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Introduction

1. Introduction

Contemporary healthcare systems face increasingly complex challenges related to population ageing (Zweifel et al., 1999; De Meijer et al., 2011), the growing prevalence of chronic diseases (Anderson et al., 2002; Vos et al., 2020), and the need of financial sustainability (Newhouse, 1992) without compromising equity in access to care (Culyer, 1993). In this context, innovation represents a crucial lever for improving the efficiency and effectiveness of healthcare delivery (Berwick et al., 2008; Skinner & Staiger, 2015), reshaping both the modes of service provision and the active role of individuals in prevention and care processes. Innovation in healthcare is not limited to the development of new technologies, but also encompasses new organizational models, information tools, and policy strategies capable of influencing behavior, individual choices, and health outcomes (Omachonu & Einspruch, 2010; Agha, 2014).

In recent years, digitalization has played a central role in this process. Digital health tools, such as telemedicine and remote monitoring, have the potential to reduce geographic and organizational barriers to access to care (Dorsey & Topol, 2016), while enabling a more continuous and personalized management of chronic conditions (Bashshur et al., 2016). At the same time, the introduction of new health technologies raises important economic and behavioral questions: individuals respond heterogeneously to innovation (Chandra et al., 2011), and the adoption of new tools may alter healthcare utilization, medication adherence, and risk perceptions (Cutler et al., 2010). In this sense, policies and products aimed at harm reduction, such as electronic cigarettes, also fit into the broader debate on healthcare innovation, as they seek to improve health outcomes through changes in behavior rather than through the complete elimination of risk (Viscusi, 2016). This dissertation is situated within this framework and adopts an applied health economics perspective to examine how different forms of innovation affect individual behavior and healthcare resource utilization.

The first chapter analyses the introduction of telemedicine, and in particular telemonitoring, as an innovation in healthcare delivery models for chronic cardiac patients. The main objective is to assess whether these digital tools act as substitutes for or complements to traditional in-person care, and to what extent they modify patterns of healthcare utilization. The analysis relies on individual-level administrative healthcare data from a local health authority in the Liguria region, which allows for a detailed observation of healthcare use before and after the introduction of telemonitoring. Using a quasi-experimental difference-in-differences design, the chapter investigates whether digital innovation reduces more intensive and costly forms of care, such

as hospitalizations, while promoting greater continuity in outpatient follow-up and a more preventive management of disease, or whether it instead generates additional demand, leading to an overall intensification of care.

The second chapter focuses on one of the main channels through which telemedicine may influence health outcomes and healthcare utilization: medication adherence. Concentrating on patients with chronic cardiac and diabetic conditions, the chapter examines whether exposure to telemedicine is associated with higher adherence to pharmacological therapies and whether such improvements translate into reduced use of acute healthcare services, such as hospitalizations and emergency department visits. The analysis again exploits longitudinal administrative healthcare data, which allow for the reconstruction of care pathways, pharmaceutical consumption, and service utilization over time. The central hypothesis is that telemedicine, by enabling more continuous monitoring, greater interaction with the healthcare system, and increased patient engagement in the care process, may act as a behavioral lever that improves adherence. From an empirical perspective, the chapter employs econometric models, including a recursive multivariate probit model, to analyze adherence as a mediating mechanism between exposure to telemedicine and healthcare utilization, shedding light on whether and how the benefits of digital health materialize indirectly through changes in care-related behaviors.

The first two chapters are analytically connected beyond the shared data source. Taken together, these two essays construct a coherent causal chain, from program exposure, through adherence improvement, to changes in acute care use.

The third chapter shifts the focus from innovation in healthcare delivery models to innovation in products and health policies, examining the case of electronic cigarettes. In this context, innovation is not understood as the elimination of risk, but rather as a harm-reduction strategy relative to highly harmful behaviors such as conventional cigarette smoking. The chapter uses longitudinal survey data representative of the U.S. population, which make it possible to observe consumption behaviors, risk perceptions, and responses to public policies over time. The empirical analysis exploits geographic and temporal variation in fiscal and regulatory policies on electronic cigarettes to identify the effects of regulation on individual behavior and beliefs about health risks. The underlying hypothesis is that fiscal and regulatory policies, while affecting behavior, may fail to modify, or may even distort, individual perceptions of the relative risks of different products, with potentially unintended consequences for welfare and public health. By employing econometric models that account for belief formation and individual heterogeneity, the chapter contributes to the debate on the interaction between information, subjective perceptions, and health regulation.

Taken together, the three chapters provide an integrated perspective on the role of innovation in contemporary healthcare systems, illustrating how digital technologies, public policies, and information interact with individual behavior and healthcare resource allocation. Although they focus on different domains, the chapters share a common emphasis on behavioral responses and on the potential unintended effects of innovation, highlighting how tools designed to improve efficiency and health outcomes may generate heterogeneous results depending on the institutional, informational, and regulatory context. This dissertation aims to contribute to both the academic and policy debates by providing empirical evidence on the opportunities and limitations of healthcare innovation, underscoring the importance of jointly considering technology, behavior, and regulation in the design of effective and sustainable health interventions.

Chapter One

2. Telemonitoring and Traditional Care: Complements or Substitutes? Evidence from a Difference-in-Differences Analysis in Italy[1]

2.1 Introduction

Health is widely recognized as a basic human right, implying that individuals should have equal access to healthcare services regardless of their demographic, socioeconomic, or geographic characteristics (World Health Organization, 2023). In practice, however, access to care remains unequally distributed (Moscelli et al., 2018), even within public health systems that provide medical services at little or no cost (Olsen and Laudicella, 2019). These disparities arise from differences in health literacy, geographic barriers, and socioeconomic conditions, among other factors (Leporatti et al., 2021). Extraordinary events, such as wars (Jacobs et al., 2020) or pandemics (Zeltzer et al., 2023a), can further restrict access to care and alter healthcare consumption patterns (Busso et al., 2022).

Advances in digital technologies have introduced telemonitoring[2] as a potential mechanism to reduce access barriers and improve the efficiency of healthcare delivery. By allowing remote consultations and continuous monitoring, it can extend medical services to patients who would otherwise face high access costs (Biancone et al., 2023). For instance, Walter et al. (2023) evaluate the introduction of a standardized virtual care program in the U.S. Military Health System using a difference-in-differences design. They find that hospitals adopting it experienced a 12% shorter average length of stay and savings of about $2,000 per patient, without adverse clinical outcomes. Similarly, Cantor et al. (2022), using data from over six million U.S. insured beneficiaries, show that the rapid diffusion of telehealth services during the COVID-19 pandemic mitigated part of the decline in healthcare utilization, particularly for preventive and non-urgent care, thereby preserving access to essential services under restrictive conditions.

Nevertheless, the evidence is mixed. Dahlgren et al. (2024) examine the introduction of direct-to-consumer telemedicine in Swedish primary care using linked registry data and an interrupted time-series design. They find that telemedicine users increased their overall healthcare utilization relative to matched controls, suggesting potentially induced demand and inefficiency.

[1] This work was conducted within the PRIN project RELIEVE and SAVE (2022), "Transforming healthcare in the post-COVID era: sustainability and value of telemedicine". Shorter versions of this work were co-authored with Lucia Leporatti, Marcello Montefiori, and Paolo Petralia and are currently under submission to international peer-reviewed journals.

[2] Telemonitoring is an application of telemedicine involving the remote observation of patients through audio, video, and digital transmission technologies (Liljeroos and Arkkukangas, 2023).

These contrasting findings indicate that the net impact of telemedicine on healthcare demand and system efficiency remains an open empirical question, particularly in contexts where evidence is scarce.

This paper examines whether telemonitoring acts as a substitute or complement to traditional in-person care for cardiac patients, and how it affects patterns of healthcare utilization. We study the introduction of telemonitoring services in Liguria, a region in northwestern Italy where no prior economic evaluations of telemedicine have been conducted. Liguria provides an informative setting because of its demographic and geographic characteristics. The region has European's highest share of individuals aged 65 and older (Eurostat, 2020) and faces substantial mobility constraints due to its mountainous terrain bordered by the sea (Istat, 2023).

To identify the causal effect of telemonitoring on healthcare utilization, we employ a difference-in-differences (DiD) framework. The underlying hypothesis is that telemonitoring may alter healthcare-seeking behavior, particularly among older and less mobile patients, by increasing the effective cost of access to care. The DiD estimates capture the Average Treatment Effect on the Treated (ATET), the mean change in outcomes for treated individuals attributable to the intervention, relative to how these outcomes would have evolved in the absence of treatment.

The empirical analysis relies on rich administrative registry data covering one of the Ligurian local health authorities (ASL 4). The dataset provides detailed semestral information on patients and their healthcare utilization over four years (2019-2022), during which telemonitoring services were introduced in the final two semesters. We estimate models with individual and time fixed effects to control for unobserved time-invariant heterogeneity. We also conduct several robust exercises to assess the sensitivity of the results to different time horizons and model specifications.

We have found three main results. First, telemonitoring does not significantly affect the number of hospitalizations but is associated with a reduction in hospitalization costs, suggesting milder or better-managed episodes. Second, it substantially increases the number and costs of cardiology visits, indicating an intensification of outpatient specialist follow-up. Third, the overall pattern points to a shift in resource utilization from hospital-based to ambulatory care, consistent with a preventive model of disease management, suggesting the presence of previously unmet care demand and highlighting the complementary, rather than substitutive, role of telemedicine in traditional care delivery, at least in the short-run.

Despite the growing international evidence on the effects of telemedicine, empirical research assessing its economic and behavioral implications in the Italian context remains scarce. Existing studies largely focus on clinical outcomes or pilot experiences, while systematic evaluations of its impact on healthcare utilization within the public system are still missing.

This research work contributes to filling this gap by providing novel evidence from Italy, specifically from Liguria, the region with the highest share of elderly residents in Europe. The case is particularly relevant because population ageing is expected to become pressing challenges for many European health systems in the coming decade (Eurostat, 2020).

By examining how telemonitoring affects healthcare consumption among older patients in such a setting, this study sheds light on behavioral patterns that are likely to emerge in other ageing societies, thus offering insights of broader policy relevance.

The rest of the chapter is organized as follows: Section 2 reviews the existing literature on telemonitoring and introduces the Italian legal context; Section 3 describes the data used in the study and the inclusion criteria adopted to define the treatment and control groups; Section 4 outlines the Difference-in-Differences empirical framework; Section 5 presents descriptive statistics and discusses the main results, supported by parallel-trend and no-anticipation tests; Section 6 explores heterogeneity in treatment effects across patient subgroups; Section 7 reports a set of robustness checks under alternative model specifications and time horizons; Section 8 concludes with a discussion of the main findings and policy implications.

2.2 Background

Our paper primarily relates to empirical literature assessing the impact of telemonitoring services on healthcare resource utilization. Telemonitoring represents one of the most advanced applications of telemedicine, particularly in cardiology, where it enables the remote and continuous observation of patients' health conditions through digital and communication technologies (Liljeroos and Arkkukangas, 2023). Most evidence focuses on cost implications and health outcome, though findings remain context dependent.

From an economic perspective, results often point to cost-effectiveness. Mokri et al. (2025) use a Markov model to assess the cost-effectiveness of remote patient monitoring for heart failure in the Netherlands, the United Kingdom, and Germany. They find that telemonitoring reduces heart failure-related hospitalization costs but increases total lifetime costs due to longer survival. In the context of chronic obstructive pulmonary disease (COPD), Achelrod et al. (2017) employ a difference-in-differences design to evaluate Europe's largest telemonitoring pilot pro-

ject. They report a 49% reduction in mortality and significant savings in COPD-related hospitalizations (-€1,056 per patient), suggesting that telemonitoring can reduce both healthcare utilization and mortality, especially among patients with severe diseases.

Several studies document positive health effects associated with telemonitoring interventions. Agboola et al. (2015) evaluate the Connected Cardiac Care Program for heart failure patients at Massachusetts General Hospital using a matched retrospective design. The program was associated with a 48% reduction in hospitalization risk within the first 30 days and a 67% reduction in mortality over the four-month duration. Similarly, Völler et al. (2021), in a randomized controlled trial in Germany, find that remote telemonitoring improved disease-specific quality of life over 12 months, despite showing no significant reduction in mortality or nonhospitalized days. These findings highlight that telemonitoring may yield important clinical and well-being benefits even in the absence of measurable cost savings or survival gains. These findings suggest that telemonitoring may be economically sustainable when its benefits in reducing hospitalizations and improving outcomes outweigh implementation and operational costs.

Empirical literature also documents substantial heterogeneity in effects across settings and populations, with some analyses suggesting inefficiencies or induced demand.

Regarding economic perspective, Sten-Gahmberg et al. (2024) evaluate a large-scale telemedicine intervention in Norway and report mixed outcomes: while participants experienced improved health-related quality of life and greater satisfaction, the number of general practitioner visits increased, and the cost-benefit ratio varied substantially depending on how non-monetary benefits were valued.

From health effects, Asch et al. (2022) find that an intensive remote monitoring program for heart failure patients did not significantly reduce readmissions or mortality over a 12-month period. Similarly, Pinnock et al. (2013), in a large, randomized trial of patients in the United Kingdom, report no significant differences between telemonitoring and conventional self-monitoring in terms of hospital admissions, quality of life, or psychological outcomes.

These studies illustrate that the effects of telemonitoring are far from uniform. Program design and patient characteristics appear to play a decisive role in determining whether telemonitoring generates efficiency gains or merely redistributes healthcare utilization across services.

One factor that may drive heterogeneous results is the structure of local healthcare systems. The Italian National Health Service operates on a universal coverage model funded primarily through general taxation. Healthcare provision is highly decentralized: regions are responsible

for organizing and delivering services within the national regulatory framework. This governance structure often produces marked heterogeneity in policy implementation, technological investment, and service accessibility across territories.

Telemonitoring in Italy has been progressively integrated into health policy following the 2008 European Commission Communication on telemedicine (European Commission, 2008) and the National Guidelines for Telemedicine. Tele-visits should not completely replace the remote doctor-patient relationship or the first in-person medical examination but are limited to monitoring patients with a pre-existing diagnosis (Ministry of Health, 2020).

Ligurian local health authorities ASL 4 has been among the first to adopt telemedicine within its regional health strategy with the project "Tigullio, Luogo di Salute", conceived as an experiment of a new model of proximity territorial healthcare (Romiti et al., 2023). The spatial and demographic peculiarities of the ASL 4 area make this case of particular interest in analyzing how remote care services can overcome geographic and demographic barriers, offering the opportunity to assess whether telemonitoring acts as a substitute or complement to traditional in-person visits and how it influences patients' healthcare consumption patterns.

2.3 Data

This study utilizes healthcare administrative data referred to the Local Health Authority of Liguria number 4 (ASL 4 - Chiavari) of the Liguria Region's Health System. ASL 4 covers the territory of the Gulf of Tigullio and its hinterland, an area comprising thirty municipalities in the central-eastern part of the region, with a total of 140,678 residents, approximately 9.33% of the Ligurian population (Istat, 2023). As shown in Figure 2.1, ASL 4 is divided into three social and health districts, which aim to ensure equal access to services and uniformity in the provision of care. In addition to providing basic assistance and promoting health, the districts are also responsible for identifying needs by evaluating the appropriateness of the demands expressed by citizens.

To analyze the effect of the introduction of telemonitoring services among cardiac patients in the Ligurian Local Health Authority (ASL 4), we assembled a comprehensive panel dataset covering the period 2019-2022. The data combine several administrative health sources and include a rich set of patient-level variables on demographic characteristics, drug purchases, and healthcare service utilization. The unit of observation is the patient-semester.

For each individual, information from the following registries was deterministically linked using anonymized personal identifiers.[3]

- Emergency Room Admissions: a registry of all patient visits to the emergency department;
- Pharmaceutical Records: a collection of information regarding drug purchases, both from direct distribution and conventional pharmacies;
- Patient Demographics: information on gender, age group, and municipality of residence;
- Exemption Registry: list of exemptions for diseases, including start and end dates of exemptions;
- Diagnostic and Therapeutic Services: visits provided by specialist physicians (outpatient specialty care);
- Hospital Discharge Records: containing information on hospitalizations.

Figure 2.1. Jurisdiction of ASL 4 and Associated Social and Health Districts

Note: The figure shows the territory covered by ASL 4, which includes the Gulf of Tigullio and its hinterland, divided into three social and health districts. The map highlights the main hospitals in the region.

For confidentiality reasons, access to information regarding deaths and patient transfers was not possible. Consequently, the date of the last occurrence of each patient in the databases was used to exclude those who had no visits, hospitalizations, or medication purchases in the period 2019-2022, as they were presumed deceased or transferred.

[3] To comply with privacy regulations, particularly the EU Regulation 2016/679, ASL 4 has implemented preliminary pseudo-anonymization of the data, and all patient information has been anonymized and linked using a unique 64-bit code generated randomly and irreversibly, to protect their identity while allowing the linkage of different occurrences within the datasets.

2.3.1 Inclusion Criteria

Many studies in literature focus on the impact of remote services on overall hospital resource consumption (Zeltzer et al., 2023a; Zeltzer et al., 2023b; Cantor et al., 2022), without concentrating on specific diseases. This study focuses on patients with severe cardiac conditions requiring life-saving implantable devices such as pacemakers, defibrillators, loop recorders, or Cardiac Contractility Modulation (CCM) systems. Patients were identified as those receiving at least one specialist service related to these devices, either during hospitalization or follow-up, through traditional in-person care or telemedicine. Individuals with specialist service codes C00481700 and C02253300 are classified as the control group (traditional care), whereas those with treatment code C02269600 constitute the treated group (telemonitoring).

These codes are included in the Diagnostic and Therapeutic Services database, where each therapeutic activity and specialist visit has been meticulously classified according to the Single Regional Catalogue of Outpatient Healthcare Services in Liguria.[4]

The analysis was restricted to residents within the ASL 4 territory in Liguria, a region characterized by a substantial influx of tourists during summer months (Osservatorio Turistico Regione Liguria, 2023).

Based on these inclusion criteria, 1,383 patients with cardiac devices were identified in the study area: 1,226 received traditional in-person visits, and 157 also received telemonitoring services.

2.3.2 Dependent Variables

This study examines the impact of telemonitoring on healthcare service utilization to determine whether the introduction of remote services has led to resource overuse, indicated by increased service usage, or if it has served as a substitute. Additionally, it explores cost implications.

We construct four main indicators of healthcare utilization and consumption behavior: number of hospitalizations; total hospitalization costs; number of cardiology visits; and total costs of cardiology visits. In addition, two alternative measures of cardiology visits and related costs were computed using discipline codes rather than specific service codes.[5]

[4] A.Li.Sa., 2020 - Azienda Ligure Sanitaria della Regione Liguria, Deliberazione n. 327 of 16/09/2020, Subject: Update no. 8 of the Single Regional Catalogue of Outpatient Healthcare Services that can be provided in the Liguria region, from the website: https://www.alisa.liguria.it/organizzazione/direzione-sanitaria/catalogo-unico-regionale-prestazioni-sanitarie-ambulatoriali.html, consulted on 27/05/2024.

[5] In the Italian healthcare system, “discipline codes” identify the medical specialty or organizational unit responsible for providing a service (e.g., cardiology, neurology), while “service codes” refer to specific diagnostic or therapeutic procedures as classified in the national tariff nomenclature.

The variables representing the number of hospitalizations and visits are numeric and were calculated by counting the number of events (hospitalizations or visits) within the relevant time periods. The number of hospitalizations was determined using the hospitalization discharge records (SDO), which include the date of each hospitalization. For the number of cardiology visits, the dataset containing specialist visit data was used, which records the date of each visit, whether scheduled or completed.

The cost variables are continuous and were calculated by summing up the associated costs. For hospitalizations, the DRG tariff[6] linked to each hospitalization was used. While DRGs provide a standardized approach for hospital billing, they represent a tariff rather than actual costs, which may lead to discrepancies in cost estimation, leading to an underestimation.

For specialist visits, the cost for each visit was derived from the tariff information recorded in the specialist visit dataset, and the total cost was computed by summing these values within the relevant time periods.

These proxies are widely used in the literature to capture healthcare utilization and provide a comprehensive view of how patients interact with the healthcare system, especially in the management of chronic conditions (Smith et al., 2020; Paré et al., 2013).

2.3.3 Independent Variables

A set of control variables was used to capture demographic characteristics, health status, treatment received, and temporal factors. These variables were either extracted from administrative datasets or computed based on available information.

Demographic Characteristics

The demographic dataset for ASL4 patients includes limited variables to protect patient anonymity. Specifically, the dataset contains information on gender, age group, and municipality of residence, linked to an anonymous ID.

The gender variable is important as it reflects gender-based differences in healthcare utilization, as highlighted by several studies (Verbrugge, 1985). It is coded as 1 for males and 0 for females.

The age group variable is categorized into three groups: 0-45 years, 46-65 years, and over 65 years. Although this classification was necessary to preserve privacy, it may limit the precision of the analysis, particularly since the "0-45" group is broad and includes both younger adults

[6] Diagnosis-Related Groups (DRGs) are a system for classifying hospital cases into groups based on diagnoses, procedures, and other factors. Each DRG is associated with a fixed reimbursement rate intended to cover the cost of care for a patient with a particular diagnosis or set of conditions. DRGs are commonly used in health economics to approximate hospital costs in the absence of detailed cost data.

and children, who may have different healthcare needs. For model estimation, this variable is treated as categorical, with values ranging from 1 to 3, corresponding to each groups.
The municipality of residence allows differentiation between individuals residing in urban versus rural areas. This distinction is relevant as it may influence healthcare utilization patterns, especially in the context of telemedicine adoption, with rural residents potentially facing different barriers to accessing healthcare services.

Health Status Characteristics
Health status information for patients was obtained from the exemption database, pharmaceutical database, and specialist services database, supplemented with an indicator of the number of comorbidities per patient calculated from diagnoses recorded in both the Diagnostic and Therapeutic Services file and the emergency department file.
From the exemption file, the number of pathology-related exemptions per patient was calculated, considering the different exemption renewals. Having an exemption for a pathology highlights a chronic pathological condition, which is useful for characterizing the patient's health status. The number of medications purchased, both through direct and conventional distribution, also helps to frame the patient's health status, not only by the number of different medications purchased but also by the various diseases they may treat. Moreover, using the diagnoses recorded in the administrative flows of hospital discharge forms and emergency department visits, the Charlson Comorbidity Index (CCI) was calculated. The CCI is a weighted index introduced in 1987 (Charlson et al., 1987) that classifies patients with comorbidities based on diagnosis codes. Each comorbidity has a weight ranging from 1 to 6, and these weights are summed to obtain a single value, where 0 indicates no comorbidity. A higher score indicates a greater risk of death or a higher likelihood of utilizing national healthcare services.

Treatment Variables
The central treatment variable, "telemedicine", differentiates between the control and treatment groups. It is coded as 0 for the control group and 1 for the treatment group.
Another key variable, "policy", indicates the introduction of telemonitoring services and takes the value 1 when a patient begins treatment in the first semester of 2022. This value remains 1 for the entire subsequent period, reflecting that the patient is considered treated from that point onward. This variable helps to examine how healthcare resource utilization changes over time for the treated group. Additionally, we interact the policy variable with the telemedicine variable to assess how the policy effect spreads over time and between the two groups.

Dependent and independent variables were computed on both a semi-annual and an annual basis to verify the stability of results across different time horizons during robustness checks. A detailed description of all variables is provided in Table 2.1.

Table 2.1. Description of Variables

Variable	Description
	Panel A. Outcomes
No. Hospital Discharges	Counting variable ∈ N= {0,1, 2, …}, it counts the number of hospitalizations for each patient
No. Cardiology Visits	Counting variable ∈ N= {0,1,2, …}, it counts the number of cardiology specialist visits for each patient
No. Cardiology Visits (by Discipline Code)	Counting variable ∈ N= {0,1, 2, …}, it counts the number of cardiology specialist visits, selected by discipline code, for each patient
Cost - Hospital Discharges (€)	Continuous variable ∈ $\mathbb{R}$, representing the cost of hospitalizations for each patient
Cost - Cardiology Visits (€)	Continuous variable ∈ $\mathbb{R}$, representing the cost of cardiology specialistic visits for each patient
Cost - Cardiology Visits (by Discipline Code) (€)	Continuous variable ∈ $\mathbb{R}$, representing the cost of cardiology specialistic visits, selected by discipline code, for each patient
	Panel B. Demographics Characteristics
Gender	Binary variable = 1 if the patient is male, 0 otherwise
Age Group	Categorical variable: 1 if the patient's age is between 0 and 45 years old; 2 if the patient's age is between 46 and 65 years old; 3 if the patient's age is above 65 years old
Area	Binary variable = 1 if it is an urban area, 0 if it is rural
	Panel C. Health Status Characteristics
No. Exemptions	Counting variable ∈ N= {0,1, 2, …}, it counts the number of exemptions for each patient
No. Distinct Drugs	Counting variable ∈ N= {0,1, 2, …}, it counts the number of drugs purchased for each patient
Charlson Index	Score of the CCI
	Panel D. Policy and Treatment Variables
Telemedicine	Binary variable = 1 if patient belongs to treatment group, 0 otherwise
Policy	Binary variable=1 from the first semester of 2022
Treat Intensity	Binary variable=1 from the moment the subject starts being treated
	Panel E. Time Horizon
Time	Categorical variable: in semester-level specifications, Time takes values from 1 to 8, where 1 corresponds to the first semester of 2019 and 8 to the second semester of 2022; in annual specifications, Time takes values from 1 to 4, where 1 corresponds to 2019 and 4 to 2022.

2.4 Empirical Strategy

To identify the causal effect of the introduction of telemonitoring services, we adopt a difference-in-differences (DiD) research design, following the framework proposed Roth et al. (2023). This approach compares the evolution of outcomes for treated and untreated individuals before and after the intervention, using the pre-treatment trajectory of the control group as the counterfactual for the treated group (Blundell & Costa Dias, 2000). The introduction of telemonitoring in the first half of 2022 constitutes a naturally occurring policy change, providing a quasi-experimental setting in which to assess its causal impact (Angrist and Pischke, 2008).
Formally, the model can be expressed as Equation (2.1):

$$Y_{it} = \alpha + \beta(Telemedicine_i * Policy_t) + \gamma_i + \delta_t + X'_{it}\theta + \varepsilon_{it} \quad (2.1)$$

where Y_{it} denotes healthcare utilization and its costs for patient i in period t; $Telemedicine_i$ is equals one if patient i belongs to the treated group and zero otherwise; $Policy_t$ is equal to one after the introduction of telemonitoring in period t and zero otherwise; γ_i and δ_t represent individual and time fixed effects, respectively; X'_{it} is the covariate's vector and θ the vector of their coefficients; ε_{it} is the error term.
The coefficient β captures the Average Treatment Effect on the Treated (ATET), representing the mean change in outcomes for treated individuals relative to the counterfactual trend that would have occurred in the absence of the intervention. It is shown in Equation (2.2).
The identification assumption underlying this design is that, in the absence of telemonitoring intervention, treated and control patients would have followed parallel trends in healthcare utilization.

$$\beta = \left[E[Y_{it}(1) - Y_{it}(0) \mid D_i = 1] - E[Y_{it}(1) - Y_{it}(0) \mid D_i = 0]\right] \quad (2.2)$$

We empirically verify the parallel trend assumption by estimating pre-treatment dynamic effects. The results show no statistically significant differences in trends between treated and control groups (p-values > 0.05), supporting the validity of the identifying assumption. In addition, a no-anticipation test confirms the absence of anticipatory behavior prior to the introduction of telemonitoring.
By including both individual and time fixed effects, we control for unobserved, time-invariant patient heterogeneity and for common shocks affecting all individuals in each period.
Heterogeneity analyses by gender, age, comorbidity, and geographical area are conducted to identify which subgroups drive the observed changes in healthcare utilization patterns.

While our main specification relies on a standard DiD framework, we verify the robustness of our findings using alternative specifications tailored to the structure of our data.

First, we perform a robustness test in which we gradually dilute the entry of treated patients into the treatment group, effectively shortening the treatment exposure window, to assess the sensitivity of the estimated effects to alternative definitions of treatment timing.

The corresponding specification is presented in Equation (2.3):

$$Y_{it} = \alpha + \beta TreatIntensity_{it} + \gamma_i + \delta_t + X'_{it}\theta + \varepsilon_{it} \quad (2.3)$$

where Y_{it} denotes the outcome of interest for individual i in period t; $TreatIntensity_{it}$ is a continuous treatment variable that measures the fraction of the semester (or year) during which patient i was exposed to telemonitoring, ranging from 0 (no exposure) to 1 (full exposure); the other variables represent individual and time fixed effects (γ_i and δ_t), capturing unobserved time-invariant heterogeneity and common shocks; X'_{it} is a vector of observed covariates with associated coefficient vector θ; ε_{it} is the idiosyncratic error term.

The coefficient β captures the dose-response treatment effect, representing how outcomes vary with the intensity and timing of exposure to telemonitoring services.

This formulation extends the baseline DiD framework to account for staggered adoption and partial treatment exposure, following recent developments in the DiD literature (Callaway and Sant'Anna, 2021).

Second, we estimate alternative model specifications tailored to the distributional properties of our outcome variables, to assess the robustness of the DiD results to different functional forms. Variables such as the number of hospitalizations and number of outpatient visits are count variables, taking values in the set of non-negative integers (0, 1, 2, …). In our dataset, these variables display a high proportion of zeros, a typical feature of healthcare utilization data (Deb & Trivedi, 1997). The Poisson model is specifically designed to handle such distributions, providing a coherent framework for modelling the conditional means of count outcomes (Cameron & Trivedi, 2013).

Formally, let Y_{it} denote the number of events experienced by individual $i$in period t.

We assume that:

$$Y_{it} \mid X_{it} v_i \sim Poisson(\lambda_{it}) \quad (2.4)$$

where $\lambda_{it} = E[Y_{it} \mid X_{it}, v_i]$ represents the conditional expectation of the count outcome, and $v_i$is an individual-specific random effect capturing unobserved time-invariant heterogeneity.

In the random-effects Poisson model, the intensity parameter λ_{it} is specified as:

$$\lambda_{it} = exp(\alpha + \beta(Telemedicine_i * Time_t) + \delta_t + X'_{it}\theta + v_i) \quad (2.5)$$

where $Telemedicine_i * Time_t$ is the interaction between treatment status and time indicator; δ_t are time fixed effects, capturing shocks, institutional changes, and seasonality common to all patients in each period; X'_{it} is a vector of time-varying covariates (e.g., age groups, gender, comorbidities, clinical severity) and θ is the associated parameter vector; v_i is an individual-specific random effect; β measures the causal effect of telemonitoring availability on the expected number of events.

The model is estimated using a random-effects Poisson estimator with standard errors clustered at the individual level, consistent with the panel structure of the data.

For cost outcomes, we employ a Tobit model to account for the fact that healthcare expenditures are continuous but bounded below at zero (Wooldridge, J. M., 2010). Cost variables in administrative health datasets typically exhibit a mass point at zero, reflecting individuals who do not consume any healthcare resources in each period, combined with a continuous right-skewed distribution among positive values. Standard linear models may inadequately capture this censoring, potentially leading to biased estimates.

Let C_{it} denote the healthcare cost incurred by individual i in period t. We model the latent (unobserved) continuous variable C^*_{it} as:

$$C^*_{it} = \alpha + \beta(Telemedicine_i * Time_t) + \delta_t + X'_{it}\theta + v_i + \epsilon_{it} \quad (2.6)$$

In this specification, $Telemedicine_i * Time_t$ represents the treatment-time interaction capturing the DiD structure in the cost domain; δ_t are time fixed effects; X_{it} is the vector of time-varying covariates (age, gender, comorbidities, clinical severity); θ is the associated parameter vector; the term v_i is an individual-specific random effect accounting for unobserved, time-invariant heterogeneity across patients; and $\varepsilon_{it} \sim N(0, \sigma^2)$ is an i.i.d. error term.[7] The parameter β captures the effect of the introduction of telemonitoring on the latent cost variable, which translates into changes in observed expenditures after accounting for censoring at zero.

[7] The Tobit model assumes that the error term ε_{it} is independent and identically distributed (i.i.d.), meaning that all disturbances share the same statistical distribution and are uncorrelated across individuals and time. Formally, this implies $\varepsilon_{it} \sim N(0, \sigma^2)$ and $\mathrm{Cov}(\varepsilon_{it}, \varepsilon_{js}) = 0$ for all $(i,t) \neq (j,s)$. This assumption ensures the tractability of the likelihood function and the consistency of parameter estimates. In empirical applications with panel data, where serial correlation and heteroskedasticity may arise, we account for potential deviations from the i.i.d. assumption by computing cluster-robust standard errors (Wooldridge, J. M., 2010).

Finally, we collapse the panel from a semi-annual to an annual frequency, increasing the number of observations per period and thereby improving the stability of estimates.

2.5 Results

This section presents the empirical results of our difference-in-differences (DiD) analysis assessing the impact of telemonitoring services on healthcare utilization among cardiac patients in an area of Liguria region. The section is organized as follows. We begin by reporting descriptive statistics that document the main characteristics of treated and control patients and pre-intervention trends in healthcare outcomes. We then present the main DiD estimates quantifying the causal effect of telemonitoring on hospital discharges and cardiology visits, and their associated costs. Finally, we assess the validity of the identification strategy by testing the parallel-trend and no-anticipation assumptions.

2.5.1 Descriptive Statistics

Table 2.2 and Table 2.3 summarize the main characteristics of the study population divided by sub-groups.

Table 2.2. Descriptive Statistics of Outcomes and Health Characteristics, by Semester

	Treated group					Control group				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Panel A. Outcomes										
No. Hospital Discharges	0.24	0.61	0.00	6.00	1237	0.23	0.58	0.00	7.00	8796
No. Cardiology Visits	1.39	1.57	0.00	24.00	1237	0.87	1.21	0.00	12.00	8796
No. Cardiology Visits (by Discipline Code)	1.30	1.55	0.00	24.00	1237	0.78	1.17	0.00	12.00	8796
Cost - Hospital Discharges	1334.14	4237.87	0.00	34546.00	1237	1057.46	3182.63	0.00	53827.90	8796
Cost - Cardiology Visits	32.68	36.69	0.00	315.02	1237	20.39	30.51	0.00	305.99	8796
Cost - Cardiology Visits (by Discipline Code)	32.38	39.50	0.00	307.55	1237	19.62	32.63	0.00	339.56	8796
Panel B. Health characteristics										
No. Exemptions	1.42	1.22	0.00	6.00	1237	1.32	1.31	0.00	7.00	8796
No. Distinct Drugs	7.77	4.26	1.00	28.00	1124	7.55	4.20	1.00	34.00	8213
Charlson Index	1.46	2.17	0.00	15.00	1069	1.53	2.18	0.00	16.00	7631

Note: Data refers to patients with cardiac implantable devices (pacemakers, defibrillators, loop recorders, or CCM). The treated group includes patients with remote monitoring, while the control group includes those with only in-person follow-ups. Statistics are computed on 1,383 patients (1,226 control and 157 treated).

Table 2.3. Sociodemographic Characteristics

	Treated		Control	
	N	%	N	%
Panel A. Gender				
Female	52	33.1	493	40.2
Male	105	66.9	733	59.8
Panel B. Age groups				
0 - 45	6	3.8	11	0.9
46 - 65	37	23.6	78	6.4
65+	114	72.6	1137	92.7
Panel C. Area				
Rural	30	19.1	255	20.8
Urban	127	80.9	971	79.2
Total	157	100.0	1226	100.0

Note: The table reports absolute (N) and relative (%) frequencies of categorical variables by treatment status. Percentages are computed within groups.

The sample consists of 1,383 patients with cardiac implantable devices residing in the ASL 4 area of Liguria, of whom 157 (11.3%) were enrolled in telemonitoring programs (treated group) and 1,226 received only traditional in-person follow-ups (control group).

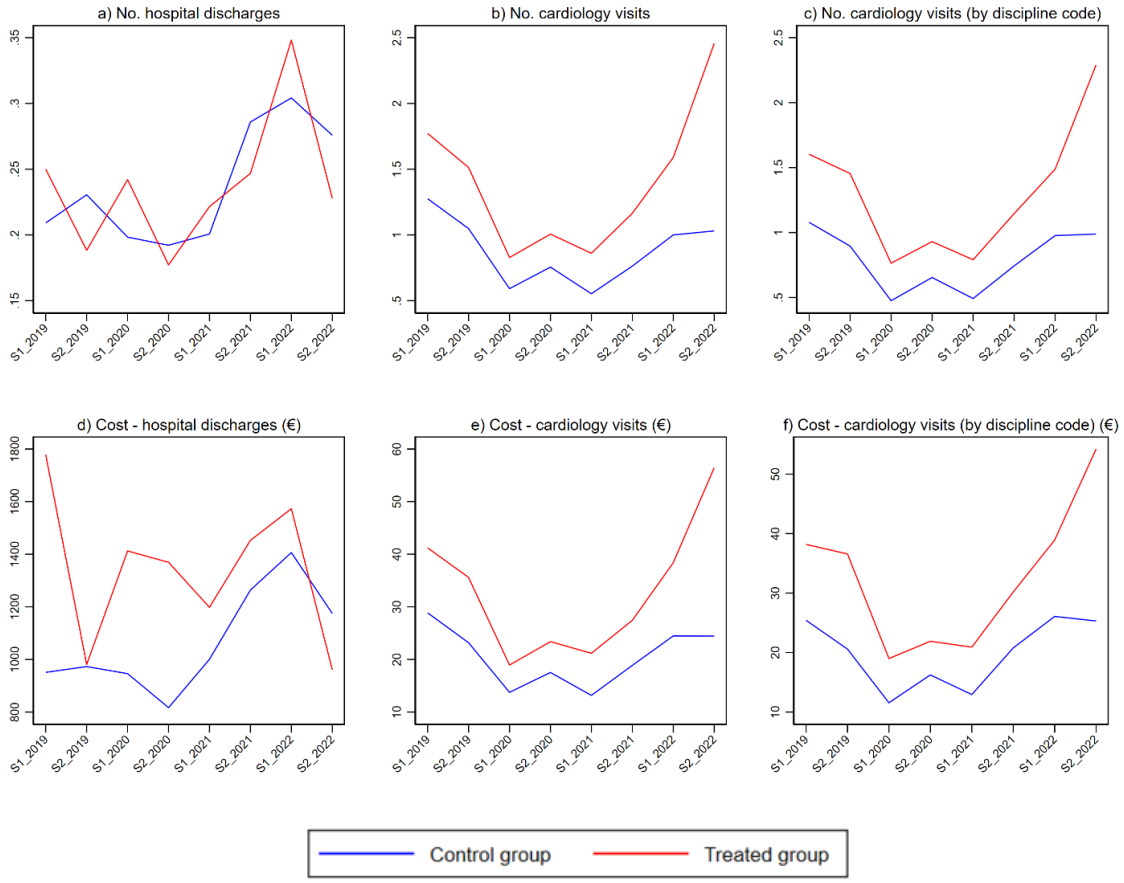
From Panel A of Table 2.2, treated patients exhibit slightly higher average use of healthcare services. The average number of hospital discharges per semester is 0.24 in the treated group and 0.23 in the control group, while the number of cardiology visits, measured both by service and discipline codes, is consistently higher among treated patients (1.3-1.4 vs. 0.8-0.9). Expenditure patterns follow a similar gradient: treated patients incur higher average costs for both hospital discharges (€1,334 vs. €1,057) and cardiology visits (€32-33 vs. €19-20), suggesting greater clinical complexity or more intensive monitoring.

Panel B reports indicators of health status. The two groups are broadly comparable in terms of the number of exemptions and distinct drugs purchased, with mean values around 1.3-1.4 and 7.5-7.8, respectively. The average Charlson Index is similar across groups (1.46 vs. 1.53).

Figure 2.2 shows semester-by-semester outcome trends from 2019 to 2022. Before the introduction of telemonitoring (first semester of 2022), treated and control groups display broadly parallel trajectories in hospitalizations and cardiology visits, supporting the parallel-trend assumption required for the difference-in-differences design. After the intervention, treated patients show a modest relative increase in cardiology visits and associated costs, consistent with intensified follow-up activity following enrolment in telemonitoring services.

These descriptive patterns suggest that treated and control patients are comparable in pre-treatment characteristics, while differences in post-intervention outcomes are consistent with the expected behavioral response to telemonitoring adoption.

