Pharmaceuticals and Digital Health: How Data-driven Insights May Reshape the Insulin Market*

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Abstract

This paper analyzes how insights from digital health data influence pharmaceutical markets. I focus on the impact of Continuous Glucose Monitors (CGMs) on insulin choice. I develop and estimate a tractable model of supply and demand for insulin embedding: (i) patient-specific learning about treatment performance through the digital device, (ii) physician-level learning about new drugs based on patient experiences and (iii) price bargaining by pharmaceutical companies and the regulator, both internalizing demand-side learning. Using French medical claims data, I find that CGMs provided patient-specific insights that steered device users toward newer insulins, with limited information spillovers to non-users. As these new criteria enter pharmaceutical demand, they alter the perceived product differentiation, and by doing so, I document how they can further affect the relative profitability of new drugs and shape future pharmaceutical innovations.

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1 Introduction

From the smartphone step counter to smartwatches, digital devices generating high-frequency health data are now widely available, transforming the landscape of individual-level information for decision-making.[1] This data is compelling for the pharmaceutical industry because prescription drugs are experience goods. Patients exhibit diverse needs, leading to idiosyncratic match values with drugs, and physicians learn about a drug's performance as they prescribe it. By generating timely information, digital technologies can affect pharmaceutical demand via two channels. First, high-frequency data can speed up physicians' learning. Second, it provides detailed patient-specific insights, broadening the criteria for evaluating drugs' effectiveness. Understanding the size of each channel is essential for policy analysis, as each carries distinct implications for pricing, detailing, and innovation incentives.

This paper offers new insights into how digital health technologies influence pharmaceutical markets by disentangling faster learning about new drugs from the effect of detailed patient-specific information. This distinction matters: faster learning upon market entry dampens the barriers to new drug adoption but leaves the perceived product differentiation unchanged once the initial uncertainty is resolved. In contrast, new criteria for evaluating drugs' performance change the information available to physicians when choosing treatments, potentially affecting how they perceive product differentiation. By reshaping physicians' preferences for treatments, the criteria brought by these new technologies may not only impact competition between existing products but also affect pharmaceutical innovations' profitability and future market entrants. By emphasizing cross-market complementarities, this paper provides new evidence that innovation in digital devices can shape outcomes in consumer goods markets like pharmaceuticals.

To answer this question, I study the impact of Continuous Glucose Monitors (CGMs) on insulin choices in diabetes treatment. CGMs generate high-frequency glucose level data for diabetic patients. The device provides detailed measurements of daily glucose variation, including overnight, and expands the criteria available to evaluate insulin treatment performance. They complement the laboratory-measured average, which can obscure substantial heterogeneity in glucose control (Figure A1). Glucose sensors offer two benefits for physicians: (i) gain direct experience with new products and (ii) tailoring treatments to patients' needs. To disentangle

[1] Examples of such technologies include Continuous Glucose Monitors (CGMs) measuring sugar levels, wearable blood pressure trackers, connected insertable cardiac monitors, sleep trackers (Handel and Kolstad (2017)).

each mechanism and isolate pricing responses, I develop an empirical framework of supply and demand for insulin, accounting for: (i) CGM-generated patient-specific information about insulins' idiosyncratic match values, (ii) physician-level learning about new drugs and (iii) price responses from bargaining with the regulator. I use patient-level claims data from the French health insurance system from 2015 to 2021, during which new insulins entered the market, and changes in the coverage policy boosted CGM adoption. My analysis highlights that CGMs produce new patient-specific criteria for evaluating drug performance, which physicians do not extrapolate to non-users. Yet, they enter pharmaceutical demand for users. I document how these criteria affect the relative profitability of new drugs and may shape future pharmaceutical innovations. The last result underscores the importance of the cross-market complementarities between medical devices and pharmaceuticals.

Several challenges arise in addressing these questions. First, consumer adoption of digital devices is often unobserved along with prescription drug consumption, making it difficult to determine how much information physicians have when prescribing. Second, the high attrition rate for digital technologies — with patients discontinuing use — can be hard to observe without data from device manufacturers. Last, inertia from habit formation arises naturally in demand for experience goods, especially in the case of chronic conditions. Identifying learning separately from switching costs is crucial for effective policy analysis (Dubé et al. (2010)). This paper overcomes these challenges by (i) inferring technology adoption from claims data since CGMs are covered by the French health insurance scheme, (ii) tracking patient attrition of the device through prescription patterns, and (iii) separating learning from switching costs by documenting the first intention insulin choice over time, as new patients are not subject to switching costs.

In the descriptive analysis, I provide three empirical facts highlighting the interaction between CGMs and insulin demand. First, approximately 34% of existing diabetic patients using long-acting insulin adopted CGM — enough to significantly affect insulin demand. Convenience is the primary driver of technology adoption, and poor diabetes control has little effect on uptake. Second, CGM users are 6 to 12% more likely to switch treatment shortly after adoption compared to non-users, suggesting a link between device use and treatment changes. However, this correlation disappears in the medium or long run, suggesting a patient-product mismatch rather than a reduction in switching costs.[2] Patients using CGMs switched from older insulin

[2]I mitigate concerns about the second channel by leveraging the entry of a bioequivalent product and physi-

products to newer alternatives, allowing physicians to gain more experience with these drugs. Third, the positive correlation between the physician-level volume of patient feedback and their switching behavior suggests that physicians may extrapolate insights across patients such that non-users might benefit from the information provided by CGM users.

The insulin market changed, regardless of CGMs, due to new product entries before and after the CGM coverage decision. A structural model is necessary to disentangle the effect of new product entries separately from CGM adoption and pin down the mechanisms at stake. Motivated by the empirical facts, I develop a tractable framework in which, on the demand side, physicians choose the most cost-effective insulin on behalf of heterogeneous patients. For patients without CGMs, physicians rely on incomplete information about the true clinical match value, a criterion imperfectly observed for new products upon entry. Direct experience with new drugs from patients allows physicians to dynamically learn about the clinical match values (Coscelli and Shum (2004)). CGMs offer new patient-specific insights about the patient's glucose profile, which can be informative about (i) a patient, irrespective of the medication, (ii) a drug, irrespective of the patient, or (iii) a particular patient with a specific drug. However, only the last two channels affect pharmaceutical demand, which implies that some complementarity between CGM and the drug's mechanism of action is crucial in influencing demand. In my empirical model, insights from CGMs affect insulin demand from users and alter physicians' dynamic learning about new products' performance. On the supply side, the regulator and insulin manufacturers bargain over price, internalizing demand-side learning and perceived product differentiation. CGMs potentially influence equilibrium insulin prices via their impact new drug learning and perceived product differentiation.

I estimate the demand model using Simulated Maximum Likelihood to account for unobserved patient experience signals. To address selection into CGM, I use a flexible specification for the patient-product match values, controlling for product-specific unobserved heterogeneity common across similar patients. The remaining within-group patient-product heterogeneity is assumed to be independent of the drivers of CGM adoption. The estimates suggest pessimistic beliefs about the performance of new products upon entry. CGM does not increase or decrease the precision of the experience signal about new drugs a physician receives during a medical appointment. It mostly influences insulin choice through an idiosyncratic match value component observed for users thanks to the device. The supply model is estimated using GMM.

cians' first intention treatment choice.

As equilibrium prices remain relatively low despite quasi-inelastic insulin demand, most of the bargaining weight can be attributed to the regulator who maximizes consumer surplus.[3]

Finally, I use the demand and supply framework estimates to compute two counterfactuals illustrating how digital devices affect pharmaceutical markets. First, I assess the short-term impact of CGMs on market outcomes by simulating the equilibrium prices and market shares absent CGMs, holding the set of existing products constant. Second, I explore the potential long-term implications of CGMs on pharmaceutical innovation by simulating the entry of alternative products under different technological environments — with and without CGM.

The first counterfactual shows that most of the short-term consumer welfare gains from CGMs go to device users, while the benefits to non-users are ten times smaller. CGMs have created more opportunities for physicians to learn about the performance of new treatments that appear suitable for patients wearing the device at the expense of older molecules. The insights generated by the device contributed heterogeneously to new drugs' adoption, ranging from a one percentage point decrease for the entering bioequivalent drug to a four percentage points increase (+16%) in 2021. The drug benefiting most from CGM adoption triggers low overnight glucose levels — a feature more complicated to detect without the device.

The second counterfactual documents the complementarity between the medical device and the pharmaceutical markets. Comparing the profits of alternative insulin products in an environment with and without CGMs suggests that the most profitable pharmaceutical innovation strategy can vary depending on the technological environment in which insulin choices are made. This result implies that devices like CGMs, which introduce new criteria for evaluating drug performance, may shape future pharmaceutical innovations.

Related literature The primary contribution of this paper is to develop an empirical framework to understand how digital technologies can overcome demand-side information frictions. In this regard, it contributes to several strands of literature. Primarily, it builds on research analyzing demand-side learning in pharmaceutical markets. The existing literature emphasizes that information frictions about drugs' clinical match values arise upon market entry and initial diagnosis (Coscelli and Shum (2004), Crawford and Shum (2005), Currie and MacLeod (2020)). These frictions decrease as physicians gain direct and indirect experience with the drug — which can come from detailing, scientific information, clinical trials, etc.

[3]In countries like the US, where the government did not intervene in drug pricing until recently, insulin prices for the same product as those offered in France are significantly higher.

(Coscelli and Shum (2004), Zhu (2023), Dickstein (2021), Grennan et al. (2024), Dubois and Tunçel (2021), Alsan et al. (2024)). Building on structural modeling of demand-side learning from experience (Roberts and Urban (1988), Erdem and Keane (1996)), my work is closely related to Crawford and Shum (2005) who focus on learning upon initial patient diagnosis. In this paper, I study learning about new products upon market entry, focusing on patients diagnosed with the disease at the time of entry. In my framework, physicians learn dynamically about drugs' clinical match values across their patient population, drawing on experiences of heterogeneous qualities depending on patients monitoring technology.[4]

When consumers learn dynamically about demand, firms have incentives to adopt forward-looking pricing strategies (Shapiro (1983), Bergemann and Välimäki (2006)). In this context, modeling pricing decisions is inherently complex, leading most of the empirical literature to focus on demand-side mechanisms while keeping prices fixed in counterfactual scenarios. Exceptions in the pharmaceutical context are Ching (2010a) and Ching (2010b). My paper contributes to this literature by building a tractable framework in which physicians' learning is internalized by the pharmaceutical manufacturers and the regulator when engaging in Nash-bargaining over the price of treatments.

This project also contributes to the literature on the impact of information frictions on market outcomes. On the demand side, previous works document how consumer choice under imperfect information affects product offerings (Brown and Jeon (2024)) and how information provision to consumers can shift the market equilibrium (Jin and Leslie (2003), Handel and Kolstad (2015), Barahona et al. (2023)). On the supply side, incomplete information about the demand curve affects firms' behavior beyond insurance markets (Hitsch (2006), Handel and Misra (2015), Doraszelski et al. (2018)). I focus on patient-level data available for decision-making. In the auto insurance market, consumer-level data generated by monitoring technologies can mitigate information asymmetries (Jin and Vasserman (2021)). Instead, I focus on demand-side information frictions and data-driven insights from a monitoring technology that informs consumers about their effective taste for alternative products.

I add to the literature on assessing the value of innovative pharmaceutical drugs and medical devices, drawing on the method developed in the empirical industrial organization literature (Trajtenberg (1989), Petrin (2002)). Igami et al. (2024) measure the welfare gains from product

[4]Beyond learning, this work adds to the literature on inertia sources in demand (Dubé et al. (2010)). In a chronic condition treatment, I document switching costs contribution separately from learning by leveraging the specificities of my institutional setting.

and process innovations. In this paper, I link the last two literatures by studying how new information technologies producing insights available for decision-making can enhance the value of pharmaceutical innovation for consumers by guiding physicians' choices.

This work also explores complementarities across related markets and how innovations in one market may shape outcomes in another. While earlier work documents the impact of upstream innovation in vertically related markets (Eizenberg (2014)), Bresnahan and Trajtenberg (1995) highlight that complementary technologies may be necessary to exploit the potential of new technologies fully. My paper emphasizes the complementarity between medical device innovation and the diffusion of new pharmaceuticals in a context where the adoption of the complementary technology is the consumer's choice. I show how innovations in the medical device market alter pharmaceutical product shares and could shape the product offering.[5]

Finally, this paper contributes to the literature on information technology adoption in healthcare. Earlier empirical works focus on the impact of electronic medical records on health care costs and hospital productivity (Agha (2014), Dranove et al. (2014), Lee et al. (2013), McCullough et al. (2016)) and, more recently, telemedicine (Zeltzer et al. (2024), Dahlstrand (2024)) or artificial intelligence (Agarwal et al. (2023)). Handel and Kolstad (2017) highlight the potential for wearable devices to overcome the lack of data on critical outcomes. Yet, to the best of my knowledge, the literature studying how new information technologies impact healthcare markets is scarce. I extend this literature by documenting the channels through which wearable devices generating high-frequency health data affect treatment choice.

The paper proceeds as follows. Section 2 provides background information on diabetes treatment in France and describes the data. Section 3 documents CGM adoption and its impact on insulin choice. Section 4 develops and estimates a demand model for insulin, with some patients using digital devices. Section 5 models the pricing decision and estimates the model's primitives. Section 6 presents the counterfactual scenarios, and Section 7 concludes.

[5]Previous work by Dranove et al. (2022) highlight that demand shocks can incentivize firms to undertake R&D activities. However, in the context of Medicare Part D, the effect favors follow-up rather than breakthrough innovations.

