1870	1870	1870
FE: Unit / Time	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A29: Lag-Lead Tests

	(1) Lead$_2$	(2) Lead$_1$	(3) Main	(4) Lag$_1$	(5) Lag$_3$	(6) Lag$_4$
PU	85.35	-29.00***	-28.13***	-27.23***	-15.96***	-13.56***
	(193.2)	(9.759)	(5.834)	(5.390)	(3.629)	(2.986)
EOU	11.93	-8.499***	-6.551***	-5.265***	-1.295	0.421
	(38.44)	(2.362)	(1.626)	(1.390)	(1.052)	(0.899)
eqi	8.638	-1.017	-0.620	-0.216	1.005	-1.065
	(13.76)	(1.762)	(1.694)	(1.205)	(1.139)	
lgdp	-54.54	49.05***	43.55***	43.89***	32.33***	26.73***
	(170.9)	(10.80)	(7.803)	(6.725)	(5.352)	(4.525)
erate2064	-0.172	-0.291	-0.234	-0.180	-0.213*	-0.315***
	(1.354)	(0.193)	(0.181)	(0.178)	(0.117)	(0.109)
broadaccess	-0.665	0.0147	0.108	0.325***	0.360***	0.300***
	(1.303)	(0.104)	(0.0921)	(0.0883)	(0.0674)	(0.0622)
envir	1.807	-2.180**	-1.261	1.443*	2.183***	1.218**
	(6.716)	(0.879)	(0.784)	(0.800)	(0.714)	(0.590)
Constant	665.8	-450.9***	-406.1***	-430.3***	-311.1***	-243.1***
	(1786.4)	(116.8)	(86.18)	(74.53)	(57.13)	(47.51)
R-squared						
Observations	1402	1636	1870	1870	1638	1404
FE: Unit / Time	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A30: Alternative Instruments

	(1) F2.ldens	(2) F1.ldens	(3) ldens	(4) l.ldens	(5) l2.ldens	(6) l3.ldens	(7) l4.ldens
PU	-192.4	-40.71***	-47.30***	-48.13***	-28.13***	-17.48***	-9.247**
	(241.3)	(11.77)	(12.35)	(11.38)	(5.834)	(4.184)	(4.478)
EOU	-21.72	-4.949**	-6.523***	-8.074***	-6.551***	-5.459***	-4.623***
	(28.60)	(1.988)	(2.082)	(2.348)	(1.626)	(1.375)	(1.228)
eqi	3.989	-0.0505	0.573	-0.948	-0.620	0.956	0.818
	(9.843)	(1.858)	(2.211)	(2.864)	(1.762)	(1.247)	(1.325)
lgdp	187.1	57.48***	60.24***	62.41***	43.55***	32.94***	19.55***
	(209.9)	(13.62)	(15.00)	(13.29)	(7.803)	(6.741)	(6.768)
erate2064	0.653	0.0278	0.182	0.0908	-0.234	-0.375***	-0.420***
	(1.618)	(0.229)	(0.291)	(0.308)	(0.181)	(0.124)	(0.106)
broadaccess	0.640	0.186**	0.215**	0.230*	0.108	-0.0671	-0.239***
	(0.637)	(0.0915)	(0.105)	(0.121)	(0.0921)	(0.0765)	(0.0807)
envir	-10.47	-1.980*	-1.571	-1.299	-1.261	-0.904	-1.600**
	(15.12)	(1.069)	(1.070)	(1.112)	(0.784)	(0.664)	(0.643)
Constant	-2018.8	-577.7***	-621.1***	-632.6***	-406.1***	-271.8***	-118.2
	(2338.7)	(151.2)	(170.2)	(150.4)	(86.18)	(72.92)	(74.74)
R-squared							
Observations	1864	2098	2332	2104	1870	1636	1402
FE: Unit / Time	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$