Figure 2.2. Outcome Trends, by Semester



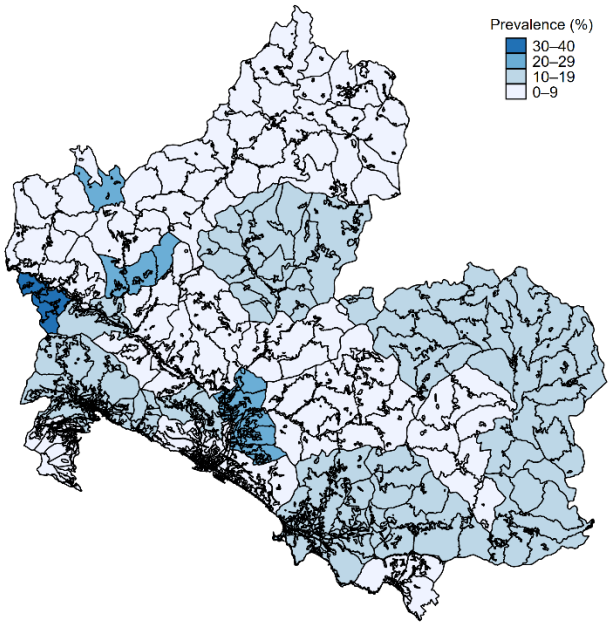
Note: The figure reports mean values of healthcare outcomes for patients with cardiac implantable devices, by treatment status (telemonitoring vs. control). Red lines represent telemonitored patients; blue lines represent patients receiving only in-person follow-ups. Values are averaged by semester between 2019 and 2022.

Table 2.3 describes sociodemographic characteristics. The treated group has a slightly higher share of men (66.9% vs. 59.8%) and a smaller percentage of older individual compared to the control group (72.6% vs 92.7% aged 65+), reflecting the clinical profile of patients eligible for telemonitoring. Most patients in both groups reside in urban areas (about 80%), consistent with the demographic distribution of the ASL 4 catchment area (Istat, 2023).

This evidence suggests that, in this initial phase of implementation, telemedicine was not primarily adopted as a tool to overcome geographical barriers.

Figure 2.3 illustrates the spatial distribution of telemonitoring use across municipalities. Prevalence is higher in coastal, the most urbanized ones, particularly around Chiavari and Rapallo, where healthcare infrastructure and broadband coverage are stronger. This pattern suggests that territorial factors such as digital connectivity and service availability may influence telemonitoring uptake.

Figure 2.3. Telemonitoring Prevalence Across Municipalities in the ASL 4 Area



Note: The map shows the percentage of cardiac patients enrolled in telemonitoring programs over the total number of patients with implantable cardiac devices, by municipality within the ASL 4 area (Liguria region, Italy). Data refers to the end of 2022. Darker shades indicate higher telemonitoring prevalence.

2.5.2 Main DiD Estimations

Tables 2.4 and 2.5 report the results of the DiD estimations for the six main outcome variables.

Table 2.4. DiD Results, by Semester

	(1) No. Hospital Discharges	(2) No. Hospital Discharges	(3) No. Cardiology Visits	(4) No. Cardiology Visits	(5) No. Cardiology Visits (by Discipline Code)	(6) No. Cardiology Visits (by Discipline Code)
ATET	-0.048	-0.015	0.632***	0.822***	0.516***	0.739***
	(0.048)	(0.039)	(0.141)	(0.084)	(0.137)	(0.082)
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	NO	YES	NO	YES	NO
Demographics	NO	YES	NO	YES	NO	YES
Severity Indexes	NO	YES	NO	YES	NO	YES
Pre Treatment Mean	0.219	0.219	0.872	0.872	0.767	0.767
N	10,033	8,540	10,033	8,540	10,033	8,540

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.5. DiD Results, by Semester (continued)

	(7) Cost - Hospital Discharges (€)	(8) Cost - Hospital Discharges (€)	(9) Cost - Cardiology Visits (€)	(10) Cost - Cardiology Visits (€)	(11) Cost - Cardiology Visits (by Discipline Code) (€)	(12) Cost -Cardiology Visits (by Discipline Code) (€)
ATET	-597.536*	-154.729	14.271***	18.458***	11.293***	16.516***
	(260.617)	(225.542)	(2.962)	(2.071)	(3.067)	(2.241)
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	NO	YES	NO	YES	NO
Demographics	NO	YES	NO	YES	NO	YES
Severity Indexes	NO	YES	NO	YES	NO	YES
Pre Treatment Mean	1032.333	1032.333	20.209	20.209	19.006	19.006
N	10,033	8,540	10,033	8,540	10,033	8,540

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We present two alternative specifications for each outcome. Columns (1), (3), (5), (7), (9) and (11) report the estimates obtained using the standard DiD model, which includes individual and time fixed effects. In this setting, time-invariant covariates, such as gender, age group, and baseline health indicators, cannot be included because they are absorbed by the individual fixed effects. To complement these results, columns (2), (4), (6), (8), (10) and (12) report estimates in which we replace individual fixed effects with a set of observable controls capturing demographic characteristics and health status that are time invariant. This alternative specification allows us to assess the contribution of these covariates and to examine whether the treatment effect is robust to their inclusion.

Across all models, the coefficient of interest identifies the Average Treatment Effect on the Treated (ATET), measuring the change in utilization for telemonitored patients after the introduction of the program in the first semester of 2022. The comparison between paired columns (e.g., (1) vs. (2)) shows that the magnitude and significance of the treatment effect remain remarkably stable across specifications, suggesting that the estimated effects are not driven by unobservable individual heterogeneity that would otherwise be captured by fixed effects.

The results show a clear pattern of expansion rather than substitution in healthcare utilization. Columns (1) and (2) show that telemonitoring does not lead to an increase in hospital admissions. The estimated ATET is small and statistically insignificant in both specifications (-0.048 in the FE model and -0.015 in the covariate-adjusted model). The stability of the coefficient across specifications reinforces the conclusion that telemonitoring does not exacerbate inpatient demand.

The results for hospitalization expenditures behave similarly. As shown in columns (7) and (8), the FE model detects a moderate and statistically significant reduction in hospital costs (-€598, $p < 0.10$), whereas the covariate-adjusted model yields a smaller and statistically insignificant estimate (-€155). This attenuation is consistent with the inclusion of health status controls, particularly comorbidity and drug use, which partially explain baseline differences in expected inpatient spending.

The clearest pattern emerges for cardiology visits. Columns (3) and (4) indicate that telemonitoring increases cardiology utilization: the number of visits rises by 0.63 per semester in the FE specification and by 0.82 in the covariate-adjusted model, with both estimates significant at the 0.1% level. Similar results are held when visits are measured using discipline codes (columns (5) - (6)), with increases of 0.52 and 0.74 visits, respectively. Relative to pre-treatment means of 0.8-0.9 visits, these effects correspond to increases of approximately 60-70%.[8]

A comparable pattern is found for specialist cardiology expenditures (columns (9) - (12)). Costs increase by €14-€18 per semester relative to pre-treatment averages of €19-€20, again representing a 55-70 % increase. Treatment effects are slightly larger in the covariate-adjusted specification, suggesting that patient characteristics, particularly age and comorbidity, may mask part of the utilization increase when not explicitly accounted for.

Taken together, the estimates provide consistent evidence of a shift from inpatient to outpatient specialist care: telemonitoring does not reduce the number of acute episodes but increases the intensity of cardiology follow-up, which is coherent with the program's preventive purpose. The substantial rise in outpatient utilization indicates that telemonitoring acts as a complement, not a substitute, to traditional care, revealing unmet demand for specialist monitoring. These findings are aligned with international evidence showing that telehealth frequently generates additional utilization rather than replacing face-to-face care. For instance, Ashwood et al. (2017) documented that most telehealth encounters represent new demand rather than substitution, while results from the UK Whole System Demonstrator trial (Steventon and Bardsley, 2012) highlight that structured telemonitoring may redirect utilization from emergency to planned specialist care. The full specification, including all control variables, is reported in Appendix Table A1.1.

[8]Percentage effects are computed by dividing the estimated ATET by the corresponding pre-treatment mean and multiplying by 100. For instance, an ATET of 0.63 cardiology visits relative to a pre-treatment mean of 0.87 implies an increase of roughly 70 % in the number of specialist consultations among telemonitored patients.

The full manual DiD model indicates that male patients drive a larger increase in cardiology visits and related costs compared with female patients. Across all outcomes, including hospitalizations and their associated costs, the older age group (65+) appears to contribute less to the overall increase in utilization than younger patients. Individuals with a higher Charlson Comorbidity Index exhibit a greater number of hospitalizations and higher inpatient costs, which is consistent with existing evidence showing that sicker patients are more likely to be admitted to hospitals and tend to have longer stays (Gaughan et al., 2013). The number of exemption codes does not display any meaningful association with the outcomes, likely because its effect is largely captured by the Charlson Index , while the number of distinct drugs prescribed shows a positive and significant association with all outcomes, suggesting that polypharmacy is a strong proxy for health complexity and intensity of care (Maher et al., 2014).

2.5.3 Validation of Identification

The validity of the DID identification strategy relies on the parallel trend's assumption. More specifically, our empirical strategy assumes that the trend in outcomes for patients who continued to receive only traditional in-person visits represents a valid counterfactual for those who integrated telemonitoring into their care routines, so that the effect of telemonitoring can be measured by this difference-in-differences. We assess the plausibility of this assumption by evaluating whether patients with different care modalities exhibited similar time trends in outcomes before the implementation of the telemonitoring reform. Figures 2.4 to 2.8 plot the outcome trends from 2019 to 2022.

Figure 2.4. Parallel Trends Test for No. Cardiology Visits

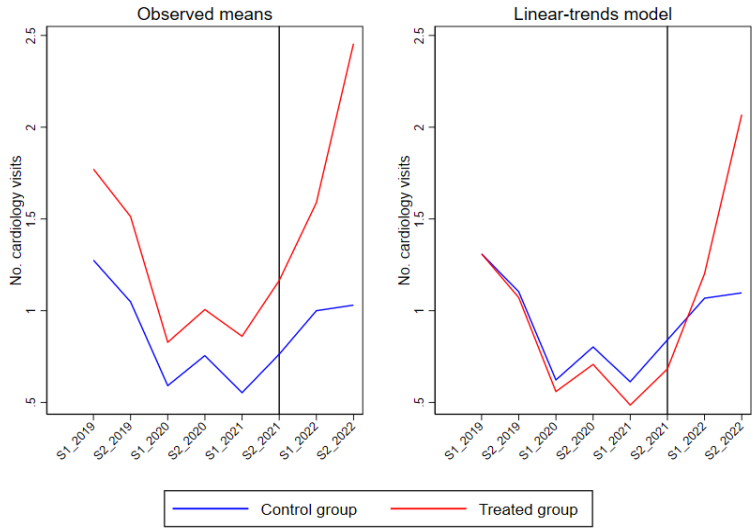


Figure 2.5. Parallel Trends Test for No. Cardiology Visits (by Discipline Code)

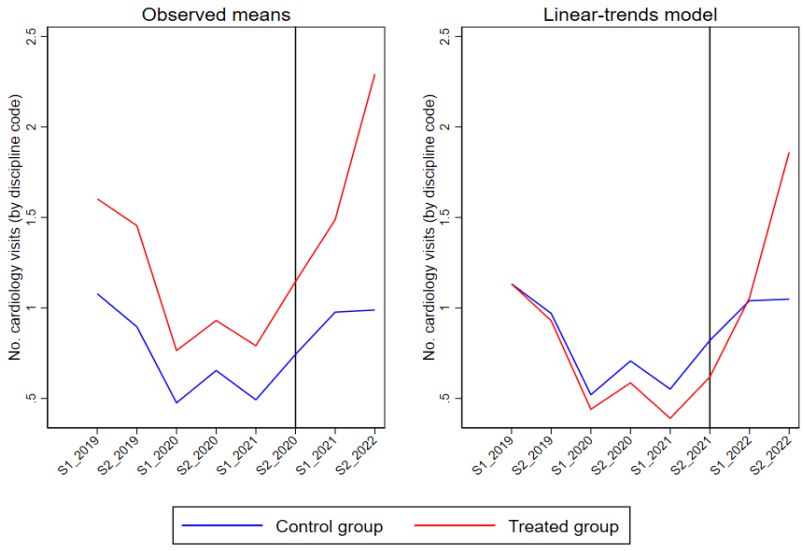


Figure 2.6. Parallel Trends Test for Cost - Hospital Discharges

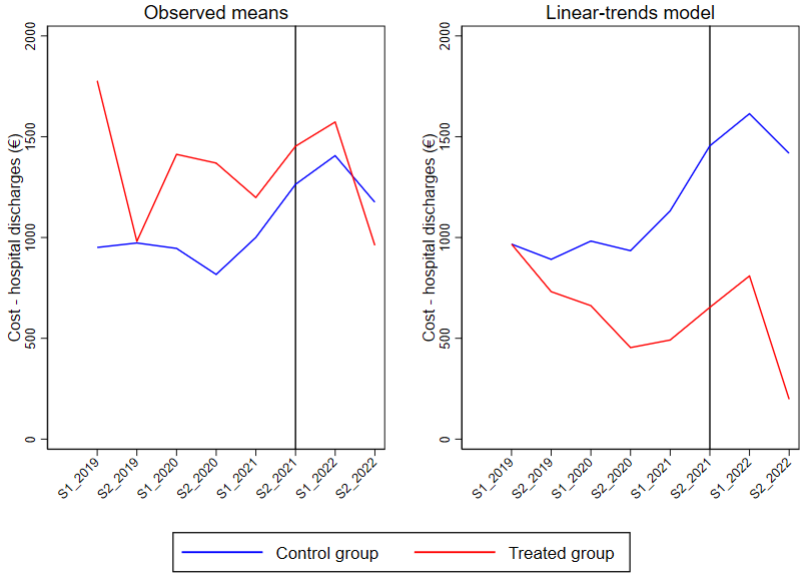


Figure 2.7. Parallel Trends Test for Cost - Cardiology Visits

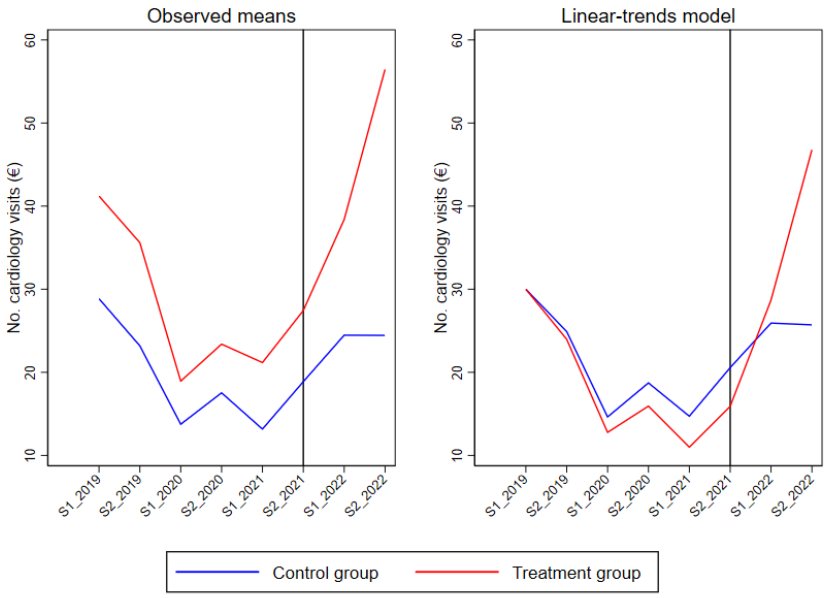
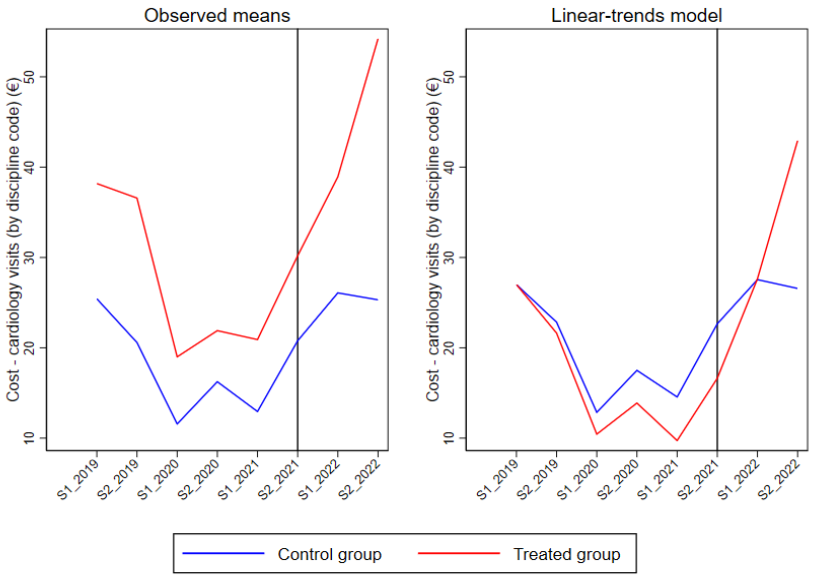


Figure 2.8. Parallel Trends Test for Cost - Cardiology Visits (by Discipline Code)



The left panel reports observed means, while the right panel shows fitted values from a model imposing separate linear trends in the pre-treatment period. The blue line represents the control group and the red line the treated group; the vertical line indicates the introduction of telemonitoring services in the Local Health Authority 4 (first semester of 2022).

For all outcomes, the trends display a marked decline during the semesters affected by the COVID-19 pandemic (from the first semester of 2020 to the first semester of 2021). For outcomes related to cardiology visits and associated costs, pre-treatment trends appear parallel, with *p*-values above 0.05, suggesting that the parallel trends assumption cannot be rejected.[9] The only exception concerns Figure 2.6, where the null hypothesis is rejected for hospital discharge costs.

In addition, we performed a no-anticipation test to ensure that no behavioral changes or adjustments in service use occurred before the formal introduction of telemonitoring. The absence of significant differences in outcomes immediately prior to the policy implementation supports the validity of the identification strategy and reduces concerns about anticipation effects.[10]

2.6 Heterogeneity

To explore whether the impact of telemonitoring differs across patient characteristics and contexts, Table 2.6 and 2.7 report heterogeneous effects by age group, gender, comorbidity level (Charlson Index), and residential area (rural vs. urban).

Table 2.6. Heterogeneity by Age and Gender, by Semester

	Age			Gender	
	0-45	46-65	65+	Male	Female
No. Hospital Discharges	-0.355**	0.014	-0.034	-0.049	-0.024
	(0.148)	(0.099)	(0.058)	(0.061)	(0.074)
No. Cardiology Visits	0.709	1.286**	0.437***	0.714***	0.475***
	(1.360)	(0.495)	(0.098)	(0.191)	(0.181)
No. Cardiology Visits (by Discipline Code)	0.439	1.128**	0.320***	0.609***	0.300*
	(1.163)	(0.487)	(0.097)	(0.187)	(0.174)
Cost -Hospital Discharges (€)	-1925.277	65.037	-522.979*	-761.255**	-153.357
	(1781.648)	(594.041)	(308.716)	(326.834)	(430.300)
Cost -Cardiology Visits (€)	6.208	22.903***	11.896***	16.645***	9.606**
	(36.765)	(8.197)	(2.792)	(3.915)	(4.207)
Cost -Cardiology Visits (by Discipline Code) (€)	9.420	18.582**	8.820***	13.783***	5.663
	(31.386)	(8.526)	(3.037)	(4.116)	(4.198)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[9] The pre-trend test evaluates the null hypothesis that the differences between treated,and control groups remain constant over the pre-treatment period, that is, that the pre-treatment trends are parallel. A statistically significant result ($p < 0.05$) therefore indicates a rejection of the parallel trends assumption.

[10] The no-anticipation test evaluates the null hypothesis that no systematic differences in outcomes existed between treated and control groups immediately before the policy implementation. A statistically significant result ($p < 0.05$) indicates rejection of this null, suggesting the presence of anticipatory behavior or pre-policy adjustments.

Table 2.7. Heterogeneity by Charlson Index and Area of Residence, by Semester

	Charlson Index		Area	
	Low	High	Rural	Urban
No. Hospital Discharges	-0.018	-0.100	-0.097	-0.024
	(0.056)	(0.084)	(0.108)	(0.052)
No. Cardiology Visits	0.627**	0.658***	0.632***	0.649***
	(0.271)	(0.198)	(0.198)	(0.168)
No. Cardiology Visits (by Discipline Code)	0.519*	0.530***	0.500***	0.521***
	(0.270)	(0.188)	(0.185)	(0.165)
Cost -Hospital Discharges (€)	-145.431	-1153.262**	-601.262	-523.746*
	(314.662)	(462.607)	(661.534)	(279.956)
Cost -Cardiology Visits (€)	10.805***	16.528***	17.492***	13.916***
	(3.491)	(5.000)	(6.309)	(3.346)
Cost -Cardiology Visits (by Discipline Code) (€)	7.062*	13.951***	14.808**	10.571***
	(3.775)	(5.130)	(6.043)	(3.534)

Standard errors in parentheses

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Results are presented per semester and expressed as differences-in-differences coefficients. The effects are largely consistent with the baseline estimates, showing a clear shift from hospital-based care toward outpatient specialist services. However, the magnitude of the effects varies across subgroups.

Starting with age, telemonitoring significantly increased the number and the cost of cardiology visits among older patients in the category 46-65 and above, while no significant change is observed for younger groups. This pattern suggests that elderly patients, typically those with higher clinical complexity, are more likely to engage with follow-up care once remote monitoring facilitates access and continuity. At the same time, the negative magnitude of hospital discharge costs indicates a reduction in inpatient expenditures, pointing to a reallocation of hospital resources for this age group. Conversely, younger patients (below 45) display smaller and statistically insignificant effects.

With respect to gender, both males and females experienced a significant rise in cardiology visits, but the effect is slightly stronger among men, possibly reflecting lower adherence to follow-up protocols for woman (Zhao et al., 2020) or differences in disease perception (Lichtman et al., 2018) and care-seeking behavior. The decrease in hospitalization costs is driven exclusively by men.

The analysis by comorbidity level (Charlson Index) shows that telemonitoring has a positive and significant effect among both low- and high-comorbidity patients, although the magnitude is somewhat larger for those with fewer pre-existing conditions. This may indicate that patients with lighter disease burdens respond more flexibly to telemonitoring, while those with multiple

comorbidities already consume a high level of healthcare services regardless of telehealth adoption. Hospitalization costs are the only exception, where the reduction is driven by patients with the highest severity index.

Regarding geographical heterogeneity, the program appears to be effective in both rural and urban settings, with comparable increases in cardiology visits and related costs and decreases in hospital discharge costs.

2.7 Robustness Checks

To ensure that our results are robust and not driven by model specification choices or by the selected time horizon, we performed a wide set of robustness checks. We tested whether our main findings remain consistent under alternative treatment definitions, model specifications, and time horizons.

2.7.1 Alternative Treatment

In Table 2.8, we re-estimate our difference-in-differences model using an alternative definition of treatment. Specifically, we stagger the entry of individuals into the treated group between the first and the second semester of 2022, the year in which telemonitoring was effectively introduced.

Table 2.8. Staggered DiD Results per Semester

	(1) No. Hospital Discharges	(2) No. Cardiology Visits	(3) No. Cardiology Visits (by Discipline Code)	(4) Cost - Hospital Discharges (€)	(5) Cost -Cardiology Visits (€)	(6) Cost -Cardiology Visits (by Discipline Code) (€)
$ATT_{g,t}$	-0.077	1.070***	0.928***	-539.055	24.084***	20.105***
	(0.050)	(0.105)	(0.104)	(295.075)	(2.620)	(2.855)
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Pre Treatment Mean	0.219	0.872	0.767	1032.333	20.209	19.006
N	10,023	10,023	10,023	10,023	10,023	10,023

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This staggered setting allows us to exploit individuals who had not yet been treated as a temporary control group and to estimate the dynamic evolution of the treatment effect relative to the moment of adoption. In this framework, the introduction of the treatment varies across groups and over time.

Table 2.8 reports the resulting group-time average treatment effects ($ATT_{g,t}$). The direction and statistical significance of the results remain largely consistent with those of the baseline specification (Table 2.4 and Table 2.5). Telemonitoring continues to be associated with a statistically significant increase in the number of Cardiology Visits and in the related costs, confirming a shift from hospital-based to outpatient specialist care. The only notable difference concerns hospital discharge costs, which lose statistical significance in this specification, although the estimated coefficient remains negative and similar in magnitude (-€539 vs. -€598 in the baseline). This suggests that the main findings are robust to alternative definitions of treatment and that the estimated effects are not sensitive to the precise timing of treatment assignment.

2.7.2 Alternative Model Specification

To further assess the robustness of our main DiD estimates, Table 2.9 reports the marginal effects obtained from non-linear panel models that better reflect the distributional properties of the outcomes. For count variables (number of hospital discharges and cardiology visits), we fit random-effects Poisson models, while for continuous outcomes (hospitalization and visit costs) we use random-effects Tobit models with lower censoring at zero. We interact time dummies with the telemonitoring group indicator, estimating models in Equations (2.4), (2.5), (2.6).

Before the pandemic (2019), treated patients exhibit slightly higher predicted utilization than controls across all outcomes. For hospital discharges (col. (1)), treated individuals show a predicted mean of 0.28 discharges in S1-2019 vs. 0.24 in the control group, and a similar gap is observed for cardiology visits (cols. (2)-(3)). This differential is consistent and statistically significant, suggesting pre-intervention differences in baseline morbidity or care needs.

A sharp decline in utilization emerges during the first pandemic year (2020). Among controls, predicted cardiology visits drop from 1.34 in S1-2019 to 0.65 in S1-2020, with a parallel reduction for discharges (0.27 to 0.24). Treated patients also experience marked reductions, but they remain systematically above controls (e.g., 0.79 vs. 0.65 Cardiology Visits in S1-2020; 0.97 vs. 0.82 in S2-2020). This pattern indicates that the treated group maintained relatively higher access even under system stress, consistent with dynamic prioritization.

In 2021-2022, utilization partially rebounds for both groups. However, the recovery is more pronounced among treated individuals, especially for cardiology care. For instance, predicted cardiology visits (discipline-coded) rise to 1.44 for treated vs. 1.03 for controls in S1-2022, widening the post-pandemic gap. The divergence becomes particularly large in S2-2022 (2.21 vs. 1.08), indicating a substantial increase in cardiology contact intensity among treated patients. The same holds, though less markedly, for hospital discharges.

Table 2.9. Marginal Effects from Poisson and Tobit Models, by Semester

	Poisson models			Tobit models		
	(1) No. Hospital Discharges	(2) No. Cardiology Visits	(3) No. Cardiology Visits (by Discipline Code)	(4) Cost - Hospital Discharges (€)	(5) Cost - Cardiology Visits (€)	(6) Cost - Cardiology Visits (by Discipline Code) (€)
S1_2019#Control	0.243***	1.341***	1.131***	1994.608***	33.037***	30.929***
	(0.020)	(0.053)	(0.050)	(70.350)	(0.850)	(0.871)
S1_2019#Treated	0.275***	1.642***	1.466***	2586.995***	39.211***	37.642***
	(0.047)	(0.152)	(0.153)	(227.745)	(2.561)	(2.668)
S2_2019#Control	0.271***	1.119***	0.945***	2042.722***	28.410***	27.066***
	(0.020)	(0.044)	(0.042)	(67.358)	(0.757)	(0.776)
S2_2019#Treated	0.200***	1.438***	1.397***	1892.643***	36.057***	37.919***
	(0.037)	(0.125)	(0.136)	(178.848)	(2.322)	(2.492)
S1_2020#Control	0.240***	0.648***	0.511***	2022.804***	21.544***	20.844***
	(0.020)	(0.033)	(0.028)	(67.730)	(0.673)	(0.689)
S1_2020#Treated	0.284***	0.794***	0.719***	2325.524***	23.314***	24.054***
	(0.072)	(0.079)	(0.084)	(198.355)	(1.905)	(2.018)
S2_2020#Control	0.236***	0.820***	0.699***	1952.078***	24.244***	24.078***
	(0.023)	(0.037)	(0.033)	(67.590)	(0.725)	(0.755)
S2_2020#Treated	0.196***	0.972***	0.886***	2268.771***	26.667***	25.917***
	(0.050)	(0.100)	(0.094)	(195.085)	(2.025)	(2.087)
S1_2021#Control	0.247***	0.591***	0.512***	2079.483***	20.869***	21.477***
	(0.023)	(0.030)	(0.026)	(71.162)	(0.684)	(0.724)
S1_2021#Treated	0.255***	0.869***	0.771***	2147.122***	25.225***	25.331***
	(0.053)	(0.075)	(0.072)	(189.329)	(1.973)	(2.064)
S2_2021#Control	0.332***	0.822***	0.793***	2255.357***	25.290***	27.605***
	(0.031)	(0.036)	(0.038)	(75.469)	(0.763)	(0.831)
S2_2021#Treated	0.290***	1.141***	1.095***	2329.631***	29.219***	31.879***
	(0.048)	(0.095)	(0.101)	(197.854)	(2.109)	(2.295)
S1_2022#Control	0.376***	1.077***	1.032***	2385.084***	29.478***	31.338***
	(0.035)	(0.046)	(0.046)	(79.213)	(0.832)	(0.896)
S1_2022#Treated	0.395***	1.555***	1.438***	2389.970***	39.754***	41.052***
	(0.060)	(0.137)	(0.134)	(200.559)	(2.367)	(2.527)
S2_2022#Control	0.335***	1.141***	1.075***	2180.657***	30.155***	31.488***
	(0.034)	(0.049)	(0.050)	(78.755)	(0.873)	(0.935)
S2_2022#Treated	0.277***	2.430***	2.206***	1992.395***	56.154***	53.380***
	(0.059)	(0.182)	(0.172)	(181.587)	(2.571)	(2.716)
Pre Treatment Mean	0.219	0.872	0.767	1032.333	20.209	19.006
N	8,540	8,540	8,540	8,540	8,540	8,540

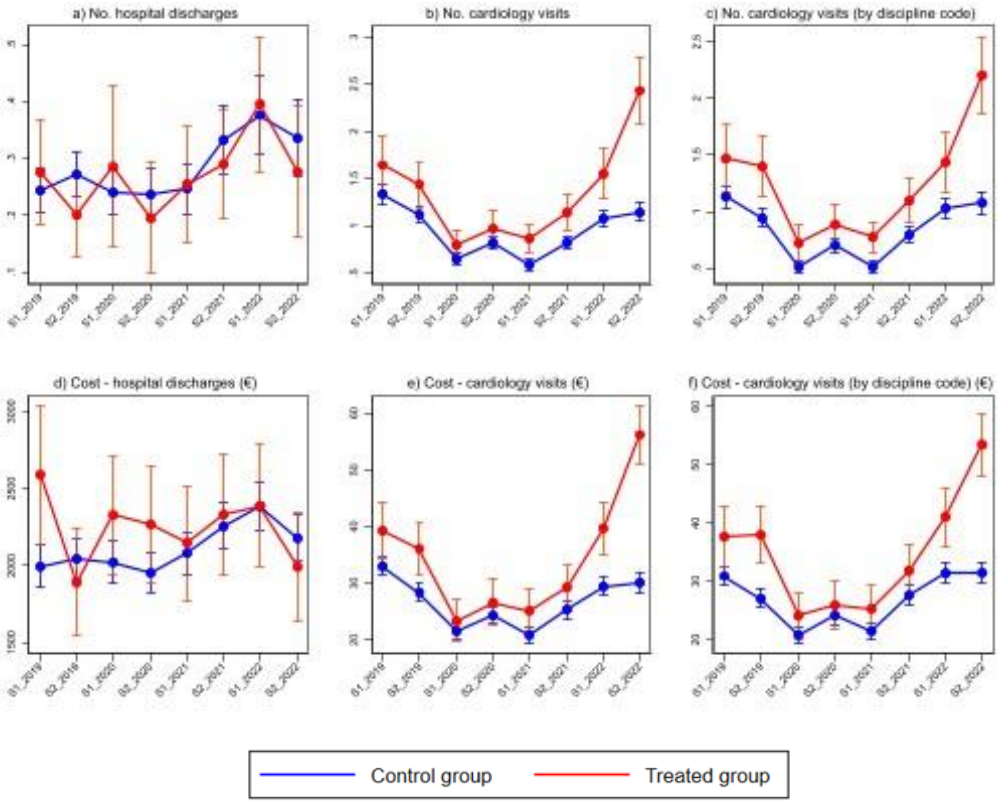
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Cost predictions (cols. (4)-(6)) follow a pattern broadly consistent with utilization. Before 2020, treated patients incur higher predicted costs than controls. During 2020-2021, expenditures decline for both groups, reflecting reduced access and postponed care. However, treated patients consistently display higher cost levels across all semesters, suggesting that reductions in service volumes did not fully offset the intensity of care received.

By 2022, cost differentials widen substantially, especially for cardiology visits. In S2-2022, predicted cardiology expenditure reaches €56.2 for treated patients compared to €30.2 for controls, mirroring the strong increase in visit volumes documented in the Poisson models. This alignment between utilization and expenditure reinforces the internal consistency of the results. Figure 2.9 complements Table 2.9 by displaying the marginal predictions graphically.

Figure 2.9. Marginal Effects from Poisson and Tobit Models, by Semester



Note: The figure displays marginal predicted values from Poisson (panels a–c) and Tobit models (panels d–f), by treatment status. Red lines refer to telemonitored patients and blue lines to controls. Predictions are estimated at the sample means and shown by semester from 2019 to 2022.

The same three main patterns clearly stand out. First, treated patients consistently exhibit higher levels of hospital and cardiology utilization throughout the entire observation window, both before and after the pandemic shock. This visual evidence reinforces the presence of systematic baseline differences in care intensity between the two groups. Second, both groups experience

a marked decline in 2020 across all outcomes, reflecting the system-wide contraction of non-urgent services during the initial pandemic phase. However, the treated group maintains higher utilization levels throughout the shock period, suggesting that these patients may have been prioritized or followed differentiated care pathways when health system capacity was constrained. Third, the post-pandemic rebound is visibly stronger among treated patients, particularly for cardiology services and their associated expenditures. By 2022, the trajectories of the two groups diverge substantially, with treated individuals showing a steeper increase in both volumes and costs. This widening gap is consistent with a catch-up effect more pronounced in the treated group and mirrors the patterns documented in the marginal tables.

Although treated patients systematically display higher levels of hospital and cardiology use, and a sharper rebound in the post-pandemic period, it remains unclear whether these differences reflect persistent effects or short-lived adjustments, considering the relatively short post-treatment window in our data. Several mechanisms may contribute to the apparent absence of a clear long-run trend. First, patient heterogeneity is likely to dampen persistence. Older and clinically complex individuals may still require routine in-person evaluation, limiting the extent to which remote monitoring substitutes for traditional care even after adoption (Busso et al., 2022; Neumann et al., 2024). Second, early adaptation dynamics may generate transitory spikes. Telemonitoring often triggers an initial phase of intensified specialist engagement as clinicians recalibrate treatment plans using incoming remote data. Once patients reach a new clinical equilibrium, the marginal need for additional visits typically stabilizes, leading to a plateau in utilization (Zeltzer et al., 2024b). Third, modality preferences and behavioral factors may constrain long-term substitution. Some patients may continue to favor face-to-face specialist care for reassurance, perceived diagnostic accuracy, or habit, even when remote monitoring is available.

Longer follow-up may be necessary to assess whether the widening gaps observed in 2022 represent temporary rebounds or the early stages of more persistent divergence. For completeness, the full set of model estimates underlying these results is reported in Table A1.2 in the Appendix.

2.7.3 Alternative Time Horizon

As a further robust exercise, we re-estimated our difference-in-differences model using an annual time horizon instead of the baseline semester aggregation.

This specification allows us to assess whether the estimated effects are sensitive to the temporal frequency of observation and to verify that our results are not driven within-year seasonality.

The results, presented in Table 2.10, remain fully consistent with those obtained using the semester-based specification.

Table 2.10. DiD Results per Year

	(1) No. Hospital Discharges	(2) No. Cardiology Visits	(3) No. Cardiology Visits (by Discipline Code)	(4) Cost - Hospital Discharges (€)	(5) Cost -Cardiology Visits (€)	(6) Cost -Cardiology Visits (by Discipline Code) (€)
ATET	-0.076	1.311***	1.082***	-1157.431*	29.949***	24.070***
	(0.095)	(0.280)	(0.273)	(529.769)	(5.830)	(6.045)
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Pre Treatment Mean	0.434	1.734	1.522	2045.738	40.234	37.670
N	5,024	5,024	5,024	5,024	5,024	5,024

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Telemonitoring continues to have a positive and statistically significant impact on cardiology visits and their associated costs, with the estimated effects roughly doubling in magnitude (e.g., +1.31 vs. +0.63 for cardiology visits, and +€29.9 vs. +€14.3 for visit costs), as expected when moving from a semi-annual to an annual unit of time. The coefficient for hospital discharges remains negative and becomes marginally significant (-€1,157; $p< 0.1$), confirming that telemonitoring is associated with a reduction in hospital-related expenditures.

2.8 Conclusions

This paper provides causal evidence on the impact of telemonitoring services on healthcare utilization among cardiac patients, using rich administrative data from a local health authority in the Liguria region of Italy. The introduction of telemonitoring in a clearly defined semester, combined with detailed panel information on patients and their healthcare use, enables the application of a difference-in-differences design that isolates the effect of remote monitoring from time-invariant patient heterogeneity and common temporal shocks (Angrist and Pischke, 2008). Several consistent findings emerge. First, telemonitoring does not significantly alter the number of hospitalizations but is associated with a reduction in hospitalization costs, particularly among patients with higher comorbidity levels. This pattern suggests that remote monitoring may help prevent the most severe or resource-intensive episodes rather than reducing the overall frequency of admissions, pointing to improvements in clinical management rather than a simple volume effect. Second, telemonitoring leads to a substantial and statistically robust increase in Cardiology Visits and related expenditures. The magnitude of these effects, around 60-70 %

relative to pre-treatment means, is large in economic terms and signals an intensification of outpatient specialist follow-up once remote monitoring is in place.

Taken together, the results indicate a reallocation of healthcare resources from hospital-based to ambulatory care, consistent with a more preventive and continuous model of patient management. Rather than substituting for traditional care, telemonitoring appears to uncover previously unmet demand for specialist follow-up, acting as a complement to in-person services and reshaping the composition of care (Bavafa et al., 2018). This interpretation is reinforced by the heterogeneous effects: utilization increases are concentrated among middle-aged and older patients, men, and individuals with lower baseline comorbidity, while the oldest and sickest patients continue to rely heavily on conventional hospital care. Geographical heterogeneity is modest, with similar patterns in rural and urban areas, suggesting that, at least in this early phase, telemonitoring has not primarily operated as a tool to offset geographical access barriers.

The dynamic analyses and robustness checks support these conclusions. Staggered adoption models, random-effects Poisson and Tobit specifications, and the use of annual instead of semi-annual outcomes all yield qualitatively similar results: telemonitoring raises cardiology utilization and spending while leaving hospital admissions largely unchanged and modestly reducing inpatient costs. Marginal predictions show that treated patients systematically exhibit higher levels of hospital and cardiology use throughout the observation window, experience a sharper contraction during the pandemic shock, and display a stronger rebound in the post-COVID period. However, the available data does not allow us to determine whether the widening gaps observed in 2022 reflect persistent long-run effects or short-lived adjustments.

From a policy perspective, these findings have several implications. First, telemonitoring should not be viewed as a cost-saving technology in the short run through reductions in service volumes alone. Instead, it appears to reconfigure the composition of care by shifting activity towards planned specialist follow-up and away from some high-cost inpatient episodes. Evaluating the welfare impact of such a shift requires considering health outcomes, patient experience, and long-term cost trajectories, not just short-run expenditure changes. Second, the concentration of effects among specific subgroups raises important questions about equity and targeting. Careful program design, including eligibility criteria, clinical protocols, and support for digitally vulnerable groups, will be crucial to ensure that telemonitoring contributes to, rather than undermines, equity objectives.

In ageing regions such as Liguria, where demographic pressure and geographic constraints challenge traditional models of service delivery, telemonitoring can nonetheless play a strategic role in strengthening health system resilience. By enabling more continuous surveillance of frail

patients and facilitating earlier detection of clinical deterioration, remote monitoring may help prevent avoidable complications and smooth demand over time, especially during periods of system stress such as pandemics. Our results suggest that these benefits are likely to materialize through complementarity with existing services rather than through wholesale substitution of face-to-face care.