2 Context and Data

2.1 Diabetes treatment in France

Diabetes is a major chronic condition affecting 1 in 10 adults worldwide.[6] The diseases is characterized by high blood sugar levels which can arise as the pancreas stops producing insulin (Type 1 Diabetes) or as the insulin produced loose its efficacy (Type 2 Diabetes). Both high and low glucose levels can lead to severe complications, including blindness, amputation, stroke, heart attack and kidney failure. The primary goal of diabetes management for the patient (he) and the physician (she) is to stabilize blood glucose within a targeted range.

As of 2021, approximately 22% of diabetic adults in France were dependent on insulin. This project focuses on the choice of long-acting insulin, referred to throughout the paper as *insulin choice*. Long-acting insulin is often combined with short-acting products. While short-acting insulin is injected around meal times to manage food intake, long-acting insulin is designed to stabilize the glucose level over 24 hours. Since these two types of insulin serve different functions, they can be studied independently. Long-acting insulins are primarily differentiated by their theoretical duration of action and must be injected daily.[7] However, the effective duration of each product varies across patients, depending on demographics, time since diagnosis and individual metabolism. Hence, the clinical benefit of a product is heterogeneous across patients.[8] Part of daily diabetes management requires patients to monitor their glucose levels; the objective is to adjust short-acting insulin doses, avoid adverse events, and prevent complications. Before 2017, glucose monitoring relied on disposable strips, representing a significant burden as one must prick his finger for each glucose measure.[9] To evaluate diabetes control, physicians relied on the three-month average glucose level (A1c), glucose measurements from strips and patient-reported adverse events. In particular, the laboratory-measured average was the gold standard for assessing good vs poor diabetes management.

Between 2015 and 2021, significant changes occurred in the insulin product space and the glucose monitoring technologies, impacting the information available to physicians to evaluate

[6] Retrieved from Diabetes Atlas https://diabetesatlas.org on October 8th, 2024. The prevalence of diabetes among adults is 5.3% in the French population, compared to 10.7% in the U.S.

[7] In May 2024, the European Medicines Agency (EMA) approved the first once-weekly long-acting insulin.

[8] Adjusting the insulin dosage has limited effects on its duration, as it impacts glucose levels throughout the entire period of action. For instance, increasing the dosage of a drug that lasts for 20 hours will not extend its duration beyond 20 hours but may cause low glucose levels throughout the day. Therefore, choosing the right product for the right patient represents a substantial decision margin.

[9] Regular glucose monitoring involves placing a drop of blood on a disposable test strip, read by a glucose meter.

treatment efficacy. On the insulin side, before 2016, the set of products available was limited, with Lantus, a 24-hour insulin, accounting for more than 60% of prescriptions. Between 2016 and 2018, four new products entered the market (Figure 1). These new insulins include a bioequivalent drug for the 24-hour insulin and three products with an extended duration. These latter target patients for whom the effective duration of the 24-hour product is less than a day and the 42-hour product specifically targets patients with a low glucose level overnight. Prescription drugs are experience goods, meaning that physicians learn about the new insulins' performance outside the controlled environment of clinical trials across a heterogeneous patient population. On the glucose monitoring side, Continuous Glucose Monitors provide glucose readings every 5 to 15 min through a sensor, generating continuous data (Figure A3). The technology contrasts with the unique snapshot provided by the disposable strip tests. In France, CGMs became widely used by patients following the Health Technology Agency (HTA) coverage decision in mid-2017. The decrease in daily glucose monitoring burden thanks to CGMs drives a broad and fast device adoption. The coverage decision targeted around 68% of diabetic patients taking long-acting insulin, and the cost of monitoring glucose in France increased by 67% between 2014 and 2023 (Figure A4).[10] Indeed, CGMs rely on a disposable sensor that must be replaced every two weeks, making this form of monitoring substantially more expensive than traditional test strips.

CGMs expand the criteria for evaluating insulin treatment by providing detailed measurements of daily glucose profile, including overnight levels. They complement traditional metrics, as the laboratory-measured average glucose does not capture the (i) within-day variation or (ii) day-to-day fluctuations in glucose levels and can obscure important heterogeneity in glucose control (Figure A1).[11] By providing insights into the glucose profile, CGMs generate some information that (i) was previously unavailable and (ii) matters when evaluating the performance of insulin therapy. In a market where new products are entering, the impact of digital devices on insulin choice can be twofold: (i) identifying poor patient-product clinical matches and (ii) gathering information about the real-life performance of new drugs. The following patient quote from a medical case study illustrates the first effect.

"Last year I found it very helpful to switch to using a [CGM]. [...] I would frequently

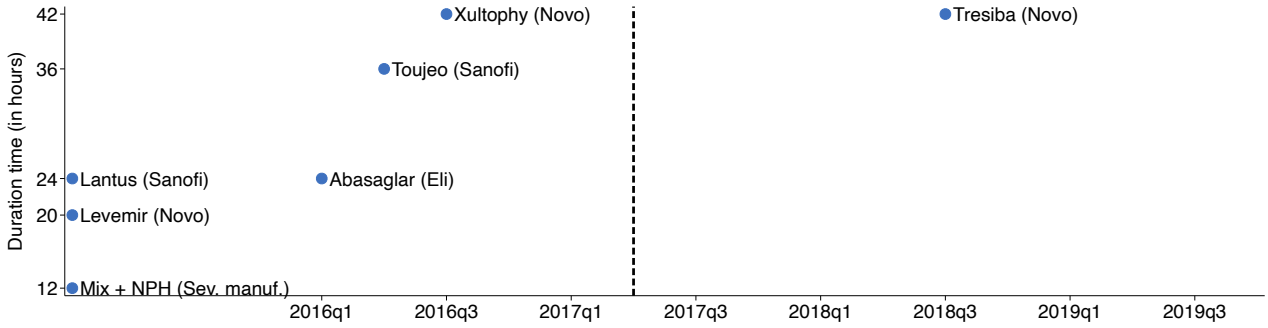
[10] Guerci et al. (2023) note that despite this restriction, some patients excluded from the coverage were prescribed the technology, leading to coverage extension in June 2023.

[11] In recent years, concerns about over-treatment have emerged, driven by physicians overestimating the benefit of low average glucose levels at the expense of the risk of low glucose underlying the variance of glucose profile. https://www.reuters.com/investigates/special-report/usa-diabetes-overtreatment/ https://www.medicalnewstoday.com/articles/326063#Millions-of-people-receive-too-much-therapy

find that, on the [24-hour] regime, I would experience night-time lows. [...] My consultant and I agreed on a trial of splitting the dose of [24-hour] between morning and evening, but this did not suit me. [...] Following this, my consultant switched me onto [36-hour], which worked much better [...]." Shields and Sankaranarayanan (2016)

Moreover, Seaquist et al. (2017) highlights the value of CGM information in the context of new insulins' prescriptions.[12] In the remainder of the paper, I will refer to products by their duration of action, '24-hour Biosimilar' for Abasaglar, Type 2 for Xultophy and 'Human' and 'Mix' for 12-hour products.

Figure 1: New products entry timeline, 2016-2019



Note: The horizontal axis corresponds to the entry date for new products. The vertical axis corresponds to the theoretical duration of each insulin. Each dot corresponds to one product, except for the 12-hour products. The dashed line corresponds to the reimbursement of the monitoring device.

2.2 Data

I rely on rich claims data from the French health insurance system. Owing to the centralized universal healthcare system, the data includes all care reimbursements to a given patient and all care prescribed by a physician.

2.2.1 Insulin prescriptions

The data on insulin prescriptions comes from pharmaceutical claims from 2015 to 2021. For each reimbursement flow, I observe the patient and prescriber IDs, the medical speciality of the prescriber, the date of the prescription, the date of the claim (i.e. the date of the pharmacy

[12] "Data from CGM profiling and glycaemic variability studies are providing new and important insights on clinical outcomes with basal insulins in patients with diabetes. These data should enhance confidence in the use of the newer basal insulins in clinical practice by providing physiological context to real-world observations from heterogeneous patient populations." Seaquist et al. (2017)

visit) and the drug characteristics at the package level. The data is exhaustive of the French population. Hence, it covers all insulin reimbursements to a given patient and all prescriptions written by a physician.[13] The prescription date allows one to account for distinct visits to a particular physician separately from refills.

2.2.2 CGM adoption and attrition

Observing patients adopting and dropping out of continuous glucose monitoring is a crucial analysis component. CGMs are registered medical devices whose coverage was enacted in France in June 2017. CGM use is inferred from pharmaceutical claims data. Like insulin reimbursements, I observe the patient and prescriber IDs, the prescription date, the pharmacy visit date, and the device characteristics. I assume the patient starts wearing the sensor on the day it is claimed at the pharmacy and stops using CGM at the expiration of the last sensor reimbursed to the patient.[14] Mismeasurement in CGM adoption can arise for patients purchasing the technology out-of-pocket (i) before June 2017 or (ii) because they are not eligible for coverage from the health insurance system.[15] In Appendix B.2, I describe how I recover the effective adoption date for eligible patients who might have adopted before June 2017. The eligibility criteria for CGM coverage include diabetic patients receiving both short- and long-acting insulin daily (basal-bolus therapy). This project focuses on long-acting insulin choice, and patients may rely exclusively on long-acting insulin. Approximately 68% of the population of interest is eligible for CGM coverage. Appendix B.2 provides more details about the risk of mismeasurement for non-eligible patients.

2.2.3 Patient-level demographics and medical conditions

Patient demographics are crucial to my analysis, as diabetes affects a diverse range of individuals, partly due to the two distinct sources of the disease (Section 2.1). The data includes the patient's age, gender, and residential area at the municipality level. Low-income individuals are identified as they benefit from free supplement insurance from the government. The medical information includes the type of diabetes and chronic conditions reported in annual patient

[13] Purchasing insulin requires a medical prescription. I observe all prescriptions filled by the patient. In practice, the prescription is written by the physician and purchased by the patient, leaving scope for non-adherence. I assume that patients always comply with their physician's prescription; hence, I observe all prescriptions written by a physician. Patients under insulin therapy must inject insulin every day, limiting the scope for non-adherence.

[14] The current CGM technologies rely on disposable sensors lasting up to 14 days. I use the duration of each sensor to infer potential attrition from continuous glucose monitoring.

[15] The first device covered by the health insurance system was approved in the EU in August 2014.

registries. These files are built from all drugs and care reimbursements to a patient over a year. They report information about anxiety, cancer, cardiovascular disease, dialysis, depression, hypercholesterolemia, hypertension, obesity, etc. Claims data register biological tests' occurrence, but the results are not reported.

2.2.4 Inpatient care/Emergency Room visits

One concern regarding CGM adoption is that patients who adopt the technology have worse diabetes management before the technology is available. To rule out this concern, inpatient care and Emergency Room (ER) visits are used to assess diabetes management before CGM adoption. The data includes all ER visits, regardless of whether they result in an inpatient stay. However, I cannot specifically identify ER visits related to diabetes unless they lead to an inpatient stay, as diagnosis codes are only recorded in those cases.

2.3 Sample selection

In this study, I focus on diabetes specialists' prescriptions from 2015 to 2021 for patients who were already taking long-acting insulin before 2016 and were between 18 and 75. This patient-physician sample and time horizon are convenient for several reasons. (i) The period covers the entry of new drugs from 2016 and CGMs coverage from 2017. (ii) Diabetes patients who had used insulin before 2016 were familiar with insulin injection and glucose monitoring before CGMs introduction.[16] (iii) I focus on adults below 75 years old to ensure the patient injects insulin himself. (iv) Diabetes specialists account for only 25% of prescriptions, but General Practitioners (GPs) renew their prescriptions. Hence, they considerably impact insulin prescribing and are likely to make an active choice during a medical appointment.[17] Appendix B.1 provides more details about the data construction and sample selection.

Table A1 provides some summary statistics about the incumbent patients followed by diabetes specialists. The final sample focuses on around 330k patients, including 28% of Type I diabetes and 39% of Type II patients using short and long-acting insulin therapy. 68% of the sample was eligible for CGM reimbursement. Patients are, on average, 57, and less than half are women. Around 13% benefited from the low-income complementary insurance during

[16] The results will not capture CGMs benefits to learn about insulin injection therapy and diagnosis matching upon insulin therapy initiation (Crawford and Shum (2005)). I exclude diabetes patients relying on a pump to inject insulin as they do not rely on long-acting insulin daily.

[17] I further restrict diabetes specialists to the ones prescribing insulin before 2016. By focusing on specialists, I also limit the extent of heterogeneity across physicians, in particular, to control for learning from indirect experience such as detailing by pharmaceutical companies (see Appendix C.2), scientific articles, etc.

2015-2022. They live in less favoured areas than the average French individual. Type II patients are more likely to take treatments for other chronic conditions such as hypertension and hypercholesterolemia.

Table A2 provides summary statistics for physicians involved in the diabetes treatment for my patient sample. It suggests significant heterogeneity across physicians involved in insulin prescription. Most appointments happen with GPs, who represent 90% of entities and 72% of visits. Yet, the median number of patients per practice is limited. I focus on diabetes specialists and hospital services who see more patients and write more prescriptions at a given practice. While they represent 25% of prescriptions, they account for 74% of treatment switches. Irrespective of their speciality, 58% of physicians faced patients wearing a CGM between 2017 and 2021.

3 Descriptive evidence

This section presents motivating evidence that the adoption of CGM by diabetic patients interacts with insulin demand. Patients treated with long-acting insulin widely adopted CGM as a monitoring system following the coverage decision. After adopting the device, patients are more likely to switch towards new insulin products. The features of the switching behavior are inconsistent with lower switching costs with the digital device. Evidence of physician-level learning about new drugs leaves scope for spillovers. These facts motivate the features of the structural model.

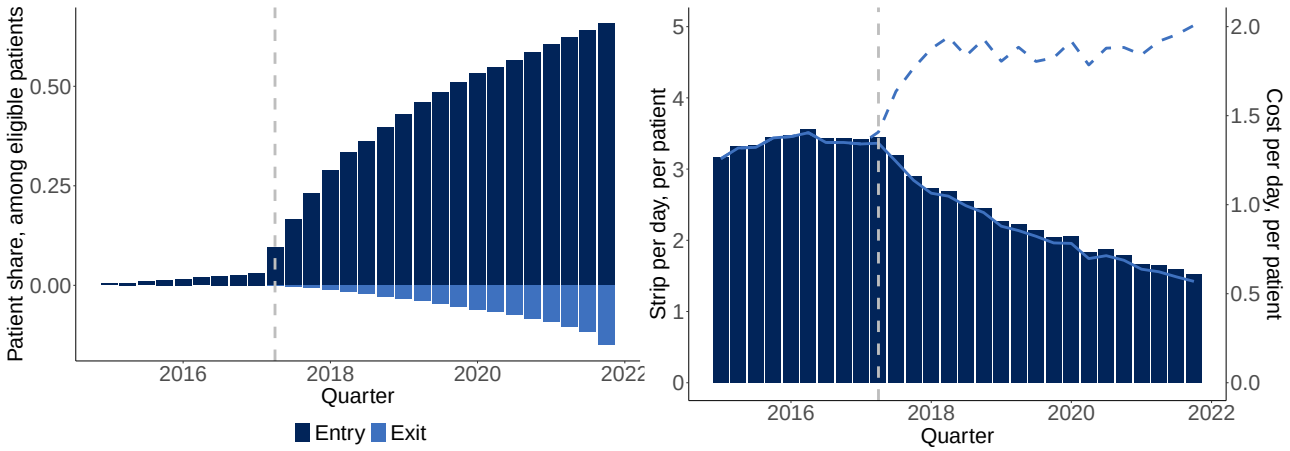
3.1 Wide CGM adoption among insulin-treated patients

Following the June 2017 coverage decision, diabetic patients taking insulin widely adopted CGM to replace disposable strips. As shown in Figure 2, around 65% of eligible insulin patients ever used the technology, with adoption being staggered. The wide adoption of CGMs decreased the consumption of disposable strips to measure glucose levels while the average cost associated with glucose monitoring increased by 43% (Figure 2b). While convenience appears as the primary driver of adoption, I further explain the adoption patterns with respect to patient and physician characteristics. Table 1 presents logistic regression results, where the AIC and pseudo-R^2 criteria indicate diabetes type, age and gender are the main patient-level factors influencing CGM adoption. Physician fixed effects account for 31% of the remaining explained

variation, whereas environmental factors, other medical conditions and prior diabetes management contribute marginally. In particular, ER visits and diabetes-related hospitalizations in 2015-2016 proxy diabetes control before CGM. A potential concern is that patients opting for continuous glucose monitoring may have been in worse condition before the technology coverage. However, the minimal contribution of hospitalizations pre-2017 in explaining adoption (1.5%) mitigates this concern in the case of CGM uptake.

I also consider whether patients adopted CGM as a result of a worsening of their condition, leading to selection concerns. I study the correlation between CGM adoption and the occurrence of diabetes-related ER visits before the adoption date. For patients adopting CGM, I consider the number of ER visits occurring in a bandwidth of 365 days before the first CGM prescription. The potential adoption date does not exist for patients not adopting the technology. Instead, I consider the maximum number of diabetes-related ER visits the patient faces in 365 days from June 2017 to January 2020.[18] If a worsening of diabetes management drives the technology adoption, ER visits should be positively correlated with CGM adoption. Table 2 presents the results, suggesting a negative correlation between the two variables. This evidence indicates that diabetes-related severe adverse events are unlikely to drive technology adoption.

Figure 2: Adoption among eligible patients



(a) Adoption over time

(b) Strips glucose monitoring, volume and cost

Note: Figure 2a presents the stock of patients who ever adopted CGM and dropped out from continuous glucose monitoring over time among eligible patients. Adoption corresponds to the first CGM prescription date. Dropout corresponds to the expiration of the last sensor claimed at the pharmacy. Figure 2b represents the average number of strips per patient among eligibles (left axis) and the average value of glucose testing (right axis) over time. The solid line corresponds to the costs of glucose strips; the dashed line includes the cost of strips and CGMs. Patients do not stop consuming glucose strips completetly after adopting a CGM as they may need to confirm symptoms of adverse events.

[18]The correlation is estimated for different bandwidths. ER visits after January 2020 are not included due to the beginning of the Covid-19 crisis.

Table 1: Drivers of adoption

Variable	Df	AIC	Pseudo R^2
Model	1898	246,802.1995	0.1346
Removing			
- Demographics	1,887	256,050.62	0.1016
- Specialist FE	35	254,621.24	0.0935
- Chronic conditions	1,886	252,170.08	0.1154
- Glucose strips 2015-2016	1,896	247,784.54	0.1311
- Environment	1,894	247,464.48	0.1322
- ER visits 2015-2016	1,892	247,357.04	0.1326

Note: The model is estimated using a logistic regression on the sample of patients eligible for the technology. Demographics include age, gender and diabetes type. Environmental factors include the deprivation index, low-income complementary insurance and city size. Chronic conditions include 12 diseases (including hypertension, hypercholesterolemia, and obesity; see list in Table A1). Glucose strips include the average number of strips in 2015-2016. Hospitalizations account for visits before CGM was available.

Table 2: CGM adoption and prior ER visits

	(1)		(2)		(3)		(4)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
ER visits (#)	-0.1241	(0.0035)	-0.1001	(0.0033)	-0.1814	(0.0043)	-0.1166	(0.0021)
Patients characteristics			✓		✓		✓	
$\overline{CGM_i}$	0.6206		0.6206		0.6206		0.6206	
$\overline{ER_i}$	0.1127		0.1127		0.0929		0.4661	
Bandwidth (days)	365		365		180		365	

Note: The model is estimated using a logistic regression on the sample of patients eligible for the technology. Standard errors are clustered at the physician level. Patient characteristics include demographics (age, gender, diabetes type), environmental factors (city size, deprivation index of the living area, low-income individual), chronic conditions (see list in Table A1) and glucose strips consumption in 2015-2016. Columns (1) to (3) focus on diabetes-related ER visits leading to inpatient stays. Colum (4) focuses on the number of ER visits leading to an inpatient stay, irrespective of the diagnosis.

3.2 CGM adoption and potential patient-insulin mismatch

Given the wide adoption of the device among insulin patients, this section aims to document how the adoption of CGM affects insulin choices. I consider the decision by diabetes specialists to switch insulin treatment, prescribing a product in a given appointment v different from the one used by the patient before the visit. I compare the decision to switch product for patients using CGM to the choice made (i) for similar patients and (ii) for the same patient before he adopts. Considering the decision by the patient i-physician k pair in appointment v,

$$Switch_{ikv} = (\beta_0 + \beta_1 First_{iv})CGM_{iv} + \gamma_1 D_i + \gamma_2 X_{kv} + \lambda_k + \delta_q(v) + \varepsilon_{ikv} \quad (1)$$

$Switch_{ikv}$ equals one when the treatment prescribed to patient i by physicians k in appointment v differs from the product patient i was using prior to the appointment, zero otherwise. CGM_{iv} is a dummy variable equal to one when the patient comes to the appointment wearing a CGM, and $First_{iv}$ equals one only for the first appointment by patient i to a specialist after adopting a CGM. D_i includes patient demographics and chronic conditions. X_{kv} proxies the physician's information set during appointment v, counting the number of visits with patients already using new products. λ_k refers to a physician fixed effect and $\delta_{q(v)}$ to a quarter fixed effect. The coefficients of interest are β_0 and β_1. $Switch_{ikv}$, the outcome of interest, may be occasional;[19] hence, I consider heterogeneous effects between the first appointment while wearing the device and subsequent appointments. The model is estimated by OLS. Table 3 presents the results. Panel A relies on eligible non-users as a control group. Panel B is restricted to users before they adopt in which case I include patient fixed effects instead of the physician fixed effects. The parameters suggest a positive correlation between wearing a CGM and changing insulin product in the short run. Considering the coefficients beyond the first appointment, the positive correlation disappears. It suggests that patients adopting the technology are more likely to switch treatment only during the first appointment wearing a CGM. The physician seems to react to the insights generated by CGM by switching their treatment for some patients while deciding to stick to the former treatment for others. This evidence is consistent with a patient-insulin mismatch, which the technology revealed to the physician.[20]

Both switching costs and information frictions can contribute to inertia in insulin choice such that either of these mechanisms could rationalize the behaviour documented in the previous paragraph. Dubé et al. (2010) highlights that the different sources of state dependence in demand lead to differences in pricing incentives. I provide evidence that the switching patterns following the adoption of CGM are inconsistent with a reduction in switching costs in the following paragraph. The structural model will thus focus on representing how CGM can reduce information friction through physicians learning from the insights produced by the device.

First, lower switching costs would increase the probability of switching insulin at any appointment. Table 3 provides evidence inconsistent with this feature as the positive correlation vanishes beyond the first appointment. Second, switching costs are particularly salient when considering switches from a branded drug to its biosimilar, as the latter must provide evidence

[19] $Switch_{ikv}$ only equals one on the appointment in which the patient switched insulin. If the change is permanent, the outcome variable only equals one once. Patients can switch back and forth between treatments.
[20] The probability of switching back to a former treatment remains low, even for patients wearing a CGM.

of bio-equivalence before entering the market.[21] Figure 3 describes the products involved in treatment switches while wearing the technology, plotting the product used at the time of the appointment (horizontal axis) against the product prescribed (vertical axis) conditional on switching insulin in that appointment. Switches from the 24-hour product towards its biosimilar remain infrequent, making lower switching costs for CGM users unlikely. Patients switch away from the 24-hour branded drug to new products with a longer duration of action. In particular, some patients switch to the 36-hour product in the first appointment following adoption, while the product has been available since 2016, before the CGM coverage decision (Figure 3a). In Appendix C.3, I rely on the relative choice between the 24-hour branded drug and its biosimilar to estimate switching costs and rule out lower costs for CGM users.[22] Altogether, this evidence suggests that CGMs provide insights to physicians about the performance of the current treatment, leading to product switches for some patients.

Table 3: Pr(Switching) estimates

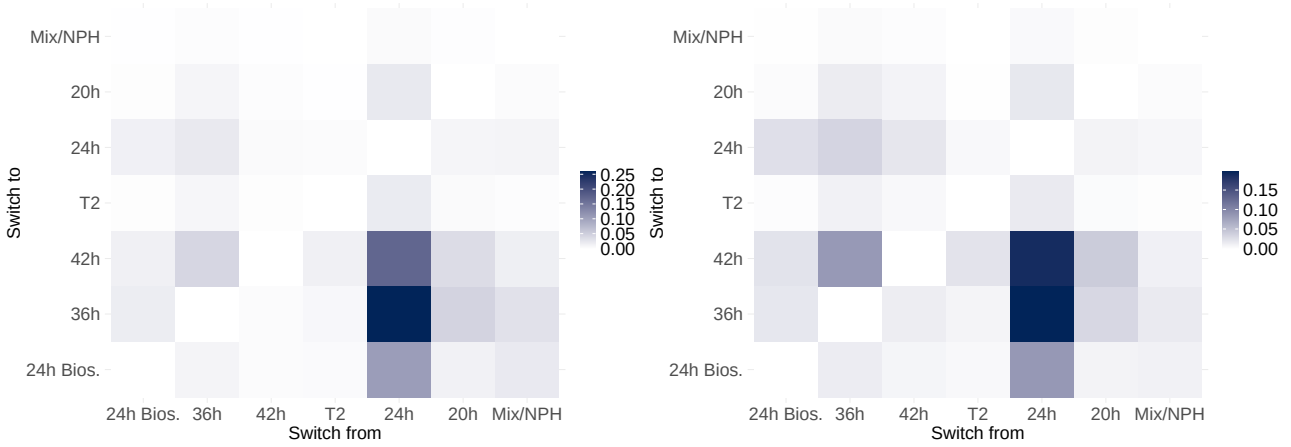
	(1)		(2)		(3)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
A. Control Group: Eligibles						
CGM_{iv}	-0.0446	(0.0008)	-0.0154	(0.0008)	-0.0295	(0.0009)
$CGM_{iv} \times First_{iv}$	0.1217	(0.0012)	0.0659	(0.0012)	0.0667	(0.0012)
$CGM\ User_i$					0.0274	(0.0008)
Physician FE		✓		✓		✓
Quarter FE		✓		✓		✓
Patient demographics				✓		✓
Patient × Physician				✓		✓
Physician information set				✓		✓
B. Control Group: Users						
CGM_{iv}	-0.0651	(0.0014)	-0.0356	(0.0014)	-0.0355	(0.0014)
$CGM_{iv} \times First_{iv}$	0.0751	(0.0014)	0.0478	(0.0014)	0.0478	(0.0014)
Patient FE		✓		✓		✓
Quarter FE		✓		✓		✓
Patient × Physician				✓		✓
Physician information set						✓

Note: The sample is restricted to patients eligible for CGM coverage. Panel A and B include quarter fixed-effect. Panel A contains physician fixed-effects and Panel B patient fixed-effects. 'Patient × Physician' controls for the time since the last interaction between the two.

[21] Information frictions can still arise from physicians' uncertainty about the bio-equivalence (Maini et al. (2022)).

[22] To that end, I compare the choice probabilities for existing patients who face both information frictions and switching costs, to the first-intention treatment choice made for 'new' insulin patients, who are only subject to information frictions.