Several limitations should be acknowledged. First, the analysis focuses on a single local health authority and a relatively small number of treated patients, which may limit external validity to other Italian regions or health systems with different institutional arrangements and technological infrastructures. Second, the follow-up window is short, providing only an early snapshot of behavioral responses and making it difficult to assess long-term effects on health outcomes, mortality, or cumulative costs. Third, although the difference-in-differences framework and extensive robustness checks mitigate many identification concerns, residual confounding due to unobserved patient characteristics, such as digital literacy, informal care arrangements, or unmeasured clinical severity, cannot be fully excluded. Finally, cost data are based on tariffs rather than true marginal costs and do not capture broader societal costs or patient-borne burdens.

These limitations open several avenues for future research. Extending the analysis to multiple regions and longer time horizons would allow for a more comprehensive assessment of the sustainability and distributional consequences of telemonitoring within the Italian National Health Service. Linking administrative data to clinical registries and patient-reported outcomes would make it possible to evaluate whether the observed shifts in utilization translate into measurable improvements in survival, quality of life, and functional status. Further work could also examine how alternative program designs, such as different intensities of monitoring, integration with primary care, or targeted outreach to high-risk patients, affect the balance between substitution and complementarity with traditional care. A particularly valuable extension would be a formal cost-effectiveness analysis incorporating health-related quality of life, such as cost per quality-adjusted life year (QALY) gained. The current study does not pursue this approach because the administrative data available from ASL 4 do not include patient-reported outcome measures or utility weights required for QALY estimation. Future work linking administrative records to validated health-status instruments would allow for a more complete welfare evaluation of telemonitoring, in line with standard health technology assessment practice (Drummond et al., 2015). Finally, structural or welfare-based evaluations that combine cost, utilization, and outcome data would provide policymakers with a richer basis for deciding how and for whom to scale up telemonitoring in ageing, resource-constrained health systems.

Chapter Two

3. Telemedicine and Healthcare Utilization Among Chronic Patients: The Mediating Role of Treatment Adherence[11]

3.1 Introduction

Therapeutic adherence is a central determinant of health outcomes in chronic disease management. It is commonly defined as the extent to which patient behavior corresponds to agreed recommendations regarding medication intake, lifestyle adjustments, and self-monitoring practices (Delamater, 2006). Far from being a static patient attribute, adherence is shaped by psychological, social, and structural factors (Holmes et al., 2014) and tends to improve when care is delivered through collaborative, patient-centered models that enable shared decision-making and continuous follow-up (David et al., 2018). As such, adherence represents a dynamic process that can be modified through targeted interventions.

Adherence is particularly relevant for patients with severe diseases, such as cardiovascular diseases and diabetes, two highly prevalent and resource-intensive chronic conditions. Evidence shows that high adherence is associated with substantial clinical benefits (Roebuck et al., 2011). Among patients with coronary artery disease, adherence to combination therapies, such as antiplatelets, statins, and β-blockers, reduces the incidence of major cardiovascular events and mortality (Frishman, 2007; Di Fusco et al., 2024). Evidence from chronic heart failure further indicates that maintaining appropriate medication supply reduces hospitalization risk and overall healthcare expenditure (Dilokthornsakul et al., 2012). For individuals with diabetes, sustained adherence to oral agents or insulin therapy is linked to improved glycemic control and reduced progression of micro- and macrovascular complications (Almalki et al., 2024).

Conversely, low adherence generates significant clinical harm and economic inefficiencies. In cardiology, suboptimal adherence has been associated with higher rates of recurrent myocardial infarction, avoidable hospitalizations, and premature death (Chowdhury et al., 2013; Volpe et al., 2014). Similarly, poor adherence in diabetes leads to worsened glycated hemoglobin (HbA1c) trajectories, greater use of emergency care, and accelerated development of complications requiring costly specialist interventions (Bitton et al., 2013; Cassina, 2022).

These patterns translate into a substantial financial burden: patients with high adherence tend to incur lower overall healthcare expenditure (Simon-Tuval et al., 2016; Juarez et al., 2013),

[11] This work was conducted within the PRIN project SURVIVE (PNRR 2022), "Shaping urban and rural contexts for healthier lives.". Shorter versions of this work were co-authored with Sara Maria Barbani, Lucia Leporatti, Marcello Montefiori, and Paolo Petralia and are currently under submission to international peer-reviewed journals.

whereas non-adherence results in increased use of acute care services and higher public spending (Bitton et al., 2013; Simon-Tuval et al., 2016).

While strategies to improve adherence typically focus on simplifying drug regimens, providing behavioral support, or enhancing health literacy (Gass et al., 2022; Di Fusco et al., 2024), greater attention should be paid to telemedicine as a potential lever for sustaining long-term engagement in chronic care. Existing studies have primarily examined telemedicine to overcome geographical and organizational barriers to access or as a tool for remote monitoring and timely clinical adjustment (Hameed et al., 2014). However, much less is known about whether telemedicine can promote higher therapeutic adherence by offering more continuous, personalized, and flexible patient-provider interactions. Evidence on this mechanism remains limited, fragmented, and context dependent.

This gap is especially relevant for regions characterized by demographic ageing and challenging territorial conditions. Liguria, in Northwest Italy, represents an illustrative case: it has the highest proportion of older adults in Europe (Eurostat, 2020) and its mountainous geography contributes to mobility constraints, isolation, and "pharmacy deserts" (Istat, 2023; Leporatti et al., 2021), all factors that may compromise continuity of care and adherence to treatment. To our knowledge, no study has examined whether telemedicine can act as an adherence-promoting tool for chronic patients in this setting, nor how improved adherence may translate into reduced hospitalizations and emergency department utilization.

This study examines these questions using administrative and telemedicine records from 2019 to 2022 for one Local Health Authority (ASL 4) of Liguria (Italy), collected as part of "Tigullio, Luogo di Salute", an initiative piloting a new model of proximity-based territorial care (Romiti et al., 2023). We focus on two chronic populations, patients with type 1 and type 2 diabetes and those with cardiovascular diseases, asking (i) whether telemedicine follow-up improves therapeutic adherence, and (ii) how changes in adherence translate into downstream healthcare utilization. To analyze these mechanisms, we estimate a Tobit model and a Recursive Multivariate Probit model to identify the mediating role of adherence in the relationship between telemedicine exposure and patterns of healthcare resource use. We also conduct robust exercises to assess the sensitivity of the results to different model specifications and high adherence definition.

We documented three main findings. First, telemedicine exposure increases adherence for selected drug classes, especially gastroprotective agents, while effects are weaker or absent for cardiovascular medications. Second, higher medication adherence is associated with a significantly lower use of acute healthcare services, particularly hospitalizations and emergency department visits, with stronger effects for diabetes-related therapies. Third, the reduction in

healthcare utilization operates primarily through improved adherence, supporting its role as a mediating channel between telemedicine and resource consumption. By exploring telemedicine as a potential adherence-enhancing instrument, this study contributes to the literature on digital care and chronic disease management. Our findings provide evidence from a demographically fragile, geographically complex European region, offering insights relevant to health systems confronting rapid population ageing and growing demands for sustainable chronic care models. The remainder of the paper is organized as follows: Section 2 provides a literature review focusing on therapy adherence and telemedicine; Section 3 discusses the data sources, inclusion criteria and the variables used; Section 4 describe the econometric methods applied; Section 5 descriptive statistics and discusses the main results on healthcare resource utilization among patients with different adherence levels and shows how telemedicine improves adherence for certain drug classes, potentially acting as a mediator in reducing costs; Section 6 explores heterogeneity in treatment effects across patient subgroups; Section 7 reports a set of robustness checks; Section 8 concludes with a discussion of the main findings and policy implications.

3.2 Background

Several studies have consistently demonstrated that high levels of adherence to prescribed therapies are associated with improved clinical outcomes and reduced healthcare resource utilization (Osterberg & Blaschke, 2005; Roebuck et al., 2011). Patients who follow treatment plans tend to experience fewer complications, reduced hospitalizations, and better management of chronic conditions (Cutler et al., 2018). This is particularly relevant in the long-term, where adherence plays a key role in determining prognosis and the sustainability of health systems.

By decreasing the need for intensive interventions and emergency care, enhanced adherence supports a more efficient allocation of resources and mitigates the burden on national healthcare services. High levels of medication adherence, regardless of the delivery model, have been consistently associated with fewer hospitalizations, fewer emergency visits, and overall reduced healthcare costs. Sokol et al. (2005) demonstrated that patients with high adherence to chronic medications, such as those for diabetes and hypertension, had significantly lower rates of hospitalization and fewer complications, reducing overall healthcare costs. This finding has been echoed by Roebuck et al. (2011), who analyzed a population with cardiovascular conditions and found that improving medication adherence led to fewer emergency visits and a lower risk of hospitalization, ultimately reducing the total healthcare costs for patients. Moreover, Pittman et al. (2011) found that in a cohort of patients on statin therapy, those with medication adherence rates greater than 80% had 25% fewer cardiovascular-related hospitalizations and reduced

healthcare spending over a one-year period. It is less clear if (and under what conditions) telemedicine and digital health can become instruments to boost adherence. Telemedicine has emerged as a strategic tool for improving access to care and transforming delivery models, particularly in the management of chronic diseases and in overcoming geographical and socio-economic barriers (Colbert et al., 2020; Walter et al., 2023). It allows for more flexible scheduling, reduces travel time and costs, and facilitates a more patient-centered approach.

A growing body of evidence links telemedicine to improved medication adherence, particularly in patients with chronic conditions like diabetes and cardiovascular diseases. For example, Lee et al. (2017) found that telemedicine reduced a key indicator of blood sugar control (HbA1c) by an average of 0.18% in type 1 diabetes patients, especially those with poor baseline control. In cardiovascular care, Gass et al. (2022) reported that 57.1% of telemedicine interventions improved adherence in patients at risk, with greater effectiveness in programs that maintained frequent human contact. However, while many studies report positive results, other evidence suggests that telemedicine does not consistently lead to improved adherence. A review by Leiz et al. (2022) found that in some studies, telemedicine interventions showed no significant impact on adherence, particularly when patient engagement or contact was insufficient. These findings underscore the variability in telemedicine's effectiveness, suggesting that not all telemedicine models are equally effective in enhancing adherence.

Despite contrasting studies on telemedicine, a key point remains: it has the potential to increase medication adherence. High levels of adherence, as consistently shown in the literature, are associated with fewer hospitalizations, fewer emergency visits, and reduced overall healthcare costs (Sokol et al., 2005; Roebuck et al., 2011; Pittman et al., 2011). Therefore, it is plausible to consider that, by improving adherence, telemedicine could indirectly lead to a reduction in healthcare expenditure, particularly in the long term. This suggests that while the direct cost savings of telemedicine remain unclear in some contexts, its role in enhancing adherence could be a pathway to more efficient healthcare systems and lower overall costs. The long-term benefits of telemedicine, particularly its impact on adherence, warrant further investigation to fully understand its potential to reduce system-wide healthcare utilization and costs.

3.3 Data

This study utilizes healthcare administrative data referred to one of the Local Health Authority of the Liguria Region's Health System (ASL 4). ASL 4 covers the territory of the Gulf of Tigullio and its hinterland, an area comprising thirty municipalities in the central-eastern part of

the region, with a total of 140,678 residents, approximately 9.33% of the Ligurian population (Istat, 2023).

The final database contains a rich set of variables derived from various health administrative data streams for the period 2019-2022 by semester, including information on patients' demographic characteristics, drug purchases, and healthcare service utilization. For each patient, information from the following records was matched:

- Emergency Room Admissions: a registry of all patient visits to the emergency department;
- Pharmaceutical Records: a collection of information regarding drug purchases, both from direct distribution and conventional pharmacies;
- Patient Demographics: information on gender, age group (0-45; 46-65; 65+), and municipality of residence;
- Exemption Registry: list of exemptions for diseases, including start and end dates of exemptions;
- Diagnostic and Therapeutic Services: visits provided by specialist physicians (outpatient specialty care);
- Hospital Discharge Records: containing information on hospitalizations.

For privacy reasons, access to information regarding deaths and patient transfers was not possible. Consequently, the date of the last occurrence of each patient in the databases was used to exclude those who had no visits, hospitalizations, or medication purchases in the period 2019-2022, as they were presumed deceased or transferred. To augment the dataset, it was possible to add further details by utilizing the common residency code of the subjects to access additional data from sources such as ISTAT and Google Mobility. From ISTAT, information on municipalities was extracted, including data on territorial types (mountain, hill, plain, urban or rural) and proximity to the coast.[12] Google Mobility provided information on the centroids of municipalities and the geographic locations of emergency services and hospitals. This was used to calculate the minimum distance to these locations, as well as to centers offering cardiac and diabetic services, both in minutes and kilometers. These data were used to create an index of access barriers to healthcare services.

[12] The classification of municipalities is based on geographical contiguity, with specific thresholds for population density and minimum population size, all within a regular grid of 1 km² cells (cf. EU Regulation 2017/2391). This system was developed by ISTAT, in collaboration with Eurostat, using data from the 2011 population census for municipalities existing as of January 1, 2018. For years prior to 2018, and starting from 2011, an elaboration is made available to facilitate diachronic analysis of statistics and indicators at the municipal level. Municipalities that ceased to exist before 2018 are assigned the Degurba 2011 classification value based on the municipality that absorbed their population.

Additionally, Google Mobility data was used to determine the location and density of pharmacies per 1000 residents.[13]

3.3.1 Inclusion Criteria

The analysis focused on two categories of patients: those with diabetes, including both type 1 and type 2 (with or without complications), and those with heart failure. The inclusion criteria adhered to the guidelines established by the Italian Ministry of Health. Heart failure patients were identified based on the presence of the exemption code "021.428", and a primary or secondary hospital discharge diagnosis coded as "428". To ensure evidence of active treatment, patients were also required to have pharmaceutical records documenting the dispensation of at least one of the following drug classes: loop or thiazide diuretics (C03CA*, C03CB*, or C03EB*), renin-angiotensin system inhibitors (C09A* or C09C*), and beta-blockers (C07AG02, C07AB02, or C07AB07).[14]

Patients with diabetes, including both type 1 and type 2 with or without complications, were identified through primary diagnosis codes from hospital admissions or emergency department visits (codes 285, 294, 295, 250), in combination with prescriptions of antidiabetic or antiepileptic drugs (A10A*, N03AX16, or N03AX12) and possession of the exemption code "013.250".[15] Individuals who held an exemption code but had no record of hospitalizations, emergency department visits, or pharmaceutical dispensations were excluded from the analysis. The study was also limited to individuals residing within the ASL 4 territory in Liguria to avoid data inconsistency due to the high influx of non-resident individuals considering the region significant tourism, particularly during the summer months (Osservatorio Turistico Regione Liguria, 2023). To assess the effect of telemedicine, patients who did not use telemedicine services were classified as the control group, while those who utilized telemedicine were categorized as the treated group.

The final dataset comprised 8,271 patients, consisting of both heart failure and diabetic patients, of whom 349 used telemedicine. These patients were distributed as follows:

[13] Data on the percentage of crowding in various locations (e.g., supermarkets, pharmacies, stations, workplaces) at the provincial level, by month, were also collected, but were ultimately not used in the analysis.

[14] The inclusion criteria for heart failure patients were inspired by the guidelines established by the Italian Ministry of Health. However, in this study, we did not apply the temporal restrictions related to the exemption code issuance (within 10 years) and hospital discharge diagnosis (within 5 years), nor the requirement for a Defined Daily Dose (DDD >50%) for the selected drug classes.

[15] The full theoretical criteria also include temporal restrictions on exemption codes (issued within the past ten years and for individuals aged ≥35), hospital or emergency department diagnoses within the last five years, recent prescriptions (DDD >50% or >30%, depending on the drug class), and disease-related outpatient services performed in the previous year. In this study, we apply a simplified version of these criteria, based on diagnoses, prescriptions, and exemption codes.

- 3,025 heart failure patients, with 129 using telemedicine.
- 6,284 diabetic patients, with 272 using telemedicine.

There were 1,038 patients identified as having both conditions, meeting the inclusion criteria for both heart failure and diabetes. This overlap is not unexpected, given the well-documented association between cardiovascular and diabetic conditions (Leon, 2015).

3.3.2 Dependent Variables

In this study, three dichotomic dependent variables were considered to assess healthcare utilization and medication adherence among patients with diabetes and heart failure. Given the focus on telemedicine, we aimed to evaluate how its implementation influences medication adherence and, in turn, how adherence affects healthcare utilization, particularly hospital admissions and emergency department (ED) visits. Using a recursive multivariate probit model, we analyzed the role of telemedicine as a common factor influencing these outcomes. Specifically, we looked at how telemedicine might improve adherence to prescribed therapies, which could subsequently reduce the need for emergency services and hospitalizations.

Medication Adherence

The primary variable of interest in this study is medication adherence, which was calculated using specific ATC medication codes for most prescribed drugs in patients with diabetes and heart failure in our sample. The ATC codes included are: A02BC02 (antacid), A10BA02 (insulin), C03CA01 (diuretics), and C07AB07 (beta-blockers). These drugs were selected based on their relevance to commonly prescribed ATC groups for these pathology.

Our study covers a four-year period, with adherence calculated by semester to enable a detailed analysis of therapy adherence over time. Adherence was assessed using an indirect method based on prescription records, from where we provide information on total therapy days calculated from daily defined doses (DDD). We use the Proportion of Days Covered (PDC), a widely recognized metric for assessing medication adherence in patients with chronic conditions. Therapeutic adherence was defined as the proportion of days in a semester during which a patient had sufficient medication coverage based on prescription data[16] as shown in Equation (3.1):

[16] The calculation was based on a multi-step process that accounted for the number of days in each month, including leap years, and adjusted for mid-month prescription refills by assigning coverage starting from the exact refill date. It also estimated the number of days covered by the dispensed medications to ensure sufficient coverage over the entire semester and allowed any surplus medication to be carried forward to subsequent months or semesters, thereby enabling a continuous representation of treatment coverage over time.

$$PDC\ (\%) = \frac{Number\ of\ days\ covered}{Number\ of\ days\ in\ the\ semester}\ x\ 100 \quad (3.1)$$

Once adherence was calculated, if it exceeded 80%, it was considered high adherence, while if it was below 80%, it was classified as low adherence, following the approach adopted by AIFA in the OsMed report.[17] The variable was then transformed into a binary (dichotomous) variable, where 1 represents high adherence and 0 represents low adherence. For patients with prolonged therapy interruptions, adherence was marked as missing starting from the next semester to avoid distortion in the calculations. Since these patients suffer from chronic conditions, we assumed a therapy change in cases of apparent cessation. We assumed the death of patients or transfer just when no other appearances were recorded by data from other sources (e.g., emergency visits, specialist appointments, exemptions renewals, and hospitalizations).[18]

Hospital Admissions

The hospital admissions variable is a dichotomous indicator that reflects whether or not a patient experienced at least one hospitalization during the relevant semester. Hospitalizations were identified using the Hospital Discharge Records (SDO), which include detailed information on patient admissions, including the date of each hospitalization. For each patient, if at least one hospitalization occurred during the semester, the variable was coded as 1; otherwise, it was coded as 0. This variable serves to capture the occurrence of hospital admissions rather than their frequency, focusing on whether the patient was admitted to the hospital during each semester.

[17] The OsMed Report is AIFA's annual publication, produced by the OsMed (Osservatorio Nazionale sull'Impiego dei Medicinali), which provides an analytical overview of medicines use in Italy. It reports detailed evidence on pharmaceutical expenditure and utilization, covering both community (territorial) and hospital settings, and both public (SSN) and out-of-pocket channels, and highlights regional heterogeneity as well as indicators related to appropriateness and the overall sustainability of pharmaceutical spending.

[18] In addition to adherence, we also calculated purchase frequency for the same set of ATC medications, as an indirect measure of medication access and adherence. For each medication, we counted the total number of purchases made in each period and divided it by the total number of days in the corresponding period, as shown below. The resulting metric reflects the percentage of days during which the patient had medication available, offering insight into the patient's medication acquisition behavior.

$$Semester\ Purchase\ Frequency\ (\%) = \frac{Number\ of\ days\ covered\ by\ purchases}{Number\ of\ days\ in\ the\ semester}\ x\ 100$$

For patients with therapy interruptions, we followed the same approach as for adherence, marking the data as missing from the next semester. This helped avoid bias from incomplete therapy periods. The results remain consistent.

Emergency Department Visits

The emergency department visits variable is dichotomous, indicating whether a patient made at least one visit to the emergency room within the semester. Data on emergency visits were drawn from the Emergency Room Admissions registry, which records the date of each visit. If a patient had at least one visit to the ED during the semester, the variable was coded as 1; if no visit occurred, it was coded as 0. This variable aims to capture the occurrence of ED visits, providing insight into the patient's need for urgent healthcare services during the study period.

3.3.3 Independent Variables

The model incorporates a set of control variables that capture demographic characteristics and health status, providing a comprehensive understanding of the factors influencing healthcare utilization and treatment adherence. Among these, the dataset includes information on patients' municipality of residence.

Demographic Characteristics

In terms of demographic characteristics, the dataset for ASL4 patients includes several variables designed to protect patient anonymity. These include gender, age group, and municipality of residence, all linked to an anonymous ID. Gender is coded as 1 for males and 0 for females, reflecting gender-based differences in healthcare utilization, as noted in previous studies (Verbrugge, 1985). Age is categorized into three groups: 0-45 years, 46-65 years, and over 65 years. While this categorization helps protect privacy, it limits the precision of the analysis, especially since the "0-45" age group includes both younger adults and children, who may have different healthcare needs. For modelling purposes, age is treated as a categorical variable, with values ranging from 1 to 3 for the respective groups. The municipality of residence differentiates individuals living in urban versus rural areas, a distinction that can influence healthcare utilization, particularly regarding telemedicine, as rural residents may face different barriers to accessing healthcare services.

Health Status Characteristics

Health status information for patients was obtained from the exemption database, pharmaceutical database, and specialist services database, supplemented with an indicator of the number of comorbidities per patient calculated from diagnoses recorded in both the Diagnostic and Therapeutic Services file and the emergency department file.

From the exemption file, the number of pathology-related exemptions per patient was calculated, considering the different exemption renewals. Having an exemption for a pathology highlights a chronic pathological condition, which is useful to understand the patient's health status.

Moreover, the Charlson Comorbidity Index (CCI), which classifies patients based on comorbidities, was calculated using diagnosis codes from hospital discharge forms and emergency department visits. The CCI assigns weighted scores to each comorbidity, ranging from 1 to 6, with higher scores indicating a greater risk of mortality and a higher likelihood of using healthcare services.

Telemedicine Variable

The treatment variable, denoted as "treated," distinguishes between the control and treatment groups in the study. This variable is defined as an interaction between the group assignment and the start of the policy intervention, which took place in the first and second semesters of 2022. Specifically, the variable takes the value of 0 for both groups prior to 2022. It remains 0 for the control group throughout the study period, while for the treatment group, the variable is activated and becomes 1 starting in 2022, reflecting the onset of the policy intervention. This specification allows for the incorporation of the temporal dimension into the analysis, ensuring that the treatment effect is captured from the moment the policy is introduced.

Healthcare Access Indicators

The model includes territorial variables capturing healthcare access and resource distribution, namely the Access Barriers Index and the number of pharmacies per 1,000 inhabitants.

The Access Barriers Index was built via principal component analysis (PCA) on z-score standardized variables related to healthcare availability and accessibility (number of primary care facilities, hospitals, specialized services, and average distances to them), combined into a single index where higher values indicate greater difficulty in accessing care. Correlations with distance-related variables confirm the index's effectiveness in identifying underserved areas.

The number of pharmacies per 1,000 inhabitants (ranging 0-3) is a continuous indicator of pharmaceutical service density. Municipalities with higher values are generally associated with better access to medications and pharmaceutical care, helping reduce disparities in treatment outcomes (Di Novi et al., 2023). This variable is particularly relevant in the context of pharmacy deserts, areas with limited access to community pharmacies, and is included to explore its relationship with treatment adherence. An additional dichotomous variable captures the presence of an emergency department (ED) within the municipality (1 if at least one ED is present, 0 otherwise), accounting for local availability of urgent care services that may influence healthcare utilization patterns.

All dependent and independent variables were computed on a semi-annual basis. A detailed description of all variables is provided in Table 3.1.

Table 3.1. Description of Variables

Variable	Description
Panel A. Outcomes	
Semi-annual Adherence to ATC A02BC02	Binary variable = 1 if adherence >80%, 0 otherwise.
Semi-annual Adherence to ATC A10BA02	Binary variable = 1 if adherence >80%, 0 otherwise.
Semi-annual Adherence to ATC C03CA01	Binary variable = 1 if adherence >80%, 0 otherwise.
Semi-annual Adherence to ATC C07AB07	Binary variable = 1 if adherence >80%, 0 otherwise.
Hospital Admissions	Binary variable = 1 if at least one hospitalization occurred during the semester, 0 otherwise.
Emergency Department Visits	Binary variable = 1 if at least one emergency department visit occurred during the semester, 0 otherwise.
Panel B. Demographic Characteristics	
Gender	Binary variable = 1 if the patient is male, 0 otherwise
Age groups	Categorical variable: 1 if the patient's age is between 0 and 45 years old; 2 if the patient's age is between 46 and 65 years old; 3 if the patient's age is above 65 years old
Area	Binary variable = 1 if it is an urban area, 0 if it is rural
Panel C. Health Status Characteristics	
No. Exemptions	Counting variable $\in$ N= {0,1, 2, …}, it counts the number of exemptions for each patient
Charlson Comorbidity Index	Score of the CCI
Panel D. Telemedicine Variable	
Treated	Binary variable=1 from the moment the subject starts being treated
Panel E. Healthcare Access Indicators	
Barrier Index	Continuous variable ranging from -5 to +7, representing a composite index of local accessibility to the National Health Service. It reflects the degree of difficulty in accessing healthcare services across municipalities.
Pharmacies per 1000 inhabitants	Continuous variable ranging from 0 to 3, representing the number of pharmacies per 1,000 inhabitants
Emergency Department	Binary variable equal to 1 if an emergency department is located in the municipality, and 0 otherwise.
Panel F. Time Horizon	
Semester	Categorical variable: 1 for the first semester of 2019 through 8 for the second semester of 2022, sequentially numbered

3.4 Empirical Strategy

The starting hypothesis of this study is that patients with higher medication adherence place a lower burden on the healthcare system by making less intensive use of healthcare resources. This hypothesis reflects the idea that better-managed chronic conditions reduce the need for costly services such as emergency department visits and hospital admissions. If this relationship

holds, it becomes crucial to identify the factors that can enhance patients' adherence to prescribed therapies.

Within this framework, telemedicine is conceptualized as a key enabling factor. By increasing proximity to patients and improving clinical monitoring and continuity of care, telemedicine may foster better adherence to treatment regimens. Adherence, in turn, can act as a transmission channel through which telemedicine affects healthcare utilization. However, the empirical identification of these relationships is complicated by potential endogeneity. Adherence is likely to be correlated with unobserved individual characteristics, such as health awareness, risk preferences, or unmeasured severity, that may simultaneously influence healthcare utilization. Ignoring this simultaneity would lead to biased estimates of the effect of adherence on hospitalizations and ED access. To address these concerns, we adopt a recursive limited dependent variable framework, modelling adherence, hospitalization, and ED access as jointly determined outcomes. This approach follows recent applications in health economics that explicitly account for endogeneity arising from simultaneous health behaviors and healthcare utilization decisions (e.g. Brugiavini et al., 2022; Di Novi et al., 2023).

3.4.1 The Relationship Between High Levels of Adherence and Resource Consumption

This study explores whether telemedicine may have enhanced therapy adherence and, over time, helped reduce healthcare utilization, including outpatient visits and emergency department admissions. To demonstrate an inverse relationship between higher adherence and healthcare resource utilization and given the panel nature of our dataset, we use a random effects Tobit model. This specification allows us to account for unobserved individual heterogeneity and the censored nature of utilization outcomes. Formally, the model is expressed as:

$$y_{it}^{*} = \beta_0 + \beta_1 X_{it} + \delta Exposure_{it} + \lambda(HighAdherence_{it} * time_t) + \\ + \partial PharmaciesPer1000_{it} + time_t + \alpha_i + u_{it} \tag{3.2}$$

where y_{it}^{*} represents the healthcare resource utilization variable (i.e. number of accesses to emergency department in the semester; number of hospitalizations in the semester); X_{it} includes the demographic and clinical regressors: age, sex, number of exemptions, Charlson Index ; the variable $Exposure_{it}$ indicates whenever the patient belong to the control group or the treatment group; $time_t$ is the semester fixed effect; the product $High\ Adherence_{it} * time_t$ is the interaction between the high level of adherence and the semester effect; $PharmaciesPer1000_{it}$ measures the density of community pharmacies per 1,000 inhabitants. The individual-specific random effect is denoted by α_i, and the error term by u_{it}.

3.4.2 The Simultaneous Relationship Between High Levels of Adherence, Telemedicine and Resource Consumption

To investigate the relationship between telemedicine, patients' adherence to therapy and medical care service utilization, we employed a simultaneous equation model for binary variables. We identified two classes of dependent variables: drug consumption and medical care utilization (hospitalizations and emergency department visits). In the medical care utilization equation, the adherence to therapy indicator is included as an explanatory variable. To explicitly account for the potential endogeneity that may arise with the inclusion of the drug consumption as regressor into the health consumption equations, we estimate a recursive multivariate probit model[19] composed of three binary equations: a reduced-form equation modelling the probability of high adherence; a structural equation modelling hospitalization; a structural equation modelling ED access. Therefore, we constructed and estimated a system of those three equations. This structure mirrors the approach adopted in prior studies analyzing health behaviors and outcomes within a simultaneous equation framework (e.g. Brugiavini et al., 2022).

The system is defined as:

$$HighAdherence_{it}^{*} = \gamma_1 * Treated_{it} + \delta_1 X_{it} + \lambda_1 * PharmaciesPer1000_{it} + \\ + \theta_1 Barrier_{index_{it}} + \mu_t + \varepsilon_{1it} \tag{3.3}$$

$$Hospitalization_{it}^{*} = \beta_1 * HighAdherence_{it} + \delta_2 X_{it} + \partial_1 ED_{access^{*}\,it} + \\ + \mu_t + \varepsilon_{2it} \tag{3.4}$$

$$ED_{access^{*}\,it} = \beta_2 * High\ Adherence_{it} + \delta_3 X_{it} + \theta_2 Barrier_{index_{it}} \\ + \eta_1 ED_{it} + \mu_t + \varepsilon_{3it} \tag{3.5}$$

where High Adherence$_{it}^{*}$, Hospitalization$_{it}^{*}$, and ED access$_{it}^{*}$ are latent variables underlying the observed binary indicators for, respectively, high medication adherence (PDC > 80%), at least one hospital admission, and at least one emergency department visit during the semester.

The model is specified as a recursive multivariate probit system, in which medication adherence acts as an endogenous regressor in the hospitalization and emergency department equations,

[19] The multivariate probit model with endogenous binary variables is a special case of simultaneous equation models (Maddala, 1983). For empirical applications using recursive specifications similar to ours see Balia and Jones (2008) and Di Novi (2010, 2013).

while being simultaneously determined in the first equation by telemedicine exposure and contextual factors. This structure allows us to explicitly model the joint determination of adherence and healthcare utilization and to account for potential endogeneity arising from unobserved patient characteristics that may simultaneously affect adherence behavior and the use of acute care services.

The vector X_{it} includes sociodemographic and clinical controls (gender, age groups, Charlson Comorbidity Index, and number of chronic condition exemptions), while μ_t denotes semester fixed effects capturing common time shocks. The variable Treated_{it} identifies exposure to telemedicine from the moment of enrolment, whereas $\text{PharmaciesPer1000}_{it}$ and BarrierIndex_{it} capture local access to pharmaceutical services and geographic barriers to healthcare, respectively. The variable ED_{it} indicates the presence of an emergency department in the municipality of residence. The unobserved error terms $(\varepsilon_{1it}, \varepsilon_{2it}, \varepsilon_{3it})$ are assumed to follow a normal distribution with zero mean, unit variances, and an unrestricted covariance matrix. Allowing correlation across equations captures unobserved heterogeneity that jointly affects adherence and healthcare utilization; in the presence of such correlation, separate estimation of the equations would yield inconsistent estimates (Green, 2017). In recursive probit models, the correlation coefficients between the error terms provide a test for residual dependence across equations. If the correlation coefficient is significantly different from zero, separate estimation of the equations would be inappropriate, and the recursive specification is required. In our case, the estimated correlation coefficients are not statistically significant, suggesting that, conditional on the recursive structure and the imposed exclusion restrictions, there is no remaining correlation between unobserved determinants of adherence and healthcare utilization. This result indicates that the endogeneity of adherence is captured by the structural specification of the model.

Identification of the system relies on exclusion restrictions, following the approach proposed by Maddala (1983). Specifically, geographic barriers to accessing pharmacies and the density of pharmacies per 1,000 inhabitants are included in the adherence equation but excluded from the hospitalization equation, under the assumption that their effect on acute care utilization operates primarily through medication adherence. Conversely, the hospitalization and emergency department equations include an indicator for the local availability of emergency services, which is excluded from the adherence equation. These restrictions ensure that the parameters of the recursive multivariate probit model are identified and allow a causal interpretation of the role of adherence as a transmission channel between telemedicine and healthcare utilization.

Although the recursive multivariate probit framework already allows us to address the endogeneity of medication adherence by jointly modelling adherence and healthcare utilization, additional concerns may arise if unobserved factors affect adherence behavior and the use of acute care services over time. To further strengthen identification and assess the robustness of our results, we therefore complement the baseline specification with an instrumental-variable strategy based on lagged dependent variables (Maddala, 1983).

Specifically, as a robustness check, we re-estimate the recursive multivariate probit system by including lagged values of the endogenous variables as instruments in the corresponding equations. Lagged adherence is used as an instrument for current adherence in the adherence equation, while lagged indicators of hospitalizations and emergency department visits are included as instruments in the respective healthcare utilization equations. This strategy exploits the persistence in health behaviors and healthcare use, under the assumption that past outcomes are correlated with current endogenous variables but affect current healthcare utilization only through their impact on present adherence and utilization decisions (Balia & Jones, 2008).

This approach follows the logic of recursive limited dependent variable models with instrumental variables, as originally discussed by Maddala (1983), and subsequently applied in the health economics literature to address endogeneity in behavioral and healthcare utilization outcomes (e.g., Cappellari and Jenkins, 2003; Balia and Jones, 2008; Di Novi, 2010, 2013). By including the lagged endogenous variables in the reduced-form equations but not in the contemporaneous structural relationships, we impose exclusion restrictions analogous to those commonly adopted in recursive probit models.

The validity of this instrumental-variable strategy relies on the assumption that, conditional on observed covariates and fixed effects, past adherence and past healthcare utilization capture persistent unobserved heterogeneity without directly affecting current outcomes beyond their effect through current endogenous variables.

The model is estimated in Stata 19, with robust standard errors clustered at the individual level.

3.5 Results

This section presents empirical results from the recursive multivariate probit analysis to investigate the contemporaneous relationship between telemedicine and healthcare resource utilization over the long term, with adherence acting as a common factor across patients with heart failure and diabetes in a region of Liguria.

The section is organized as follows. It begins with descriptive statistics documenting the main characteristics of the two patient subgroups, then we report the findings from the Tobit and the

recursive multivariate probit model, which demonstrates that, in some cases, telemedicine, by improving adherence, may help reduce hospitalizations and emergency department.

3.5.1 Descriptive Statistics

Table 3.2 presents the sociodemographic characteristics of the study population, divided by treatment status (telemedicine users vs. controls) for both heart failure and diabetic patients.
Both groups exhibit similar trends in gender distribution, with a higher proportion of males in the treated groups compared to the controls for the heart failure patients (58.9% vs 50.3%) and more mixed results in the diabetic sample (47.8% vs 50.6%).

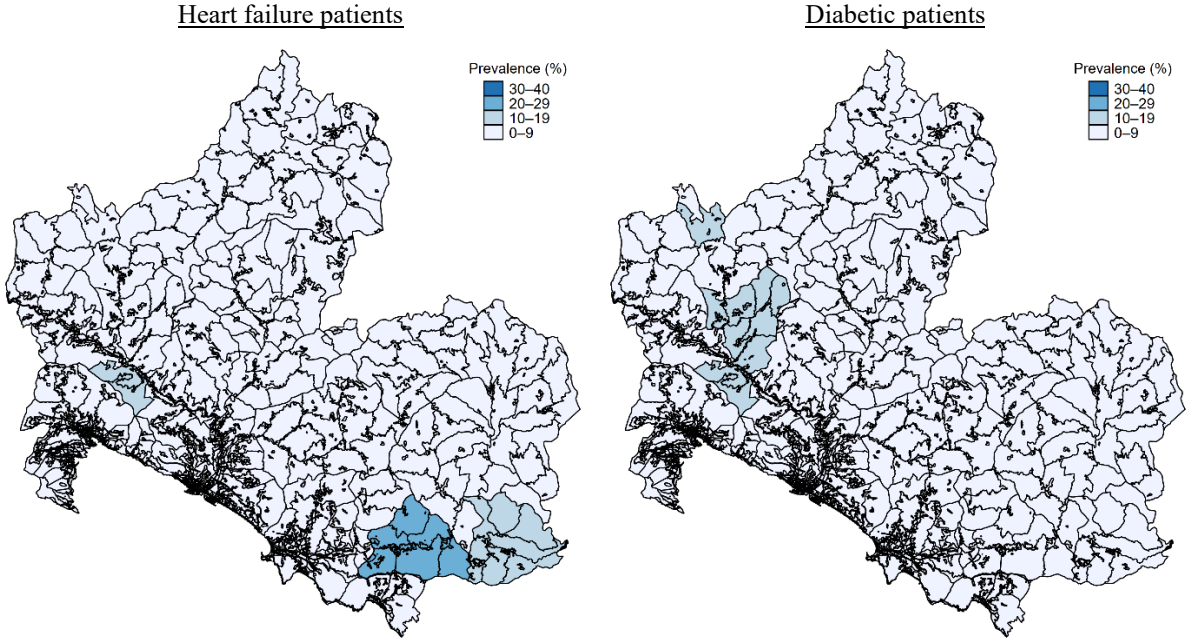
Table 3.2. Sociodemographic Characteristics

	Heart failure patients				Diabetic patients			
	Treated		Control		Treated		Control	
	N	%	N	%	N	%	N	%
Panel A. Gender								
Female	53	41.1	1439	49.7	142	52.2	2880	49.4
Male	76	58.9	1457	50.3	130	47.8	2954	50.6
Panel B. Age groups								
0 - 45	2	1.6	11	0.4	40	14.7	270	4.6
46 - 65	25	19.4	195	6.7	57	21.0	974	16.7
>65	102	79.1	2690	92.9	175	64.3	4590	78.7
Panel C. Area								
Rural	33	25.6	569	19.6	54	19.9	1121	19.2
Urban	96	74.4	2327	80.4	218	80.1	4713	80.8
Total	129	100.0	2896	100.0	272	100.0	5834	100.0

Note: The table reports absolute (N) and relative (%) frequencies of categorical variables by treatment status. Percentages are computed within groups.

In terms of age, most patients are over 65, especially in the control groups (92.9% for heart failure, 78.7% for diabetes), while treated patients tend to be younger.
Geographically, both groups are more likely to live in urban areas. The rural population is similarly lower among control groups (19.6% for heart failure and 19.2% for diabetics) compared to the treated group (25.6% and 19.9%, respectively).
Figure 3.1 gives a graphical illustration of the spatial distribution of telemonitoring use across municipalities.

Figure 3.1. Telemonitoring Prevalence Across Municipalities, by Disease



Note: The map shows the percentage of cardiac patients enrolled in telemonitoring programs over the total number of patients divided by diseases, by municipality within the ASL 4 area (Liguria region, Italy). Data refers to the end of 2022. Darker shades indicate higher telemonitoring prevalence.

Tables 3.3 and 3.4 present a comprehensive comparison of adherence, healthcare utilization, health status, and access to services between the treated (telemedicine users) and control groups for both heart failure and diabetic patients.