Figure 3: Switching matrices with the sensor



(a) Switches at $CGM_{iv} \times First_{iv}$ (b) Switches when $CGM_{iv} = 1$

Note: Figure 3a focuses on the switches occurring at the first appointment after the patient starts to use a CGM, and Figure 3b on the switches at any point with a CGM. The horizontal axis corresponds to the product used before the prescription. The vertical axis corresponds to the product prescribed by the physician during that appointment.

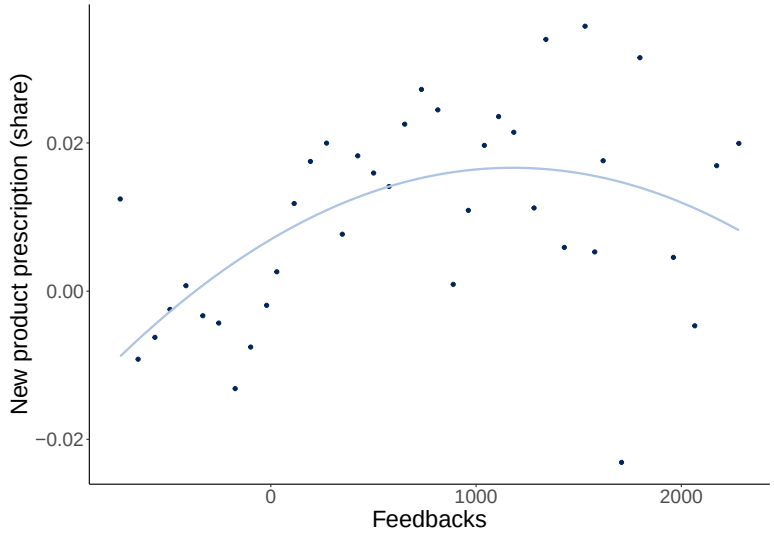
3.3 Physician-level learning

The previous section documents treatment switches with the digital device towards newer treatments. Physicians, being less familiar with these products, encounter more learning opportunities thanks to these switches, allowing them to better understand the performance of new drugs. Information externalities arise if physicians apply insights from CGM users to non-users. I study the correlation between a physician's prescription behavior of new products and her prior product experience to document learning across patients for a given physician.

For each physician k, new product j and quarter q, I compute the product-level prescription share among the patients not already using product j at the time of the appointment. This way, if product j is prescribed to them in quarter q, they were switched to that product by the physician. The number of appointments up to the previous period where the patient already used the new product j at the beginning of the visit approximates physicians' information about a given new product j. Indeed, the patient could share information about the drug's performance in his daily life. Figure 4 presents a binned scatter plot of a product's information set at the physician level (horizontal axis) and its prescription share to 'new' patients (vertical axis). It suggests a positive correlation between the physician's information set about patients' experience with product j and her propensity to prescribe the product to patients who are not already using the product as they come. This evidence suggests physicians extrapolate information from patients' experiences across individuals, leaving scope for information spillovers

between patients adopting a CGM and those not adopting. In Appendix C.4, I document whether the composition of the information set (between patients providing feedback with or without the technology) impacts the strength of the correlation.

Figure 4: Physician prescription share and the information set size



Note: The horizontal axis corresponds to the amount of feedback from real-life experience with the new product j received by the physician up to the previous period. The vertical axis corresponds to product j prescription share for patients not using the product before the appointment. For each variable, I consider the residuals from a linear model controlling for physician fixed effects, product-specific quarter fixed effects, and the average demographics of the patient visiting physician k in a given period. The figure focuses on prescriptions by diabetes specialists and excludes the new Type 2 product directed towards a subset of patients. The information set proxy (horizontal axis) is computed at the hospital level for specialists working in the hospital. Figure A12 focuses on individual physicians working outside the hospital.

4 Insulin demand modelling

Following the evidence from the previous paragraphs, this section develops a model of demand for insulin that accounts for the potential impact of a digital device on prescription drug choices. The device is a monitoring technology which generates high-frequency patient-level data. The insights from these data are potentially informative of the patient-insulin clinical match value. Moreover, physicians may extrapolate the information from the digital technology across patients, generating externalities.

4.1 Setting

Consider a patient (he), indexed by i, who has been diagnosed with diabetes before the start of the period. He is familiar with insulin injections and glucose monitoring. The patient is followed by a physician k (she), the expert who decides on treatment. At a given physician practice, the flow of medical appointments leading to an insulin prescription is indexed by $v \in \{0, ..., V_k\}$. Physicians differ in the number of patients they see, V_k, and the characteristics of their patient population. The physician prescribes insulin $j \in \mathcal{J}_v$ to patient i during a medical appointment. The set of available insulin, $\mathcal{J}_v$, evolves as new products enter the market. Patients differ in their true clinical match value with product j, $\Theta_{ij} \in \mathbb{R}$.

When selecting the treatment for patient i, the physician faces uncertainty regarding Θ_{ij}. This uncertainty stems from the gap between the average treatment effect from clinical trials and the drug's performance in real-life use among heterogeneous patients. I assume that the true clinical match value, Θ_{ij}, depends on the preference for the drug's effect on the average glucose level, μ_{ij}, and the preference for the drug's effect on the glucose profile, ν_{ij}, such that $\Theta_{ij} = \mu_{ij} + \nu_{ij}$.[23] The physician forms beliefs about the true value of Θ_{ij}, updated based on experience signals from her patient population.

In the absence of CGM, the physician learns about the drug's effect on the average glucose level, μ_{ij}, from blood test results and about the drug's effect on the glucose profile, ν_{ij}, from adverse events reported by the patient.[24] However, because the glucose profile is not perfectly measured without CGM, learning about the patient-product clinical match value, Θ_{ij}, cannot be complete. Physicians' belief about Θ_{ij} remains biased as they learn without the information produced by CGM. I denote $\theta_{ij} \equiv \Theta_{ij} - \Delta\nu_{ij}$ where $\Delta\nu_{ij}$ captures the bias corresponding to the preference for the profile that is unobserved without a CGM. θ_{ij} is the sum of the preference for the drug's effect on the average glucose level, μ_{ij}, and the preference for the effect on the glucose profile from adverse events, $\nu_{ij} - \Delta\nu_{ij}$. θ_{ij} is referred to as the *partial information clinical match value*.

The benefits from CGM data are twofold:

1. **Comprehensive measurement of glucose profile:** The digital device provides detailed information about the glucose profile for patient i. As the drug's effect on the

[23] Each argument is combining the value of the attribute and the utility weight for that attribute.
[24] The beliefs about μ_{ij} may be inconsistent upon the product's entry but physicians update their beliefs from unbiased signals generated by lab results.

profile is completely observed for the patients wearing the sensor, learning about ν_{ij} is assumed to be complete and immediate once a patient uses the device. These insights are patient-specific and uninformative for non-users.

2. **Experience signal about θ_{ij}:** The CGM data generated when the patient was using product j produce a signal about the partial information clinical match value, θ_{ij}. The properties of this experience signal can differ from the signal had the patient not used a CGM.

The decision to adopt a CGM and the timing of adoption is exogenous from the insulin choice perspective. Let $a_{iv} \in \{0, 1\}$ indicate the adoption of the digital device, $a_{iv} = 1$ if the patient uses a CGM, 0 otherwise. The physician observes a_{iv} and the data generated by the device when $a_{iv} = 1$.

Considering the flow of appointments to physician k. At each visit v,

1. **Patient arrival:** A patient i is coming for an insulin prescription using a digital or a traditional glucose monitoring device, a_{iv}. The patient's identity, choice of monitoring technology, and the set of insulins available are taken as given.

2. **Belief updating:** The physician observes the last product used by i until v, $j_{i,v-1}$, and its effect on patient i's glucose levels. She updates her beliefs about the clinical benefit of $j_{i,v-1}$ for *any* patient. Physicians learn across patients from experience signals. This experience signal enters the information set of physician k at time v, $\mathcal{I}_{kv}$.[25]

3. **Treatment choice:** Given $\mathcal{I}_{kv}$, the physician, k, chooses the treatment $j \in \mathcal{J}_v$ that maximises ones expected payoff.

4.2 Demand

Physicians are incentivized to prescribe the most cost-effective treatment for a given patient. The indirect utility of the physician k-patient i pair when choosing product j is

$$U_{ikjv} = \Theta_{ij} - \alpha p_{jv} \tag{2}$$

[25]The physician receives an experience signal only during a medical appointment linked to an insulin prescription. The empirical specification will impose some restrictions on the extent of learning across patients.

p_{jv} is the price of product j in appointment v. α measures the price sensitivity of the patient-physician pair. Θ_{ij} is the true clinical match value between patient i and drug j. Given the physician information set, $\mathcal{I}_{kv}$, the monitoring device, a_{iv}, the choice of treatment is made according to

$$\max_{j \in \mathcal{J}_v} \mathbb{E}(U_{ikjv} | \mathcal{I}_{kv}; a_{iv}) = \max_{j \in \mathcal{J}_v} \left\{ \mathbb{E}(\Theta_{ij} | \mathcal{I}_{kv}; a_{iv}) - \alpha p_{jv} \right\} \tag{3}$$

where $\mathcal{J}_v = \mathcal{J}^{Old} \cup \mathcal{J}_v^{New}$. $\mathcal{J}_v^{New}$ corresponds to the set of insulins entering after 2015 available at the time of appointment v. Given the chronic feature of the disease, there is no outside option and the physician must prescribe one of the available treatment options. Two disruptions happen simultaneously: new prescription drugs and insights from a new monitoring technology. Given the information set, $\mathcal{I}_{kv}$, monitoring choice, a_{iv}, and product j, the physician's expectation of the true value for Θ_{ij} is:

$$\mathbb{E}(\Theta_{ij} | \mathcal{I}_{kv}; a_{iv}, j) = \begin{cases} \Theta_{ij} & \text{if } a_{iv} = 1 \text{ and } j \in \mathcal{J}^{Old} \\ \theta_{ij} & \text{if } a_{iv} = 0 \text{ and } j \in \mathcal{J}^{Old} \\ \mathbb{E}(\mu_{ij} | \mathcal{I}_{kv}; a_{iv} = 1) + \nu_{ij} & \text{if } a_{iv} = 1 \text{ and } j \in \mathcal{J}_v^{New} \\ \mathbb{E}(\mu_{ij} + \nu_{ij} | \mathcal{I}_{kv}; a_{iv} = 0) & \text{if } a_{iv} = 0 \text{ and } j \in \mathcal{J}_v^{New} \end{cases} \tag{4}$$

In what follows, I provide the intuition for $\mathbb{E}(\Theta_{ij} | \mathcal{I}_{kv}; a_{iv}, j)$ without $(a_{iv} = 0)$ and with $(a_{iv} = 1)$ a CGM, for old $(j \in \mathcal{J}^{Old})$ and new $(j \in \mathcal{J}_v^{New})$ insulins.

4.2.1 Absent the digital device, $a_{iv} = 0$

Old treatments ($\mathcal{J}^{Old}$)

The physician had lots of experience prescribing $j \in \mathcal{J}^{Old}$. She knows the drug's effect on the average glucose level, μ_{ij}, for each drug and each existing diabetes patient. She has only partial information about the drug's effect on the glucose profile, ν_{ij}, as the exact patient profile i remains unobserved. Without the technology, for product $j \in \mathcal{J}^{Old}$,

$$\mathbb{E}(\Theta_{ij} | \mathcal{I}_{kv}; a_{iv} = 0) = \mu_{ij} + \mathbb{E}(\nu_{ij} | \mathcal{I}_{kv}, a_{iv} = 0) \equiv \theta_{ij} \tag{5}$$

θ_{ij} is independent of k and v because all physicians have already learned about this value for old drugs.

New treatments ($\mathcal{J}_v^{New}$)

For new treatments upon entry, unlike Equation (5), the physician has imperfect information about the drug's effect on the mean glucose level, μ_{ij}. Thus, θ_{ij}, the partial information clinical match value, is imperfectly known. Upon product entry, at $t = 0$, the physician forms a prior belief about θ_{ij}, distributed according to the cumulative distribution function $F(\theta_{ij})$. I allow physicians to have non-rational expectations about new drugs initially such that it is possible that $\mathbb{E}(\theta_{ij}|\mathcal{I}_{k0}; a_{iv}) \neq \theta_{ij}$. The physician updates her belief based on patient experience signals using the new product j when coming at time v. They learn *across* patients, using the signal produced by patient i to update the prior belief for any patient i'. These signals, $e^v_{ii'kj}$, are assumed to be unbiased with respect to $\theta_{i'j}$ but noisy.[26] They are drawn from a known distribution with CDF, $G(e^v_{ii'kj}|\theta_{i'j}, \sigma_{ii'v})$ where $\sigma_{ii'v}$ correspond to the noise of the signal provided by patient i in appointment v. The signal enters the information set of physician k at $v' \geq v$, $\mathcal{I}_{kv'}$. Without the digital device, for $j \in \mathcal{J}_v^{New}$,

$$\mathbb{E}(\Theta_{ij}|\mathcal{I}_{kv}; a_{iv} = 0) = \mathbb{E}(\mu_{ij} + \nu_{ij}|\mathcal{I}_{kv}; a_{iv} = 0) = \mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv} = 0) \tag{6}$$

where $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv} = 0)$ is the mean of physician k's belief about θ_{ij} at time v given that $a_{iv} = 0$. This average varies (i) over time as a physician gathers more experience and (ii) across physicians as they see different patient populations. Section 4.3.3 details the learning process.

4.2.2 With the digital device, $a_{iv} = 1$

The digital device generates information about (i) the glucose profile for patient i, leading to complete learning about ν_{ij} for all drugs, and (ii) the partial information match value, θ_{ij}, for the product used by the patient coming at v.

Old treatments ($\mathcal{J}^{Old}$)

Given the patient's monitoring device, $a_{iv} = 1$, for drug $j \in \mathcal{J}^{Old}$,

$$\begin{aligned}\mathbb{E}(\Theta_{ij}|\mathcal{I}_{kv}; a_{iv} = 1) &= \mathbb{E}(\mu_{ij} + \nu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) \\ &= \mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) + \nu_{ij} \\ &= \Theta_{ij} = \theta_{ij} + \Delta\nu_{ij}\end{aligned} \tag{7}$$

[26] The physicians are assumed to be able to extrapolate the information provided by patient i for patient i'.

where $\Delta\nu_{ij}$ corresponds to the bias due to the difference between the drug's true effect on the profile and the effect learned without the CGM. Since there is no uncertainty about μ_{ij} for old drugs, $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) = \mu_{ij}$. The insights about ν_{ij} from CGM are patient-specific and uninformative for non-users who keep facing Equation (5).

Thanks to the digital device, learning about the performance of old treatments for patient i is complete. Since there is no outside option, pharmaceutical demand is affected by the monitoring technology only if $\Delta\nu_{ij}$ differs across alternatives.

Claim 1. *In a mature market ($\mathcal{J}_v = \mathcal{J}^{Old}$), when a digital device generates new insights about the patient-product clinical match value, if there exist at least two $j, j' \in \mathcal{J}$, such that $\Delta\nu_{ij} \neq \Delta\nu_{ij'}$ then $\mathbb{E}(\Theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) - \mathbb{E}(\Theta_{ij'}|\mathcal{I}_{kv}, a_{iv} = 1) \neq \mathbb{E}(\Theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 0) - \mathbb{E}(\Theta_{ij'}|\mathcal{I}_{kv}, a_{iv} = 0)$.*

Despite the lack of product entry, the digital device can affect insulin demand from device users. This impact is driven by new patient-specific insights for which some treatments are more suited. The magnitude of this effect at the market level strongly relies on device adoption. When data insights do not emphasize differences across products, demand for existing pharmaceutical alternatives remains unaffected.

New treatments ($\mathcal{J}_v^{New}$)

Similarly, for new treatments $j \in \mathcal{J}_v^{New}$, as the CGM allows inferring the effect of treatments on the glucose profile,

$$\begin{aligned}\mathbb{E}(\Theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) &= \mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) + \nu_{ij} \\ &= \mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) + \Delta\nu_{ij}\end{aligned}$$

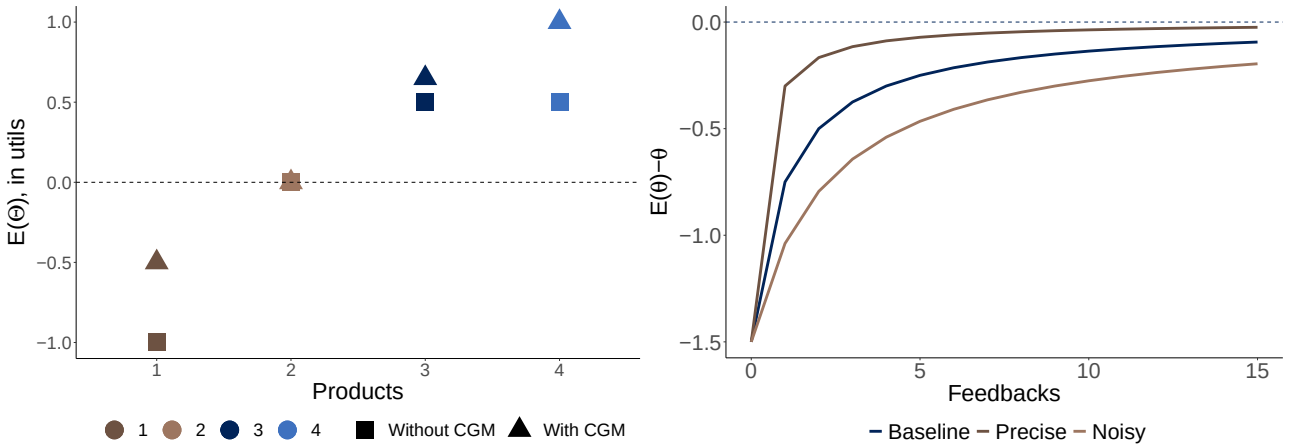
where $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 1)$ can differ from $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 0)$ for the product the patient was using when coming at time v. Indeed, observing the performance of a new drug j for a patient i using the digital device, $a_{iv} = 1$, might provide information about θ_{ij} in a different fashion than had the patient come without the technology $a_{iv} = 0$. Whether this experience signal is more, less or equally informative about θ_{ij} than signals received without a CGM is an empirical question. I do not assume the digital device generates complete learning about θ_{ij}. Yet, if the insights from CGM provide precise information about the performance of drug j, the belief of physician k after seeing CGM information, $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 1)$, should be close to its true value and precise.

Summary Figure 5 summarizes the two effects of CGM on the physician's expectation about the true clinical match value, Θ_{ij}. First, Figure 5a presents the impact of comprehensive measurement of glucose profile, abstracting away from the dynamic learning about new drugs. Considering the expected match values for a given patient, the horizontal axis corresponds to different products and the vertical axis to the expected clinical match, $\mathbb{E}(\Theta_{ij})$, with (triangle) and without (square) the device. This figure highlights how insights produced by the CGM about the glucose profile can affect the physician's expectation about the match value by correcting the initial bias in physicians' belief about Θ_{ij}. Without the device (square), the physician is indifferent between prescribing products 3 and 4 for patient i, conditional on the price, as their perceived match value is the same. With information about the glucose profile (triangles), product 4 dominates product 3, and the difference between products 1 and 2 shrinks. In this example, the technology increases the perceived differentiation between products 2, 3 and 4 while it decreases between products 1 and 2. If patient i was prescribed product 3 prior to CGM, the insights generated by the device induce a treatment switch from product 3 to product 4 (up to the effect of treatment price). Second, Figure 5b focuses on the learning dynamics about θ_{ij} for new drugs. It represents the impact of experience signals generated by patients using new drug j and a CGM at the time of the appointment v. CGMs affect the noise of the experience signal. Considering the physician's expectation about the partial information match value, θ_{ij}, the horizontal axis corresponds to the number of experience signals received. The vertical axis corresponds to the difference between the expected partial match value and its true value.[27] This example assumes normally distributed priors and signals. If experience signals produced by CGMs are more precise (dark brown) than traditional feedbacks (navy line), for a given number of experience signals received (horizontal axis), the difference between the physician's expectation, $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}, a_{iv})$, and the true value for θ_{ij} is smaller. Hence, the physician can learn faster about θ_{ij} thanks to CGMs.[28]

[27] Signals are assumed to be unbiased with respect to the true θ_{ij}, irrespective of the technology. Yet, beliefs are allowed to be inconsistent such that the initial prior mean may differ from its true value.

[28] The figure highlights that after receiving a very precise signal, the belief is immediately very close to the true match value. This figure assumes signals are always received from CGM or traditional measurement. In practice, the updating combines both as physicians are learning across patients.

Figure 5: Impact of CGM on the perceived match value



(a) Comprehensive glucose profile

(b) Experience signal about θ_{ij}

Note: Figure 5a plots the physician's expectation about Θ_{ij} (vertical axis) for different products (horizontal axis), with (▲) and without (■) insights from CGM. This example abstracts away from the dynamic learning about θ_{ij} for new drugs. Figure 5b plots the evolution of a physician's belief about θ_{ij} (vertical axis) as she receives more experience signals (horizontal axis) from patients who return to her practice while using new product j. One feedback corresponds to one visit where the patient shares his experience with product j. I assume physicians form normally distributed priors about θ_{ij} at $t = 0$ and update their beliefs from normally distributed signals received from patients using product j. Signals are unbiased with respect to the true value, θ_{ij} but noisy, denoting the variance of the signal from patient i' for patient i, $\sigma^2_{i'iv'}$. Here, a physician receives either precise ($\sigma_{i'iv'} = 1$) or noisy ($\sigma_{i'iv'} = 3$) signals compared to baseline ($\sigma_{i'iv'} = 2$). For exhibition purposes, in this simple example, the noise is the same for signals received from $i' \neq i$.

Consumer welfare under imperfect information In this setting, there exists a discrepancy between the decision utility and the one experienced by the patient. Similar concerns arise when the expected utility anticipated at the time of the decision-making and the utility under rational expectations differ (Brown and Jeon (2024)). Uncertainty and incomplete learning distort the decision utility, hence the demand for insulin, while the underlying experience utility relies on Θ_{ij}, the true clinical match value. The experience utility from patient i using product j is

$$U_{ikjv} = \Theta_{ij} - \alpha p_{jv} = \mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv}) - \Big[\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}, a_{iv}) - \theta_{ij} + \Delta\nu_{ij}(a_{iv} - 1)\Big]$$

For old products, $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv}) = \theta_{ij}$. Following Dubois et al. (2018) and denoting $j^* = \arg\max_j \mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv})$, the expected experienced utility for patient i from the choice made on his behalf by physician k at v is:

$$\begin{aligned} W_{ikv} &= \mathbb{E}_\varepsilon[U_{ikj^*v}] \\ &= \mathbb{E}_\varepsilon\Big[\max_j\{\mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv})\}\Big] - \mathbb{E}_\varepsilon\Big[\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv}) - \theta_{ij} + \Delta\nu_{ij}(a_{iv} - 1)\Big] \end{aligned} \tag{8}$$

where the second term accounts for the difference between the realized and expected clinical match value.

4.2.3 Discussion

This framework relies on several assumptions regarding physician and patient behavior. First, the patient-product clinical match value is unaffected by the technology. It assumes that the information generated by CGMs does not affect the effect of insulin j on the average or profile of glucose level for patient i.[29]

Second, focusing on patients diagnosed before new products' entry, it is assumed physicians know the partial information clinical match value, θ_{ij}, for these patients among old alternatives. This feature circumvents the initial condition problem that arises in a dynamic setting.

Third, physicians are altruistic and myopic. They are altruistic as they choose the treatment to maximize a weighted sum of the expected patient-level clinical benefit and treatment prices. As physicians' altruism and price sensitivity cannot be separately identified, a low α can be driven by a low sensitivity to price and a high level of altruism. Physicians are also assumed to be myopic, which excludes exploration by physicians who could prescribe a less valuable treatment to learn about the clinical match value of new drugs. The low probability of returning to a former treatment, even for patients using the digital device, mitigates this concern. Physicians do not exploit patients with digital devices to collect valuable information about treatments at the expense of a dominated choice for the patient himself. Physicians may be reluctant to prescribe treatments for which the outcome is more uncertain. I approximate this feature in the econometrics model by allowing for pessimistic initial priors, capturing the reluctance to switch patients to new treatments.

4.3 Empirical model and identification

This section presents the empirical counterpart of the theoretical framework developed in the previous section. Following the last section, the indirect utility driving the choice of insulin j by physician k for patient i coming at v is specified as follows.

$$\begin{aligned}\mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv}) &= \mathbb{E}(\mu_{ij} + \nu_{ij}|\mathcal{I}_{kv}; a_{iv}) - \alpha p_{jv} \\ &= \mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv}) + \Delta\nu_{ij} a_{iv} - \alpha p_{jv} + \delta f(age_{jv}) + \varepsilon_{ikjv}\end{aligned} \tag{9}$$

[29] Under this assumption, the average and profile of the glucose levels for patient i can still be affected by the technology thanks to the better fine-tuning of short-acting insulin around mealtime.

where p_{jv} is the daily price of insulin j at time v, age_{jv}, the time since product j is available, enters quadratically,[30] $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv}) + \Delta\nu_{ij}a_{iv}$ is the expected patient-drug clinical match value and ε_{ikjv} an idiosyncratic shock, unobserved to the econometrician, iid and following a Type I EV distribution. The next paragraphs discuss the restriction imposed on the clinical match value heterogeneity and the potential threats to identification arising from endogenous digital device adoption. Then, I present the parametric assumptions of new products' updating of prior beliefs. Finally, I discuss the identification of the price coefficient and conclude this section with an overview of the estimation procedure.

4.3.1 Heterogeneity in patient-drug clinical match value

The patient-insulin clinical match value varies from one patient to another based on physiologic and metabolic factors. To accommodate this feature while keeping the model tractable, I assume patients can be classified, *ex-ante*, into N distinct groups, $n \in \{1, ..., N\}$. Physicians know the group each existing patient belongs to.[31] The classification is performed in two-steps. First, patients are classified into three categories depending on their diabetes type and insulin therapy. Second, I use a k-means algorithm in each group to classify patients into two to three sub-groups. The variables used to generate the clusters include patients' demographics, environment, chronic conditions, diabetes management, and health status before CGM is available.

Within a cluster, n, the *partial-information clinical match value*, θ_{nj}, is proxied by a group-specific product fixed effect. This flexible parametrization allows preferences for certain products to vary across groups based on factors observed by the physician when deciding on treatment but unobserved in the data. θ_{nj} is assumed to be equal for bioequivalent products, as the drug's approval requires evidence of equivalence. For new drugs, physicians have imperfect information about θ_{nj} upon product entry. Physicians' initial belief about the performance of drug j can be inconsistent such that $\mathbb{E}(\theta_{nj}|\mathcal{I}_{k0}; a_{iv}) = \theta^0_{ikj} \neq \theta_{nj}$. Each physician's belief about θ_{nj} evolves as she gathers more direct patient experience such that $\mathbb{E}(\theta_{nj}|\mathcal{I}_{kv}; a_{iv})$ varies over time. The term also differs across physicians as they see different patients with different experiences, summarized in $\mathcal{I}_{kv}$. The learning process also applies to the 24-hour biosimilar as physicians' uncertainty about the equivalence may drive the slow uptake in prescription shares

[30] For new products, it approximates physician learning from alternative sources such as word of mouth, scientific conferences/articles or detailing. Learning from indirect experiences is assumed to be constant across physicians at a given time.