For heart failure patients (Table 3.3), the treated group consistently shows higher adherence to therapy across all ATC categories. For example, adherence to ATC A02BC02 (antacids) is 74.66% in the treated group compared to 70.91% in the control group, and adherence to ATC A10BA02 (medications for heart failure) is 62.62% in the treated group, significantly higher than 43.18% in the control group. Similarly, adherence to other cardiovascular drugs (ATC C03CA01 and C07AB07) is higher in the treated group. Healthcare utilization is lower in the treated group: the number of primary care services used per semester is 0.53 in the treated group versus 0.55 in the control group, and the number of hospitalizations is 0.38 for both groups, but the treated group shows a trend toward lower resource use. Additionally, treated patients have slightly more exemptions (1.75 vs. 1.37), which reflects a higher burden of chronic conditions, yet they still utilize fewer resources. The Charlson Comorbidity Index scores are similar (2.77 vs. 2.75), indicating comparable overall health status between the groups. Health access is also slightly better for the treated group, with a higher Barrier Index and more pharmacies per 1,000 inhabitants (0.55 vs. 0.52), suggesting that telemedicine might be more beneficial in regions with better access to healthcare.

Table 3.3. Descriptive Statistics of Heart Failure Patients, by Semester

	Treated group					Control group				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Panel A. Adherence to therapy										
Adherence -ATC A02BC02	74.66	33.28	0.00	100.00	525	70.91	34.62	0.00	100.00	7577
Adherence -ATC A10BA02	62.62	30.84	0.00	100.00	169	43.18	28.58	0.00	100.00	2247
Adherence -ATC C03CA01	59.31	34.44	0.00	100.00	573	51.58	33.80	0.00	100.00	7873
Adherence -ATC C07AB07	23.14	20.40	0.00	100.00	370	19.07	17.67	0.00	100.00	4819
Panel B. Facilities use										
No. ED access	0.53	1.00	0.00	9.00	1018	0.55	0.95	0.00	15.00	18272
No. Hospital Discharges	0.38	0.75	0.00	5.00	1018	0.38	0.77	0.00	10.00	18272
Panel C. Health Status Characteristics										
No. Exemptions	1.75	1.49	0.00	7.00	1018	1.37	1.32	0.00	9.00	18272
Charlson Index	2.77	2.32	0.00	15.00	986	2.75	2.46	0.00	16.00	18037
Panel D. Health Access Indicators										
Barrier Index	-2.01	2.51	-5.23	6.77	1032	-2.35	2.39	-5.23	6.77	23168
Pharmacies per 1000 inhabitants	0.55	0.61	0.00	2.89	1032	0.52	0.56	0.00	2.89	23168

Note: Data refers to patients with heart failure. The treated group includes patients who received telemedicine follow-up, while the control group consists of patients who received only in-person care. The table reports adherence to therapy, healthcare utilization, health status characteristics, and access to care indicators.

Table 3.4. Descriptive Statistics of Diabetic Patients, by Semester

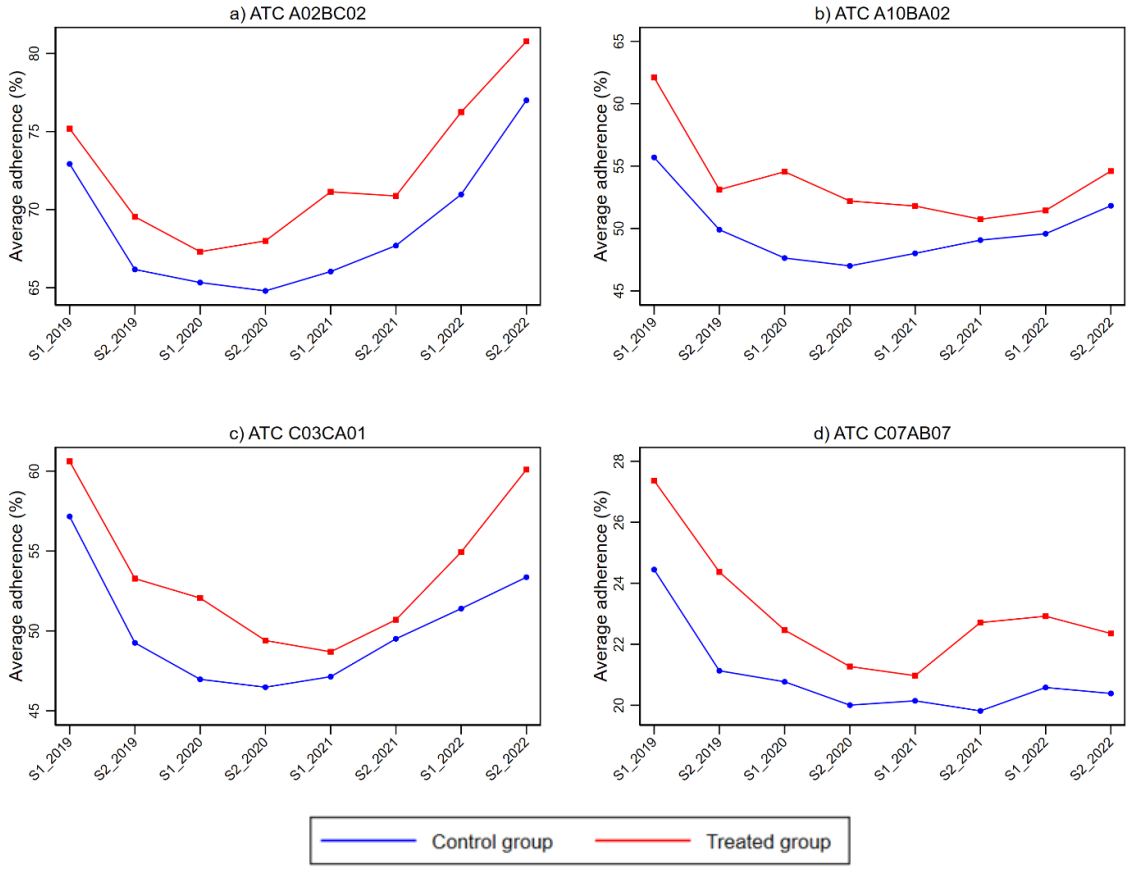
	Treated group					Control group				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Panel A. Adherence to therapy										
Adherence -ATC A02BC02	71.38	35.47	0.00	100.00	739	67.59	35.57	0.00	100.00	11897
Adherence -ATC A10BA02	53.63	34.61	0.00	100.00	663	50.16	32.11	0.00	100.00	12685
Adherence -ATC C03CA01	51.06	34.70	0.00	100.00	459	50.13	33.45	0.00	100.00	6781
Adherence -ATC C07AB07	23.42	22.35	0.00	100.00	305	21.42	19.55	0.00	100.00	5529
Panel B. Facilities use										
No. ED access	0.43	0.96	0.00	13.00	2180	0.38	0.82	0.00	18.00	39436
No. Hospital Discharges	0.24	0.62	0.00	6.00	2180	0.26	0.66	0.00	11.00	39436
Panel C. Health Status Characteristics										
No. Exemptions	1.86	1.30	0.00	7.00	2180	1.59	1.26	0.00	9.00	39436
Charlson Index	2.12	2.50	0.00	15.00	1826	2.09	2.55	0.00	17.00	33953
Panel D. Health Access Indicators										
Barrier Index	-2.34	2.38	-5.23	6.77	2176	-2.39	2.33	-5.23	6.77	46672
Pharmacies per 1000 inhabitants	0.56	0.63	0.00	2.89	2176	0.53	0.58	0.00	2.89	46672

Note: Data refers to patients with diabetes. The treated group includes patients who received telemedicine follow-up, while the control group consists of patients who received only in-person care. The table reports adherence to therapy, healthcare utilization, health status characteristics, and access to care indicators.

For diabetic patients (Table 3.4), treated patients also show higher adherence across all medication categories. For instance, adherence to ATC A02BC02 (antacids) is 71.38% in the treated group compared to 67.59% in the control group, and adherence to ATC A10BA02 (insulin and antidiabetic medications) is 53.63% in the treated group versus 50.16% in the control group. In terms of healthcare utilization, treated diabetic patients have lower hospitalization rates (0.24 vs. 0.26). The number of exemptions is higher in the treated group (1.86 vs. 1.59), which might reflect a greater burden of disease in this cohort, yet the treated group uses fewer resources. The Charlson Index scores are also comparable (2.12 vs. 2.09), indicating similar health conditions between the groups. Access to healthcare is slightly better for treated patients, as shown by the higher Barrier Index and more pharmacies per 1,000 inhabitants (0.56 vs. 0.53).

Figure 3.2 illustrates the adherence trends by treatment groups across different ATC categories.

Figure 3.2. Adherence Trends by ATC Class, 2019-2022



The data clearly show that, throughout the study period, the treated group (telemedicine users) consistently maintains higher adherence levels compared to the control group. Moreover, the figure shows a clear drop in adherence across all drug classes during the COVID-19 years,

plausibly reflecting disruptions in access and medication procurement. As the pandemic subsided, and even more markedly after the treated group began receiving the intervention in 2022, adherence increased substantially, with the largest gains observed among patients who were also monitored remotely.

3.5.2 The Relationship Between High Levels of Adherence and Resource Consumption

Figure 3.3-3.4 reports the estimated marginal effects, estimated using the random effects Tobit regression (see Equation (3.2)), of the interaction term $High\ Adherence_{it} * time_t$ and help in the identification of resource use patter splitting patients between those who are highly adherent and those with low level of adherence.

Figure 3.3. Resource Utilization by Adherence Status, 2019-2022

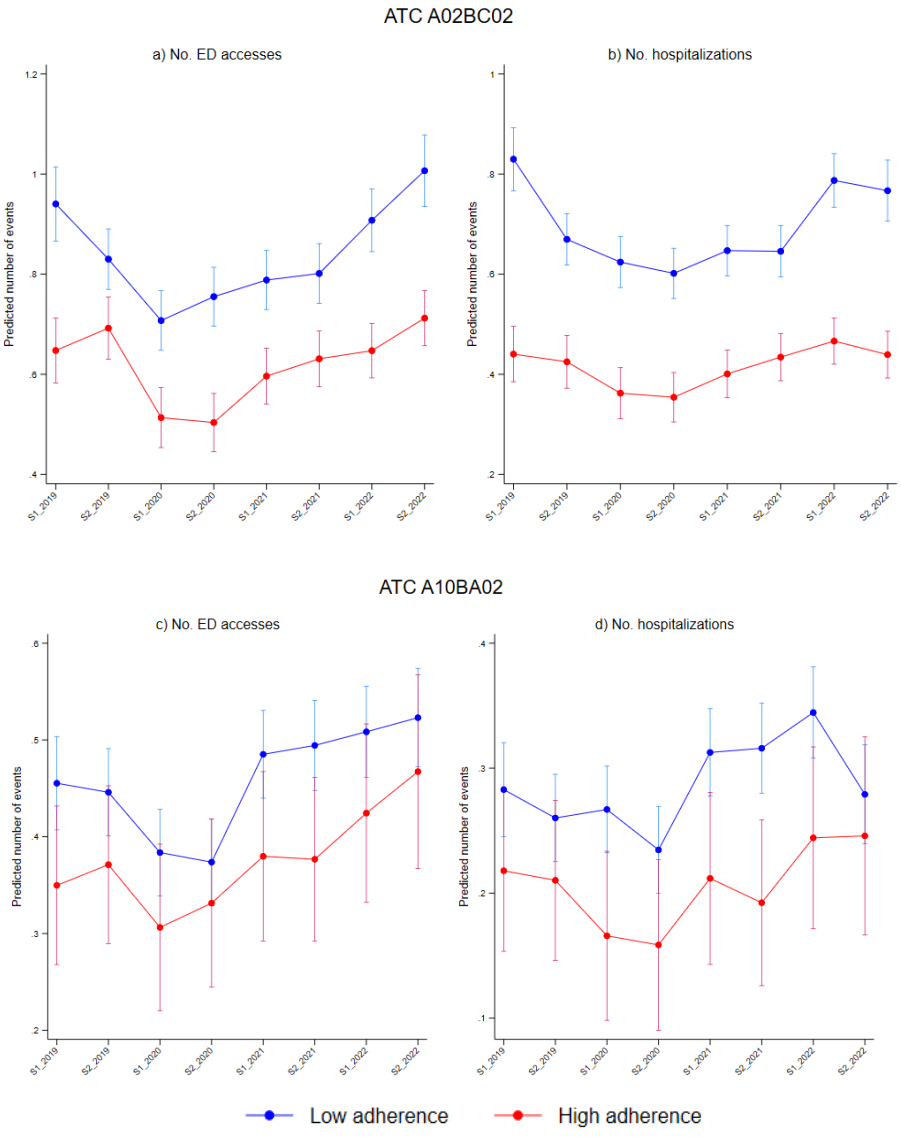
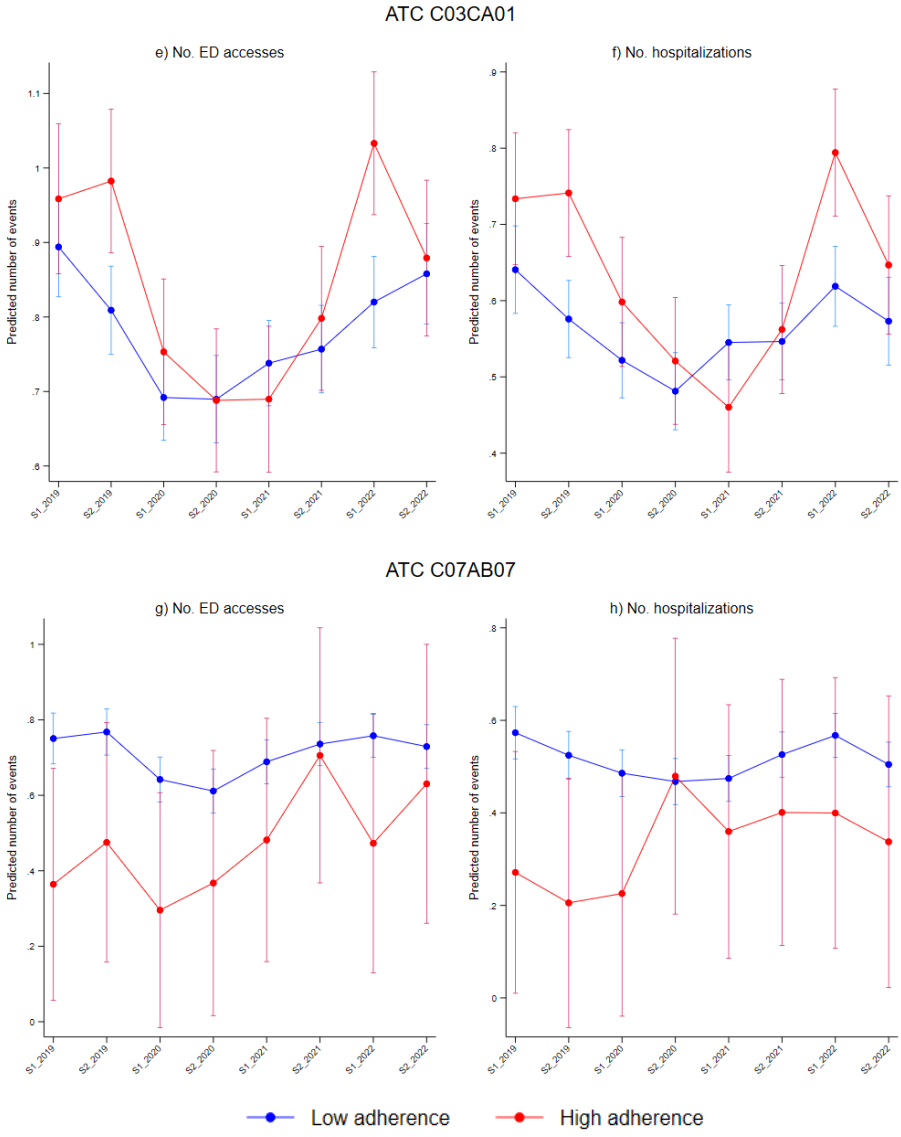


Figure 3.4. Resource Utilization by Adherence Status, 2019-2022 (continue)



Results reveal a negative association between adherence and healthcare resource consumption, with higher adherence corresponding to lower rates of hospitalizations and emergency visits, findings that align with the literature on adherence-related cost savings (Cutler et al., 2018; Roebuck et al., 2011). This effect is particularly evident for diabetes medications (Figure 3.3), where higher adherence is associated with fewer emergency department visits and fewer hospitalizations. Conversely, the relationship is less evident for cardiovascular medications (Figure 3.4). This may be due to several reasons, for example, the fact that not taking these medications often leads to long-term consequences, as cardiovascular diseases are considered "silent killers" (Di Novi et al., 2020). The results of the models are reported in Tables A2.1 and A2.2 in the Appendix.

3.5.3 The Simultaneous Relationship Between High Levels of Adherence, Telemedicine and Resource Consumption

To further investigate the dynamics between medication adherence and healthcare resource use, we estimate a recursive multivariate probit model that jointly examines the probability of high adherence, hospitalizations, and emergency department visits (see Table 3.5).

Table 3.5. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treated	0.381***	0.060	0.191	-0.124
	(0.094)	(0.153)	(0.113)	(0.216)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Time Control	YES	YES	YES	YES
Panel B. Hospitalization				
High Adherence	-0.388***	-0.215**	0.021	-0.004
	(0.053)	(0.070)	(0.071)	(0.398)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Panel C. Emergency Department Visits				
High Adherence	-0.285***	-0.049	-0.006	-0.644**
	(0.061)	(0.082)	(0.084)	(0.244)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Rho21	0.021	-0.014	0.010	-0.012
	(0.031)	(0.044)	(0.035)	(0.043)
Rho31	0.020	0.010	-0.023	-0.039
	(0.028)	(0.034)	(0.036)	(0.137)
Rho32	-0.026	-0.057	0.002	0.115
	(0.035)	(0.044)	(0.047)	(0.104)
N	16705	11270	11890	8543

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel A presents the results for adherence, where telemedicine is positively associated with higher adherence to prescribed therapies. The effect of telemedicine on adherence is statistically significant for some drug classes but varies across therapeutic groups. Specifically, telemedicine has a positive and significant effect on adherence to gastroprotective agents (A02BC02; coefficient = 0.381, p < 0.01), indicating that digital interventions are particularly effective in improving adherence to medications requiring frequent monitoring and patient education. For antidiabetic medications (A10BA02), the effect is positive but not statistically significant (coefficient = 0.060, p = 0.694). Conversely, adherence to cardiovascular medications shows mixed results. For diuretics (C03CA01), the effect of telemedicine is positive but modest (coefficient = 0.191, p = 0.091), while for beta-blockers (C07AB07), the effect is negative and

statistically insignificant (coefficient = -0.124, p = 0.566). This disparity in the results between diabetes medications and cardiovascular drugs could be explained by the nature of the diseases. Cardiovascular medications are typically associated with conditions that may not manifest immediate consequences if missed (Di Novi et al., 2020). The adverse effects of non-adherence to these drugs tend to appear more gradually over time. In contrast, medications for diabetes often require more immediate action to manage blood sugar levels, which may lead to more immediate feedback on treatment adherence. Given that our study focuses on a two-semester treatment period, the lack of immediate effects for cardiovascular drugs may reflect the longer-term nature of the consequences associated with non-adherence to these medications.

Panel B and Panel C present the results for hospitalizations and ED visits, where we observe that higher adherence is associated with lower utilization of acute care services, supporting the hypothesis that improved adherence reduces healthcare resource consumption. Specifically, higher adherence is significantly negatively associated with the probability of hospitalization. For antidiabetic medications, this relationship is strong and statistically significant for both types of hospitalizations considered: diabetic drugs (A02BC02 and A10BA02) lead to significantly fewer hospitalizations (coefficients = -0.388, $p < 0.01$; -0.215, $p < 0.05$) as well as fewer ED visits (coefficients = -0.285, $p < 0.01$; -0.049, $p = 0.545$) for A02BC02 and C07AB07. These findings suggest that better adherence to diabetes medications translates into a significant reduction in both hospitalizations and ED visits.

In contrast, the relationship between adherence to cardiovascular medications and acute care use is less consistent. While adherence to diuretics (C03CA01) shows a statistically insignificant effect on hospitalizations (coefficient = 0.021, $p = 0.803$), adherence to beta-blockers (C07AB07) is associated with a marginal reduction in ED visits (coefficient = -0.644, $p < 0.05$), but with no significant effect on hospitalizations (coefficient = -0.004, $p = 0.992$). These mixed results suggest that while telemedicine may have a strong effect on adherence in chronic disease management, its impact on healthcare utilization varies depending on the therapeutic class and type of healthcare service examined.

The bottom panel of Table 3.5 reports the estimated correlation coefficients between the error terms of the three equations. None of the estimated parameters is statistically different from zero across therapeutic classes, suggesting that, conditional on observed covariates and on the recursive structure of the model, there is no residual correlation between the unobserved determinants of adherence, hospitalizations, and emergency department visits. This result indicates that the recursive specification adequately captures the endogeneity of medication adherence and that remaining unobserved heterogeneity does not simultaneously affect the outcomes once

adherence is accounted for, in line with previous applications of recursive probit models in health economics (Giachello et al., 2024).

The full set of estimates for all model covariates is reported in Appendix Table A2.3.

3.6 Heterogeneity

The heterogeneity analysis was conducted to investigate how the relationship between telemedicine, medication adherence and healthcare utilization varies across different demographic and clinical subgroups, specifically by age group, gender, comorbidity level, and residential area type. The detailed results of this analysis, presented across various drug classes, are available in Tables 3.6 to 3.9.

Table 3.6. Heterogeneity by ATC A02BC02, by Semester

	Age		Gender		Charlson Index		Area	
	0-65	65+	Female	Male	Low	High	Rural	Urban
				Panel A. Adherence				
Treated	0.597***	0.338***	0.257**	0.568***	0.384*	0.380***	0.386*	0.373***
	(0.184)	(0.107)	(0.124)	(0.141)	(0.218)	(0.103)	(0.220)	(0.103)
				Panel B. Hospitalization				
High Adherence	-0.190	-0.409***	-0.412***	-0.330***	-0.281**	-0.366***	-0.477***	-0.347***
	(0.166)	(0.057)	(0.073)	(0.075)	(0.131)	(0.056)	(0.130)	(0.060)
				Panel C. Emergency Department Visits				
High Adherence	-0.474***	-0.270***	-0.301***	-0.368***	-0.099	-0.290***	-0.594***	-0.317***
	(0.160)	(0.061)	(0.075)	(0.076)	(0.148)	(0.065)	(0.146)	(0.062)
N	2109	14596	8427	8278	2882	13823	3147	13558

Standard errors in parentheses

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

Table 3.7. Heterogeneity by ATC A10BA02, by Semester

	Age		Gender		Charlson Index		Area	
	0-65	65+	Female	Male	Low	High	Rural	Urban
				Panel A. Adherence				
Treated	-0.089	0.089	-0.105	0.200	0.099	0.017	0.058	0.029
	(0.315)	(0.176)	(0.225)	(0.205)	(0.259)	(0.188)	(0.314)	(0.176)
				Panel B. Hospitalization				
High Adherence	-0.203	-0.312***	-0.238**	-0.257**	-0.055	-0.222**	-0.319*	-0.191**
	(0.204)	(0.078)	(0.098)	(0.121)	(0.143)	(0.089)	(0.166)	(0.082)
				Panel C. Emergency Department Visits				
High Adherence	-0.065	-0.150*	-0.300***	-0.032	-0.193	-0.227**	0.108	-0.323***
	(0.210)	(0.082)	(0.104)	(0.125)	(0.188)	(0.098)	(0.180)	(0.085)
N	1853	9417	5834	5436	3002	8268	2396	8874

Standard errors in parentheses

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

Table 3.8. Heterogeneity by ATC C03CA01, by Semester

	Age		Gender		Charlson Index		Area	
	0-65	65+	Female	Male	Low	High	Rural	Urban
				Panel A. Adherence				
Treated	-0.354	0.256**	0.153	0.272	-0.590	0.220*	0.200	0.173
	(0.422)	(0.117)	(0.148)	(0.173)	(0.545)	(0.117)	(0.212)	(0.134)
				Panel B. Hospitalization				
High Adherence	-0.445**	-0.002	0.010	-0.064	0.080	-0.099	-0.014	-0.055
	(0.221)	(0.071)	(0.112)	(0.096)	(0.283)	(0.073)	(0.138)	(0.075)
				Panel C. Emergency Department Visits				
High Adherence	0.298	0.103	0.126	0.064	-0.094	0.009	-0.103	-0.100
	(0.338)	(0.082)	(0.109)	(0.094)	(0.361)	(0.077)	(0.194)	(0.085)
N	646	11244	5797	6093	1283	10607	2661	9229

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

Table 3.9. Heterogeneity by ATC C07AB07, by Semester

	Age		Gender		Charlson Index		Area	
	0-65	65+	Female	Male	Low	High	Rural	Urban
				Panel A. Adherence				
Treated	0.236	-0.519	-0.213	0.025	0.413	-0.251	0.309	-0.268
	(0.298)	(0.383)	(0.292)	(0.308)	(0.319)	(0.279)	(0.211)	(0.299)
				Panel B. Hospitalization				
High Adherence	-0.053	-0.309	-0.163	0.399	-0.766**	-0.062	0.481	-0.030
	(0.701)	(0.252)	(0.251)	(0.362)	(0.352)	(0.284)	(0.600)	(0.245)
				Panel C. Emergency Department Visits				
High Adherence	-0.407	-0.643***	-0.375	0.015	-0.541*	-0.408	-0.990**	-0.066
	(0.549)	(0.159)	(0.334)	(0.432)	(0.324)	(0.314)	(0.447)	(0.215)
N	957	7586	4521	4022	1181	7362	1670	6873

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

For ATC A02BC02 (gastroprotective agents), Panel A of Table 3.6 shows that telemedicine effects on adherence are generally positive and statistically significant across most subgroups, with the strongest effect observed in the 0-65 age group (0.597, $p < 0.01$). The treatment effect is also notably significant for men (0.568, $p < 0.01$) and urban residents (0.373, $p < 0.01$). In contrast, the effect is weaker for older female individuals (0.338, $p<0.01$; 0.257, $p < 0.05$) and for those living in rural areas (0.386, $p < 0.10$), indicating that telemedicine interventions may be more effective in younger populations and urban areas.

Panel B of Table 3.6 shows that higher adherence is significantly associated with fewer hospitalizations, especially among 65+ individuals (-0.409, $p < 0.01$) and females (-0.412, $p < 0.01$). Furthermore, adherence reduces hospitalizations more substantially for individuals in rural areas (-0.477, $p < 0.01$) and those with a high Charlson Comorbidity Index (-0.366, $p < 0.01$). Similarly, Panel C reveals that higher adherence leads to fewer emergency department (ED)

visits, particularly among the 0-65 age group (-0.474, $p < 0.01$), males (-0.368, $p < 0.01$), and rural residents (-0.594, $p < 0.01$).

The effects on hospitalizations and ED visits are generally more pronounced. Higher adherence is associated with fewer hospitalizations among the 65+ group (-0.312, $p < 0.01$), males (-0.257, $p < 0.05$), and individuals with a high Charlson Comorbidity Index (-0.222, $p < 0.05$). Furthermore, ED visits are significantly reduced for females (-0.300, $p < 0.01$) and urban residents (-0.323, $p < 0.01$), while weaker effects are seen in other subgroups. In contrast, ATC C03CA01 (diuretics), Table 3.8, demonstrates more consistent results, with positive and significant effects on adherence observed for the 65+ age group (0.256, $p < 0.05$), but weak or insignificant effects for younger individuals and those in rural areas. Higher adherence is associated with fewer hospitalizations among the 0-65 group (-0.445, $p < 0.05$), while no effects are seen in other subgroups or for the emergency department visits. Finally, for ATC C07AB07 (beta-blockers), shown in Table 3.9, the effects on adherence are weak and not statistically significant across subgroups. However, hospitalizations are significantly reduced for those with few comorbidity (-0.766, $p < 0.05$). Additionally, ED visits decreased significantly for 65+ individuals (-0.643, $p < 0.01$) and rural residents (-0.990, $p < 0.01$), suggesting that adherence to cardiovascular medications is particularly beneficial in reducing acute care utilization, especially among older and rural patients.

3.7 Robustness check

To ensure that our results are robust and not driven by model specification choices, we performed a set of robustness checks. We tested whether our main findings remain consistent under alternative model specifications and treatment definitions.

3.7.1 Dynamic Specification with Lagged Dependent Variables

To address potential concerns related to endogeneity, particularly the possibility that unobserved factors might simultaneously influence both medication adherence and acute care utilization, we conducted a robustness check by re-estimating the multivariate probit model, including lagged dependent variables as instruments for current adherence and healthcare utilization. The results remain consistent with the main specification.

Table 3.10 presents the estimates from the re-estimated multivariate probit model that incorporates the lagged dependent variables. In Panel A, the treatment effect on adherence is positive and statistically significant for ATC A02BC02, with a coefficient of 0.283 ($p < 0.05$).

Table 3.10. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence, Including Lagged Dependent Variables

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treatment	0.283**	0.064	0.021	-0.105
	(0.094)	(0.181)	(0.110)	(0.276)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Time Control	YES	YES	YES	YES
Panel B. Hospitalization				
High Adherence	-0.295***	-0.194**	-0.035	0.194
	(0.043)	(0.059)	(0.057)	(0.174)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Panel C. Emergency Department Visits				
High Adherence	-0.108**	-0.130**	-0.059	-0.122
	(0.037)	(0.046)	(0.048)	(0.136)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Rho21	-0.005	-0.061	0.045	0.021
	(0.035)	(0.043)	(0.045)	(0.062)
Rho31	0.076**	0.061	0.080*	-0.078
	(0.026)	(0.033)	(0.034)	(0.102)
Rho32	-0.043	0.038	0.126***	-0.102
	(0.024)	(0.030)	(0.031)	(0.097)
N	12367	8944	8499	6357

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In contrast, the effect of treatment on adherence for ATC A10BA02, ATC C03CA01, and ATC C07AB07 is statistically insignificant, highlighting the heterogeneity in the impact of telemedicine across different therapeutic classes.

Panel B reports the relationship between high adherence and hospitalizations. The inclusion of lagged dependent variables strengthens the evidence of a significant negative relationship between adherence and hospitalizations. For ATC A02BC02, high adherence is associated with significantly fewer hospitalizations (-0.295, $p < 0.01$). Similarly, ATC A10BA02 shows a significant reduction in hospitalizations (-0.194, $p < 0.05$). However, for ATC C03CA01 and ATC C07AB07, the relationship is weaker, with the effect being statistically insignificant, suggesting that adherence to these medications may not have the same impact on reducing hospitalizations.

Finally, Panel C examines the relationship between high adherence and emergency department (ED) visits. For ATC A02BC02, high adherence significantly reduces the number of ED visits (-0.108, $p < 0.05$), as does adherence to ATC A10BA02 (-0.130, $p < 0.05$). In contrast, the effects for ATC C03CA01 and ATC C07AB07 are weaker, and the coefficients are statistically

insignificant, indicating that the reduction in ED visits is more pronounced for some medications than for others. While not all correlation coefficients are statistically significant, the presence of significant correlations across selected equations provides evidence against full independence of the system, supporting the use of a recursive multivariate probit specification. The full set of results of this robustness check are shown in Appendix Table A2.4.

3.7.2 Alternative Definition of High Adherence

As further robustness check, we assess whether our main results are sensitive to the definition of high medication adherence. While the baseline specification classifies patients as highly adherent when the Proportion of Days Covered (PDC) exceeds 80%, alternative thresholds are commonly used in the literature and may capture different degrees of treatment compliance (Karve et al., 2009). We therefore re-estimate the recursive multivariate probit model using two alternative cut-offs, defining high adherence as PDC ≥ 70% and PDC ≥ 90%, respectively. Table 3.11 reports the estimates obtained using the lower adherence threshold (PDC ≥ 70%).

Table 3.11. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence (Adherence Threshold ≥ 70%)

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treated	0.373***	0.055	0.194	-0.021
	(0.097)	(0.147)	(0.111)	(0.239)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Time Control	YES	YES	YES	YES
Panel B. Hospitalization				
High Adherence	-0.357***	-0.196**	0.028	0.188
	(0.053)	(0.068)	(0.068)	(0.278)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Panel C. Emergency Department Visits				
High Adherence	-0.278***	-0.090	-0.023	-0.369
	(0.061)	(0.076)	(0.081)	(0.196)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Rho21	0.025	-0.014	0.010	-0.010
	(0.031)	(0.044)	(0.035)	(0.043)
Rho31	0.031	0.004	-0.013	-0.065
	(0.028)	(0.033)	(0.035)	(0.091)
Rho32	-0.005	-0.041	0.033	0.018
	(0.035)	(0.041)	(0.046)	(0.079)
N	16705	11270	11890	8543

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results are largely consistent with the baseline findings. Telemedicine exposure remains positively and significantly associated with adherence to gastroprotective agents (ATC A02BC02; coefficient = 0.373, $p < 0.01$), while no statistically significant effects are observed for antidiabetic drugs or cardiovascular medications. In line with the main specification, higher adherence is associated with a significantly lower probability of hospitalization for ATC A02BC02 and ATC A10BA02, and with fewer emergency department visits for gastroprotective agents. The magnitude of the coefficients is comparable to the baseline model, suggesting that the results are not driven by a specific choice of the adherence threshold. The estimated correlation coefficients between the unobserved components of the equations are small in magnitude and statistically insignificant across all drug classes. This pattern indicates limited residual correlation in unobserved heterogeneity once the dynamic and structural components of the model are accounted for and does not undermine the validity of the recursive specification.
Table 3.12 presents the estimates obtained using a more PDC ≥ 90% as threshold.

Table 3.12. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence (Adherence Threshold ≥ 90%)

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treated	0.414***	0.105	0.137	-0.067
	(0.091)	(0.157)	(0.124)	(0.215)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Time Control	YES	YES	YES	YES
Panel B. Hospitalization				
High Adherence	-0.410***	-0.151	0.023	-0.060
	(0.053)	(0.079)	(0.080)	(0.421)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Panel C. Emergency Department Visits				
High Adherence	-0.290***	-0.047	0.053	-0.725**
	(0.061)	(0.088)	(0.088)	(0.251)
Demographic and Clinical Controls	YES	YES	YES	YES
Municipal Controls	YES	YES	YES	YES
Rho21	0.020	-0.013	0.010	-0.013
	(0.031)	(0.044)	(0.035)	(0.043)
Rho31	0.016	-0.019	-0.027	-0.004
	(0.028)	(0.037)	(0.038)	(0.139)
Rho32	-0.039	-0.056	-0.026	0.128
	(0.035)	(0.045)	(0.046)	(0.104)
N	16705	11270	11890	8543

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Even under this stricter criterion, the qualitative pattern of results remains unchanged. Telemedicine continues to exhibit a positive and statistically significant association with adherence to ATC A02BC02 (coefficient = 0.414, $p < 0.01$), while its effect on other therapeutic classes remains statistically insignificant. Moreover, high adherence is again associated with a significant reduction in hospitalizations and emergency department visits for selected drug classes, particularly gastroprotective agents, although some estimates become less precisely estimated due to the smaller share of patients classified as highly adherent under this threshold. As in the previous specification, the estimated correlation coefficients are generally small and statistically insignificant, indicating that the main conclusions are not driven by residual correlation between unobserved determinants of adherence and healthcare utilization. These sensitivity analyses confirm that our main conclusions are robust to alternative operationalizations of medication adherence. The full set of estimates for these robustness checks is reported in Appendix Tables A2.5 and A2.6.

3.7.3 Causal Mediation Analysis

As a further robustness exercise, we formalise the mediation structure implicit in our recursive multivariate probit model by implementing the causal mediation analysis framework of Imai et al. (2010). This approach, grounded in the potential outcomes literature, decomposes the total effect of telemedicine on acute care utilisation into two components: the Natural Indirect Effect (NIE), which captures the portion of the total effect that operates through changes in medication adherence, and the Natural Direct Effect (NDE), which captures any remaining effect not transmitted through the mediator. The key identifying assumption is sequential ignorability: that is, conditional on observed covariates, adherence is as good as randomly assigned given treatment status, a condition supported by the recursive structure of our main model.

We estimate the mediation model specifying a probit model for the mediator (high adherence indicator) and a linear probability model for each outcome, separately for all four ATC drug classes and both outcomes (hospitalisations and ED visits). Covariates are identical to those in the main specification. Results are reported in Table 3.13. The NIE is negative and statistically significant exclusively for ATC A02BC02 (gastroprotective agents), for both hospitalisations (NIE = -0.032, $p = 0.002$) and ED visits (NIE = -0.029, $p = 0.005$). This confirms that telemedicine raises adherence to gastroprotective agents and that this improvement translates into a significant reduction in acute care use. For all other drug classes (A10BA02, C03CA01, C07AB07), the NIE is close to zero and not statistically significant, indicating that adherence to these therapies does not constitute a relevant mediating channel.

Table 3.13. Causal Mediation Analysis: Natural Indirect Effect (NIE), Natural Direct Effect (NDE), and Total Effect (TE) by ATC Drug Class and Outcome

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A02BC02		A10BA02		C03CA01		C07AB07	
	Hosp.	ED	Hosp.	ED	Hosp.	ED	Hosp.	ED
NIE	-0.0317***	-0.0290***	0.0005	0.0001	0.0019	0.0026	0.0007	0.0027
	(0.0102)	(0.0102)	(0.0018)	(0.0015)	(0.0047)	(0.0049)	(0.0015)	(0.0041)
NDE	0.0390	0.0549*	0.0478	0.0748*	0.0272	0.0504	0.0447	0.0572
	(0.0283)	(0.0299)	(0.0359)	(0.0413)	(0.0340)	(0.0355)	(0.0381)	(0.0394)
TE	0.0074	0.0259	0.0483	0.0749*	0.0291	0.0530	0.0454	0.0599
	(0.0269)	(0.0289)	(0.0360)	(0.0413)	(0.0337)	(0.0351)	(0.0382)	(0.0399)
N	16705	16705	11270	11270	11890	11890	8543	8543

Outcome model: Linear. Mediator model: Probit.
NIE = Natural Indirect Effect (mediated through adherence); NDE = Natural Direct Effect. TE = Total Effect.
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The NDE is not statistically significant for any drug class, suggesting that the effect of telemedicine on acute care, where present, operates primarily through the adherence pathway rather than through direct clinical monitoring. These results are fully consistent with the main multivariate probit findings and confirm the robustness of the mediation interpretation to an alternative, formally grounded identification strategy.

3.8 Conclusions

This study examined whether telemedicine exposure can improve medication adherence among chronic patients and whether adherence acts as a channel through which telemedicine affects the use of acute care services. Using administrative healthcare data from ASL 4 (Liguria) over 2019-2022 and exploiting the roll-out of telemedicine follow-up in 2022, we modelled adherence, hospitalizations, and emergency department (ED) visits within a recursive multivariate probit framework.

Three main conclusions emerge. First, higher adherence is associated with a lower number of hospitalizations and ED visits, but the effect is heterogeneous across therapeutic classes.

Second, in the main specification (Table 3.5), telemedicine significantly increases the probability of high adherence for gastroprotective agents (A02BC02), while effects are not statistically different from zero for insulin/antidiabetic medications (A10BA02), for diuretics (C03CA01) and beta-blockers (C07AB07). These results align with prior evidence that digital care and remote follow-up can enhance medication-taking behavior in chronic conditions, particularly for therapies requiring regular monitoring and patient engagement, but that the effectiveness of telemedicine may vary by treatment complexity and patient behavior (Sten-Gahmberg et al., 2024). Third, higher adherence is associated with lower utilization of acute

care services, particularly for drug classes which are more directly linked to short-run decompensation or preventable exacerbation. High adherence is strongly and negatively related to hospitalizations for A02BC02 and A10BA02, and it is negatively associated with ED use for A02BC02 and C07AB07. While the coefficients are not directly interpretable as marginal effects, the consistent sign and statistical significance for key classes support the hypothesis that adherence improvements may translate into reductions in potentially avoidable acute care use.

The robust exercise that augments the recursive system with lagged outcomes yields a qualitatively similar picture. Telemedicine remains positively associated with adherence for A02BC02, and adherence continues to be negatively related to hospitalizations for A02BC02 and A10BA02 and to ED use for A02BC02 and A10BA02, although magnitudes are attenuated for ED compared to the baseline model. These patterns suggest that the main results are not driven solely by time-invariant unobservable or by short-run shocks correlated with both adherence and utilization. Different definitions of adherence don't change the main results. A causal mediation analysis following Imai et al. (2010) further corroborates these findings. The Natural Indirect Effect is negative and significant only for A02BC02, and the Natural Direct Effect is not significant for any drug class. This confirms that the adherence channel identified in the main model is both statistically robust and causally interpretable.

The heterogeneity analysis further indicates that effects vary across patient profiles and territorial contexts. For some drug classes, the association between telemedicine and adherence appears stronger in specific demographic groups and, importantly for this setting, differences emerge by rural versus urban residence. Together, these results point to a meaningful role for local accessibility and care proximity in shaping adherence-related outcomes, consistent with the relevance of territorial barriers and service distribution in Liguria.

From a policy perspective, the findings support telemedicine as a potentially effective component of chronic care pathways, but they also indicate that "one-size-fits-all" digital follow-up is unlikely to deliver uniform gains. Telemedicine protocols may generate the greatest returns when targeted to therapies and patients for whom adherence is highly responsive to monitoring, frequent reinforcement, and continuity of contact. Conversely, for complex self-management conditions, stronger adherence effects may require more intensive and integrated models, combining telemonitoring, behavioral support, and structured feedback loops, rather than relying on teleconsultation alone.

This study has limitations. First, telemedicine exposure is measured through administrative program participation and does not allow us to distinguish intensity, modality, or content of digital

interactions, which may be key determinants of effectiveness. Second, despite exploiting recursive structure and conducting robust checks, residual selection into telemedicine cannot be entirely ruled out, particularly if patients who enroll differ in unobserved motivation or caregiver support. Third, the treatment window covers only two semesters post-implementation; for cardiovascular therapies whose benefits materialize over longer horizons, the short follow-up may limit our ability to detect downstream utilization effects.

Future research should extend the time horizon and exploit richer measures of telemedicine intensity and content to identify which program components drive adherence changes. Another promising direction is to evaluate integrated digital ecosystems that combine remote monitoring, automated alerts, and targeted coaching, and to test whether these models generate stronger effects for therapies with delayed clinical consequences. More generally, evaluating how telemedicine can reduce inequalities in access and continuity of care, especially in geographically constrained regions, remains an important agenda for both research and policy.

Chapter Three

4. Government Regulation and Potential Misinformation: The Case of E-Cigarettes[20]

4.1 Introduction

Economic theory has long recognized the importance of information in shaping consumer behavior and market outcomes (Stigler, 1961). In the context of public health, imperfect information and misperceptions of product risk are often invoked as key rationales for government intervention (Viscusi, 1990). When individuals underestimate the health risks of harmful behaviors, such as smoking, policymakers may implement regulations or information campaigns to correct these beliefs and promote healthier choices (National Cancer Institute, 2008). However, less studied is the inverse possibility: that regulation itself, when poorly calibrated or ambiguously communicated, may exacerbate misinformation, distort consumer beliefs, and lead to unintended welfare-reducing consequences.

How individuals form beliefs about new health technologies remains a central question in the economics of information and health behavior (Costa-Font & McGuire, 2009). A large literature highlights that individuals act not on objective health data alone, but on subjective beliefs, which are often biased, incomplete, or shaped by social and institutional narratives (Dake, 1991; Peters & Alovic, 1996; Arni et al., 2021). Models of rational addiction (Becker & Murphy, 1988) and health capital investment (Grossman, 1972) both imply that distorted or misinformed perceptions can lead to suboptimal health choices. These effects are especially salient for novel products such as Electronic Nicotine Delivery Systems (ENDS), whose health profile is evolving and often misunderstood.

ENDS are handheld devices that heat a liquid, typically containing nicotine and flavorings, to produce an inhalable aerosol. ENDS were designed to replicate the nicotine delivery experience of conventional cigarettes (World Health Organization, 2013; Sugerman, 2014) but with fewer toxic compounds and lower associated health risks (National Academies of Sciences, 2018). Unlike combustible cigarettes, e-cigarettes do not contain tar or produce carbon monoxide, two major contributors to cancer and cardiovascular disease (Czogala et al., 2013; Australian Department of Health, 2025). Although not risk-free, leading health agencies estimate that e-cigarettes entail substantially lower risks of cancer, stroke, heart disease, and respiratory illness relative to traditional smoking (Farsalinos et al., 2015; McNeill et al., 2018; Margham et al.,

[20] This work was conducted during a visiting research period at San Diego State University (California, United States), within the Center for Health Economics and Policy Studies (CHEPS), under the supervision of Prof. Joseph J. Sabia.

2021). Public Health England (2015) concluded that vaping is approximately 95% less harmful than smoking, a view echoed by the UK's National Health Service (2022, 2025).

Despite this, public beliefs increasingly deviate from scientific evidence. Recent surveys find that a growing share of smokers and non-smokers alike believe that e-cigarettes are as harmful or more harmful than combustible cigarettes (Darden, 2024; Jin et al., 2024). This misalignment between perceived and actual risk has important behavioral implications: individuals who might benefit from switching to ENDS may instead persist in using combustible tobacco due to exaggerated concerns about vaping. This is particularly troubling given that smokers, who stand to gain the most from harm reduction, appear most influenced by these misperceptions (Viscusi, 2016; Farsalinos et al., 2014).

This paper investigates whether government regulation of ENDS has contributed to this misinformation in the United States of America. We examine how ENDS-specific taxes shapes risk beliefs and behavioral responses.

Our contribution is threefold. First, we document that higher ENDS taxes are associated with significant reductions in e-cigarette use, both at the extensive margin (current use) and at the intensive margin, including frequent use (more than 20 days per month) and everyday vaping. Second, we provide quasi-experimental evidence that ENDS taxes do not meaningfully affect individuals' risk perceptions or misinformation related to e-cigarettes across a wide range of belief measures, even in contexts where such policies may reduce youth vaping in the short run (Courtemanche, 2017). Third, we show that baseline risk perceptions condition behavioral responses to taxation: the effects of ENDS taxes on vaping behavior are larger among individuals who initially perceive e-cigarettes as relatively less harmful.

Taken together, our findings suggest that well-intentioned regulatory interventions can induce substantial behavioral responses without necessarily shifting underlying beliefs, offering a cautionary tale for economists and policymakers working at the intersection of information, regulation, and health behavior. More broadly, this study contributes to ongoing debates on the design of optimal harm-reduction policies in tobacco and nicotine markets.

4.2 Background

E-cigarettes were introduced to the U.S. market in 2006, following their initial development in China, where they were first marketed as smoking cessation tools (Wang et al., 2019). Between 2011 and 2019, prior-month e-cigarette use among U.S. high school students rose from 1.5 to 27.5%, prompting the U.S. Surgeon General to declare high rates of teen ENDS use an "epidemic" (U.S. Office of the Surgeon General, 2018). However, owed to a number of factors,

including the COVID-19 pandemic (Denlinger-Apte et al., 2022) as well as a number of policy strategies designed to reduce ENDS use, most notably raising the minimum legal purchasing age for tobacco products (Friedman 2015; Hansen et al. 2023), there was a precipitous decline in teen ENDS use over the 2019-2024 period, with the vaping prevalence rate falling by over 70 to 7.8% in 2024. Among young adults aged 18-24, ENDS use similarly rose from 2.7 in 2014 to 9.3% in 2019 before falling to 7.9 in 2023 (Centers for Disease Control and Prevention, 2020; U.S. Department of Health and Human Services, 2023). For adults aged 25 and older, the prevalence of e-cigarette use remained relatively stable, reported at 2.4% in 2014-2015 and 2.3% in the 2018-2019 wave of the TUS-CPS (U.S. Department of Health and Human Services, 2020), and reaching 3.0% in 2023 (U.S. Department of Health and Human Services, 2025).

One of the fiercest debates among tobacco control advocates is whether increases in access to ENDS products improves or diminishes tobacco-related health (National Academies of Sciences, 2018). On the one hand, if e-cigarettes and combustible cigarettes are substitutes, then increased (decreased) access to ENDS may serve (prevent) harm reduction (Abouk et al. 2023; Friedman 2015). But if e-cigarettes and combustible cigarettes are complements (Cotti et al., 2018), then ENDS access may unambiguously harm tobacco-related public health.

4.2.1 Current Scientific Evidence on Health Risks of ENDS Use

While ENDS use is relatively recent, precluding life-course studies of its longer-run effects, e-cigarette use is not without health risks. The level of risk depends on a variety of factors, including product characteristics (e.g., wattage, temperature, model), frequency and method of use, and potential post-sale modifications[21] (World Health Organization, 2024).

ENDS use has been linked to heightened risk of respiratory disease and cardiovascular ailments for several reasons (World Health Organization, 2020; National Academies of Sciences, 2018; U.S. Department of Health and Human Services, 2016). First, the aerosol produced by e-cigarettes contains ultrafine particles that can trigger pulmonary and systemic inflammation (Brook et al., 2010; Pope et al., 2009; Mehta et al., 2013) as well as airway inflammation (McCauley et al., 2012; Li et al., 2020). Moreover, inhalation of e-cigarettes has also been linked to increased exhaled nitric oxide levels, which may be a marker of pulmonary inflammation (Schober et al., 2013).

[21] "Post-sale modifications" refer to user-driven changes to e-cigarette devices, such as increasing power settings or using non-standardized, DIY e-liquids (World Health Organization, 2020). These practices can significantly elevate toxicant emissions. Higher power increases aldehyde production (Gillman et al., 2016), while adding DIY additives to unflavored or menthol/tobacco-flavored e-liquids raises emissions to levels comparable with commercial flavored products (El-Hellani et al., 2022).

Second, nicotine from ENDS products may increase heart rate and blood pressure (Yan & D'Ruiz, 2015; Szołtysek-Bołdys et al., 2013; Skotsimara et al., 2018), leading to arterial stiffness, an additional risk factor for cardiovascular disease (Flouris et al., 2012; Darabseh et al., 2020). Finally, among youth, nicotine from ENDS products may impede brain development, cognitive functions, attention, mood, and psychosocial health (Romer, 2010; U.S. Department of Health and Human Services, 2016).[22]

While e-cigarettes are not riskless, the scientific consensus at present is that ENDS are far less risky to one's health than combustible tobacco products. Experts' reviews conclude that e-cigarette use carries 5 to 37% of the harm of combustible tobacco smoking (Dave et al., 2019). Combustible cigarette smoking is the leading cause of preventable death in the United States causing 480,000 deaths per year (Centers for Disease Control and Prevention, 2024). Cigarettes are responsible for increased risk of cancers of the larynx, lung, bronchus, trachea, mouth, stomach and much more, stroke, heart disease, and severe respiratory ailments including emphysema (Centers for Disease Control and Prevention, 2025; U.S. Department of Health and Human Services, 2020).

Compared to traditional cigarettes, e-cigarettes pose a substantially lower risk to not only a user's health, but also the health of third parties exposed to e-cigarette aerosol. For instance, while traditional cigarette smoking is known to increase arterial stiffness and impair endothelial function, e-cigarette aerosol exposure appears to have a much less pronounced effect on these parameters (Flouris et al., 2012; Szołtysek-Bołdys et al., 2013). In addition, unlike traditional tobacco cigarettes, e-cigarettes do not contain tar[23] (Australian Government Department of Health and Aged Care, 2025) and do not produce carbon monoxide (Czogala et al., 2013), which limits their ability to cause cancer, respiratory, and heart disease.

Externality costs to third parties also appear to be less for e-cigarettes relative to combustible cigarettes: passive exposure to e-cigarette aerosol leads to nicotine absorption at levels approximately ten times lower than those resulting from combustible tobacco smoke. While approximately 20-27% of aerosol particles may deposit in the circulatory system and organs, a proportion comparable to that observed with traditional cigarette smoke (Zhang et al., 2013), aerosol particles are far less carcinogenic (Margham et al., 2021) and produce fewer cytotoxic effects

[22] In animal experiments, (1) chronic exposure to ENDS aerosols may lead to developmental alterations in cardiac structure and function, where defects such as pericardial edema and reduced cardiac performance have been reported (Palpant et al., 2015), and (2) exposure to ENDS aerosols impairs alveolar macrophage function, increasing susceptibility to respiratory infections (Sussan et al., 2015; Breland et al., 2017).

[23] Professor Michael Russell wrote: "People smoke for nicotine, but they die from the tar" and proposed that the tar-to-nicotine ratio could be the key to safer smoking, specifically advocating for a low-tar, medium-nicotine cigarette (Russell, 1976).

(Arsalinos et al., 2013) than combustible smoke (Emma et al., 2023) due to lower levels of toxicity and minimal passive emissions (McAuley et al., 2012).[24]

Adding to the medical evidence that e-cigarettes are less harmful to one's health than traditional cigarettes, several recent studies have shown that switching from combustible cigarettes to nicotine vaping may generate important short and medium-run health benefits. In a randomized clinical context, Caponnetto et al. (2013) reports that access to ENDS is linked to reductions in combustible cigarette consumption and improvements in respiratory symptoms, such as coughing and shortness of breath. Similarly, Hajek et al. (2019) compare the health impacts of assigning smokers to ENDS versus traditional nicotine replacement therapies, finding that those with access to ENDS demonstrate higher one-year smoking cessation rates and more pronounced declines in cough and phlegm production. Additionally, Polosa et al. (2020) investigate individuals with chronic obstructive pulmonary disease (COPD) and observe that those who transition from smoking to ENDS experience measurable improvements in pulmonary function, respiratory symptoms, and exercise tolerance. Among youth, the perception of safety and absence of immediate harm can lead to underestimation of addiction risk, reinforcing habitual use[25] (Arnett, 2000; Gerrard et al., 1996; Romer & Jamieson, 2001; Nichter et al., 1997). Moreover, genetic predispositions may also influence nicotine dependence and responsiveness to pricing policies (Benjamin et al., 2020; Beauchamp et al., 2011).

In summary, the best medical evidence to date suggests that while e-cigarettes are not harmless, they do appear to be less harmful than combustible cigarettes. This remains a central reason why some leading governments, such as the United Kingdom, have adopted a harm-reduction approach (National Health Service, 2025), aligning with research suggesting that switching from smoking to reduced-risk alternatives like vaping could yield significant health improvements and substantial cost savings for the NHS (Moscone, 2023).

[24] In addition, in vitro research indicates that ENDS aerosols, particularly when generated at high voltages, can reduce cardiomyoblast viability, whereas cigarette smoke is cytotoxic at all concentrations (Farsalinos et al., 2014).

[25] Although e-cigarettes are generally perceived as less addictive than traditional tobacco products, the evidence on nicotine dependence remains inconclusive given that it varies substantially depending on the device used. While traditional cigarettes provide a relatively consistent dose, some ENDS, especially pod-based systems using nicotine salts, can deliver equal or even higher amounts of nicotine (Hajek et al., 2020). This variability makes it difficult to generalize about addiction risk as showed by mixed empirical findings. Jankowski et al. (2019) report higher dependence levels among e-cigarette users, while Liu et al. (2017) finds that cigarette smokers show faster time to first use and stronger cravings. González et al. (2017) and Etter et al. (2015) concluded that e-cigarettes are less addictive than tobacco.

4.2.2 Formation of Risk Beliefs about E-Cigarette Health Risks

Risk perception plays a crucial role in shaping consumer habits, influencing decision-making processes and behaviors, particularly in the health domain (Lee et al., 2005). Individuals may misperceive health risks of consumer behaviors, leading to behaviors that are sub-optimal.[26]

Public perceptions of e-cigarette health risks are shaped by personal experience, media narratives, and regulatory messaging. According to Viscusi (2016), many individuals assess e-cigarette risks in comparison to conventional cigarettes, often leading to systematic overestimation. Although e-cigarettes are generally perceived as less harmful, estimated at 27% for lung cancer risk and 33% for overall mortality, these values still far exceed toxicological benchmarks. This misperception is largely driven by prior beliefs about cigarette risks, which statistically explain up to 99% of perceived vaping harm, reflecting a cognitive bias rooted in product novelty and uncertainty. Darden (2024) documented a similar pattern of misinformation among adults. He finds that 56% of smokers believe e-cigarettes are "as harmful" or "more harmful" than traditional cigarettes. This misperception significantly decreases the likelihood of switching to ENDS, even when combustible cigarette prices rise. Correctly informed smokers are notably more responsive to price incentives and more inclined to substitute toward e-cigarettes.[27]

Further evidence comes from Jin et al. (2024), who examine the impact of the 2019 misinformation shock that incorrectly linked e-cigarettes to the EVALI outbreak. This event led to a marked shift in public perception, increasing the belief that e-cigarettes are as harmful as or even more harmful than traditional cigarettes. Based on their demand models, the authors estimate a 30% decline in both e-cigarettes use and their adoption for smoking cessation. These effects reflect a distortion in risk beliefs, and underscore how inaccurate health narratives can seriously undermine harm-reduction efforts.[28]

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[26] For instance, in the area of tobacco use, many people exhibit optimism bias, assuming that health risks are more applicable to others than to themselves (Arnett, 2000; Becker, 1974; Ditto, Jemmott & Darley, 1988; Festinger, 1957). This cognitive distortion is particularly relevant in the context of tobacco and nicotine consumption, where risk perceptions influence product choices.

[27] Using a randomized price experiment embedded in a survey of 943 current or recent smokers, Darden estimates a multinomial logit model to analyze behavioral responses to cigarette price increases (ranging from $1 to $4). Respondents were classified based on changes in cigarette and e-cigarette consumption. Smokers with accurate risk perceptions were 23.9 percentage points more likely to have considered exclusive e-cigarette use and 16.5 points more likely to simultaneously reduce cigarette use and increase e-cigarette consumption ("pure substitution"), implying a substitution elasticity 57.6% higher than that of misinformed smokers. In a subsequent policy simulation, Darden shows that heterogeneity in beliefs and substitution behavior has critical implications for optimal taxation: even under strong substitutability assumptions, the optimal e-cigarette tax remains positive, contrary to models that ignore informational heterogeneity.

[28] Cross-country survey data from Cornell (2021-2023) reveal that misperceptions about the relative harm of e-cigarettes are widespread and, in some contexts, growing. In several countries, the share of respondents viewing

4.2.3 Information, Tobacco Control Policy and Tobacco-Related Risk Perception

While imperfect information is often used as a welfare rationale for government intervention, it is less studied how government intervention can shape individuals' perceptions of risk and subsequent behavior when using a new consumer product. Some of these interventions are direct (i.e., the provision of information by the public) while others are more indirect (e.g., state spending or taxation).

With respect to combustible tobacco, a milestone in public health history is the 1964 U.S. Surgeon General's Report on Smoking and Health (Surgeon General, 1964), the first official federal document to clearly state that cigarette smoking causes serious health harms, such as lung cancer and cardiovascular disease. The report played a pivotal role in raising public awareness of tobacco-related risks and shifting individuals' perceptions of smoking. For example, in 1958, only 44% of Americans believed that smoking caused cancer, whereas by 1968, that figure had risen to 78% (U.S. National Library of Medicine, n.d.).

Along the same lines, Byrne et al. (2015) explore how graphic warning labels influence health risk beliefs related to smoking. They find that fear-evoking labels are more effective in inducing both cessation intentions and actual quitting behavior. Consistent evidence is provided by Kenkel et al. (2023), who examine the impact of graphic warning labels on tobacco product choices, showing that decisions to quit smoking or switch to alternative tobacco products are primarily driven by emotional responses, such as fear and disgust, rather than by increased health knowledge. While not specifically examining information campaigns, Tauras and Chaloupka (2004) explore the relationship between state-level spending on tobacco control programs and perceptions of smoking among adolescents. These authors find that an increase in state tobacco control spending leads to an increase in the share of teens who view smoking as a "risky health behavior", assess that smoking is a behavior that will be met with social disapproval, and believe that smoking is indicative of poor judgment.

With respect to ENDS, there have been a handful of studies that have explored how government policy regarding ENDS impacts perceptions and behavior. A notable example is the 2019 outbreak of e-cigarette, or vaping, product use-associated lung injury (EVALI), a severe respiratory condition initially attributed to all vaping products. As of February 18, 2020, the CDC

e-cigarettes as more harmful has increased, suggesting a shift from uncertainty to active misinformation. In Austria, for example, the share perceiving less harm fell from 32% to 22%, while those perceiving more harm rose from 17% to 18%. In China, perceptions of lower harm rose modestly (42% to 48%), but higher harm perceptions nearly tripled (6% to 17%). Conversely, countries like Japan (62% less vs. 4% more), Sweden (52% vs. 6%), and the UK (51% vs. 9%) exhibit more balanced and informed risk assessments. These patterns support findings by Jin et al. (2024), illustrating how misinformation can transform uncertainty into false certainty, ultimately undermining harm-reduction efforts.

reported 2,807 hospitalizations and 68 deaths across the U.S. linked to EVALI (Centers for Disease Control and Prevention, 2020). Jin et al. (2024) studied the impact of government provision of information following the EVALI outbreak. Although subsequent investigations identified illicit THC-containing vaping products and individuals with underlying substance use issues as the primary sources of the outbreak (Trivers et al., 2021), early public communication by the Centers for Disease Control and Prevention (CDC) failed to make this distinction clear. Initial guidance included broad and urgent recommendations that all individuals refrain from using any vaping products, regardless of type. Only later did the CDC clarify that the health risks were primarily associated with THC-containing products obtained from informal or illicit sources (CDC, 2020). Using data from 2012 to 2022 and an interrupted time series, Jin et al. (2024) show that misinformation spread from the CDC surrounding EVALI led to a 32% decline in adult smokers turning to e-cigarettes to quit smoking traditional cigarette smoking.

Also, Dave et al. (2020) studied the impact of warnings from the Centers for Disease Control and Prevention (CDC) in the immediate aftermath of the EVALI outbreak. Using data on adults from 2012 to 2020, authors show that the CDC's early warnings led to a sharp rise in the belief that vaping was more dangerous than smoking. Subsequent clarifications only partially corrected these misperceptions, leaving many consumers misinformed about the relative risks. The authors find that the share of adults who perceived e-cigarettes as more harmful than combustible cigarettes increased by approximately 16 percentage points following the initial warning. In contrast, the subsequent clarification led to only a modest 2-point decline, suggesting that initial risk beliefs were sticky and not fully revised, even when more accurate information became available. Finally, two studies of which we are aware have studied how e-cigarette taxation affects nicotine vaping. Abouk et al. (2023) use data from 2014-2019 Monitoring the Future and find that a one dollar increase in ENDS taxes (in 2019$) is associated with a statistically significant increase of 2.9 percentage points in the share of youth who perceive regular ENDS use as "greatly risky". Darden (2024) shows that smokers' beliefs about the relative harms of e-cigarettes influence their responsiveness to price changes: using an online survey and a randomized pricing experiment, he finds that individuals who believe e-cigarettes are as or more harmful than cigarettes are less likely to substitute toward e-cigarettes when cigarette prices increase. Although he does not study tax policy or how it shapes beliefs, his findings suggest that misperceptions can limit the effectiveness of price-based harm reduction strategies.

4.2.4 ENDS Regulations

In recent years, regulatory approaches to ENDS in the United States have shifted between restrictive frameworks and harm reduction paradigms. Among the most prominent policy tools are taxation, minimum legal purchasing age laws, retail licensing requirements, flavor restrictions, clean indoor air laws, and restrictions on online sales.

ENDS taxation remains one of the most widely adopted strategies, implemented in at least 54 countries (Dauchy & Fuss, 2023). Although no federal tax exists in the U.S., state and local taxes have shown significant price pass-through effects, considering that approximately 90% of tax increases are reflected in retail prices (Cotti et al., 2022). Empirical evidence suggests that a $1 increase in ENDS taxes leads to a 15.3% reduction in use among adults aged 21+ (Pesko et al., 2020), a 2-3 percentage point decline among young adults aged 18-25 (Friedman & Pesko, 2022), and a 4.6% decline among adults aged 21-39 (Dave et al., 2022). However, such reductions are often offset by increased combustible cigarette use, including a 5.3% rise in daily smoking among adults (Pesko et al., 2020), a 3.7 percentage point increase in past-month cigarette use among young adults (Friedman & Pesko, 2022), and a 0.5 percentage increase in smoking prior to pregnancy (Abouk et al., 2023).

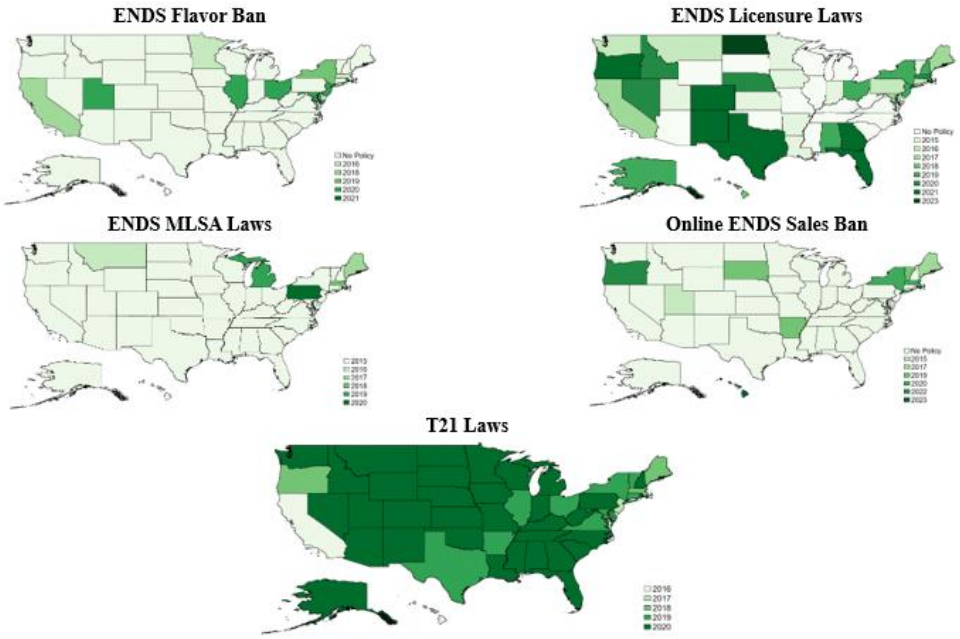
Minimum Legal Purchasing Age (MLPA) laws establish the legal age threshold for purchasing tobacco and ENDS products. Historically set at 18 years in most U.S. jurisdictions, the federal Tobacco-21 law, enacted in December 2019, raised this age to 21 nationwide. Evidence shows that Tobacco-21 reduces both vaping and cigarette smoking among youths (Abouk et al., 2024; Friedman et al., 2019; Hansen et al., 2023). On the supply side, retail licensing laws, enacted in 34 states and D.C. as of March 2024, require retailers to obtain state-issued licenses to sell ENDS (CDC, 2024). These laws are intended to regulate market access, facilitate enforcement of age restrictions, and impose penalties for non-compliance. However, recent studies yield mixed results: while some show reductions in ENDS use (Jun & Kim, 2021; Du et al., 2020), others find limited or no impact, particularly among youth (Courtemanche et al., 2024).

Additional restrictions include flavor bans, implemented by seven states and over 380 local jurisdictions, which appear effective in curbing youth ENDS use but may also trigger substitution toward combustible tobacco (Cotti et al., 2024; Saffer et al., 2024).

To prevent regulatory evasion via online purchases, more than 14 states have adopted internet sales restrictions, five of which explicitly cover ENDS (Public Health Law Center, 2022), although compliance issues remain prevalent (Nali et al., 2021). Finally, clean indoor air laws extend existing smoke-free legislation to include ENDS aerosols, thereby prohibiting their use in enclosed public spaces such as workplaces, restaurants, and bars. As of March 2024, 19 states

and D.C. have adopted such laws (CDC, 2024a). These measures serve dual purposes: protecting non-users from secondhand exposure and deformalizing nicotine use. Empirical studies report that these laws are associated with reductions in both ENDS and traditional cigarette use, particularly among young and working-age adults (Friedman et al., 2021). The implementation of these altered ENDS policies, along with their geographic and temporal variation, is depicted in Figure 4.1.

Figure 4.1. Geographic and Temporal Variation in ENDS Policies, 2015-2023



Note: The figure illustrates the geographic and temporal variation in state-level ENDS-related policies in the United States between 2015 and 2023. Shaded areas indicate the year in which each policy was in effect.

Building on this literature, this study has three aims. First, using longitudinal PATH data, we test whether ENDS taxes still discourage vaping both the extensive and intensive margins, assessing their effectiveness in reducing engagement in a less harmful but not risk-free behavior. Second, we examine whether the expansion of ENDS taxation over time has shaped perceived risk, potentially worsening misinformation about e-cigarettes' absolute or relative harms. Third, we investigate whether baseline risk perceptions heterogeneously shape behavioral responses to taxation, shedding light on the interplay between information, beliefs, and policy-induced incentives.

4.3 Data

4.3.1 PATH Data

Our primary data source is restricted-use microdata from the 2013-2023 Population Assessment of Tobacco and Health (PATH) Study, accessed under a restricted data-use agreement.[29] The Population Assessment of Tobacco and Health (PATH) Study is a nationally representative longitudinal survey conducted in the United States to monitor tobacco product use and its effects on population health. Launched in 2013, it is one of the first large-scale collaborative research projects between the National Institutes of Health (NIH) and the Food and Drug Administration (FDA), following the 2009 Congressional mandate granting the FDA regulatory authority over tobacco products. When weighted, the samples are nationally representative. These data are useful for our purposes as they provide detailed information on youth and adult Electronic Nicotine Delivery Systems (ENDS) and combustible cigarette use, as well as beliefs about the absolute and relative risks of ENDS. Moreover, being an individual-level panel, they allow us to study dynamics in belief formation, cessation, and initiation of tobacco use (ENDS only, combustible only, or dual use).

Our analyses will cover eight waves: Wave 1 (2013-2014), Wave 2 (2014-2015), Wave 3 (2015-2016), Wave 4 (late 2016-2018), Wave 4.5 (2017-2018)[30], Wave 5 (2018-2019), and Wave 6 (2021), Wave 7 (2022-2023). Overall, the dataset comprises more than 593,000 observations corresponding to approximately 74,000 unique individuals across all 50 U.S. states and the District of Columbia. In addition to risk belief questions, which will be described later, we also collect information on ENDS use and combustible tobacco use including current use of e-cigarettes and combustible cigarettes, frequent and everyday ENDS use.

The PATH questionnaires are administered separately to adults (18+) and youth (under 18), using questionnaires that are distinct but partially overlapping. During data cleaning and dataset construction, we used the codebooks to harmonize survey items across waves, since question wording was not always identical over time and variable identifiers frequently changed. We then identified vaping- and smoking-related measures that were asked in both the youth and adult samples and that could be consistently aligned across waves, considering the intended

[29] Access was obtained through an approved restricted-use data agreement and was conducted within the secure research environment of CHEPS at San Diego State University.

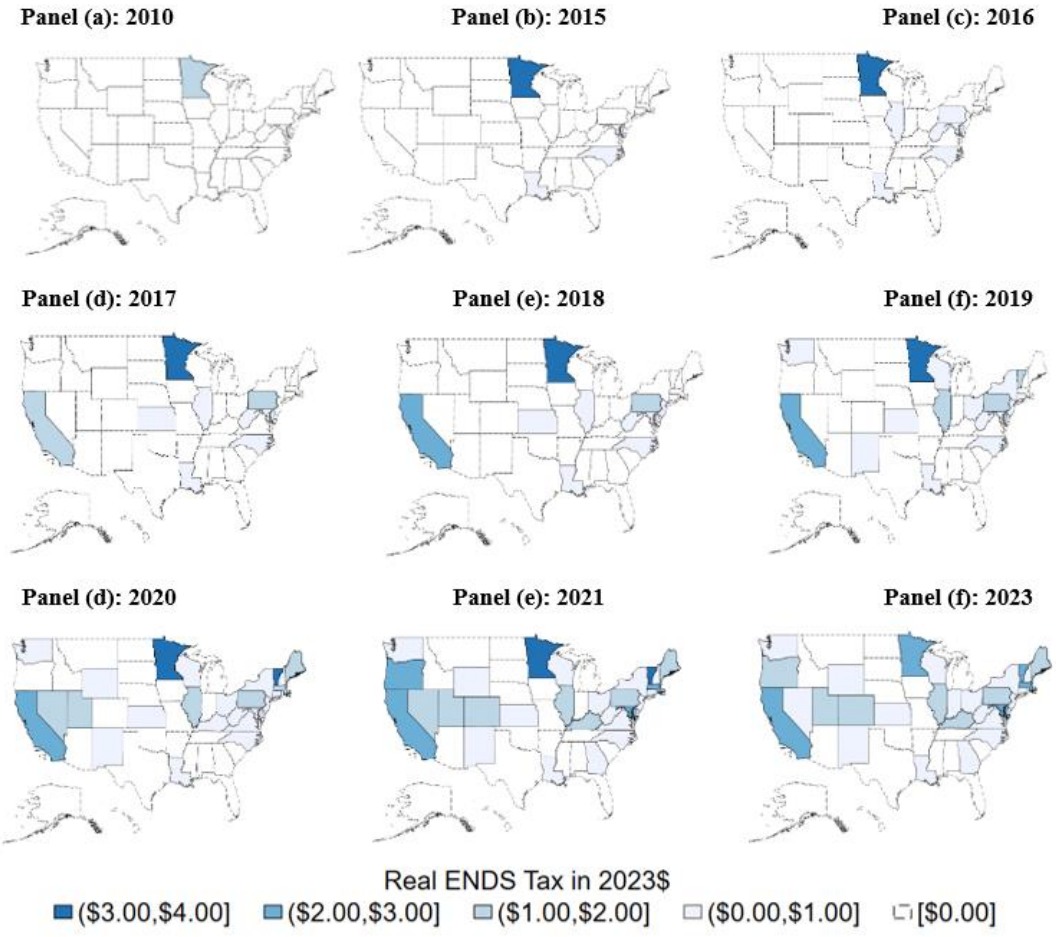
[30] In addition to the main PATH waves (e.g., Waves 1-7), PATH fielded an interim "special collection" labeled Wave 4.5, positioned between Waves 4 and 5. Wave 4.5 differs from the core waves in that it was not designed as a full, stand-alone wave covering the entire PATH sample with the same instrument structure. Instead, it represents an intermediate data collection with more targeted content and sampling/fieldwork objectives, primarily aimed at maintaining continuity in measurement during the interval between major waves and capturing timely information on evolving tobacco and nicotine-product use and related beliefs.

universe for each item (e.g., questions asked of all respondents versus those asked only of current vapers, frequent vapers, or other subgroups). Importantly, because young respondents may age into the adult sample over the panel, the unique respondent identifier allows us to link individuals across waves even when they transition between questionnaires, thereby preserving longitudinal continuity in the analysis.

4.3.2 ENDS Taxes

Our key policy variable measures the ENDS tax rate per milliliter of e-liquid, expressed in 2023 dollars. Figure 4.2 documents geographic and temporal variation in ENDS taxes over 2010-2023.

Figure 4.2. Geographic, Temporal, and Intensity Variation in ENDS Taxes, 2010-2023



Note: The figure depicts state-level variation in ENDS excise taxes in the United States from 2010 to 2023. Panels report the effective tax rate per milliliters of e-liquid, expressed in 2023 dollars. Shaded areas indicate the applicable tax bracket in each state-year, while unshaded states correspond to zero ENDS excise taxes. Tax rates reflect closed-system ENDS products and are harmonized across heterogeneous tax structures by converting ad valorem and sales taxes into per-mL excise-tax equivalents following Cotti et al. (2025).

To ensure comparability across heterogeneous tax structures, we convert ad valorem and sales taxes into per-mL excise-tax equivalents following Cotti et al. (2025), who rely on NielsenIQ retail scanner data and assume a 35% retailer markup (based on e-cigarette company purchasing forms). We focus on taxes applying to closed-system ENDS, products sold in standardized, pre-filled units such as cartridges or pods (e.g., JUUL), as these products are the most directly comparable across jurisdictions and time and less sensitive to cross-state differences in refill bottle sizes and packaging that can complicate measurement for open-system products. The resulting closed system tax-rate values are reported in Appendix Table A3.1. For completeness and comparability, Appendix Table A3.2 reports the corresponding open-system tax rates (i.e., taxes applicable to refillable devices and bottled e-liquid), although we do not use them in the analysis. For the three sub-state jurisdictions that levy ENDS taxes, we incorporate city and county components into our state-level measure by constructing a population-weighted prevailing ENDS tax, consistent with prior work (e.g., Dave et al. 2025). Early adoption was limited to a small number of states and characterized by relatively low tax levels, while from the mid-to-late 2010s onward both the number of adopting jurisdictions and the magnitude of taxes increased markedly. By 2023, several states had implemented ENDS excise taxes exceeding $2 per mL, with a subset reaching levels above $3 per mL (in 2023 dollars), indicating a clear intensification and diffusion of ENDS taxation over time.

4.3.3 Dependent Variables

We examine a set of dependent variables capturing both tobacco use and risk perceptions related to e-cigarettes. As an initial benchmark, consistent with the tax-and-demand literature, we estimate models in which the outcomes are indicators for current vaping and current smoking, defined as any e-cigarette use and any combustible cigarette smoking, respectively, in the past 30 days. These outcomes allow us to assess whether ENDS taxes affect contemporaneous vaping and smoking behavior in expected directions and to compare our estimates with prior studies. We also consider measures of more intensive use, including frequent vaping (vaping on at least 20 days in the past month) and daily vaping (vaping every day in the past month).

Our primary outcomes, however, are measures of risk perceptions elicited in the PATH survey. PATH includes a wide range of questions capturing both relative and absolute risk beliefs about ENDS among youth and adults. While we examined the full set of available risk-perception measures, the results are consistent across outcomes. For parsimony and ease of interpretation, we therefore focus on one measure of relative risk and one measure of absolute risk in the main analysis.

The main relative risk-belief outcome is perceived relative harm of e-cigarettes compared with combustible cigarettes[31], based on the question:

"Do you think using e-cigarettes is less harmful, about the same, or more harmful than smoking cigarettes?" (response categories: less harmful, about the same, more harmful).

We also analyze perceived absolute harm[32] from intermittent ENDS use, based on the item:

"How much do you think people harm themselves when they use e-cigarettes or other electronic nicotine products on some days but not every day?" (response categories: no harm, a little harm, some harm, a lot of harm)[33].

For the absolute risk-perception item, we collapse responses into three ordered groups: no or low perceived risk (responses 1-2), medium perceived risk (response 3), and high perceived risk (responses 4). This recoding increases cell sizes while preserving the ordinal structure and substantive interpretation of the underlying risk beliefs.[34] The recoded measures are used both as dependent variables and, in stratified analyses, as baseline belief indicators to assess heterogeneity in behavioral responses to taxation.
A detailed description of all variables is provided in Table 4.1.

4.3.4 Independent Variables

The empirical model includes a comprehensive set of controls capturing individual demographics, pandemic-related shocks, macroeconomic conditions, and contemporaneous policies that may jointly influence risk beliefs and tobacco-use behaviors. Individual-level covariates are drawn from PATH and are merged with time-varying state-level measures using respondents' state of residence and interview timing.
A detailed description of all the variables is provided in Table 4.1.

[31] Additional measures of relative risk perceptions capture beliefs about product heterogeneity across ENDS types. Specifically, we use parallel survey questions eliciting perceptions of the harmfulness of flavored ENDS relative to tobacco-flavored or unflavored products. Respondents are asked: "Do you think using menthol or mint flavored e-cigarettes is less harmful, about the same, or more harmful than using tobacco-flavored or unflavored e-cigarettes?" and "Do you think using flavored e-cigarettes (other than menthol or mint) is less harmful, about the same, or more harmful than using tobacco-flavored or unflavored e-cigarettes?" Possible responses for both questions are less harmful, about the same, and more harmful.
[32] An additional measure of absolute risk perceptions is based on the survey question: "How harmful do you think e-cigarettes or other ENDS are to health?". Possible response categories include not at all harmful, slightly harmful, somewhat harmful, very harmful, and extremely harmful.
[33] These data are not collected in the first two waves of the PATH among adults. In contrast, youths are asked, "How much do you think people harm themselves when they use e-cigarettes?"
[34] The analyses were also conducted using the original coding of the question, and the results remained unchanged.