[31] For newly diagnosed patients, the physician may not be able to identify i's type straight away, leading to experimentation and exploration. The structural estimation of the model abstracts away from these considerations by focusing on existing diabetes patients.

(Maini et al. (2022)). Paragraph 4.3.3 below details the specification for beliefs and signals.

The change in the preference for the effect of drug j on the glucose profile for patient i, $\Delta\nu_{ij}$ is proxied by patients' sensitivity to insulin duration of action, d_j. To accommodate for patient-level heterogeneity and non-linearities, $\Delta\nu_{ij} = \beta_1(x_i)d_j + \beta_2(x_i)d_j^2$ where x_i includes observable demographics and chronic conditions. The digital device reveals the patient's true sensitivity to insulins' length of action, which may deviate from the group average captured by θ_{nj}.

Identification Partial information clinical match values, θ_{nj} are identified from within-group choice probabilities for patients without the technology. There is no outside option. Hence, I normalize θ_{nj} for the 24-hour product to zero for each group of patients. The sensitivity to insulin duration parameters, $\beta_1(x_i)$ and $\beta_2(x_i)$, are identified from the choice probabilities for patients using the technology and their deviation compared to non-users within a group. The causal impact of the digital device on insulin choice can be estimated if ε_{ikjv} is uncorrelated with CGM adoption, a_{iv}. Paragraph 4.3.2 discusses this assumption.

4.3.2 Endogenous CGM adoption

I take the adoption of the digital device as given, and the identification of the causal effect of the digital device on insulin demand relies on the taste shock, ε_{ikjv}, being uncorrelated with CGM adoption, a_{iv}. One potential threat to the identification lies in patient-level unobserved characteristics that may vary over time. First, as mentioned in Section 4.2, only unobserved components leading to differences in product-level clinical match value matter. Any individual and time-specific component that does not vary across drug choice alternatives cancels out in the logit specification. Second, the cluster-level product fixed effect captures product-level unobserved heterogeneity across patients' groups. As a result, the remaining threats lie in within-group product-specific unobservables that correlate with adoption which I will not be able to account for.

4.3.3 New products' learning dynamics

In the case of product entry, physicians are learning about the partial information clinical match value of drug j for patient i, θ_{ij}, throughout prescriptions. These parameters are constant within a group of patients such that physicians learn about θ_{nj} if patient i belongs to group n. I assume that patients in the same cluster, followed by the same physician, are subject to the same priors

and that there is no learning across clusters.[32] As a result, belief and signals can be written as a function of the patient providing the information i, his cluster n, the physician's identity k and the glucose monitoring technology used by i at v, a_{iv}. The distributions of beliefs and signals, e, are assumed as follows.

$$\begin{aligned} \theta_{nj} &\sim \mathcal{N}(\theta_j^0, V_j^0) \\ e_{ikj}^v &\sim \mathcal{N}(\theta_{nj}, (\sigma_0 + \sigma_1 a_{iv})^2) \end{aligned} \tag{10}$$

Each physician has normally distributed prior belief about θ_{nj} with initial mean θ_j^0 and precision V_j^0 upon introduction. The initial prior is assumed to be constant across physicians.[33] Experience signals received from patients, e_{ikj}^v, are normally distributed. They are unbiased but noisy, and the signal's noise depends on the technology used. Physicians cannot be misled about the θ_{nj} by CGM insights. The device provides at least an uninformative signal about this value. Whether signals from CGM are more, less or equally informative about θ_{nj} than signals from traditional tools depends on the sign of σ_1. Consider a patient i in group n previously prescribed $j \in \mathcal{J}_v^{New}$ visiting physician k at v. Given the normally distributed beliefs and signals, k's posterior belief about j, $\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv}) \equiv \theta_{nkj}^v$, after receiving i's experience, e_{ikj}^v, and given the prior belief, θ_{nkj}^{v-1}, is given by:

$$\mathbb{E}(\theta_{ij}|\mathcal{I}_{kv}; a_{iv}) \equiv \theta_{nkj}^t = \begin{cases} \theta_{nkj}^{v-1} \frac{\sigma_0^2}{\sigma_0^2 + V_{nkj}^{v-1}} + e_{ikj}^v \frac{V_{nkj}^{v-1}}{\sigma_0^2 + V_{nkj}^{v-1}} & \text{if } a_{iv} = 0 \\ \theta_{nkj}^{v-1} \frac{(\sigma_0+\sigma_1)^2}{(\sigma_0+\sigma_1)^2 + V_{nkj}^{v-1}} + e_{ikj}^v \frac{V_{nkj}^{v-1}}{(\sigma_0+\sigma_1)^2 + V_{nkj}^{v-1}} & \text{if } a_{iv} = 1 \end{cases} \tag{11}$$

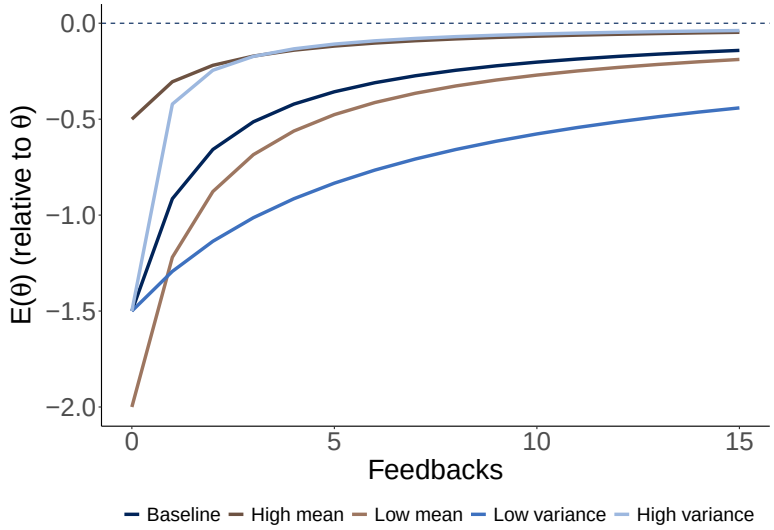
Figure 5b presents the effect of the signal's precision on the belief over the number of signals.

Identification Aside from the real-life partial information clinical match value for product j and cluster n, θ_{nj}, the parameters driving the evolution of the prior beliefs include the initial prior mean and variance, θ_j^0 and V_j^0, and parameters driving the signal's noise, σ_0 and σ_1. Figure 6 presents the intuition for identifying the remaining parameters. In particular, the prior mean is identified by the extent of prescription without experience and the variance by the extent of updating.

[32] This is similar to assuming $\sigma_{ii'v} = \infty$ if i and i' do not belong to the same cluster n.

[33] Initial prior belief could be influenced by the sources of indirect learning such as clinical trials, medical conferences, detailing, etc. The model is estimated on a subset of diabetes specialists working outside the hospital. Hence, they are assumed to receive similar information about new products upon entry. In Figure A11, I provide evidence that most diabetes specialists interact with the three pharmaceutical companies. Interactions happen on average once per year.

Figure 6: Identification of beliefs



Note: This figure plots the evolution of physicians belief about θ_{nj} (vertical axis), as she receives more experience signals (horizontal axis) from patients who return to her practice while using new product j. One feedback corresponds to one visit where the patient shares his experience with product j. Physicians are assumed to form normally distributed priors about the partial information clinical match value, θ_{nj} at $t = 0$ and update their beliefs from normally distributed signals. Here, $\theta_{nj} = 0$ and the figure plots alternative updating of beliefs over time for higher/lower prior mean (in blue) and higher/lower prior variance (in brown).

Discussion The learning framework relies on several assumptions and presents several restrictions. First, learning from experience across physicians is limited. It is approximated by the product's time on the market. Beliefs are physician-specific. The only source of information sharing between two physicians comes from patients who may visit several physicians.[34] Second, there is no learning across patient types or time discounting for old signals. I assume physicians do not forget about the past information received from patients. Last, direct experience is the only source of physician-specific learning. Physicians are assumed to be homogeneous regarding indirect sources of information such as detailing and equally likely to prescribe new drugs after conditioning on experience. By focusing on diabetes specialists working outside the hospital, there is limited heterogeneity in physician's propensity to be detailed or not by insulin manufacturers. In Appendix A11, I provide suggestive evidence that each insulin manufacturer has detailed most diabetes specialists since at least 2014. Section 3.1 suggests that physicians are heterogeneous regarding their propensity to face CGM patients (Table 1). This heterogeneity may threaten the parameters identification if physicians more likely to face

[34]In Figure A10, I provide descriptive evidence about the limited practice size for diabetes specialists working outside the hospital context. It limits concerns about spillovers across physicians working at the same practice.

CGM patients are more likely to prescribe new drugs to patients with the device. In Figure A13, I plot the physician-level propensity to see CGM patients against their propensity to switch CGM patients at the first appointment after patient adoption. The figure suggests no correlation between the two dimensions.

4.3.4 Price and choice set exogeneity

I assume that the price of each drug and the timing of the new drug's entry are exogenous. The endogeneity of insulin price is unlikely to arise in this context as the drug price is set at the national level, and the empirical specification includes product fixed effects. The patient and visit specific taste shock, ε_{ikjv}, is assumed to be uncorrelated with the price of each insulin p_{jv}. Second, the timing of the new drug's entry is also assumed to be independent of the individual-level taste shock.

4.3.5 Estimation

Given what precedes,

$$\begin{aligned}\mathbb{E}(U_{ikjv}|\mathcal{I}_{kv};a_{iv}) &= \mathbb{E}(\theta_{ij}|\mathcal{I}_{kv};a_{iv}) + (\beta_1(x_i)d_j + \beta_2(x_i)d_j^2)a_{iv} - \alpha p_{jv} + \delta f(age_{jv}) + \varepsilon_{ikjv} \\ &= u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}) + \varepsilon_{ikjv}\end{aligned} \tag{12}$$

The likelihood of observing choice j by physician k for patient i, $\mathcal{L}_{ikjv}$, using a_{iv}, in appointment v is given by

$$\begin{aligned}\mathcal{L}_{ikjv} &= \Pr(\mathbb{E}(U_{ikjv}|\mathcal{I}_{kv};a_{iv}) > \mathbb{E}(U_{ikj'v}|\mathcal{I}_{kv};a_{iv})\ \forall j' \neq j) \\ &= \frac{\exp(u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}))}{\sum_{\forall j'}\exp(u_{ikj'v}(p_{j'v}, d_{j'}, a_{iv}|\mathcal{I}_{kv}))}\end{aligned} \tag{13}$$

While physicians observe the realization of the signal, e^v_{ikj}, the econometrician does not, such that the likelihood for a given sequence of choices by physician k has to integrate over the distribution of unobserved signals. Given $y^v_{ikj} = 1$ for the chosen alternative and 0 otherwise, physician's k individual likelihood is given by

$$\mathcal{L}_k = \int_{-\infty}^{\infty}\left[\prod_{v=0}^{V^k}\prod_{\forall j}\left(\frac{\exp(u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}))}{\sum_{\forall j'}\exp(u_{ikj'v}(p_{j'v}, d_{j'}, a_{iv}|\mathcal{I}_{kv}))}\right)^{y^v_{ikj}}|\vec{e}_k\right]dF(\vec{e}_k) \tag{14}$$

where $\vec{e}_k = \{e^1_{ikj}, ..., e^{V_k}_{ikj}\}$, is the vector of signals observed by physician k. Without spillovers within a physician, across patient types, n, the likelihood function can be written at the cluster and physician level. I simulate $M = 200$ Halton draws from a normal distribution to approximate the integral.[35] Given the number of physicians, $\mathcal{K}$, the demand model parameters are estimated by Simulated Maximum Likelihood by taking the simulated log-likelihood of the sample.

$$\log L = \frac{1}{\mathcal{K}} \sum_{\forall k} \log \frac{1}{M} \sum_{\forall m} \left[\prod_{v=0}^{V^k} \prod_{\forall j} \left(\frac{\exp(u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}))}{\sum_{\forall j'} \exp(u_{ikj'v}(p_{j'v}, d_{j'}, a_{iv}|\mathcal{I}_{kv}))} \right)^{y_{ikjv}} |\vec{e}^m_k \right] \tag{15}$$

4.4 Results

4.4.1 Estimates

Table 4 presents the dynamic elements of the preferences, including estimates of the initial prior distribution parameters, the precision of experience signals, the price sensitivity and the contribution of learning from indirect experience. Prior means are expressed relative to the 24-hour clinical match value, normalized to zero for each group of patients. The price sensitivity of demand is negative but small and non-significant. Table 5 presents the corresponding mean own and cross-price elasticities of demand for each product, suggesting that demand is highly inelastic. It aligns with the literature studying pharmaceutical demand, close to the estimates for insulins from Einav et al. (2018) for elderly in the US, -0.02.

The initial prior means about the partial information clinical match value, $\widehat{\theta^0_j}$, are negative compared to the reference product, normalized to zero, but also their true value, $\widehat{\theta}_{nj}$, as displayed in Table 6. Physicians are reluctant to switch existing patients to new products initially.

The estimated parameters highlight heterogeneity across new products' priors. Beliefs about the 24-hour biosimilar's performance appear particularly pessimistic and uncertain. The 36-hour product faces a higher prior mean and a lower level of uncertainty, in line with the features of this entering product. Experience signals are quite imprecise as their magnitude is between 1.6 to 3.8 times the magnitude of the initial level of uncertainty. The digital technology does not increase nor decrease the precision of the experience signal physicians use to learn about the partial information match value of new products, θ_{nj}.

Table 6 presents the partial information clinical matches values, θ_{nj}, for three patient groups.

[35] The draws are generated once and used across iterations.

In most cases, new products (excluding the 24-hour biosimilar) outperform the 24-hour treatment, even under partial learning, once uncertainty is resolved. On the other hand, Figure 8 plots the partial information match value, $\widehat{\theta}_{nj}$, together with the average clinical match value in a given cluster, n, $\widehat{\Theta}_{nj}$.[36] Within each cluster, differences in $\widehat{\theta}_{nj}$ across products capture the perceived product differentiation without the device and $\widehat{\Theta}_{nj}$ the perceived differentiation with the device. The figure highlights that, for specific patient groups, some products benefit from the information provided by CGM as the match value with the device is higher than its counterpart without the technology, and some alternatives are weakly worse off.

Table 4: Dynamic parameters

				Mean, θ_j^0		S.D., $(V_j^0)^{0.5}$	
		Coef.	se	Coef.	se	Coef.	se
Prior	24-hour biosimilar			-6.05	(0.14)	3.34	(0.11)
	36-hour			-3.43	(0.10)	2.21	(0.05)
	42-hour			-3.49	(0.12)	2.65	(0.08)
	Type 2			-4.25	(0.11)	2.77	(0.09)
Signal S.D.	σ_0	4.30	(0.11)				
	σ_1 (w. CGM)	-0.04	(0.12)				
Price		-0.11	(0.20)				
Age	Cst	-0.52	(0.02)				
	square	0.04	(0.00)				

Note: Standard errors are computed from the average of the score. The model is estimated on a sample of 150 diabetes specialists working outside of the hospital setting.

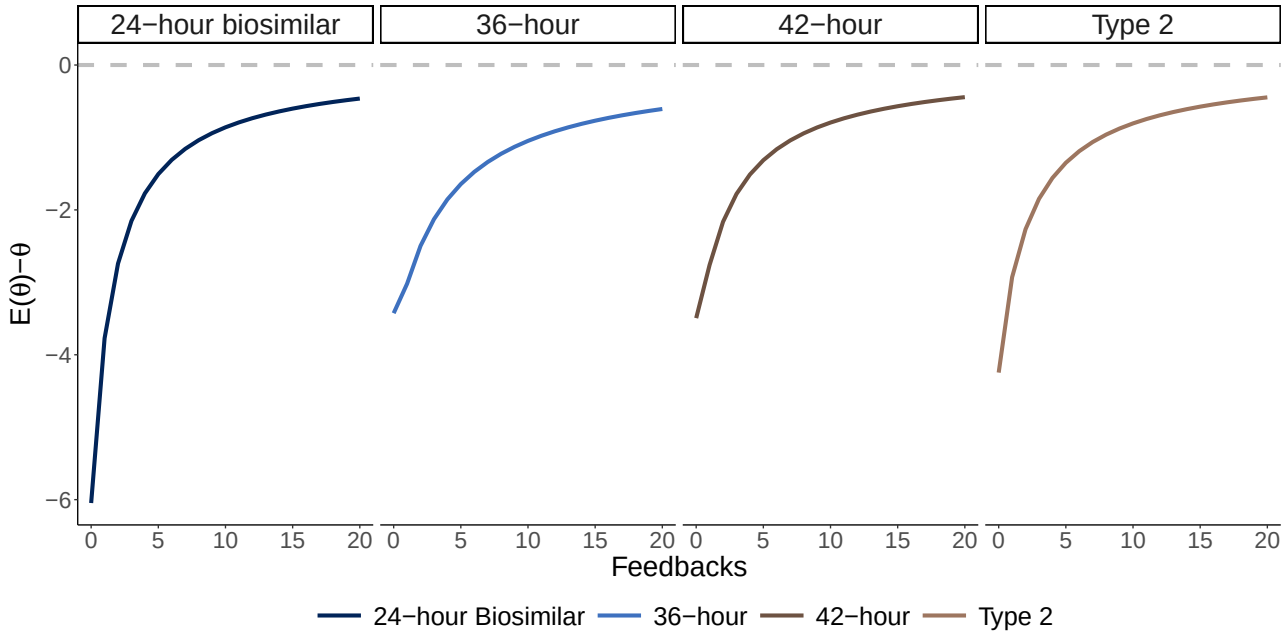
Table 5: Own and cross-price elasticities

	24h	20h	Mix	Human	24h Bios.	36h	42h
Own-price elasticity	-0.050	-0.066	-0.047	-0.046	-0.052	-0.048	-0.049
Cross-price elasticity	0.011	0.003	0.002	0.001	0.002	0.019	0.020

Note: Average across patients.

[36] $\widehat{\Theta}_{nj} = \sum_{\forall i \in n} \widehat{\Theta}_{ij} = \sum_{\forall i \in n} \widehat{\theta}_{nj} + \widehat{\beta}_1(x_i)d_j + \widehat{\beta}_2(x_i)d_j^2$

Figure 7: Partial information prior mean, θ^t_{nj}



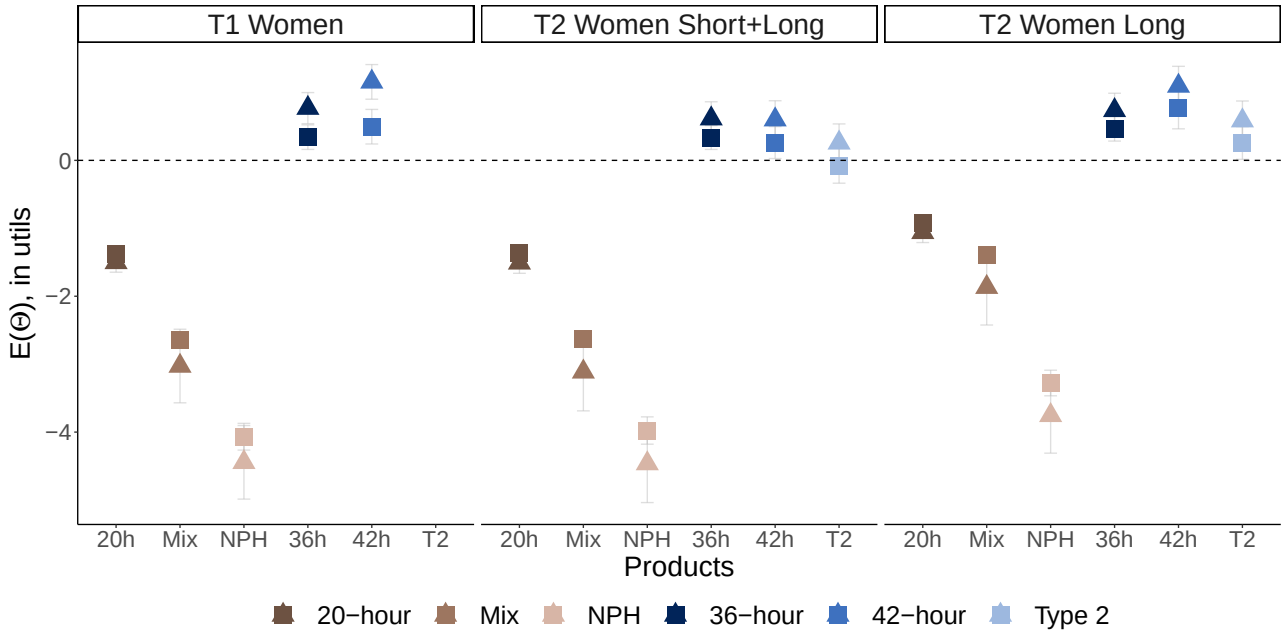
Note: This figure presents the evolution of beliefs (vertical axis) as a physician collects more experience signals (horizontal axis) from patients who return to her practice while using new product j, given the parameters estimated in the demand model (Table 4). The figure plots the beliefs for Type 2 male patients under a short+long therapy, assuming signals are received from patients not using a CGM.

Table 6: Partial information clinical match values, θ_{nj}

		20	Mix	Human	36	42	T2
Type 1 'Old male'	Coef	-1.72	-2.43	-4.37	0.31	0.40	
	SE	0.03	0.06	0.12	0.11	0.15	
Type 2 short+long 'Male'	Coef	-1.53	-2.53	-4.41	0.39	0.31	-0.10
	SE	0.03	0.06	0.13	0.10	0.14	0.15
Type 2 long 'Male'	Coef	-1.12	-1.52	-3.31	0.03	0.47	0.23
	SE	0.02	0.06	0.11	0.11	0.17	0.13

Note: Standard errors are computed from the average of the score. Type 1 and 2 correspond to the patient's type of diabetes. Type 1 patients must use both short- and long-acting insulins daily. Type 2 patients may rely on short- and long-acting insulins ('short+long') or long-acting insulin only ('long').

Figure 8: Perceived match value with/without a CGM



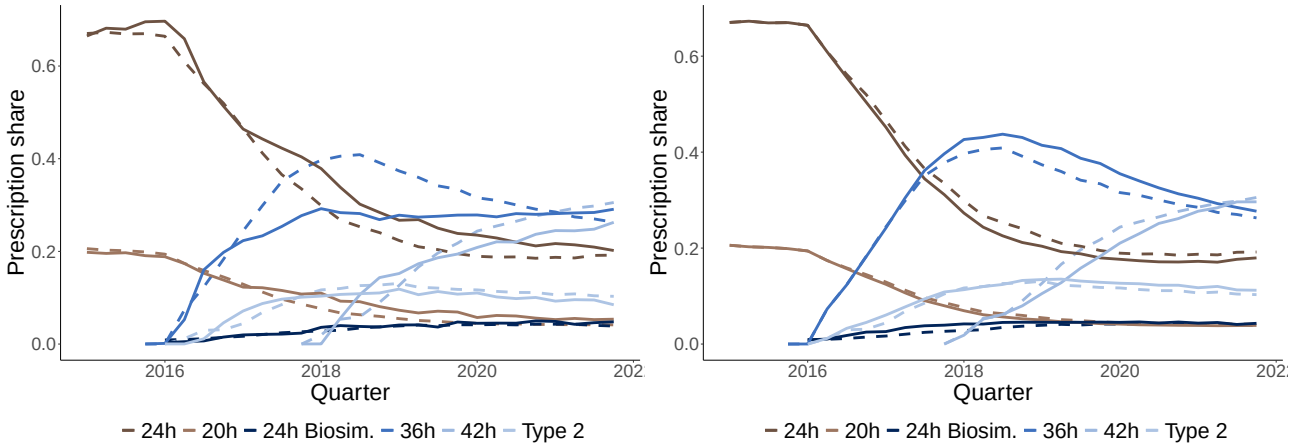
Note: This figure presents the perceived match value, $E(\Theta_{ij})$, without the technology (■) and with CGM (▲) in utils (vertical axis) for each product (horizontal axis). The expectation is taken assuming the number of experience signals received by a given physician for each drug tends to infinity such that the uncertainty around θ_{ij} for new drugs is resolved. Hence, the perceived match value without the technology corresponds to θ_{nj} while the perceived match value with the technology is $\theta_{nj} + \Delta\nu_{nj}$ where $\Delta\nu_{nj}$ is the average across patients within a cluster. The 24-hour product (not represented) corresponds to the normalized good in each group. 'Mix' corresponds to insulin mixes, 'NPH' to human insulins and 'Type 2' to the mix of long-acting insulin and another molecule, only intended for Type 2 diabetes patients. Only three clusters out of seven patient groups are represented. The remaining clusters are presented in Figure A14.

4.4.2 Model fit

Before moving to the supply side and counterfactual analysis, this section provides descriptive evidence of how the estimates for the demand model fit the data. To that extent, the parameters are used to simulate the choice probabilities for each product at each prescription. When comparing the model's prediction to the data, I fix past choices to update physicians' priors to avoid accumulating prediction errors over time. To demonstrate the ability of the model to generate the diffusion pattern observed in the data, I also compute the average predicted choice probabilities in a fully simulated environment in which predicted choice at v affects learning in future prescriptions. Figure 9 plots the simulated average choice probabilities per product and quarter over the realized prescription shares (Figure 9a) and against the 'fully simulated' average choice probabilities (Figure 9b). The parameters tend to overestimate the prescription of the 36-hour product compared to the observed choice of physicians in the years right after the introduction of the product. To a lesser extent, the model also slightly overestimates the prescription of the 42-hour drug from 2019 to 2021. Figure A15 compares the realized and

predicted choice, and Table A6 presents the frequency of accurate prediction across years and patients' groups. The accuracy rates range from 31 to 82%, similar to those in Dickstein (2021) who estimates a demand model with learning for antidepressants in the US.

Figure 9: Model fit



(a) Realized vs predicted (dashed) shares

(b) Fully simulated vs predicted (dashed) shares

Note: Figure 9 compares each product's actual and predicted choice probabilities over time. For clarity, insulin mixes and human insulins are not represented.

5 Supply: considering pricing response

5.1 Empirical model

To understand how digital devices may shift market equilibrium, this section presents the price-setting mechanism and estimates the primitives of the supply side. It accounts for the pricing response from drug manufacturers to the introduction of a digital medical device. The entry of innovations in drugs and devices are taken as given. This assumption is motivated by the time of drug and device development.[37]

Even when decision-makers are myopic, as assumed here, a demand system subject to consumer learning presents dynamic features. Current sales affect future demand. Modelling supply in markets with dynamic demand is inherently complex as firms have incentives to exploit this feature and set their price in a forward-looking manner (Shapiro (1983), Bergemann and Välimäki (2006)). Firms' optimal pricing policy depends on the distribution of perceived quality of their own and competing products across consumers. To overcome the complexity induced

[37]Drug development can take more than 10 years. One of the first patents for Abbott Freestyle Libre approved in the EMA in 2014 dates back to 2006/2007 (Litvinova et al. (2023)).

by forward-looking drug manufacturers and dynamic demand, I rely on the characteristics of the institutional setting. In France, the price for prescription drugs is set through bargaining between drug manufacturers and the regulator. The price is set upon entry for an extended period and renegotiated over time. Rises are difficult to bargain, preventing manufacturers from exploiting the market dynamic by setting a low price upon introduction to raise it in later periods in the spirit of Shapiro (1983).