Table 4.1. Description of Variables

Variable	Description
Panel A. Outcomes	
Current ENDS Use	Binary variable = 1 if vaped at least once in the past 30 days
Frequent ENDS Use	Binary variable = 1 if vaped on ≥20 days in the past 30 days
Everyday ENDS Use	Binary variable = 1 if vaped on all 30 days in the past 30 days
Current Cigarette Use	Binary variable = 1 if smoked at least once in the past 30 days
Relative Harm (ENDS vs Cigarettes)	Categorical variable: 1 less harmful, 2 about the same, 3 more harmful
Absolute ENDS Harm	Categorical variable: 1 no harm, 2 a little harm, 3 some harm, 4 a lot of harm
Absolute ENDS Harm (recoded)	Categorical variable: 1 no/low risk, 2 medium risk, 3 high risk
Panel B. Demographic characteristics	
Age	Counting variable ∈ N= {12, 13, …90}
Gender	Binary variable = 1 if female, 0 otherwise
Race	Categorical variable: 1 White, 2 Black, 3 Asian, 4 Other
Hispanic	Binary variable = 1 if Hispanic
Panel C. Covid-19 shocks	
Cumulative COVID-19 death rate	Continuous variable ∈ [0,0.004]
Cumulative COVID-19 case rate	Continuous variable ∈ [0,0.380]
Panel D. Macroeconomic conditions	
Unemployment rate	Continuous variable ∈ [1.7,9.866]
Poverty rate	Continuous variable ∈ [3.7,23.1]
Panel E. ENDS policies	
ENDS Tax (2023$)	Continuous variable ∈ [0,3.773]
Flavored ENDS ban	Continuous variable ∈ [0,1]
Tobacco 21 law	Continuous variable ∈ [0,1]
ENDS MLSA law	Binary variable = 1 if any MLSA law is in effect, 0 otherwise
Indoor vaping ban	Binary variable = 1 if any indoor vaping ban law is in effect, 0 otherwise
ENDS licensure law	Binary variable = 1 if any licensure law is in effect, 0 otherwise
ENDS online sales ban	Continuous variable ∈ [0,1]
Panel F. Cigarette policies	
Cigarette Tax (2023$)	Continuous variable ∈ [0.17,5.994]
Indoor smoking ban	Binary variable = 1 if any indoor smoke ban law is in effect, 0 otherwise
Panel G: Alcohol and marijuana policies	
Beer tax (2023$)	Continuous variable ∈ [0.022,1.687]
Recreational Marijuana Law (RML)	Continuous variable ∈ [0,1]
Medical Marijuana Law (MML)	Continuous variable ∈ [0,1]
Decriminalization Marijuana Law (DML)	Continuous variable ∈ [0,1]

Demographic Control

In terms of demographic characteristics, we control for core demographic characteristics measured in each PATH wave, as gender, age group, race/ethnicity, and state of residence.

Gender is coded as a binary variable, reflecting gender-based differences in tobacco consumption, as noted in previous studies (Hitchman & Fong, 2011).

Age is observed in years and ranges from 12 to 90, spanning both adolescents and adults, groups that may respond differently to tobacco taxation due to differences in economic resources (Deaton, 1997) and in the information availability (Chaloupka & Warner, 2000).

Race is captured using four mutually exclusive categories (White, Black, Asian, and Other, including multiracial), and Hispanic ethnicity is measured with a dichotomous indicator. Cultural background may also shape consumers' vaping-related behaviors and perceptions (Trinidad et al., 2009).

COVID-19 Shocks

To account for pandemic-era disruptions that may have shifted both information environments and substance-use patterns, we control for the severity of the COVID-19 shock in the respondent's state using the cumulative COVID-19 death rate and number of cases (expressed as a ratio) matched to the interview period.

Macroeconomic Conditions

Because risk perceptions and tobacco use are sensitive to broader economic conditions (Jofre-Bonet et al., 2018), and because policy adoption may co-move with these conditions (Poterba, 1994), we include time-varying state measures of the unemployment rate and the poverty rate.

ENDS Policies

Beyond ENDS taxes, we control for the broader set of vaping regulations that could independently affect access, norms, and perceptions. Specifically, we include indicators for restrictions on flavored ENDS sales[35], minimum legal sales age (MLSA) rules and Tobacco-21 law[36], indoor vaping restrictions, and ENDS retail licensure requirements; where applicable, we also account for ENDS online sales bans.[37]

[35] Flavored vape restrictions are defined as the proportion of the state population covered by restrictions on flavored electronic cigarette sales in each quarter, accounting for partial implementation across jurisdictions and time within the quarter.

[36] Tobacco 21 law measures the proportion of a state's population subject to a minimum legal sales age of 21 for tobacco products in a given quarter.

[37] E-cigarette shipment ban measures the proportion of a state's population subject to a prohibition on direct-to-consumer shipment of electronic cigarette products in a given quarter.

Cigarette Policies

Since ENDS regulation often occurs alongside conventional tobacco control, we additionally condition on cigarette policies that directly influence smoking incentives and may shape beliefs. These controls include cigarette excise taxes per pack (in 2023 dollars) and indoor smoking restrictions.

Alcohol and Marijuana Policies

Finally, to capture correlated substance-policy regimes and broader regulatory climates, we control for beer taxes (in 2023 dollars) and marijuana policy using indicators for medical marijuana laws (MML), recreational marijuana laws (RML), and marijuana decriminalization laws (DML)[38].

4.4 Empirical Strategy

4.4.1 Effects of ENDS Taxes on ENDS Use

Using panel data from the Population Assessment of Tobacco and Health (PATH), we begin with a two-way fixed effects (TWFE) strategy estimated via ordinary least squares (OLS) to examine how taxes affect ENDS use. Our primary outcomes are current ENDS use and current cigarette use, with supplementary analyses focusing on measures of use intensity. We therefore estimate the following model:

$$ENDSUse_{isqt} = \beta_0 + \beta_1 ENDSTax_{sqt} + X_{isqt}\beta_2 + \gamma_i + \alpha_s + +\delta_q + \tau_t + \varepsilon_{isqt} \qquad (4.1)$$

where $ENDSUse_{isqt}$ is the outcome (our measures of ENDS and cigarette use for 2013-2023) for whether individual i, residing in state s, surveyed in quarter q and year t. The key explanatory variable, $ENDSTax_{sqt}$, captures exposure to ENDS tax per mL of e-liquid in 2023 dollars in a particular state, at a particular quarter and year. The vector X_{isqt} includes individual demographic characteristics (age, gender, and race/ethnicity), state macroeconomic conditions (unemployment rate and poverty rate), COVID-19 (cumulative COVID-19 case and death rate), other e-cigarette policies (ENDS licensure requirements for retailers, clean indoor air law for vaping, online purchase shipment bans, minimum legal age sale, flavor bans, Tobacco-21 law), combustible tobacco policies (combustible cigarette taxes, clean indoor air laws for smoking), and alcohol and marijuana policies (beer tax, recreational marijuana law, marijuana decriminalization law and medical marijuana law). The model includes individual fixed effects γ_i, to

[38] Medical marijuana laws, recreational marijuana laws, and marijuana decriminalization laws measure the proportion of a state's population subject to each marijuana policy in a given quarter.

account for time-invariant unobserved heterogeneity, state fixed effects α_s, year fixed effects τ_t and quarter fixed effects δ_q, controlling for common temporal shocks, and ε_{isqt} is the error term.

As a robustness check, we also estimate a nonlinear specification using a logistic model. Specifically, we model the probability of current ENDS use (or current cigarette use) as:

$$\begin{aligned}\Pr\left(ENDSUse_{isqt} = 1 \mid ENDSTax_{sqt}, X_{isqt}, \alpha_s, \delta_q, \tau_t\right) = \\ = \Lambda(\beta_0 + \beta_1 ENDSTax_{sqt} + X'_{isqt}\beta_2 + \alpha_s + +\delta_q + \tau_t)\end{aligned} \tag{4.2}$$

where $\Lambda(z) = \frac{1}{1+e^{-z}}$ is the logistic cumulative distribution function. In this specification, we include the same set of covariates and state, quarter, and year fixed effects as in the TWFE model. In all models, standard errors are clustered at the state level to account for within-state correlation over time.

The same models were re-estimated stratifying the sample by individuals' baseline beliefs, to assess whether responses to taxes vary with people's initial perceptions.

4.4.2 Effects of ENDS Taxes on Risk Beliefs

To examine how policy and information shocks shape individuals' relative risk perceptions of e-cigarettes, we used an ordered logit model that explicitly accounts for the ordinal nature of our risk-perception outcomes (coded into three ordered categories). We assume the existence of a latent continuous index $RiskBeliefs^*_{isqt}$such that:

$$RiskBeliefs^*_{isqt} = \beta_0 + \beta_1 ENDSTax_{sqt} + X'_{isqt}\beta_2 + \alpha_s + \delta_q + \tau_t + u_{isqt} \tag{4.3}$$

and the observed outcome $RiskBeliefs_{isqt} \in \{1,2,3\}$ is generated by threshold crossings:

$$\begin{aligned}RiskBeliefs_{isqt} = 1 \text{ if } Y^*_{isqt} \le \kappa_1, \\ Y_{isqt} = 2 \text{ if } \kappa_1 < Y^*_{isqt} \le \kappa_2, \\ Y_{isqt} = 3 \text{ if } Y^*_{isqt} > \kappa_2\end{aligned} \tag{4.4}$$

with u_{isqt}following a logistic distribution. The key explanatory variable is $ENDSTax_{sqt}$. The vector X'_{isqt} includes individual demographic characteristics, state macroeconomic conditions, COVID-19, other e-cigarette policies, combustible tobacco policies, and alcohol and marijuana policies. The ordered logit model respects the ordered categorical structure of the outcome by allowing covariates to shift the latent risk-perception index and, hence, the probability of being

in each category. In all models, standard errors are clustered at the state level to account for within-state correlation over time.

As a robustness check, we re-estimate the relationship using a two-way fixed effects (TWFE) strategy estimated via OLS. Specifically, for PATH, we estimate the following reduced-form model:

$$RiskBeliefs_{isqt} = \beta_0 + \beta_1 ENDSTax_{sqt} + X_{isqt}\beta_2 + \gamma_i + \alpha_s + +\delta_q + \tau_t + \varepsilon_{isqt} \quad (4.5)$$

Where $RiskBeliefs_{isqt}$ is an indicator for individual risk perception of person i, residing in state s, surveyed in quarter q and year t. This specification includes the same set of covariates as in the TWFE model and controls for state, quarter, and year fixed effects $(\alpha_s, \delta_q, \tau_t)$, while incorporating survey weights.

The model includes individual fixed effects γ_i, to account for time-invariant unobserved heterogeneity, state fixed effects α_s, year fixed effects τ_t and quarter fixed effects δ_q, controlling for common temporal shocks, and ε_{isqt} is the error term. The analysis incorporates survey weights to ensure national representativeness. This framework allows us to isolate plausibly exogenous variation in risk perceptions driven by changes in policy environment and public health communications. As an additional analysis exploiting the longitudinal structure of the PATH data, we examine whether ENDS taxes affect transitions into and out of e-cigarette use, focusing on cessation margins. Results are not reported, as we find no statistically significant effects of ENDS taxes on cessation, in the full sample or in analyses stratified by baseline beliefs.[39]

[39]We estimate a discrete-time hazard (transition) model that captures the conditional probability of changing ENDS use status between consecutive survey waves.
Specifically, we estimate the following model:

$$\Pr(E_{isqt} = 1 \mid t-1 < T \leq t = \Lambda(\delta_0 + \delta_1 ENDSTax_{sqt} + X'_{isqt}\delta_2 + \gamma_i + \alpha_s + \delta_q + \tau_t$$

where E_{isqt} is an indicator equal to one if individual i, residing in state s, surveyed in quarter q and year t, experiences a transition in ENDS use status between periods $t-1$ and t, and zero otherwise. The function $\Lambda(\cdot)$ denotes the logistic cumulative distribution function, reflecting the binary nature of the transition outcome in each discrete time interval.
The parameter of interest, δ_1, captures the effect of ENDS taxes on the conditional probability of transitioning across the margins of ENDS use between consecutive survey waves.
For the cessation analysis, the sample is limited to individuals who are ENDS users at baseline. Here, $E_{isqt} = 1$ if the respondent transitions to non-ENDS use at period t, conditional on use at $t-1$, and zero otherwise.
The vector X_{isqt}includes the same set of individual-level demographic characteristics, state-level macroeconomic conditions, COVID-19 measures, e-cigarette regulations, combustible tobacco policies, and alcohol and marijuana policies used in the main TWFE specifications. All models include individual fixed effects (γ_i), state fixed effects (α_s), quarter fixed effects (δ_q), and year fixed effects (τ_t), thereby accounting for time-invariant unobserved heterogeneity and common temporal shocks. Survey weights are applied to ensure national representativeness, and standard errors are clustered at the state level to account for serial correlation within states over time.

4.5 Results

This section presents the empirical results of the analysis examining how ENDS taxation affects e-cigarette use and risk perceptions in the study sample. We begin by reporting descriptive statistics on the demographic composition of current ENDS users, current cigarette smokers, and non-users, together with summary measures of tobacco use outcomes, COVID-19 shocks, macroeconomic conditions, and the policy environment. We then document time trends in ENDS use by intensity (current, frequent, and everyday) and by age group. Next, we present the main two-way fixed effects (TWFE) estimates of the effect of ENDS taxes on ENDS participation and intensity. We subsequently examine whether ENDS taxes are associated with changes in individuals' beliefs about the health risks of e-cigarettes using ordered logit models for the risk-perception outcomes. Finally, we investigate treatment-effect heterogeneity by stratifying the sample according to baseline risk perceptions, to assess whether behavioral responses to ENDS taxes differ across belief groups and to provide additional insight into the mechanisms underlying the main findings.

4.5.1 Descriptive Statistics

Table 4.2 presents the demographic characteristics of the study sample, reported separately for current ENDS use, current cigarette use and no ENDS/cigarette use.

Table 4.2. Demographic Characteristics

	Current ENDS use		Current cigarette use		No smoker/vaper	
	N	%	N	%	N	%
Male	19425	54.6	41094	54.5	101984	46.7
Female	16122	45.4	34328	45.5	116593	53.3
12-14	462	1.3	180	0.2	13047	6.0
15	530	1.5	210	0.3	4783	2.2
16	781	2.2	344	0.5	4632	2.1
17	1054	3.0	512	0.7	4474	2.0
18-24	10182	28.6	9689	12.8	21791	9.9
25-29	5511	15.5	8716	11.5	14939	6.8
30-39	7064	19.9	15901	21.1	29751	13.6
40-59	7638	21.5	27164	36.0	62636	28.6
60-79	2289	6.4	12182	16.1	52865	24.1
80-90	66	0.2	571	0.8	10109	4.6
White	26851	77.7	55275	74.9	159358	76.2
Black	3918	11.3	12246	16.6	26085	12.5
Asian	1154	3.3	1853	2.5	13047	6.2
Other	2657	7.7	4427	6.0	10603	5.1
No Hispanic	29571	84.2	63551	85.8	177040	82.6
Hispanic	5537	15.8	10534	14.2	37262	17.4

Note: The table reports absolute (N) and relative (%) frequencies of categorical variables by groups. Percentages are computed within groups

To assess whether responses along the cessation margins vary with individuals' baseline beliefs about the relative risks of e-cigarettes, we re-estimate the discrete-time hazard models stratifying the sample by baseline risk perceptions, following the same approach used in the analyses of current use and beliefs.

The table reports absolute frequencies and within-group percentages for all variables. Overall, both current ENDS users and current cigarette smokers are predominantly male (54.6% and 54.5%, respectively), whereas the group of non-smokers/non-vapers includes a higher proportion of females (53.3%). Marked differences emerge in the age profile of the three groups. Current ENDS use is concentrated among young adults, with individuals aged 18-24 accounting for 28.6% of ENDS users (compared with 12.8% among cigarette smokers and 9.9% among non-users), while current cigarette use is more prevalent in older age groups, particularly 40-59 years (36.0%) and 30-39 years (21.1%). In contrast, non-users show a more evenly distributed and older age composition, with substantial shares in the 40-59 (28.6%) and 60-79 (24.1%) categories; adolescents (12-17) represent a relatively larger fraction among non-users (6.0% aged 12-14 and about 2% in each of the 15-17 categories) but remain uncommon among both ENDS and cigarette users. Racial composition is broadly similar across groups, with White respondents representing around three-quarters of each subgroup (ENDS: 77.7%; cigarettes: 74.9%; non-users: 76.2%). However, Black respondents constitute a higher proportion among cigarette smokers (16.6%) than among ENDS users (11.3%) and non-users (12.5%), whereas Asian respondents are more represented among non-users (6.2%) than among ENDS users (3.3%) and cigarette smokers (2.5%). Finally, most participants are non-Hispanic in all groups (82.6-85.8%), with the highest share of Hispanic individuals observed among non-users (17.4%), followed by ENDS users (15.8%) and cigarette smokers (14.2%).

Table 4.3 reports descriptive statistics for the full study sample, including measures of tobacco and ENDS use, COVID-19 shocks, macroeconomic conditions, and tobacco, alcohol, and marijuana policies.

Panel A summarizes tobacco use outcomes. In the full sample, 7% of individuals report current ENDS use while, in this category, frequent and everyday ENDS use are observed in 3% of observations, respectively. Current cigarette smoking is reported by approximately 18% of the sample.

Panel B reports COVID-19-related shocks at the state level. Both cumulative COVID-19 death rates and case rates exhibit limited variation across observations, with average values close to zero for death rates and modest dispersion for case rates, reflecting substantial heterogeneity across states and over time.

Panel C presents macroeconomic conditions. The average unemployment rate is approximately 4.8%, with moderate variation across state-quarter observations, while the poverty rate averages around 12%, indicating relatively stable economic conditions over the study period.

Table 4.3. Descriptive Statistics

	Mean	SD	Min	Max	N
Panel A. Vape and tobacco use					
Current ENDS Use	0.07	0.26	0.00	1.00	310304
Frequent ENDS Use	0.03	0.17	0.00	1.00	310304
Everyday ENDS Use	0.03	0.16	0.00	1.00	310304
Current Cigarette Use	0.18	0.38	0.00	1.00	311531
Panel B. Covid-19 shocks					
Cumulative COVID-19 death rate	0.00	0.00	0.00	0.00	311746
Cumulative COVID-19 case rate	0.06	0.10	0.00	0.38	311746
Panel C. Macroeconomic conditions					
Unemployment rate	4.79	1.31	1.70	9.87	311746
Poverty rate	12.34	3.01	3.70	23.10	311746
Panel D. ENDS policies					
ENDS Tax (2023$)	0.31	0.72	0.00	3.77	311746
Flavored ENDS ban	0.05	0.19	0.00	1.00	311746
Tobacco 21 law	0.36	0.48	0.00	1.00	311746
ENDS MLSA law	0.87	0.33	0.00	1.00	311746
Indoor vaping ban	0.22	0.42	0.00	1.00	311746
ENDS licensure law	0.32	0.47	0.00	1.00	311746
ENDS online sales ban	0.04	0.20	0.00	1.00	311746
Panel E. Cigarette policies					
Cigarette Tax (2023$)	2.09	1.31	0.17	5.99	311746
Indoor smoking ban	0.70	0.46	0.00	1.00	311746
Panel F. Alcohol and marijuana policies					
Beer Tax (2023$)	0.35	0.30	0.02	1.69	311746
Recreational Marijuana Law (RML)	0.22	0.41	0.00	1.00	311746
Medical Marijuana Law (MML)	0.61	0.49	0.00	1.00	311746
Decriminalization Marijuana Law (DML)	0.45	0.50	0.00	1.00	311746

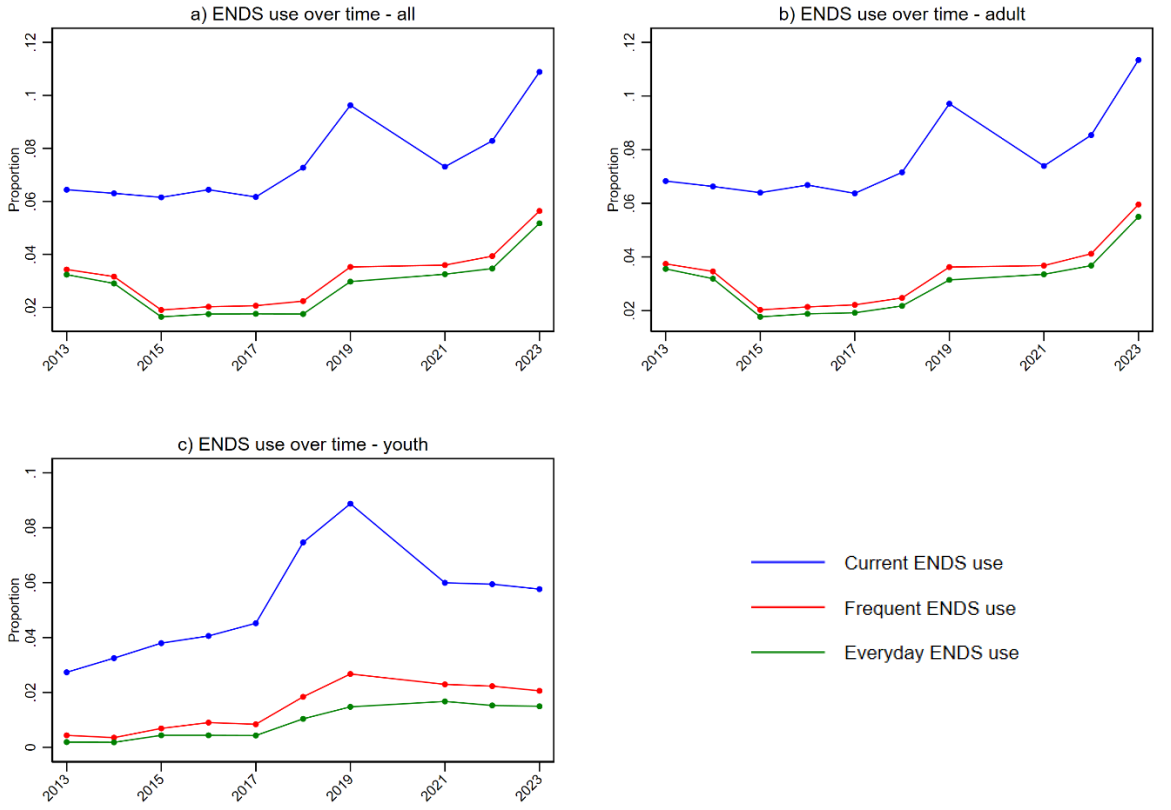
Panels D and E summarize tobacco and ENDS policy environments. ENDS-specific policies show substantial variation across state-quarters. For instance, flavored ENDS bans and indoor vaping bans affect, on average, 5% and 22% of the population, respectively, while Tobacco 21 laws cover approximately 36% of the population. ENDS minimum legal sales age laws are widespread, with an average exposure of 87%. Cigarette policies exhibit higher overall coverage, with indoor smoking bans affecting roughly 70% of the population and cigarette taxes averaging about $2.10 per pack (in 2023 dollars).

Panel F reports alcohol and marijuana policies. Beer taxes average approximately $0.35 per unit, while marijuana policies display substantial heterogeneity. Medical marijuana laws are in effect for about 61% of the population on average, recreational marijuana laws for 22%, and decriminalization policies for roughly 45% of the population.

Figure 4.3 depicts trends in ENDS use over time, distinguishing between current, frequent, and everyday use for the full sample and separately for adults and youth. By construction, frequent

and everyday ENDS use are nested within current use, allowing for a clear comparison of usage intensity over time.

Figure 4.3. ENDS Use Overtime



Note: The figure reports weighted proportions of ENDS use over time. Panel (a) refers to the full sample, panel (b) to adults (18+), and panel (c) to youth (<18). Estimates are computed using survey weights to ensure national representativeness.

In the full sample, current ENDS use shows a gradual increase over the study period, with a pronounced rise around 2018-2019, followed by some fluctuation and a renewed increase toward the end of the sample. Frequent and everyday ENDS use follow similar trajectories at lower levels, indicating that growth in overall ENDS use is accompanied by increases in higher-intensity consumption. Among adults, trends closely mirror those observed in the full sample. Current ENDS use increases steadily over time, with frequent use rising in parallel and everyday use remaining comparatively limited throughout the period. This pattern suggests that, among adults, the expansion of ENDS use is driven primarily by non-daily users rather than by a substantial shift toward everyday consumption. In contrast, youth exhibit more pronounced dynamics. Current ENDS use among youth rises sharply through the late 2010s, peaking around 2019 before declining slightly in subsequent years. Frequent and everyday use among youth

also increase during this period, though they remain well below the prevalence of current use, highlighting heterogeneity in intensity of use within the youth population. This is consistent with previous studies (Denlinger-Apte et al., 2022; Friedman 2015; Hansen et al. 2023) and with the stricter policies introduced to curb the spread of the vaping epidemic.

Table 4.4 reports descriptive statistics for the risk-perception variables used in the analysis, separately for current ENDS use, current cigarette use and no ENDS/cigarette users. The table reports absolute frequencies and within-group percentages for each response category.

Table 4.4. Risk Perception

	Current ENDS use		Current cigarette use		No smoker/vaper	
	N	%	N	%	N	%
Panel A. Relative harm (ENDS vs cigarettes)						
Less harm	16878	47.8	19832	27.2	41930	19.9
About the same	16309	46.2	44281	60.7	139378	66.3
More harmful	2088	5.9	8864	12.1	28897	13.7
Panel B. Absolute ENDS harm						
No harm	1999	7.4	2050	4.2	1730	1.0
A little harm	8162	30.3	8807	18.1	12133	7.0
Some harm	11909	44.2	24163	49.7	67563	39.1
A lot of harm	4853	18.0	13586	28.0	91450	52.9
Panel C. Absolute ENDS harm (recoded)						
No/low risk	10162	37.7	10857	22.3	13862	8.0
Medium risk	11909	44.2	24163	49.7	67563	39.1
High risk	4853	18.0	13586	28.0	91450	52.9

Note: The table reports absolute (N) and relative (%) frequencies of categorical variables by groups. Percentages are computed within groups

The distribution of responses highlights a clear gradient in perceived risk, with current ENDS users expressing the lowest perceived harm and non-users the highest. In Panel A (relative harm), nearly all ENDS users view vaping as less harmful (47.8%) or about the same as cigarettes (46.2%), with only 5.9% rating it more harmful. Cigarette smokers more often report ENDS as "about the same" (60.7%) and are roughly twice as likely as ENDS users to rate them more harmful (12.1%). Non-smokers/non-vapers show an even more skeptical pattern, with 66.3% reporting "about the same," 13.7% rating ENDS as more harmful, and only 19.9% as less harmful.

Panel B (absolute harm) reinforces these differences: ENDS users mostly endorse intermediate categories ("some harm," 44.2%; "a little harm," 30.3%), smokers shift toward higher perceived harm ("a lot of harm," 28.0%), and non-users overwhelmingly select "a lot of harm" (52.9%), with very few choosing "no harm" (1.0%). Panel C (recoded measure) summarizes this gradient: "high risk" perceptions rise from 18.0% among ENDS users to 28.0% among smokers and

52.9% among non-users, while "no/low risk" perceptions decline correspondingly (37.7%, 22.3%, and 8.0%).

4.5.2 Effect of ENDS Taxes on ENDS Use

Table 4.5 reports TWFE estimates of the effect of ENDS taxes on ENDS use and cigarette smoking.

Table 4.5. TWFE Estimates of ENDS Taxes on ENDS Use

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Current ENDS use						
ENDS Tax (2023$)	-0.005***	-0.005***	-0.012***	-0.012***	-0.005***	-0.007**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Pre Treatment Mean	0.066	0.066	0.066	0.066	0.066	0.066
N	286,988	286,988	286,988	286,988	305,084	305,084
Panel B. Frequent ENDS use						
ENDS Tax (2023$)	-0.005***	-0.004***	-0.006***	-0.007***	-0.003	-0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Pre Treatment Mean	0.024	0.024	0.024	0.024	0.024	0.024
N	286,988	286,988	286,988	286,988	305,084	305,084
Panel C. Everyday ENDS use						
ENDS Tax (2023$)	-0.004***	-0.004***	-0.005***	-0.005***	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Pre Treatment Mean	0.021	0.021	0.021	0.021	0.021	0.021
N	286,988	286,988	286,988	286,988	305,084	305,084
Panel D. Current cigarette use						
ENDS Tax (2023$)	0.003	0.002	0.004	0.004	0.003	0.004
	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
Pre Treatment Mean	0.187	0.187	0.187	0.187	0.187	0.187
N	288,106	288,106	288,106	288,106	306,306	306,306
Demographic	YES	YES	YES	YES	YES	YES
Macroeconomic and COVID-19	NO	YES	YES	YES	YES	YES
ENDS policies	NO	NO	YES	YES	YES	YES
Tobacco policies	NO	NO	YES	YES	YES	YES
Beer Tax	NO	NO	NO	YES	YES	YES
Marijuana policies	NO	NO	NO	YES	YES	YES
State Fixed Effect	YES	YES	YES	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES	YES	YES	YES
Individual Fixed Effect	NO	NO	NO	NO	YES	YES

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

Panel A focuses on current ENDS use, which represents the primary outcome of interest, while Panels B and C examine frequent and everyday ENDS use as measures of usage intensity. Panel D reports results for current cigarette use.

Across specifications, higher ENDS taxes are associated with statistically significant reductions in current ENDS use. In the fully specified models, which include demographic controls, macroeconomic conditions, COVID-19 shocks, and a comprehensive set of tobacco, alcohol, and marijuana policies, with the full set of fixed effects, a one-dollar increase in ENDS taxes (in 2023 dollars) reduces the probability of current ENDS use by approximately 0.7 percentage points. Relative to the pre-treatment mean, this corresponds to a non-negligible decline in ENDS participation.

Similar patterns emerge when examining measures of usage intensity. Panels B and C show that ENDS taxes are associated with significant reductions in both frequent and everyday ENDS use, with larger proportional effects relative to their respective baseline means. These findings suggest that higher taxes not only reduce ENDS participation but also discourage more intensive patterns of use among existing users. Estimates for frequent and everyday ENDS use become imprecise once individual fixed effects are included. This is expected given that high-intensity ENDS use is relatively rare and highly persistent over time, leaving limited within-individual variation (i.e., few switchers) to identify the effect. Accordingly, specifications with individual fixed effects should be interpreted as relying on a much smaller set of individuals who change intensity of use over the sample period.

In contrast, Panel D shows no statistically significant effect of ENDS taxes on current cigarette uses across specifications, providing no evidence of substitution from ENDS toward combustible cigarettes in response to higher ENDS taxation.

Appendix Tables A3.3-A3.6 report the full specifications for current ENDS use, frequent ENDS use, everyday ENDS use, and current cigarette use. Across outcomes, the auxiliary covariates display broadly stable and plausible patterns (e.g., ENDS outcomes are negatively associated with age and female gender, while smoking exhibits different demographic gradients), whereas the coefficients on time-varying state-level controls and other policy variables are generally modest and often imprecisely estimated once fixed effects are included. Importantly, the ENDS tax coefficient remains noticeable and negative for ENDS outcomes, while it is close to zero for cigarette smoking, indicating that the main conclusions are not driven by the inclusion of additional controls or by correlated policy changes.

4.5.3 Effect of ENDS Taxes on Risk Beliefs

Table 4.6 reports ordered logit estimates of the effect of ENDS taxes on individuals' risk perceptions related to e-cigarette use. All models account for the ordinal nature of the outcomes and include state, year, and quarter fixed effects, as well as a rich set of individual characteristics, macroeconomic controls, COVID-19 shocks, and tobacco, alcohol, and marijuana policies. Standard errors are clustered at the state level.

Table 4.6. OLogit Estimates of ENDS Taxes on Risk Beliefs

	(1)	(2)	(3)	(4)
Panel A. Relative harm (ENDS vs cigarette)				
ENDS Tax (2023$)	-0.065**	-0.060*	0.012	0.006
	(0.024)	(0.024)	(0.037)	(0.034)
cut1	-1.097***	-0.800	-0.636	-0.283
	(0.253)	(0.433)	(0.411)	(0.650)
cut2	2.314***	2.610***	2.775***	3.129***
	(0.259)	(0.434)	(0.413)	(0.654)
Pre Treatment Mean	1.8129	1.8129	1.8129	1.8129
N	277,910	277,910	277,910	277,910
Panel B. Absolute ENDS harm (recoded)				
ENDS Tax (2023$)	-0.017	-0.012	0.001	-0.002
	(0.034)	(0.028)	(0.045)	(0.043)
cut1	-1.176**	-1.502**	-1.264*	-1.036
	(0.456)	(0.523)	(0.514)	(0.640)
cut2	1.084*	0.758	0.996*	1.225
	(0.450)	(0.515)	(0.507)	(0.638)
Pre Treatment Mean	2.3028	2.3028	2.3028	2.3028
N	216,468	216,468	216,468	216,468
Demographic	YES	YES	YES	YES
Macroeconomic and COVID-19	NO	YES	YES	YES
ENDS policies	NO	NO	YES	YES
Tobacco policies	NO	NO	YES	YES
Beer tax	NO	NO	NO	YES
Marijuana policies	NO	NO	NO	YES
State Fixed Effect	YES	YES	YES	YES
Year and quarter Fixed Effect	YES	YES	YES	YES
Individual Fixed Effect	NO	NO	NO	NO

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Across all risk-perception outcomes and model specifications, the results provide no evidence that increases in ENDS taxes significantly affect individuals' beliefs about the health risks of

e-cigarettes. Estimated coefficients on ENDS taxes are generally small in magnitude and statistically insignificant once the models are fully specified, indicating that changes in the fiscal environment do not translate into systematic shifts in perceived risk.

Panel A focuses on perceived relative harm of e-cigarettes compared with combustible cigarettes. While point estimates are negative and statistically significant in more parsimonious specifications, these effects attenuate and lose statistical significance as additional controls and policy variables are included. In the fully specified models, the estimated effects are close to zero and imprecisely estimated.

Panel B examines perceptions of absolute harm from intermittent ENDS use, using the recoded outcome measures. Across specifications, ENDS taxes are not significantly associated with shifts in absolute risk perceptions. Estimated coefficients fluctuate around zero and remain stable as the specification is enriched, providing no evidence that higher taxes increase perceived harm of e-cigarettes along the extensive margin of risk beliefs.

Appendix Tables A3.7 and A3.8 report the full ordered-logit specifications for relative and absolute risk perceptions, respectively. The covariates display broadly stable patterns: for both outcomes, perceived risk is increasing in age and is higher among females. In Table A3.7, Black and Hispanic respondents are more likely to report higher relative harm of ENDS (vs cigarettes), while estimates for other race categories are smaller and less precisely estimated. In Table A3.8, race effects are generally modest, whereas Hispanic ethnicity remains positively associated with higher absolute harm. By contrast, coefficients on time-varying state-level conditions (COVID-19 shocks and macroeconomic indicators) and on concurrent policy controls are typically small and imprecise once fixed effects are included.

4.5.4 Effect of ENDS Taxes on ENDS Use by Baseline Risk Perception

We next examine whether baseline beliefs about the health risks of ENDS condition behavioral responses to ENDS taxation. We stratify the sample by respondents' baseline perception of ENDS' relative harm compared with cigarettes (less harmful, about the same, more harmful) and in absolute terms (no/low risk, medium risk, high risk) and re-estimate TWFE models for current ENDS use and for intensity outcomes (frequent and everyday use) within each belief group. Tables 4.7 and 4.8 report the saturated specifications under alternative fixed-effect structures for the relative risk perception.

Table 4.7. TWFE Estimates of ENDS Taxes on Current ENDS Use, by Relative Risk

	(1) Current ENDS use	(2) Current ENDS use	(3) Current ENDS use	(4) Current ENDS use	(5) Current ENDS use	(6) Current ENDS use
Panel A. Less harmful than cigarette						
ENDS Tax (2023$)	-0.008**	-0.008**	-0.015**	-0.016**	-0.005	-0.006
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)
Pre Treatment Mean	0.108	0.108	0.108	0.108	0.108	0.108
N	118,436	118,436	118,436	118,436	124,111	124,111
Panel B. About the same as cigarette						
ENDS Tax (2023$)	-0.004*	-0.003	-0.010***	-0.010***	-0.005*	-0.008*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Pre Treatment Mean	0.042	0.042	0.042	0.042	0.042	0.042
N	141,187	141,187	141,187	141,187	150,969	150,969
Panel C. More harmful than cigarette						
ENDS Tax (2023$)	-0.007**	-0.006*	-0.012*	-0.012*	-0.009	-0.004
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.006)
Pre Treatment Mean	0.030	0.030	0.030	0.030	0.030	0.030
N	26,124	26,124	26,124	26,124	28,618	28,618
Demographic	YES	YES	YES	YES	YES	YES
Macroeconomic and COVID-19	NO	YES	YES	YES	YES	YES
ENDS policies	NO	NO	YES	YES	YES	YES
Tobacco policies	NO	NO	YES	YES	YES	YES
Beer Tax	NO	NO	NO	YES	YES	YES
Marijuana policies	NO	NO	NO	YES	YES	YES
State Fixed Effect	YES	YES	YES	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES	YES	YES	YES
Individual Fixed Effect	NO	NO	NO	NO	YES	YES

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results indicate economically meaningful and statistically precise responses among individuals with low perceived risk, and muted responses among those holding higher-risk beliefs. In the fully controlled specification without individual fixed effects, a $1 increase in ENDS taxes reduces current ENDS use by 1.56 p.p. among those who perceive ENDS as less harmful, 1.00 p.p. among those who perceive them as about the same, and 1.20 p.p. among those who perceive them as more harmful, corresponding to roughly 15%, 24%, and 40% of each group's pre-treatment mean. The pattern is not monotone in beliefs: the middle-belief group ("about the same") shows the smallest tax responsiveness, while the low-belief group responds most strongly. This is plausible, as low-belief individuals likely have the highest propensity to use

ENDS and the greatest scope to adjust along both margins, making demand more price sensitive. High-belief individuals may have already self-selected out of vaping before tax changes, leaving less room to respond. The intermediate group may combine heterogeneous types, attenuating the average response within that category.

Table 4.8. TWFE Estimates of ENDS Taxes on Frequent and Everyday ENDS Use, by Relative Risk

	(1) Frequent ENDS use	(2) Frequent ENDS use	(3) Frequent ENDS use	(4) Everyday ENDS use	(5) Everyday ENDS use	(6) Everyday ENDS use
Panel A. Less harmful than cigarette						
ENDS Tax (2023$)	-0.011***	-0.006**	-0.006*	-0.010***	-0.006**	-0.005*
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Pre Treatment Mean	0.044	0.044	0.044	0.038	0.038	0.038
N	118,436	124,111	124,111	118,436	124,111	124,111
Panel B. About the same as cigarette						
ENDS Tax (2023$)	-0.004	-0.001	-0.002	-0.002	0.001	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Pre Treatment Mean	0.013	0.013	0.013	0.012	0.012	0.012
N	141,187	150,969	150,969	141,187	150,969	150,969
Panel C. More harmful than cigarette						
ENDS Tax (2023$)	-0.003	0.002	0.001	-0.003	0.001	0.001
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Pre Treatment Mean	0.009	0.009	0.009	0.007	0.007	0.007
N	26,124	28,618	28,618	26,124	28,618	28,618
Demographic	YES	YES	YES	YES	YES	YES
Macroeconomic and COVID-19	YES	YES	YES	YES	YES	YES
ENDS policies	YES	YES	YES	YES	YES	YES
Tobacco policies	YES	YES	YES	YES	YES	YES
Beer Tax	YES	YES	YES	YES	YES	YES
Marijuana policies	YES	YES	YES	YES	YES	YES
State Fixed Effect	YES	NO	YES	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES	YES	YES	YES
Individual Fixed Effect	NO	YES	YES	NO	YES	YES

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the intensity outcomes, the same qualitative gradient emerges: among respondents who view ENDS as less harmful, a $1 tax increase is associated with reductions of roughly 0.6-1.1 p.p. in frequent use and 0.5-1.0 p.p. in everyday use, relative to baseline means of 0.044 and 0.038, whereas coefficients are small and generally imprecise among those who perceive ENDS

as equally or more harmful than cigarettes. These results suggest that taxation primarily discourages ENDS participation and intensity among individuals who perceive vaping as relatively low risk, while responses are weaker among those with higher baseline risk perceptions.

Turning to absolute risk perceptions, Tables 4.9 and 4.10 point to a similar, but more ordered, pattern of heterogeneity.

Table 4.9. TWFE Estimates of ENDS Taxes on Current ENDS Use, by Absolute Risk

	(1) Current ENDS use	(2) Current ENDS use	(3) Current ENDS use	(4) Current ENDS use	(5) Current ENDS use	(6) Current ENDS use
			Panel A. No/low risk			
ENDS Tax (2023$)	-0.017***	-0.016***	-0.030***	-0.029***	-0.009*	-0.009
	(0.004)	(0.004)	(0.007)	(0.006)	(0.004)	(0.006)
Pre Treatment Mean	0.178	0.178	0.178	0.178	0.178	0.178
N	61,162	61,162	61,162	61,162	64,411	64,411
			Panel B. Medium risk			
ENDS Tax (2023$)	-0.004*	-0.003	-0.011**	-0.012**	-0.004	-0.007
	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)
Pre Treatment Mean	0.064	0.064	0.064	0.064	0.064	0.064
N	113,639	113,639	113,639	113,639	119,751	119,751
			Panel C. High risk			
ENDS Tax (2023$)	-0.003**	-0.004**	-0.007**	-0.007**	-0.005***	-0.006**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Pre Treatment Mean	0.026	0.026	0.026	0.026	0.026	0.026
N	96,608	96,608	96,608	96,608	104,411	104,411
Demographic	YES	YES	YES	YES	YES	YES
Macroeconomic and COVID-19	NO	YES	YES	YES	YES	YES
ENDS policies	NO	NO	YES	YES	YES	YES
Tobacco policies	NO	NO	YES	YES	YES	YES
Beer tax	NO	NO	NO	YES	YES	YES
Marijuana policies	NO	NO	NO	YES	YES	YES
State Fixed Effect	YES	YES	YES	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES	YES	YES	YES
Individual Fixed Effect	NO	NO	NO	NO	YES	YES

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the fully controlled specification without individual fixed effects (Table 4.9, col. (4)), a $1 increase in ENDS taxes reduces current ENDS use by 2.90 p.p. among individuals reporting no/low risk (Panel A. -0.029), compared with 1.20 p.p. among those reporting medium risk (Panel B. -0.012) and 0.71 p.p. among those reporting high risk (Panel C. -0.007). Relative to the corresponding pre-treatment means (0.178, 0.064, and 0.026), these effects remain economically meaningful (roughly 17%, 18%, and 27%, respectively).

Table 4.10. TWFE Estimates of ENDS Taxes on Frequent and Everyday ENDS Use, by Absolute Risk

	(1) Frequent ENDS use	(2) Frequent ENDS use	(3) Frequent ENDS use	(4) Everyday ENDS use	(5) Everyday ENDS use	(6) Everyday ENDS use
Panel A. No/low risk						
ENDS Tax (2023$)	-0.015***	-0.015***	-0.025***	-0.022***	-0.011**	-0.012*
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
Pre Treatment Mean	0.076	0.076	0.076	0.067	0.067	0.067
N	61,162	61,162	61,162	64,411	64,411	64,411
Panel B. Medium risk						
ENDS Tax (2023$)	-0.005**	-0.004*	-0.003	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)
Pre Treatment Mean	0.020	0.020	0.020	0.017	0.017	0.017
N	113,639	113,639	113,639	119,751	119,751	119,751
Panel C. High risk						
ENDS Tax (2023$)	-0.002*	-0.002	-0.002	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Pre Treatment Mean	0.008	0.008	0.008	0.006	0.006	0.006
N	96,608	96,608	96,608	104,411	104,411	104,411
Demographic	YES	YES	YES	YES	YES	YES
Macroeconomic and COVID-19	YES	YES	YES	YES	YES	YES
ENDS policies	YES	YES	YES	YES	YES	YES
Tobacco policies	YES	YES	YES	YES	YES	YES
Beer Tax	YES	YES	YES	YES	YES	YES
Marijuana policies	YES	YES	YES	YES	YES	YES
State Fixed Effect	YES	NO	YES	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES	YES	YES	YES
Individual Fixed Effect	NO	YES	YES	NO	YES	YES

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When individual fixed effects are included (cols. (5)-(6)), the estimates for the low- and medium-risk groups become smaller and less precisely estimated, whereas the high-risk group continues to display a negative and statistically significant response (e.g., -0.005 to -0.006).

The results for use intensity are even more concentrated in the low-risk group. In Table 4.10, the fully controlled estimates for respondents with no/low absolute risk imply sizable reductions in both frequent and everyday ENDS use, relative to baseline means of 0.076 and 0.067. By contrast, for the medium- and high-risk groups, coefficients for frequent and especially everyday use are generally small and statistically indistinguishable from zero across specifications, suggesting limited adjustment along the intensive margin once individuals perceive ENDS as meaningfully risky.

4.6 Heterogeneity

We further explore heterogeneity in the effects of ENDS taxes on e-cigarette use by re-estimating the baseline TWFE models separately by age group, gender, and race/ethnicity. This analysis allows us to assess whether the behavioural response to ENDS taxation varies systematically across demographic groups.

Age Heterogeneity

Table 4.11 reports estimates stratified by age group. ENDS taxes are associated with statistically significant reductions in current ENDS use among youth (ages 12-17) and 30+, with effect sizes that are larger in magnitude for younger people. In contrast, estimated effects among young adults and adult aged 25-30 are statistically indistinguishable from zero in fully specified models. This pattern suggests that younger individuals are more sensitive to ENDS taxation than older adults.

Table 4.11. TWFE Estimates of ENDS Taxes on Current ENDS Use by Age

	(1) Current ENDS use	(2) Current ENDS use	(3) Current ENDS use
Panel A. youth (12-17)			
ENDS Tax (2023$)	-0.017*	-0.020**	-0.022*
	(0.007)	(0.007)	(0.009)
Pre Treatment Mean	0.052	0.052	0.052
N	84,858	93,100	93,100
Panel B. young adult (18-24)			
ENDS Tax (2023$)	-0.013	-0.001	-0.011
	(0.010)	(0.008)	(0.011)
Pre Treatment Mean	0.163	0.163	0.163
N	64,136	68,444	68,444
Panel C. adult (25-30)			
ENDS Tax (2023$)	-0.014	-0.009	-0.005
	(0.012)	(0.008)	(0.015)
Pre Treatment Mean	0.117	0.117	0.117
N	29,031	30,234	30,234
Panel D. adult (30+)			
ENDS Tax (2023$)	-0.009***	-0.002	-0.003
	(0.002)	(0.002)	(0.002)
Pre Treatment Mean	0.045	0.045	0.045
N	108,963	113,306	113,306
Demographic	YES	YES	YES
Macroeconomic and COVID-19	YES	YES	YES
ENDS policies	YES	YES	YES
Tobacco policies	YES	YES	YES
Beer Tax	YES	YES	YES
Marijuana policies	YES	YES	YES
State Fixed Effect	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES
Individual Fixed Effect	NO	YES	YES

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Gender Heterogeneity

Table 4.12 presents results stratified by gender. Higher ENDS taxes are associated with significant reductions in current ENDS use for both males and females, with broadly similar magnitudes across groups. While point estimates are slightly larger for males in some specifications, differences across genders are modest and not systematic. Overall, the findings indicate that ENDS taxation reduces vaping participation for both men and women, with no strong evidence of differential responsiveness by gender.

Table 4.12. TWFE Estimates of ENDS Taxes on Current ENDS Use by Gender

	(1) Current ENDS use	(2) Current ENDS use	(3) Current ENDS use
	Panel A. Male		
ENDS Tax (2023$)	-0.012***	-0.003	-0.007
	(0.002)	(0.002)	(0.004)
Pre Treatment Mean	0.076	0.076	0.076
N	142,346	151,591	151,591
	Panel B. Female		
ENDS Tax (2023$)	-0.012**	-0.007**	-0.007*
	(0.003)	(0.002)	(0.003)
Pre Treatment Mean	0.057	0.057	0.057
N	144,642	152,952	152,952
Demographic	YES	YES	YES
Macroeconomic and COVID-19	YES	YES	YES
ENDS policies	YES	YES	YES
Tobacco policies	YES	YES	YES
Beer Tax	YES	YES	YES
Marijuana policies	YES	YES	YES
State Fixed Effect	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES
Individual Fixed Effect	NO	YES	YES

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Racial Heterogeneity

Table 4.13 reports estimate by race. Among White individuals, higher ENDS taxes are consistently associated with statistically significant reductions in current ENDS use across specifications. For Black, Asian, and Other racial groups, estimated effects are not statistically distinguishable from zero. These differences likely reflect lower baseline prevalence of ENDS use and smaller sample sizes within these subgroups, which limit statistical power rather than indicating qualitatively different behavioral responses.

Taken together, the heterogeneity analysis suggests that the behavioral effects of ENDS taxation are concentrated among white youth people on both genders. Importantly, these patterns complement the earlier findings on heterogeneity by baseline risk perceptions, reinforcing the

conclusion that ENDS taxes primarily operate through price sensitivity among active or potential users rather than through changes in beliefs or uniform behavioral responses across the population.

Table 4.13. TWFE Estimates of ENDS Taxes on Current ENDS Use by Race

	(1) Current ENDS use	(2) Current ENDS use	(3) Current ENDS use
	Panel A. White		
ENDS Tax (2023$)	-0.013***	-0.006**	-0.007**
	(0.002)	(0.002)	(0.003)
Pre Treatment Mean	0.067	0.067	0.067
N	203,596	207,138	207,138
	Panel B. Black		
ENDS Tax (2023$)	-0.008	-0.005	-0.011
	(0.008)	(0.005)	(0.009)
Pre Treatment Mean	0.063	0.063	0.063
N	46,317	48,069	48,069
	Panel C. Asian		
ENDS Tax (2023$)	-0.004	0.007	0.003
	(0.011)	(0.005)	(0.011)
Pre Treatment Mean	0.039	0.039	0.039
N	9,082	9,325	9,325
	Panel D. Other		
ENDS Tax (2023$)	-0.007	-0.010	-0.007
	(0.009)	(0.007)	(0.010)
Pre Treatment Mean	0.090	0.090	0.090
N	27,993	28,527	28,527
Demographic	YES	YES	YES
Macroeconomic and COVID-19	YES	YES	YES
ENDS policies	YES	YES	YES
Tobacco policies	YES	YES	YES
Beer Tax	YES	YES	YES
Marijuana policies	YES	YES	YES
State Fixed Effect	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES
Individual Fixed Effect	NO	YES	YES

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.7 Robustness Checks

4.7.1 Effects of ENDS Taxes on ENDS use

As a robustness check, we re-estimate the effects of ENDS taxes on ENDS use and cigarette smoking using a nonlinear specification based on a logistic model. We estimate logit regressions for current ENDS use, frequent ENDS use, everyday ENDS use, and current cigarette use, and report average marginal effects to facilitate interpretation and comparability with the linear TWFE estimates. The set of covariates and policy controls mirrors the one used in the main specifications, and all models include state, year, and quarter fixed effects, with standard errors

clustered at the state level. The excluded specifications correspond to models that would additionally include individual fixed effects, which are not feasible in the logit setting.[40]

Table 4.14 reports four progressively saturated specifications rather than the six specifications presented in the TWFE framework.

Table 4.14. Logit Marginal Effects of ENDS Taxes on ENDS Use

	(1)	(2)	(3)	(4)
Panel A. Current ENDS use				
ENDS Tax (2023$)	-0.004**	-0.004**	-0.010***	-0.011***
	(0.001)	(0.001)	(0.002)	(0.002)
Pre Treatment Mean	0.066	0.066	0.066	0.066
N	286,988	286,988	286,988	286,988
Panel B. Frequent ENDS use				
ENDS Tax (2023$)	-0.004***	-0.004***	-0.005**	-0.006**
	(0.001)	(0.001)	(0.002)	(0.002)
Pre Treatment Mean	0.024	0.024	0.024	0.024
N	286,943	286,943	286,943	286,943
Panel C. Everyday ENDS use				
ENDS Tax (2023$)	-0.003***	-0.003***	-0.004**	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Pre Treatment Mean	0.021	0.021	0.021	0.021
N	286,895	286,895	286,895	286,895
Panel D. Current cigarette use				
ENDS Tax (2023$)	-0.001	-0.001	0.004	0.004
	(0.002)	(0.002)	(0.004)	(0.004)
Pre Treatment Mean	0.187	0.187	0.187	0.187
N	288,106	288,106	288,106	288,106
Demographic	YES	YES	YES	YES
Macroeconomic and COVID-19	NO	YES	YES	YES
ENDS policies	NO	NO	YES	YES
Tobacco policies	NO	NO	YES	YES
Beer tax	NO	NO	NO	YES
Marijuana policies	NO	NO	NO	YES
State Fixed Effect	YES	YES	YES	YES
Year and quarter Fixed Effect	YES	YES	YES	YES
Individual Fixed Effect	NO	NO	NO	NO

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results from the logit models closely align with those obtained from the linear TWFE framework. Higher ENDS taxes are associated with statistically significant reductions in the probability of current ENDS use. In the fully specified models, a one dollar increase in ENDS taxes reduces the likelihood of current ENDS use by approximately 1.1 percentage points, corresponding to a sizable decline relative to the pre-treatment mean. Similar patterns emerge for frequent and everyday ENDS use, with proportionally larger effects relative to baseline prevalence, while estimates for current cigarette use remain small and statistically insignificant across all specifications. These findings indicate that the main conclusions are robust to alternative

[40] Individual fixed effects are not included in logit specifications due to incompatibility with the fixed-effects logit estimator and substantial loss of observations.

functional form assumptions for binary outcomes and are not driven by the linear probability model.

4.7.2 Effects of ENDS Taxes on Risk Beliefs

As a robust check, we re-estimate the relationship between ENDS taxes and risk perceptions using a linear two-way fixed effects framework. In addition to re-specifying the model using OLS rather than ordered logit, we extend the analysis to alternative measures of risk perceptions. Table 4.15 reports the corresponding OLS estimates.

Table 4.15. TWFE Estimates of ENDS Taxes on Risk Beliefs

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Relative harm (ENDS vs cigarette)					
ENDS Tax (2023$)	-0.017**	-0.016*	0.003	0.002	-0.004	-0.001
	(0.006)	(0.006)	(0.010)	(0.009)	(0.007)	(0.011)
Pre Treatment Mean	1.813	1.813	1.813	1.813	1.813	1.813
N	277,910	277,910	277,910	277,910	295,005	295,005
	Panel B. Absolute ENDS harm (recoded)					
ENDS Tax (2023$)	-0.006	-0.005	-0.000	-0.001	-0.012	-0.007
	(0.011)	(0.009)	(0.015)	(0.014)	(0.009)	(0.014)
Pre Treatment Mean	2.303	2.303	2.303	2.303	2.303	2.303
N	216,468	216,468	216,468	216,468	230,846	230,846
	Panel C. Perceived ENDS harm (recoded)					
ENDS Tax (2023$)	-0.002	-0.002	0.001	0.000	-0.006	-0.006
	(0.007)	(0.006)	(0.013)	(0.013)	(0.009)	(0.014)
Pre Treatment Mean	2.586	2.586	2.586	2.586	2.586	2.586
N	168,967	168,967	168,967	168,967	179,024	179,024
	Panel D. Nicotine harm (ENDS) (recoded)					
ENDS Tax (2023$)	0.004	0.005	0.009	0.007	0.003	0.009
	(0.007)	(0.007)	(0.010)	(0.011)	(0.008)	(0.011)
Pre Treatment Mean	2.593	2.593	2.593	2.593	2.593	2.593
N	168,565	168,565	168,565	168,565	180,031	180,031
	Panel E. Menthol/mint relative harm					
ENDS Tax (2023$)	-0.002	-0.001	0.000	-0.003	0.004	0.003
	(0.003)	(0.002)	(0.006)	(0.006)	(0.005)	(0.007)
Pre Treatment Mean	2.111	2.111	2.111	2.111	2.111	2.111
N	157,887	157,887	157,887	157,887	168,291	168,291
	Panel F. Flavors relative harm					
ENDS Tax (2023$)	0.004	0.003	-0.003	-0.005	0.001	-0.006
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Pre Treatment Mean	2.090	2.090	2.090	2.090	2.090	2.090
N	167,715	167,715	167,715	167,715	178,999	178,999
Demographic	YES	YES	YES	YES	YES	YES
Macroeconomic and COVID-19	NO	YES	YES	YES	YES	YES
ENDS policies	NO	NO	YES	YES	YES	YES
Tobacco policies	NO	NO	YES	YES	YES	YES
Beer Tax	NO	NO	NO	YES	YES	YES
Marijuana policies	NO	NO	NO	YES	YES	YES
State Fixed Effect	YES	YES	YES	YES	NO	YES
Year and quarter Fixed Effect	YES	YES	YES	YES	YES	YES
Individual Fixed Effect	NO	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Across all outcomes and specifications, we find no evidence that increases in ENDS taxes significantly affect individuals' risk perceptions. Estimated coefficients are uniformly small, statistically insignificant, and stable across increasingly saturated model specifications. These findings closely mirror the results from the main ordered logit models, indicating that the null effect of ENDS taxation on risk beliefs is robust to alternative functional form assumptions, outcome definitions, and estimation strategies.

4.7.3 Effects of ENDS Taxes on ENDS Use by Baseline Risk Perceptions

As a robustness check, we re-estimate the heterogeneity analysis using nonlinear logit models and report average marginal effects (AME). This exercise assesses whether the differential responses to ENDS taxation across baseline belief groups are sensitive to the linear probability model framework. As in the main analysis, we stratify the sample by baseline risk perceptions, elicited both in relative terms (less harmful / about the same / more harmful than cigarettes) and in absolute terms (no/low / medium / high risk), and estimate separate models for current, frequent, and everyday ENDS use.

Tables 4.16 and 4.17 show that the AMEs closely track the TWFE results.

Table 4.16. Logit Marginal Effects of ENDS Taxes on Current ENDS Use, by Relative Risk

	(1) Current ENDS use	(2) Frequent ENDS use	(3) Everyday ENDS use
Panel A. Less harmful than cigarette			
ENDS Tax (2023$)	-0.017**	-0.011**	-0.010**
	(0.006)	(0.004)	(0.003)
Pre Treatment Mean	0.108	0.044	0.038
N	120,762	120,741	120,730
Panel B. About the same than cigarette			
ENDS Tax (2023$)	-0.010***	-0.003	-0.002
	(0.003)	(0.002)	(0.002)
Pre Treatment Mean	0.042	0.013	0.012
N	143,392	143,378	143,225
Panel C. More harmful than cigarette			
ENDS Tax (2023$)	-0.008	-0.002	-0.001
	(0.005)	(0.004)	(0.003)
Pre Treatment Mean	0.030	0.009	0.007
N	26,429	26,095	26,095
Demographic	YES	YES	YES
Macroeconomic and COVID-19	YES	YES	YES
ENDS policies	YES	YES	YES
Tobacco policies	YES	YES	YES
Beer Tax	YES	YES	NO
Marijuana policies	YES	YES	NO
State Fixed Effect	YES	YES	YES
Year and quarter Fixed Effect	YES	YES	YES
Individual Fixed Effect	NO	NO	NO

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.17. Logit Marginal Effects of ENDS Taxes on Current ENDS Use, by Absolute Risk

	(1) Current ENDS use	(2) Frequent ENDS use	(3) Everyday ENDS use
Panel A. Less harmful than cigarette			
ENDS Tax (2023$)	-0.028***	-0.020***	-0.019***
	(0.006)	(0.0058)	(0.005)
Pre Treatment Mean	0.178	0.076	0.067
N	62,462	62,443	62,438
Panel B. About the same as cigarette			
ENDS Tax (2023$)	-0.013***	-0.004	-0.002
	(0.003)	(0.002)	(0.002)
Pre Treatment Mean	0.064	0.020	0.017
N	115,650	115,598	115,539
Panel C. More harmful than cigarette			
ENDS Tax (2023$)	-0.006*	-0.000	0.000
	(0.002)	(0.002)	(0.002)
Pre Treatment Mean	0.026	0.008	0.006
N	98,121	98,035	98,005
Demographic	YES	YES	YES
Macroeconomic and COVID-19	YES	YES	YES
ENDS policies	YES	YES	YES
Tobacco policies	YES	YES	YES
Beer Tax	YES	YES	NO
Marijuana policies	YES	YES	NO
State Fixed Effect	YES	YES	YES
Year and quarter Fixed Effect	YES	YES	YES
Individual Fixed Effect	NO	NO	NO

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For relative-risk beliefs (Table 4.16), a $1 increase in ENDS taxes is associated with statistically significant declines in vaping among respondents who perceive ENDS as less harmful than cigarettes: the probability of current use falls by 1.7 p.p., with further reductions for frequent (1.1 p.p.) and everyday use (1,0 p.p.). Effects are smaller for the "about the same" group, remaining significant for current use (1.0 p.p.) but close to zero for frequent and everyday use, and become statistically indistinguishable from zero for respondents who perceive ENDS as more harmful than cigarettes across all three outcomes. A similar gradient emerges for absolute-risk beliefs (Table 4.17). Among individuals reporting no/low risk, a $1 increase in ENDS taxes reduces the probability of current ENDS use by 2.8 p.p. and decreases frequent and everyday use by 2.0 p.p. and 1.9 p.p., respectively. For the medium-risk group, the effect remains statistically significant for current use (1.3 p.p.) but is small and imprecise for frequent and everyday use. For the high-risk group, marginal effects are substantially smaller; only current use shows a modest decline (0.6 p.p.), while effects on frequent and everyday use are near zero. As an additional robustness exercise, we assessed whether the TWFE estimates are sensitive to staggered adoption of ENDS tax schedules across states. Given that staggered treatment timing can introduce bias when treatment effects are heterogeneous across cohorts (Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021), we re-estimated the main specifications using the Callaway–

Sant'Anna (2021) estimator. The resulting estimates are qualitatively consistent with the baseline TWFE results, with no meaningful differences in sign, magnitude, or statistical significance for either the behavioral or the belief outcomes. We also explored a specification that partitions the tax variable into incremental blocks to assess whether larger tax increases generate systematically stronger behavioral responses; this likewise yields no evidence of non-linearity or threshold effects, reinforcing the robustness of the baseline estimates.

4.8 Conclusion

This paper studies whether a prominent form of government regulation, state taxation of electronic nicotine delivery systems (ENDS), contributes to misinformation by shifting consumers' beliefs about the health risks of e-cigarettes. Motivated by economic models in which policy can affect behavior both through prices and through informational content or signals (Byrne et al., 2015; Pesko et al., 2020), we combine rich longitudinal microdata from the Population Assessment of Tobacco and Health (PATH) Study (2013-2023) with detailed measures of ENDS tax intensity harmonized across heterogeneous state tax structures.

Three findings emerge. First, ENDS taxes meaningfully reduce vaping. In two-way fixed effects models with extensive controls and fixed effects, higher taxes are associated with statistically significant declines in current ENDS use and, in most specifications, also reductions at the intensive margin (frequent and everyday use). These results are reinforced by nonlinear logit models. Our evidence supports the view that ENDS taxation remains an effective instrument for discouraging engagement in nicotine vaping, including higher-intensity consumption. Second, we find no robust evidence that ENDS taxes systematically shift risk beliefs. Across ordered logit specifications and linear fixed-effects robustness checks, estimated relationships between ENDS tax changes and perceived relative or absolute harm of e-cigarettes are small and statistically indistinguishable from zero in fully specified models. This null result is informative: although taxes clearly change behavior, they do not appear to operate through measurable changes in the beliefs captured by PATH risk-perception modules. Third, we document an economically meaningful interaction between baseline beliefs and tax responsiveness. Behavioral responses to ENDS taxes are concentrated among individuals who initially perceive e-cigarettes as relatively less harmful (or as low risk in absolute terms). This pattern is consistent with a framework in which perceived benefits from vaping (relative to perceived costs) govern price sensitivity: when perceived harm is already high, many individuals may have already selected out of ENDS use or limited intensity, leaving less behavioral margin for taxation to affect. Taken together, these results yield two broader implications for the economics of health

regulation and misinformation. First, our findings caution against interpreting fiscal regulation as an informational intervention. In the ENDS context, taxation appears to function primarily as a pecuniary deterrent rather than as a policy signal that reshapes subjective risk assessments. This has direct relevance for welfare analysis in environments where consumer misperceptions are salient: when misinformation about relative harm is widespread, policies that reduce the use of a lower-risk substitute may not correct beliefs and may not improve choices through information channels. To this end, other means such as information campaigns could be more effective (MacMonegle et al., 2022). These findings are particularly relevant considering the European Commission's 2025 Tobacco Tax Directive, which extends excise duties to e-liquids and reduced-risk products on the assumption that consumer responses are primarily price-driven. However, when tax rates are raised uniformly across nicotine product categories without differentiation by harm profile, price signals may inadvertently suggest that reduced-risk alternatives are as dangerous as combustible tobacco, removing smokers' incentive to switch (Alvarado et al., 2021; Moscone, 2023). Our results, showing that taxes reduce vaping without correcting misperceptions of relative risk, are consistent with this concern and reinforce the case for coordinating fiscal instruments with explicit risk communication strategies. Second, we find that tax responsiveness is concentrated among individuals with more favorable baseline risk perceptions of ENDS. This pattern is consistent with a selection mechanism whereby individuals who perceive ENDS as less harmful are more likely to be active users and therefore have greater scope to adjust consumption along both the extensive and intensive margins in response to price increases. By contrast, individuals holding higher-risk beliefs may have already been partially selected out of vaping prior to tax changes, leaving less behavioral margin for further adjustment. Tax responsiveness is weakest among those who perceive ENDS as about as harmful as cigarettes, a group that likely combines heterogeneous types and attenuates average responses.

This study has limitations pointing to fruitful directions for future research. Our belief measures capture perceptions in discrete categories and may not fully reflect nuanced beliefs about product heterogeneity, nicotine content, or long-run risks. Our analysis focuses on taxes as the policy margin; other instruments, such as warning labels, flavor restrictions, licensing regimes, and public health communications, may carry more direct informational content and could interact with taxes in shaping beliefs and behavior. Future work could more explicitly model dynamic belief updating in response to multi-dimensional policy environments and information shocks, and investigate whether taxes affect information acquisition (e.g., attention to health news or reliance on informal sources) even when average stated beliefs do not shift.

Conclusion

5. Conclusion

This dissertation examined the role of innovation in contemporary healthcare systems from an applied health economics perspective, focusing on individuals' behavioral responses and the implications for healthcare resource utilization and welfare. Through three distinct yet complementary empirical contributions, the dissertation has investigated how digital technologies, organizational models, and public policies influence care-related behaviors, individual choices, and health outcomes, highlighting both the potential benefits and the critical challenges associated with the adoption of new tools in healthcare.

The first chapter analyzed the introduction of telemonitoring as an innovation in care delivery models for chronic cardiac patients within an Italian local health authority, assessing its impact on patterns of healthcare utilization. The results show that telemonitoring does not act as a substitute for traditional care, at least in the short run, but rather as a complement. Moreover, the adoption of telemonitoring does not reduce the overall number of hospitalizations, but it is associated with a decrease in hospitalization costs, suggesting improved management of acute episodes. At the same time, a significant increase in outpatient specialist visits and related expenditures is observed, indicating an intensification of clinical follow-up. The findings suggest a reallocation of resource use away from more costly inpatient care toward more continuous and potentially preventive outpatient management, consistent with the idea that telemedicine may address previously unmet care needs.

The second chapter explored one of the main mechanisms through which telemedicine may affect health outcomes and healthcare utilization: medication adherence. Using longitudinal administrative data from an Italian local health authority on patients with chronic cardiac and diabetic conditions, the analysis shows that exposure to telemedicine is associated with improved adherence for some classes of medications, with heterogeneous effects across conditions and therapies. The results further indicate that higher adherence is strongly correlated with reduced use of acute healthcare services, particularly hospitalizations and emergency department visits. The econometric analysis suggests that adherence plays an important mediating role between telemedicine adoption and reductions in healthcare utilization, indicating that the benefits of digital health may materialize indirectly through changes in care-related behaviors rather than through immediate effects on care intensity.

The third chapter shifted the focus from innovation in care delivery models to innovation in products and health policies, analyzing the case of electronic cigarettes as a harm-reduction

tool. Using longitudinal survey data representative of the U.S. population and exploiting geographic and temporal variation in e-cigarette taxation, the chapter shows that fiscal policies significantly affect consumption behavior, reducing e-cigarette use at both the extensive and intensive margins. However, these policies do not appear to substantially alter individuals' risk perceptions, which often remain misaligned with scientific evidence on the relative risks of different products. The results further indicate that behavioral responses to policy interventions depend critically on individuals' baseline beliefs, suggesting that regulatory measures not accompanied by effective information strategies may generate unintended and potentially welfare-reducing effects.

The results across the three chapters highlight how innovation in healthcare interacts in complex ways with individual behavior and the organization of care systems. The digital technologies and public policies analyzed in this dissertation do not generate automatic or uniform effects but instead produce heterogeneous responses that depend on institutional context, individual characteristics, and behavioral mechanisms at play. Innovation thus emerges not only as a technological or regulatory lever, but as a process that requires careful consideration of behavioral and informational dynamics.

The findings suggest that the adoption of telemedicine should be evaluated not only in terms of immediate cost containment but also considering its potential to improve continuity of care and to positively influence patient behavior, particularly medication adherence. Policies that promote the integration of telemedicine with traditional care, rather than its substitution, may therefore be more effective in the long run. At the same time, the case of electronic cigarettes underscores the importance of coordinating fiscal and regulatory instruments with clear and coherent information interventions, to avoid distortions in risk perceptions that may limit the effectiveness of harm-reduction strategies.

This dissertation nevertheless has some limitations. First, the analyses of telemedicine focus on a specific geographic context and a relatively short time horizon, which may limit the generalizability of the results and the ability to capture longer-term effects. Second, while administrative data provides a high level of detail on healthcare utilization, they do not allow for the direct observation of certain relevant dimensions, such as individual preferences or perceived quality of care. Similarly, in the chapter on electronic cigarettes, measures of risk perceptions are based on self-reported data, which may be subject to response bias.

These limitations point to several directions for future research. Future studies could extend the analysis of telemedicine to different geographic settings and longer time horizons, to assess whether the observed effects persist or evolve over time. Further research could also explore

more deeply the role of informational mechanisms and patient-provider interactions in shaping adherence and health outcomes. Incorporating cost-effectiveness frameworks, including cost-per-QALY analyses, into the evaluation of telemedicine programs would also substantially enrich the evidence base available to policymakers, documenting the utilization shifts as measurable gains in quality of life, and at what cost (Drummond et al., 2015). Finally, in the context of harm-reduction policies, it would be valuable to analyze the joint effects of regulation, taxation, and information campaigns in an integrated framework, to better understand how to design interventions that are both effective and consistent with public health objectives.

Appendices

Appendix 1

Table A1.1. Manual DiD Estimates, by Semester

	(1) No. Hospital Discharges	(2) No. Cardiology Visits	(3) No. Cardiology Visits (by Discipline Code)	(4) Cost - Hospital Discharges (€)	(5) Cost - Cardiology Visits (€)	(6) Cost - Cardiology Visits (by Discipline Code) (€)
ATET	-0.015	0.822***	0.739***	-154.729	18.458***	16.516***
	(0.039)	(0.084)	(0.082)	(225.542)	(2.071)	(2.241)
Male	0.002	0.197***	0.217***	140.422	5.813***	5.905***
	(0.015)	(0.037)	(0.032)	(76.471)	(0.872)	(0.870)
Age 46 - 65	-0.127	-0.014	-0.021	-737.292	-5.017	-3.080
	(0.076)	(0.182)	(0.160)	(383.858)	(4.346)	(4.344)
Age 65+	-0.162*	-0.428*	-0.453**	-1393.032***	-13.719***	-13.142**
	(0.072)	(0.173)	(0.153)	(365.533)	(4.130)	(4.131)
Charlson Index	0.058***	0.014	-0.002	267.977***	0.173	-0.027
	(0.004)	(0.009)	(0.008)	(18.283)	(0.207)	(0.207)
No. Exemptions	0.002	0.023	0.015	-45.604	0.610	0.345
	(0.006)	(0.014)	(0.012)	(29.797)	(0.330)	(0.333)
No. Distinct Drugs	0.004***	0.009***	0.007***	20.129***	0.213***	0.194***
	(0.000)	(0.001)	(0.001)	(1.575)	(0.016)	(0.017)
Constant	0.147*	1.261***	1.161***	1301.525***	31.297***	28.590***
	(0.075)	(0.178)	(0.157)	(381.044)	(4.241)	(4.262)
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Pre Treatment Mean	0.214	1.008	0.861	1004.219	22.853	20.377
N	8,540	8,540	8,540	8,540	8,540	8,540

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.2. Poisson and Tobit Estimates, by Semester

	Poisson models			Tobit models		
	(1) No. Hospital Discharges	(2) No. Cardiology Visits	(3) No. Cardiology Visits (by Discipline Code)	(4) Cost - Hospital Discharges (€)	(5) Cost - Cardiology Visits (€)	(6) Cost - Cardiology Visits (by Discipline Code) (€)
S1_2019#Treated	0.123	0.203*	0.259*	893.337**	7.223*	8.238*
	(0.183)	(0.101)	(0.114)	(340.712)	(3.090)	(3.346)
S2_2019#Control	0.109	-0.181***	-0.180**	77.568	-5.759***	-5.090***
	(0.101)	(0.051)	(0.059)	(155.290)	(1.349)	(1.476)
S2_2019#Treated	-0.198	0.070	0.211*	-168.000	3.587	8.565**
	(0.197)	(0.097)	(0.107)	(319.741)	(2.906)	(3.145)
S1_2020#Control	-0.014	-0.728***	-0.795***	45.584	-15.158***	-14.106***
	(0.108)	(0.056)	(0.064)	(156.121)	(1.358)	(1.485)
S1_2020#Treated	0.156	-0.523***	-0.454***	514.217	-12.610***	-9.302**
	(0.260)	(0.108)	(0.126)	(316.740)	(2.880)	(3.116)
S2_2020#Control	-0.030	-0.492***	-0.481***	-69.458	-11.311***	-9.269***
	(0.114)	(0.056)	(0.061)	(157.476)	(1.371)	(1.499)
S2_2020#Treated	-0.218	-0.322**	-0.245*	429.015	-8.033**	-6.668*
	(0.264)	(0.111)	(0.115)	(315.814)	(2.872)	(3.107)
S1_2021#Control	0.013	-0.819***	-0.793***	136.139	-16.159***	-13.128***
	(0.113)	(0.058)	(0.061)	(158.820)	(1.383)	(1.513)
S1_2021#Treated	0.048	-0.434***	-0.384***	242.416	-9.965***	-7.486*
	(0.216)	(0.096)	(0.103)	(315.814)	(2.872)	(3.107)
S2_2021#Control	0.312**	-0.489***	-0.355***	408.710*	-9.877***	-4.360**
	(0.111)	(0.056)	(0.063)	(160.102)	(1.395)	(1.526)
S2_2021#Treated	0.174	-0.161	-0.033	520.339	-4.726	1.208
	(0.181)	(0.093)	(0.103)	(315.810)	(2.872)	(3.107)
S1_2022#Control	0.436***	-0.218***	-0.092	602.451***	-4.397**	0.522
	(0.111)	(0.056)	(0.061)	(161.726)	(1.410)	(1.542)
S1_2022#Treated	0.484**	0.149	0.240*	609.637	7.839**	12.207***
	(0.170)	(0.097)	(0.103)	(315.854)	(2.872)	(3.108)
S2_2022#Control	0.320**	-0.161**	-0.051	294.420	-3.544*	0.712
	(0.117)	(0.057)	(0.064)	(165.258)	(1.443)	(1.577)
S2_2022#Treated	0.129	0.595***	0.668***	-3.593	25.535***	25.793***
	(0.222)	(0.084)	(0.089)	(315.809)	(2.872)	(3.107)
Male	0.065	0.198***	0.251***	134.978	5.694***	5.768***
	(0.056)	(0.035)	(0.036)	(76.386)	(0.866)	(0.897)
Age 46 - 65	-0.426*	-0.054	-0.077	-725.434	-4.732	-2.901
	(0.197)	(0.166)	(0.165)	(383.293)	(4.317)	(4.477)
Age 65+	-0.499**	-0.359*	-0.423**	-1331.147***	-12.354**	-11.752**
	(0.182)	(0.154)	(0.158)	(366.155)	(4.119)	(4.272)
Charlson Index	0.148***	0.011	-0.004	268.814***	0.175	-0.033
	(0.018)	(0.009)	(0.009)	(18.256)	(0.206)	(0.213)
No. Exemptions	0.023	0.023	0.015	-46.014	0.611	0.331
	(0.020)	(0.014)	(0.015)	(29.750)	(0.328)	(0.342)
No. Distinct Drugs	0.011***	0.008***	0.008***	20.050***	0.213***	0.197***
	(0.002)	(0.001)	(0.001)	(1.573)	(0.016)	(0.017)
Constant	-1.790***	0.105	0.010	1150.656**	29.300***	26.379***
	(0.197)	(0.160)	(0.165)	(383.897)	(4.248)	(4.418)
Pre Treatment Mean	0.219	0.872	0.767	1032.333	20.209	19.006
N	8540	8540	8540	8540	8540	8540

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 2

Table A2.1. Tobit Estimates of the Relationship Between Adherence and Resource Consumption Among Diabetic Patients

	(1) No. ED Visits	(2) No. Hospital Discharges	(3) No. ED Visits	(4) No. Hospital Discharges
	ATC A02BC02		ATC A10BA02	
S1_2019#High adherence	-0.302***	-0.518***	-0.113**	-0.109*
	(0.047)	(0.062)	(0.048)	(0.063)
S2_2019#High adherence	-0.151***	-0.301***	-0.082*	-0.088
	(0.044)	(0.057)	(0.047)	(0.063)
S1_2020#High adherence	-0.204***	-0.386***	-0.086*	-0.208***
	(0.043)	(0.056)	(0.049)	(0.065)
S2_2020#High adherence	-0.275***	-0.366***	-0.059	-0.147**
	(0.042)	(0.055)	(0.050)	(0.066)
S1_2021#High adherence	-0.198***	-0.359***	-0.112**	-0.198***
	(0.041)	(0.054)	(0.050)	(0.067)
S2_2021#High adherence	-0.192***	-0.391***	-0.117**	-0.230***
	(0.041)	(0.054)	(0.049)	(0.065)
S1_2022#High adherence	-0.262***	-0.425***	-0.085	-0.173**
	(0.042)	(0.056)	(0.053)	(0.070)
S2_2022#High adherence	-0.302***	-0.497***	-0.057	-0.116
	(0.046)	(0.061)	(0.058)	(0.076)
Treatment	-0.071	-0.248***	0.089*	-0.046
	(0.050)	(0.077)	(0.047)	(0.066)
Controls	YES	YES	YES	YES
Semester Fixed Effects	YES	YES	YES	YES
N	17071	17071	11437	11437

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table A2.2. Tobit Estimates of the Relationship Between Adherence and Resource Consumption Among Heart Failure Patients

	(1) No. ED Visits	(2) No. Hospital Discharges	(3) No. ED Visits	(4) No. Hospital Discharges
	ATC C03CA01		ATC C07AB07	
S1_2019#High adherence	0.043	0.080	-0.376**	-0.410**
	(0.060)	(0.076)	(0.156)	(0.200)
S2_2019#High adherence	0.165***	0.239***	-0.324*	-0.463**
	(0.058)	(0.074)	(0.167)	(0.215)
S1_2020#High adherence	0.059	0.171**	-0.375**	-0.490**
	(0.058)	(0.074)	(0.164)	(0.211)
S2_2020#High adherence	-0.009	0.092	-0.272	0.126
	(0.057)	(0.073)	(0.185)	(0.237)
S1_2021#High adherence	-0.052	-0.095	-0.232	-0.084
	(0.058)	(0.074)	(0.170)	(0.218)
S2_2021#High adherence	0.023	0.084	0.000	0.265
	(0.058)	(0.074)	(0.178)	(0.228)
S1_2022#High adherence	0.214***	0.305***	-0.313*	-0.254
	(0.058)	(0.074)	(0.180)	(0.231)
S2_2022#High adherence	0.034	0.067	-0.137	-0.174
	(0.064)	(0.082)	(0.194)	(0.249)
Treatment	-0.089	-0.183**	-0.037	-0.028
	(0.058)	(0.082)	(0.072)	(0.094)
Controls	YES	YES	YES	YES
Semester Fixed Effects	YES	YES	YES	YES
N	12117	12117	8701	8701

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table A2.3. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treated	0.381***	0.060	0.191	-0.124
	(0.094)	(0.153)	(0.113)	(0.216)
Age 46-65	0.618*	0.029	0.554	-0.045
	(0.270)	(0.221)	(0.563)	(0.497)
Age 65+	0.821**	-0.046	0.583	-0.572
	(0.266)	(0.214)	(0.554)	(0.483)
Male	0.004	0.096	0.028	-0.151
	(0.035)	(0.054)	(0.045)	(0.140)
No. Exemptions	0.066***	0.075***	0.081***	0.160***
	(0.013)	(0.020)	(0.016)	(0.039)
Charlson Index	-0.011	-0.034**	0.029***	-0.067
	(0.007)	(0.012)	(0.008)	(0.038)
Pharmacies per 1000 inh.	-0.027	0.081	0.034	-0.001
	(0.033)	(0.046)	(0.040)	(0.104)
Barrier index	0.008	-0.003	-0.001	0.012
	(0.008)	(0.013)	(0.010)	(0.032)
Constant	-0.747**	-0.928***	-1.453**	-1.484**
	(0.268)	(0.224)	(0.557)	(0.495)
Panel B. Hospitalization				
High Adherence	-0.388***	-0.215**	0.021	-0.004
	(0.053)	(0.070)	(0.071)	(0.398)
Dummy ED	1.881***	1.715***	2.089***	2.005***
	(0.058)	(0.080)	(0.066)	(0.080)
Age 46-65	0.273	0.273	0.521	0.375
	(0.218)	(0.200)	(0.377)	(0.251)
Age 65+	0.220	0.225	0.293	0.264
	(0.214)	(0.195)	(0.370)	(0.245)
Male	0.062*	0.116***	0.071*	0.084*
	(0.027)	(0.035)	(0.032)	(0.039)
No. Exemptions	-0.022*	0.013	-0.030*	-0.039**
	(0.010)	(0.015)	(0.012)	(0.014)
Charlson Index	0.081***	0.090***	0.084***	0.085***
	(0.006)	(0.007)	(0.007)	(0.009)
Constant	-1.635***	-2.065***	-2.063***	-1.985***
	(0.218)	(0.200)	(0.374)	(0.249)
Panel C. Emergency Department Visits				
High Adherence	-0.285***	-0.049	-0.006	-0.644**
	(0.061)	(0.082)	(0.084)	(0.244)
Age 46-65	-0.170	-0.156	-0.379	-0.226
	(0.172)	(0.141)	(0.404)	(0.155)
Age 65+	-0.126	-0.183	-0.551	-0.142
	(0.169)	(0.137)	(0.399)	(0.147)
Male	0.006	-0.035	0.001	-0.102**
	(0.024)	(0.027)	(0.027)	(0.032)
No. Exemptions	-0.018*	0.008	-0.028**	-0.012
	(0.009)	(0.012)	(0.010)	(0.012)
Charlson Index	0.064***	0.059***	0.060***	0.080***
	(0.005)	(0.006)	(0.006)	(0.007)
Barrier index	-0.009	0.001	-0.016**	-0.009
	(0.006)	(0.006)	(0.006)	(0.007)
Constant	-0.117	-0.506***	0.237	-0.281
	(0.169)	(0.140)	(0.400)	(0.149)
Rho21	0.021	-0.014	0.010	-0.012
	(0.031)	(0.044)	(0.035)	(0.043)
Rho31	0.020	0.010	-0.023	-0.039
	(0.028)	(0.034)	(0.036)	(0.137)
Rho32	-0.026	-0.057	0.002	0.115
	(0.035)	(0.044)	(0.047)	(0.104)
N	16705	11270	11890	8543

Standard errors in parentheses

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

Table A2.4. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence, Including Lagged Dependent Variables

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treated	0.283**	0.064	0.021	-0.105
	(0.094)	(0.181)	(0.110)	(0.276)
Age 46-65	0.200	-0.161	-0.232	0.097
	(0.235)	(0.187)	(0.595)	(0.229)
Age 65+	0.304	-0.289	-0.224	-0.377*
	(0.233)	(0.182)	(0.589)	(0.190)
Male	0.040	0.068	0.014	-0.196
	(0.030)	(0.042)	(0.037)	(0.128)
No. Exemptions	0.019	0.020	0.044***	0.064
	(0.011)	(0.016)	(0.013)	(0.040)
Charlson Index	-0.013*	-0.026**	0.026***	-0.031
	(0.006)	(0.009)	(0.007)	(0.026)
Pharmacies per 1000 inh.	-0.023	0.046	0.011	0.017
	(0.025)	(0.031)	(0.032)	(0.105)
Adherence [t-1]	0.025***	0.034***	0.026***	0.049***
	(0.000)	(0.001)	(0.001)	(0.003)
Constant	-1.815***	-2.617***	-1.999***	-3.870***
	(0.234)	(0.197)	(0.589)	(0.302)
Panel B. Hospitalization				
High Adherence	-0.295***	-0.194**	-0.035	0.194
	(0.043)	(0.059)	(0.057)	(0.174)
Dummy ED	1.905***	1.800***	1.983***	1.873***
	(0.065)	(0.079)	(0.085)	(0.116)
Age 46-65	-0.076	0.378	0.804	0.407
	(0.289)	(0.224)	(0.467)	(0.245)
Age 65+	-0.042	0.400	0.808	0.371
	(0.285)	(0.216)	(0.457)	(0.235)
Male	0.083**	0.137***	0.097**	0.106*
	(0.032)	(0.039)	(0.037)	(0.046)
No. Exemptions	0.011	0.018	-0.003	0.005
	(0.012)	(0.016)	(0.013)	(0.015)
Charlson Index	0.085***	0.087***	0.082***	0.088***
	(0.006)	(0.007)	(0.007)	(0.010)
Hospitalization [t−1]	0.196***	0.195***	0.196***	0.230***
	(0.036)	(0.051)	(0.044)	(0.053)
Constant	-1.719***	-2.366***	-2.743***	-2.387***
	(0.287)	(0.221)	(0.460)	(0.240)

Table A2.4. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence, Including Lagged Dependent Variables (continue)

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel C. Emergency Department Visits				
High Adherence	-0.108**	-0.130**	-0.059	-0.122
	(0.037)	(0.046)	(0.048)	(0.136)
Age 46-65	-0.036	-0.260	-0.146	-0.129
	(0.230)	(0.137)	(0.342)	(0.241)
Age 65+	0.049	-0.235	-0.155	-0.033
	(0.226)	(0.131)	(0.334)	(0.234)
Male	0.019	-0.040	0.021	-0.095**
	(0.025)	(0.029)	(0.030)	(0.035)
No. Exemptions	0.007	0.022	0.015	0.024
	(0.009)	(0.013)	(0.010)	(0.012)
Charlson Index	0.065***	0.059***	0.067***	0.080***
	(0.005)	(0.006)	(0.006)	(0.008)
Barrier index	-0.012*	0.000	-0.009	-0.006
	(0.006)	(0.007)	(0.006)	(0.008)
ED access [t-1]	0.335***	0.229***	0.311***	0.313***
	(0.026)	(0.034)	(0.030)	(0.037)
Constant	-0.723**	-0.574***	-0.531	-0.760**
	(0.226)	(0.134)	(0.335)	(0.236)
Rho21	-0.005	-0.061	0.045	0.021
	(0.035)	(0.043)	(0.045)	(0.062)
Rho31	0.076**	0.061	0.080*	-0.078
	(0.026)	(0.033)	(0.034)	(0.102)
Rho32	-0.043	0.038	0.126***	-0.102
	(0.024)	(0.030)	(0.031)	(0.097)
N	12367	8944	8499	6357

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2.5. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence (Adherence Threshold ≥ 70%)

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treated	0.373***	0.055	0.194	-0.021
	(0.097)	(0.147)	(0.111)	(0.239)
Age 46-65	0.715**	-0.040	0.643	0.002
	(0.271)	(0.201)	(0.562)	(0.499)
Age 65+	0.936***	-0.088	0.672	-0.489
	(0.267)	(0.194)	(0.554)	(0.485)
Male	-0.021	0.097	0.034	-0.126
	(0.035)	(0.051)	(0.043)	(0.123)
No. Exemptions	0.066***	0.077***	0.076***	0.155***
	(0.013)	(0.019)	(0.016)	(0.035)
Charlson Index	-0.009	-0.033**	0.027**	-0.057
	(0.007)	(0.011)	(0.008)	(0.031)
Pharmacies per 1000 inh.	-0.015	0.069	0.029	0.006
	(0.033)	(0.045)	(0.039)	(0.104)
Barrier index	0.007	0.001	-0.003	0.001
	(0.009)	(0.013)	(0.010)	(0.030)
Constant	-0.745**	-0.731***	-1.452**	-1.519**
	(0.269)	(0.204)	(0.556)	(0.498)
Panel B. Hospitalization				
High Adherence	-0.357***	-0.196**	0.028	0.188
	(0.053)	(0.068)	(0.068)	(0.278)
Dummy ED	1.880***	1.715***	2.088***	2.006***
	(0.058)	(0.080)	(0.066)	(0.080)
Age class 46-65	0.282	0.274	0.518	0.374
	(0.218)	(0.201)	(0.377)	(0.248)
Age class >65	0.229	0.227	0.290	0.272
	(0.215)	(0.196)	(0.370)	(0.242)
Male	0.058*	0.115***	0.071*	0.086*
	(0.027)	(0.035)	(0.032)	(0.039)
No. Exemptions	-0.023*	0.013	-0.030**	-0.041**
	(0.010)	(0.015)	(0.012)	(0.014)
Charlson Index	0.081***	0.090***	0.084***	0.086***
	(0.006)	(0.007)	(0.007)	(0.009)
Constant	-1.638***	-2.062***	-2.062***	-1.998***
	(0.218)	(0.201)	(0.373)	(0.246)
Panel C. Emergency Department Visits				
High Adherence	-0.278***	-0.090	-0.023	-0.369
	(0.061)	(0.076)	(0.081)	(0.196)
Age 46-65	-0.160	-0.157	-0.376	-0.224
	(0.172)	(0.141)	(0.403)	(0.158)
Age 65+	-0.115	-0.185	-0.548	-0.127
	(0.169)	(0.137)	(0.398)	(0.150)
Male	0.003	-0.034	0.001	-0.100**
	(0.024)	(0.027)	(0.027)	(0.032)
No. Exemptions	-0.019*	0.009	-0.028**	-0.015
	(0.009)	(0.012)	(0.010)	(0.011)
Charlson Index	0.064***	0.059***	0.060***	0.081***
	(0.005)	(0.006)	(0.006)	(0.007)
Barrier index	-0.009	0.001	-0.016**	-0.009
	(0.005)	(0.006)	(0.006)	(0.007)
Constant	-0.116	-0.494***	0.237	-0.300*
	(0.168)	(0.140)	(0.399)	(0.152)
Rho21	0.025	-0.014	0.010	-0.010
	(0.031)	(0.044)	(0.035)	(0.043)
Rho31	0.031	0.004	-0.013	-0.065
	(0.028)	(0.033)	(0.035)	(0.091)
Rho32	-0.005	-0.041	0.033	0.018
	(0.035)	(0.041)	(0.046)	(0.079)
N	16705	11270	11890	8543

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

Tabel A2.6. Multivariate Probit Estimates of Hospitalization, ED Visits, and Adherence (Adherence Threshold ≥ 90%)

	(1) ATC A02BC02	(2) ATC A10BA02	(3) ATC C03CA01	(4) ATC C07AB07
Panel A. Adherence				
Treated	0.414***	0.105	0.137	-0.067
	(0.091)	(0.157)	(0.124)	(0.215)
Age 46-65	0.611*	0.061	4.395***	-0.097
	(0.268)	(0.258)	(0.112)	(0.500)
Age 65+	0.800**	-0.049	4.365***	-0.643
	(0.264)	(0.252)	(0.048)	(0.485)
Male	0.002	0.107	0.046	-0.187
	(0.034)	(0.061)	(0.051)	(0.149)
No. Exemptions	0.061***	0.064**	0.089***	0.159***
	(0.013)	(0.022)	(0.018)	(0.040)
Charlson Index	-0.011	-0.036**	0.039***	-0.069
	(0.007)	(0.014)	(0.009)	(0.042)
Pharmacies per 1000 inh.	-0.020	0.086	0.025	0.015
	(0.032)	(0.051)	(0.044)	(0.106)
Barrier index	0.008	-0.002	-0.007	0.012
	(0.008)	(0.015)	(0.011)	(0.032)
Constant	-0.801**	-1.078***	-5.528***	-1.466**
	(0.266)	(0.262)	(0.083)	(0.498)
Panel B. Hospitalization				
High Adherence	-0.410***	-0.151	0.023	-0.060
	(0.053)	(0.079)	(0.080)	(0.421)
Dummy ED	1.880***	1.716***	2.090***	2.008***
	(0.058)	(0.080)	(0.066)	(0.080)
Age 46-65	0.275	0.272	0.518	0.375
	(0.214)	(0.201)	(0.378)	(0.252)
Age 65+	0.221	0.226	0.291	0.261
	(0.211)	(0.196)	(0.371)	(0.246)
Male	0.061*	0.114***	0.071*	0.084*
	(0.027)	(0.035)	(0.032)	(0.039)
No. Exemptions	-0.022*	0.010	-0.030*	-0.039**
	(0.010)	(0.015)	(0.012)	(0.014)
Charlson Index	0.081***	0.090***	0.084***	0.085***
	(0.006)	(0.007)	(0.007)	(0.009)
Constant	-1.638***	-2.081***	-2.061***	-1.982***
	(0.214)	(0.201)	(0.375)	(0.250)
Panel C. Emergency Department Visits				
High Adherence	-0.290***	-0.047	0.053	-0.725**
	(0.061)	(0.088)	(0.088)	(0.251)
Age 46-65	-0.172	-0.156	-0.391	-0.230
	(0.172)	(0.141)	(0.404)	(0.155)
Age 65+	-0.130	-0.183	-0.562	-0.147
	(0.169)	(0.136)	(0.399)	(0.147)
Male	0.006	-0.035	0.000	-0.104**
	(0.024)	(0.027)	(0.027)	(0.032)
No. Exemptions	-0.019*	0.007	-0.030**	-0.012
	(0.009)	(0.012)	(0.010)	(0.011)
Charlson Index	0.064***	0.059***	0.059***	0.080***
	(0.005)	(0.006)	(0.006)	(0.007)
Barrier index	-0.009	0.001	-0.016**	-0.008
	(0.006)	(0.006)	(0.006)	(0.007)
Constant	-0.119	-0.508***	0.241	-0.275
	(0.169)	(0.139)	(0.399)	(0.149)
Rho21	0.020	-0.013	0.010	-0.013
	(0.031)	(0.044)	(0.035)	(0.043)
Rho31	0.016	-0.019	-0.027	-0.004
	(0.028)	(0.037)	(0.038)	(0.139)
Rho32	-0.039	-0.056	-0.026	0.128
	(0.035)	(0.045)	(0.046)	(0.104)
N	16705	11270	11890	8543

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

Appendix 3

Table A3.1. Closed System ENDS Taxes (2023$) Across States and Years

State	Effective Date	Closed System ENDS Tax per mL Fluid, Q1-4 Average (2023 $)									
		2010	2015	2016	2017	2018	2019	2020	2021	2022	2023
California	04/2017, 07/2017, 07/2018, 07/2019, 07/2020, 07/2021, 07/2022, 07/2023	$0.00	$0.00	$0.00	$1.49	$2.36	$2.21	$2.08	$2.05	$2.25	$2.30
Colorado	01/2021, 01/2022, 01/2023	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$1.02	$1.11	$1.52
Connecticut	10/2019	$0.00	$0.00	$0.00	$0.00	$0.00	$0.12	$0.47	$0.45	$0.42	$0.40
Delaware	01/2018	$0.00	$0.00	$0.00	$0.00	$0.06	$0.06	$0.06	$0.06	$0.05	$0.05
D.C.	10/2015, 10/2016, 10/2017, 10/2018, 10/2019, 10/2021, 10/2022	$0.00	$0.65	$2.56	$2.41	$2.54	$3.43	$3.25	$3.01	$2.52	$2.40
Georgia	01/2021	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.06	$0.05	$0.05
Illinois	01/2016, 04/2016, 07/2016, 01/2017, 01/2018, 01/2019, 07/2019, 01/2020, 01/2021, 01/2022, 01/2023	$0.00	$0.00	$0.41	$0.43	$0.42	$1.01	$1.28	$1.21	$1.12	$1.08
Indiana	07/2022	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.24	$0.46
Kansas	01/2017, 07/2017	$0.00	$0.00	$0.00	$0.16	$0.06	$0.06	$0.06	$0.06	$0.05	$0.05
Kentucky	07/2020, 10/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.65	$1.50	$1.39	$1.33
Louisiana	07/2015, 10/2015, 07/2023	$0.00	$0.03	$0.06	$0.06	$0.06	$0.06	$0.06	$0.06	$0.05	$0.10
Massachusetts	04/2020, 07/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$1.56	$2.56	$2.37	$2.28
Maine	01/2020, 04/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$1.53	$1.46	$1.36	$1.31
Maryland	07/2015, 10/2015, 01/2016, 01/2017, 01/2018, 01/2019, 01/2020, 01/2021, 04/2021, 01/2022, 01/2023	$0.00	$0.07	$0.20	$0.20	$0.19	$0.19	$0.18	$2.15	$2.46	$2.37
Minnesota	07/2010, 10/2010, 01/2015	$1.24	$3.71	$3.66	$3.59	$3.50	$3.44	$3.40	$3.24	$3.00	$2.89
Nevada	01/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$1.07	$1.02	$0.95	$0.91

State	Effective Date	2010	2015	2016	2017	2018	2019	2020	2021	2022	2023
New Hampshire	01/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.35	$0.34	$0.31	$0.30
New Jersey	07/2018, 10/2018	$0.00	$0.00	$0.00	$0.00	$0.03	$0.12	$0.12	$0.11	$0.10	$0.10
New Mexico	07/2019	$0.00	$0.00	$0.00	$0.00	$0.00	$0.26	$0.52	$0.50	$0.46	$0.44
New York	10/2019, 01/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.08	$0.97	$0.92	$0.85	$0.82
North Carolina	04/2015, 07/2015	$0.00	$0.04	$0.06	$0.06	$0.06	$0.06	$0.06	$0.06	$0.05	$0.05
Ohio	10/2019, 01/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.02	$0.12	$0.11	$0.10	$0.10
Oregon	01/2021	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$2.21	$2.06	$1.97
Pennsylvania	07/2016, 10/2016	$0.00	$0.00	$0.72	$1.51	$1.47	$1.45	$1.43	$1.36	$1.26	$1.21
Utah	07/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$1.00	$1.91	$1.77	$1.70
Vermont	07/2019	$0.00	$0.00	$0.00	$0.00	$0.00	$1.67	$3.29	$3.13	$2.91	$2.79
Virginia	07/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.04	$0.07	$0.07	$0.07
Washington	10/2019	$0.00	$0.00	$0.00	$0.00	$0.00	$0.08	$0.32	$0.30	$0.28	$0.27
West Virginia	07/2016	$0.00	$0.00	$0.05	$0.09	$0.09	$0.09	$0.09	$0.08	$0.08	$0.08
Wisconsin	10/2019	$0.00	$0.00	$0.00	$0.00	$0.00	$0.01	$0.06	$0.06	$0.05	$0.05
Wyoming	07/2020	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.27	$0.51	$0.47	$0.46

Source: Standardized ENDS taxes are from Cotti et al (2023,2024).

Table A3.2. Open System ENDS Taxes (2023$) Across States and Years

State	Open System ENDS Tax, Q1-4 Average (2023 $)									
	2010	2015	2016	2017	2018	2019	2020	2021	2022	2023
California	$0.00	$0.00	$0.00	$0.33	$0.52	$0.49	$0.46	$0.46	$0.50	$0.51
Colorado	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.23	$0.25	$0.34
Connecticut	$0.00	$0.00	$0.00	$0.00	$0.00	$0.02	$0.08	$0.08	$0.07	$0.07
Delaware	$0.00	$0.00	$0.00	$0.00	$0.06	$0.06	$0.06	$0.06	$0.05	$0.05
District of Columbia	$0.00	$0.15	$0.57	$0.53	$0.56	$0.76	$0.72	$0.67	$0.56	$0.53
Georgia	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.05	$0.05	$0.05
Illinois	$0.00	$0.00	$0.41	$0.43	$0.42	$1.01	$1.28	$1.22	$1.12	$1.08
Indiana	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.07	$0.14
Kansas	$0.00	$0.00	$0.00	$0.16	$0.06	$0.06	$0.06	$0.06	$0.05	$0.05
Kentucky	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.05	$0.11	$0.11	$0.10
Louisiana	$0.00	$0.03	$0.06	$0.06	$0.06	$0.06	$0.06	$0.06	$0.05	$0.10
Maine	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.34	$0.33	$0.30	$0.29
Maryland	$0.00	$0.07	$0.20	$0.20	$0.19	$0.19	$0.18	$2.16	$2.46	$2.37
Massachusetts	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.35	$0.57	$0.53	$0.51
Minnesota	$0.27	$0.82	$0.81	$0.80	$0.78	$0.76	$0.75	$0.72	$0.67	$0.64
Nevada	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.24	$0.23	$0.21	$0.20
New Hampshire	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.06	$0.06	$0.06	$0.05
New Jersey	$0.00	$0.00	$0.00	$0.00	$0.03	$0.11	$0.11	$0.10	$0.09	$0.09
New Mexico	$0.00	$0.00	$0.00	$0.00	$0.00	$0.05	$0.10	$0.09	$0.09	$0.08
New York	$0.00	$0.00	$0.00	$0.00	$0.00	$0.02	$0.21	$0.20	$0.19	$0.18
North Carolina	$0.00	$0.04	$0.06	$0.06	$0.06	$0.06	$0.06	$0.06	$0.05	$0.05
Ohio	$0.00	$0.00	$0.00	$0.00	$0.00	$0.02	$0.12	$0.11	$0.10	$0.10
Oregon	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.49	$0.46	$0.44
Pennsylvania	$0.00	$0.00	$0.16	$0.34	$0.33	$0.32	$0.32	$0.30	$0.28	$0.27
Utah	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.22	$0.42	$0.39	$0.38
Vermont	$0.00	$0.00	$0.00	$0.00	$0.00	$0.37	$0.73	$0.70	$0.65	$0.62
Virginia	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.04	$0.07	$0.07	$0.07
Washington	$0.00	$0.00	$0.00	$0.00	$0.00	$0.03	$0.11	$0.10	$0.09	$0.09
West Virginia	$0.00	$0.00	$0.05	$0.09	$0.09	$0.09	$0.09	$0.08	$0.08	$0.08
Wisconsin	$0.00	$0.00	$0.00	$0.00	$0.00	$0.01	$0.03	$0.00	$0.00	$0.00
Wyoming	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.06	$0.11	$0.11	$0.10

Source: Standardized ENDS taxes are from Cotti et al (2023,2024)

Table A3.3. TWFE Estimates of ENDS Taxes on Current ENDS Use

	(1) Current ENDS use	(2) Current ENDS use	(3) Current ENDS use	(4) Current ENDS use	(5) Current ENDS use	(6) Current ENDS use
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Female	-0.013***	-0.013***	-0.013***	-0.013***		
	(0.002)	(0.002)	(0.002)	(0.002)		
Black	-0.026***	-0.026***	-0.026***	-0.026***		
	(0.005)	(0.005)	(0.005)	(0.005)		
Asian	-0.046***	-0.046***	-0.046***	-0.046***		
	(0.005)	(0.005)	(0.005)	(0.005)		
Other	0.013***	0.013***	0.013***	0.013***		
	(0.003)	(0.003)	(0.003)	(0.003)		
Hispanic	-0.026***	-0.026***	-0.026***	-0.026***		
	(0.003)	(0.003)	(0.003)	(0.003)		
ENDS Tax (2023$)	-0.005***	-0.005***	-0.012***	-0.012***	-0.005***	-0.007**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Cumulative COVID-19 death rate		2.811	1.763	1.448	1.819	2.987
		(2.974)	(2.880)	(2.755)	(2.978)	(2.791)
Cumulative COVID-19 case rate		0.009	0.012	0.023	0.020	0.004
		(0.056)	(0.053)	(0.050)	(0.043)	(0.046)
Unemployment rate		0.000	-0.000	-0.000	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty rate		0.000	0.000	0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Flavored ENDS ban			0.015***	0.014**	0.006	0.008
			(0.004)	(0.004)	(0.004)	(0.005)
Tobacco 21 law			0.000	-0.000	0.001	-0.001
			(0.003)	(0.003)	(0.002)	(0.002)
ENDS MLSA law			-0.002	-0.001	-0.001	-0.001
			(0.003)	(0.002)	(0.003)	(0.003)
Indoor vaping ban			-0.002	-0.002	0.001	-0.001
			(0.003)	(0.003)	(0.002)	(0.002)
ENDS licensure law			0.005	0.006*	0.006**	0.005**
			(0.003)	(0.003)	(0.002)	(0.002)
ENDS online sales ban			-0.006	-0.006	-0.009	-0.007
			(0.004)	(0.004)	(0.005)	(0.005)
Indoor smoking ban			0.003	0.002	0.001	0.008
			(0.005)	(0.005)	(0.004)	(0.005)
Cigarette tax (2023$)			0.005*	0.005*	0.001	0.003
			(0.002)	(0.002)	(0.001)	(0.002)
Beer Tax (2023$)				0.006	0.003	0.002
				(0.037)	(0.005)	(0.023)
RML				0.002	0.002	-0.000
				(0.004)	(0.004)	(0.004)
MML				0.000	0.002	0.002
				(0.003)	(0.002)	(0.002)
DML				0.009*	0.003	0.007
				(0.004)	(0.003)	(0.004)
Constant	0.190***	0.183***	0.176***	0.170***	0.082*	0.077
	(0.003)	(0.010)	(0.011)	(0.014)	(0.041)	(0.041)
Pre Treatment Mean	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661
N	286,988	286,988	286,988	286,988	305,084	305,084

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3.4. TWFE Estimates of ENDS Taxes on Frequent ENDS Use

	(1) Frequent ENDS use	(2) Frequent ENDS use	(3) Frequent ENDS use	(4) Frequent ENDS use	(5) Frequent ENDS use	(6) Frequent ENDS use
Age	-0.001***	-0.001***	-0.001***	-0.001***	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.008***	-0.008***	-0.008***	-0.008***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Black	-0.020***	-0.020***	-0.020***	-0.020***		
	(0.003)	(0.003)	(0.003)	(0.003)		
Asian	-0.022***	-0.022***	-0.022***	-0.022***		
	(0.003)	(0.003)	(0.003)	(0.003)		
Other	0.003	0.003	0.003	0.003		
	(0.002)	(0.002)	(0.002)	(0.002)		
Hispanic	-0.021***	-0.021***	-0.021***	-0.021***		
	(0.002)	(0.002)	(0.002)	(0.002)		
ENDS Tax (2023$)	-0.005***	-0.004***	-0.006***	-0.006***	-0.003	-0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Cumulative COVID-19 death rate		0.763	0.694	1.201	2.608	2.940
		(1.928)	(1.992)	(1.811)	(1.921)	(1.925)
Cumulative COVID-19 case rate		0.064	0.078	0.072	0.077*	0.074
		(0.041)	(0.043)	(0.039)	(0.035)	(0.038)
Unemployment rate		-0.001	-0.000	-0.000	-0.000	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty rate		0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Flavored ENDS ban			-0.001	0.000	-0.007	-0.006
			(0.003)	(0.004)	(0.004)	(0.004)
Tobacco 21 law			0.001	0.001	0.001	0.001
			(0.002)	(0.002)	(0.002)	(0.002)
ENDS MLSA law			-0.001	-0.000	-0.000	-0.000
			(0.001)	(0.001)	(0.002)	(0.002)
Indoor vaping ban			-0.001	-0.001	-0.001	-0.001
			(0.002)	(0.002)	(0.002)	(0.002)
ENDS licensure law			0.002	0.001	0.003	0.002
			(0.002)	(0.002)	(0.001)	(0.002)
ENDS online sales ban			-0.001	-0.000	0.001	0.001
			(0.003)	(0.003)	(0.003)	(0.004)
Indoor smoking ban			-0.005	-0.003	-0.001	0.000
			(0.003)	(0.003)	(0.001)	(0.003)
Cigarette tax (2023$)			0.004*	0.004*	0.002	0.003
			(0.002)	(0.002)	(0.001)	(0.002)
Beer Tax (2023$)				-0.003	0.001	-0.004
				(0.026)	(0.004)	(0.017)
RML				-0.003	-0.003	-0.003
				(0.003)	(0.002)	(0.003)
MML				-0.000	0.001	0.001
				(0.002)	(0.002)	(0.002)
DML				-0.000	0.001	-0.001
				(0.003)	(0.002)	(0.003)
Constant	0.082***	0.075***	0.070***	0.069***	-0.011	-0.014
	(0.002)	(0.007)	(0.008)	(0.010)	(0.024)	(0.025)
Pre Treatment Mean	0.0244	0.0244	0.0244	0.0244	0.0244	0.0244
N	286,988	286,988	286,988	286,988	305,084	305,084

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3.5. TWFE Estimates of ENDS Taxes on Everyday ENDS Use

	(1) Everyday ENDS use	(2) Everyday ENDS use	(3) Everyday ENDS use	(4) Everyday ENDS use	(5) Everyday ENDS use	(6) Everyday ENDS use
Age	-0.001***	-0.001***	-0.001***	-0.001***	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.007***	-0.007***	-0.007***	-0.007***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Black	-0.019***	-0.019***	-0.019***	-0.019***		
	(0.003)	(0.003)	(0.003)	(0.003)		
Asian	-0.020***	-0.020***	-0.020***	-0.020***		
	(0.003)	(0.003)	(0.003)	(0.003)		
Other	0.001	0.001	0.001	0.001		
	(0.002)	(0.002)	(0.002)	(0.002)		
Hispanic	-0.019***	-0.019***	-0.019***	-0.019***		
	(0.002)	(0.002)	(0.002)	(0.002)		
ENDS Tax (2023$)	-0.004***	-0.004***	-0.005***	-0.005***	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Cumulative COVID-19 death rate		1.092	1.060	1.425	2.566	2.911
		(1.590)	(1.694)	(1.567)	(1.699)	(1.751)
Cumulative COVID-19 case rate		0.042	0.051	0.047	0.063	0.060
		(0.036)	(0.039)	(0.036)	(0.036)	(0.039)
Unemployment rate		-0.001	-0.001	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty rate		0.000	0.000	0.000	0.000	0.001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Flavored ENDS ban			-0.002	-0.000	-0.006	-0.006
			(0.003)	(0.003)	(0.003)	(0.004)
Tobacco 21 law			0.001	0.002	0.001	0.000
			(0.002)	(0.002)	(0.002)	(0.002)
ENDS MLSA law			-0.001	-0.001	-0.000	-0.001
			(0.001)	(0.001)	(0.002)	(0.002)
Indoor vaping ban			-0.001	-0.001	-0.000	-0.001
			(0.002)	(0.002)	(0.002)	(0.002)
ENDS licensure law			0.001	0.001	0.002	0.001
			(0.002)	(0.002)	(0.001)	(0.001)
ENDS online sales ban			-0.000	0.000	0.002	0.002
			(0.002)	(0.003)	(0.003)	(0.003)
Indoor smoking ban			-0.004	-0.002	-0.001	0.001
			(0.002)	(0.003)	(0.002)	(0.003)
Cigarette tax (2023$)			0.003	0.003*	0.001	0.002
			(0.001)	(0.001)	(0.001)	(0.002)
Beer Tax (2023$)				-0.001	-0.003	-0.005
				(0.023)	(0.005)	(0.016)
RML				-0.002	-0.002	-0.003
				(0.002)	(0.002)	(0.003)
MML				-0.000	0.001	0.001
				(0.001)	(0.002)	(0.002)
DML				0.000	0.000	-0.001
				(0.003)	(0.002)	(0.003)
Constant	0.072***	0.067***	0.063***	0.062***	-0.012	-0.016
	(0.002)	(0.006)	(0.006)	(0.009)	(0.023)	(0.025)
Pre Treatment Mean	0.0211	0.0211	0.0211	0.0211	0.0211	0.0211
N	286,988	286,988	286,988	286,988	305,084	305,084

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3.6. TWFE Estimates of ENDS Taxes on Current Cigarette Use

	(1) Current cigarette use	(2) Current cigarette use	(3) Current cigarette use	(4) Current cigarette use	(5) Current cigarette use	(6) Current cigarette use
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Female	-0.039***	-0.039***	-0.039***	-0.039***		
	(0.004)	(0.004)	(0.004)	(0.004)		
Black	0.037***	0.037***	0.037***	0.037***		
	(0.010)	(0.010)	(0.010)	(0.010)		
Asian	-0.087***	-0.087***	-0.087***	-0.087***		
	(0.013)	(0.013)	(0.013)	(0.013)		
Other	0.031***	0.031***	0.031***	0.031***		
	(0.007)	(0.007)	(0.007)	(0.007)		
Hispanic	-0.023***	-0.023***	-0.023***	-0.023***		
	(0.006)	(0.006)	(0.006)	(0.006)		
ENDS Tax (2023$)	0.003	0.002	0.004	0.004	0.003	0.004
	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
Cumulative COVID-19 death rate		-5.996	-5.835	-5.624	-4.660	-4.758
		(3.318)	(3.353)	(3.597)	(3.587)	(3.544)
Cumulative COVID-19 case rate		0.108	0.119	0.114	0.009	0.023
		(0.091)	(0.078)	(0.079)	(0.069)	(0.067)
Unemployment rate		0.001	0.000	0.000	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Poverty rate		-0.000	-0.000	0.000	-0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Flavored ENDS ban			-0.002	-0.003	-0.001	-0.003
			(0.004)	(0.005)	(0.005)	(0.005)
Tobacco 21 law			-0.006	-0.006	-0.003	-0.003
			(0.005)	(0.005)	(0.003)	(0.004)
ENDS MLSA law			0.005	0.005	-0.003	-0.003
			(0.003)	(0.004)	(0.003)	(0.003)
Indoor vaping ban			-0.002	-0.002	0.004	0.003
			(0.004)	(0.004)	(0.003)	(0.003)
ENDS licensure law			-0.005	-0.005	-0.001	-0.001
			(0.003)	(0.003)	(0.002)	(0.002)
ENDS online sales ban			0.002	0.002	-0.003	-0.005
			(0.006)	(0.006)	(0.005)	(0.006)
Indoor smoking ban			0.009*	0.006	0.001	0.004
			(0.004)	(0.005)	(0.004)	(0.006)
Cigarette tax (2023$)			-0.002	-0.002	-0.002	-0.004
			(0.004)	(0.004)	(0.002)	(0.003)
Beer Tax (2023$)				0.004	-0.012*	-0.005
				(0.044)	(0.006)	(0.029)
RML				0.001	0.001	0.001
				(0.004)	(0.003)	(0.004)
MML				-0.005	-0.002	-0.002
				(0.004)	(0.003)	(0.003)
DML				-0.005	-0.003	-0.005
				(0.007)	(0.003)	(0.003)
Constant	0.244***	0.239***	0.239***	0.244***	0.214**	0.209**
	(0.006)	(0.012)	(0.014)	(0.021)	(0.066)	(0.070)
Pre Treatment Mean	0.1872	0.1872	0.1872	0.1872	0.1872	0.1872
N	288,106	288,106	288,106	288,106	306,306	306,306

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3.7. OLogit Estimates of the Effect of ENDS Taxes on Relative Risk

	(1) Relative ENDS harm	(2) Relative ENDS harm	(3) Relative ENDS harm	(4) Relative ENDS harm
Age	0.015***	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.388***	0.388***	0.388***	0.388***
	(0.019)	(0.019)	(0.019)	(0.019)
Black	0.598***	0.598***	0.598***	0.598***
	(0.031)	(0.031)	(0.031)	(0.031)
Asian	0.201*	0.201*	0.201*	0.201*
	(0.079)	(0.079)	(0.079)	(0.079)
Other	0.155***	0.155***	0.155***	0.155***
	(0.035)	(0.035)	(0.035)	(0.035)
Hispanic	0.686***	0.686***	0.686***	0.686***
	(0.057)	(0.057)	(0.057)	(0.057)
ENDS Tax (2023$)	-0.065**	-0.060*	0.012	0.006
	(0.024)	(0.024)	(0.037)	(0.034)
Cumulative COVID-19 death rate		10.671	12.861	13.163
		(34.207)	(31.552)	(31.096)
Cumulative COVID-19 case rate		0.426	0.717	0.769
		(0.703)	(0.659)	(0.662)
Unemployment rate		0.003	0.006	0.008
		(0.016)	(0.015)	(0.015)
Poverty rate		0.008	0.008	0.004
		(0.008)	(0.008)	(0.007)
Flavored ENDS ban			-0.120	-0.094
			(0.071)	(0.066)
Tobacco 21 law			0.019	0.027
			(0.065)	(0.063)
ENDS MLSA law			0.068*	0.080*
			(0.034)	(0.033)
Indoor vaping ban			-0.007	-0.011
			(0.044)	(0.038)
ENDS licensure law			-0.045	-0.046
			(0.042)	(0.040)
ENDS online sales ban			-0.031	-0.008
			(0.063)	(0.062)
Indoor smoking ban			-0.057	0.021
			(0.077)	(0.078)
Cigarette tax (2023$)			-0.040	-0.041
			(0.040)	(0.039)
Beer Tax (2023$)				0.289
				(0.427)
RML				-0.065*
				(0.026)
MML				0.061
				(0.041)
DML				0.074
				(0.064)
cut1	-1.097***	-0.800	-0.636	-0.283
	(0.253)	(0.433)	(0.411)	(0.650)
cut2	2.314***	2.610***	2.775***	3.129***
	(0.259)	(0.434)	(0.413)	(0.654)
Pre Treatment Mean	1.8129	1.8129	1.8129	1.8129
N	277,910	277,910	277,910	277,910

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3.8. OLogit Estimates of the Effect of ENDS Taxes on Absolute Risk

	(1) Absolute ENDS harm	(2) Absolute ENDS harm	(3) Absolute ENDS harm	(4) Absolute ENDS harm
Age	0.016***	0.016***	0.016***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.542***	0.542***	0.543***	0.543***
	(0.018)	(0.018)	(0.018)	(0.018)
Black	0.161***	0.161***	0.161***	0.161***
	(0.041)	(0.041)	(0.041)	(0.041)
Asian	0.021	0.021	0.021	0.021
	(0.089)	(0.089)	(0.089)	(0.089)
Other	-0.056	-0.056	-0.056	-0.056
	(0.033)	(0.033)	(0.033)	(0.033)
Hispanic	0.493***	0.493***	0.493***	0.493***
	(0.041)	(0.041)	(0.041)	(0.041)
ENDS Tax (2023$)	-0.017	-0.012	0.001	-0.002
	(0.034)	(0.028)	(0.045)	(0.043)
Cumulative COVID-19 death rate		65.577	38.873	41.694
		(39.965)	(31.942)	(35.124)
Cumulative COVID-19 case rate		-1.742*	-1.366	-1.228
		(0.852)	(0.811)	(0.787)
Unemployment rate		-0.009	-0.002	0.001
		(0.018)	(0.013)	(0.012)
Poverty rate		-0.000	-0.001	-0.003
		(0.008)	(0.008)	(0.008)
Flavored ENDS ban			-0.005	0.009
			(0.067)	(0.073)
Tobacco 21 law			0.101	0.107
			(0.070)	(0.069)
ENDS MLSA law			0.104**	0.117***
			(0.033)	(0.033)
Indoor vaping ban			0.012	0.012
			(0.034)	(0.033)
ENDS licensure law			-0.016	-0.015
			(0.036)	(0.036)
ENDS online sales ban			0.004	0.016
			(0.048)	(0.047)
Indoor smoking ban			-0.099*	-0.060
			(0.045)	(0.057)
Cigarette tax (2023$)			-0.007	-0.004
			(0.036)	(0.035)
Beer Tax (2023$)				0.121
				(0.404)
RML				-0.029
				(0.046)
MML				0.047
				(0.035)
DML				0.173***
				(0.047)
cut1	-1.176**	-1.502**	-1.264*	-1.036
	(0.456)	(0.523)	(0.514)	(0.640)
cut2	1.084*	0.758	0.996*	1.225
	(0.450)	(0.515)	(0.507)	(0.638)
Pre Treatment Mean	2.3028	2.3028	2.3028	2.3028
N	216,468	216,468	216,468	216,468

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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