I assume that the regulation leads to an equilibrium price as the outcome of a Nash-bargaining between drug manufacturers and the regulator, similar to Tunçel (2024). Unlike other pharmaceuticals, the insulin market is concentrated with three companies offering the full set of products in France. The bargaining is assumed to happen at the drug portfolio level for each manufacturer. The profit for firm f offering products $j \in \mathcal{J}_f$ in year t is

$$\pi_f(\mathbf{p}_t) = \sum_{\forall j \in \mathcal{J}_f} (p_{jt} - c_{jt}) q_{jt}(\mathbf{p}_t) \tag{16}$$

where $q_{jt}(\mathbf{p}_t) = \sum_{\forall i,k} \sum_{\forall v \in t} s_{ikjv}(\mathbf{p}_t)$ is the total demand for drug j across appointments v happening in year t. This profit function assumes that manufacturers have rational expectations about demand realization in the coming 12 months following the price negotiation. The manufacturer anticipates physicians' learning altering initial market shares for new products upon entry. Individual choice probabilities are derived from Equation (13). From 2017 onwards, drug manufacturers also have rational expectations about the CGM coverage decision, the adoption among the pool of participants, a_{iv}, and how the digital device shifts demand via $\Delta\nu_{ij}$. This last assumption presupposes that the drug manufacturers, when bargaining over the prices, have superior information to that of physicians about the clinical benefit of each own and competing new drug in real-life conditions.[38] When bargaining with firm f, the regulator is assumed to maximize the *ex-ante* consumer surplus generated by the portfolio of drugs offered by f in year t, given by

$$\Delta_f CS(\mathbf{p}_t) = \sum_{\forall i,k} \sum_{\forall v \in t} \frac{1}{\lambda} \ln \Big(\sum_{\forall j \in \mathcal{J}} \exp(u_{ikjv}(p_{jt(v)}, d_j, a_{iv} | \mathcal{I}_{kv})) - \sum_{\forall i,k} \sum_{\forall v \in t} \frac{1}{\lambda} \ln \Big(\sum_{\forall j' \notin \mathcal{J}_f} \exp(u_{ikj'v}(p_{j't(v)}, d_{j'}, a_{iv} | \mathcal{I}_{kv})) \tag{17}$$

The parameter λ corresponds to the scaling factor for consumer surplus from the regulator's

[38] Hitsch (2006) and Handel and Misra (2015) study firms pricing decision when they have incomplete information about the true demand curve but assume no learning on the demand side. Firms are assumed to have accurate information about the clinical match value of new products in real-life conditions.

perspective. It can be different from α, allowing the price sensitivity of physicians, estimated from the demand model, not to accurately scale utils into dollars for the regulator. Under Nash-bargaining, both parties have symmetric information. The regulator also forms rational expectations about the adoption of the digital device and the impact of the device on consumer surplus when bargaining over insulin prices from 2017 onwards. I follow Grennan and Town (2020) in assuming that the surplus the regulator considers when setting drug prices does not account for the difference between the decision and experience utility. Under these assumptions, access to the digital device affects equilibrium prices. The regulator and the manufacturer anticipate that physicians are choosing treatment relying on this new information source when bargaining over prices. Denoting b_{ft} the bargaining ability of firms f in year t, the equilibrium prices maximize the Nash product for the manufacturer's profit and the regulator surplus, taking other prices as given:

$$\max_{\mathbf{p}_{jt}, j \in \mathcal{J}_f} [\pi_f(\mathbf{p}_t)]^{b_{ft}} [\Delta_f CS(\mathbf{p}_t)]^{1-b_{ft}} \tag{18}$$

The portfolio of each pharmaceutical company is treated as an indivisible block. Which product to include in the portfolio is taken as exogenous, and bargaining over a subset of products is not considered. The first order condition with respect to the price of drug $j \in \mathcal{J}_f$ is given by

$$b_{ft} \frac{\partial \pi_f(\mathbf{p}_t)/\partial p_{jt}}{\pi_f(\mathbf{p}_t)} + (1 - b_{ft}) \frac{\partial \Delta_f CS(\mathbf{p}_t)/\partial p_{jt}}{\Delta_f CS(\mathbf{p}_t)} = 0 \tag{19}$$

The scaling factor of the consumer surplus, λ, does not affect the equilibrium outcome, while the price sensitivity of demand matters.[39] The details for the first-order condition computation are provided in Appendix D. When a firm offers two products, j and j', the first order conditions give the following expression for the marginal cost of product j in year t, c_{jt}:

$$c_{jt} = p_{jt} + \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)} + \left(\beta_{ft} h_{j't} + \frac{\partial q_{j't}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)} \right) \frac{\left(q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} \right)}{\left(q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} \right)} \right]^{-1} \tag{20}$$

[39] The regulator does not internalize the impact of pharmaceutical prices on innovation through profits.

where $h_{jt} = \frac{\partial \Delta_f CS(\mathbf{p}_t)/\partial p_{jt}}{\Delta_f CS(\mathbf{p}_t)}$ and $\beta_{ft} = \frac{1-b_{ft}}{b_{ft}}$. For single-product firms,

$$c_{jt} = p_{jt} + \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)}\right]^{-1} \tag{21}$$

The unknowns from Equation (20) are the marginal costs, c_{jt}, and the bargaining parameters, b_{ft}, as the remaining elements are observed or can be computed from the estimates of the demand system. The marginal costs and bargaining weights parameters must be recovered to compute the equilibrium prices under alternative scenarios. These parameters are held fixed in counterfactuals.

5.2 Estimation and results

To recover the primitives of the supply model, it is further assumed that

$$\begin{aligned} c_{jt} &= \gamma mc_j + \zeta_{jt} \\ \frac{1-b_{ft}}{b_{ft}} &= \beta_f \end{aligned} \tag{22}$$

mc_j are molecule-level costs of production for a daily dose, using the estimates from Gotham et al. (2018), and ζ_{jt} is an unobserved cost shock.[40] Bargaining weights are assumed to be firm-specific and constant over time. Combining Equation (20) and the restrictions from (22), we get:

$$\zeta_{jt} = p_{jt} - \gamma mc_j + \left[\beta_f h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)} + \left(\beta_f h_{j't} + \frac{\partial q_{j't}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)}\right) \frac{\left(q_{j't}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}\right)}{\left(q_{jt}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}\right)}\right]^{-1} \tag{23}$$

The above equation highlights the usual endogeneity issue that arises on the supply side between the price and the marginal cost shock. I rely on traditional instruments correlated with price but uncorrelated with the idiosyncratic cost shock, such as the number of competing products. Including firm fixed effects and marginal costs in the set of exogenous variables, the bargaining weights and marginal cost parameter can be estimated via GMM using the following moment conditions:

$$E[\zeta_{jt}|Z_{jt}] = 0 \tag{24}$$

[40] Gotham et al. (2018) estimates the cost of production for a 1,000 insulin units vial relying on Indian customs data for raw molecules and excipients quantities and prices. Among others, the marginal cost to consider in the demand model may deviate from these estimates as pens, the most common injection device, are more costly than vials.

In the main specification, the coefficient for production costs, γ, is set to 1.3 as it is difficult to estimate precisely both marginal costs and firm-specific bargaining weights. To set γ, the model is estimated for $\gamma \in [1, 2]$, and the value minimizing the GMM objective function is kept in the main specification. An alternative specification could assume $\gamma = 1$, yet, several reasons rationalize $\gamma > 1$. I rely on the 'competitive' estimates from Gotham et al. (2018). It can also be explained by the cost of the injection device, which is not included in the current estimate, and distribution costs.[41] The results are presented in Table 7. Insulin mixes (including the new Type II drug) and human insulins are removed from the estimation such that their prices are held fixed in the counterfactuals.

The bargaining weights capture the ability of the drug manufacturer to set a price above marginal cost when bargaining with the regulator. The manufacturer-level bargaining weights are estimated between 5 to 7%. These estimates are significantly lower than those estimated in the pharmaceutical context by Dubois et al. (2022) for Canada and Tunçel (2024) in France for the anti-depressants market. The difference in the price elasticity of demand can drive this difference. With demand being nearly inelastic to prices, the regulator is the primary force preventing pharmaceutical companies from setting excessively high prices.[42] The average per-product margin implied by the model lies between 53 and 85%.

Table 7: Bargaining weights estimates

	Coef.	S.E.	b_f
Firm 1	15.383	0.914	0.061
Firm 2	19.031	2.722	0.050
Firm 3	13.360	1.811	0.070
γ		1.300	
N		30	

Note: One-step GMM. Jackknife standard errors. γ is set to 1.3 by comparing the value of the GMM objective function for $\gamma \in [1, 2]$. The estimation excludes insulin mixes, human insulin and the Type 2 product, whose prices are held fixed in counterfactuals.

[41] Most patients in France rely on insulin pens to inject their insulin, while the current estimates are computed for vials. Robustness checks can be performed to account for the cost of the injection device.

[42] In countries like the US, where the government does not intervene in drug pricing, insulin prices for the same product as those offered in France are significantly higher.

6 Data-driven insights, physician learning and cross-markets complementarities in insulin demand

The estimates from the previous sections are used to measure the impact of the insights generated by digital wearables on pharmaceutical demand through several counterfactual scenarios. This equilibrium framework is used to understand: (i) The impact of information provision. (ii) The cost of relying on partial information. (iii) How does CGM information affect the profitability of pharmaceutical innovations.

6.1 Defining relevant market outcomes

Before turning to the implementation and comparison of counterfactual scenarios, I define the indicators relevant when trying to understand whether and how the market dynamic shifted thanks to the device. This section will mainly focus on four ingredients of market outcomes: (i) market shares, (ii) firms' profit, (iii) physician-level learning and (iv) consumer welfare.

The first two market outcomes are straightforward to compute from the predicted choice probabilities and equilibrium prices. Physician-level learning is studied through the end-of-period belief about θ_{nj}, denoted $\theta^{V_k}_{nkj}$. Computing consumer welfare under different scenarios is more intricate as decision-makers face imperfect and incomplete information about the patient-product clinical benefit. As mentioned in section 4, a discrepancy exists between the decision and experienced utility. Denoting $\mathbf{p}$ the equilibrium prices, $\mathbf{d}$ the vector of product durations and $\mathbf{a}$ the vector of CGM usage in the patient population, the expected indirect utility for patient i from the choice made on his behalf by physician k at time v is:

$$\begin{aligned} W_{ikv}(\mathbf{p},\mathbf{d},\mathbf{a}) &= \mathbb{E}_{\varepsilon}[\bar{u}_{ikj^*v}(\mathbf{p},\mathbf{d},\mathbf{a})] \\ &= \ln\Big(\sum_{\forall j}\exp(u_{ikjv}(p_{jt(v)},d_j,a_{iv}|\mathcal{I}_{kv}))\Big) - \sum_{\forall j} s_{ikjv}(\mathbf{p},\mathbf{d},\mathbf{a})\Big[\theta^{v}_{nkj} - \theta_{nj} + \Delta\nu_{ij}(d_j)(a_{iv}-1)\Big] \end{aligned} \tag{25}$$

where $s_{ikjt}(\mathbf{p},\mathbf{d},\mathbf{a})$ denotes the choice probability, given by Equation (13). The value of learning is taken into account in the second component of the indirect utility which accounts for the difference between the expected match value at the time of the decision, $\theta^{v}_{nkj} + \Delta\nu_{ij}a_{iv}$ and its true value, $\Theta_{ij} = \theta_{nj} + \Delta\nu_{ij}$. This expression allows comparing consumer welfare under

alternative market outcomes, m from the compensating variation.[43] The welfare induced by the digital device for the patients is beyond what is measured in this project, as I restrict my attention to the long-acting insulin market.

6.2 Digital device adoption and the insulin market

The model is used to evaluate the impact of CGM on the insulin market, taking patient adoption patterns as given. To that extent, I simulate a scenario where CGMs are no longer used, setting a_{it} equal to zero for all patients, and compare the equilibrium prices and market shares with and without CGM adoption.

Figure 10 illustrates the difference in consumer welfare induced by the introduction of CGMs. Figure 10a shows the compensating variation (vertical axis), in euros per day, following a prescription happening in period t (horizontal axis). The average consumer welfare is presented for patients with a CGM (blue curve) and those not using one (brown curve). Three key insights emerge. First, the average welfare gains for CGM users are nearly ten times higher than for non-users, indicating limited information spillovers between the two groups. Second, among CGM users, welfare gains are larger in the early months of CGM coverage and decrease over time. It suggests that the technology is most valuable for patients when physicians face greater uncertainty about treatment quality. Despite the decreasing trend, CGMs should continue generating positive welfare gains over the long run — as physicians gather sufficient experience about new drugs — thanks to the information about the glucose profile, $\Delta\nu_{ij}$. Third, for non-users, the welfare gains take longer to materialize. Physicians must observe the performance of new drugs from patients with the device for the information to benefit non-users. Over time, non-users gains should converge to zero as physicians accumulate enough knowledge about new drugs. Figure 10b displays the distribution of consumer welfare gains across patients using CGM, distinguishing between individuals with Type I and Type II diabetes and different demographic characteristics. Patients with Type I diabetes benefit more than those with Type II, and women tend to benefit more than men within each diabetes type. These findings align with the medical literature, which suggests that patients with longer diabetes durations and women are more prone to low glucose levels overnight, a condition for which CGMs provide

[43] The compensating variation is computed as

$$CV_{ikt}(\mathbf{p}^m, \mathbf{d}^m, \mathbf{a}^m) = \frac{1}{\alpha}\big(W_{ikt}(\mathbf{p}^m, \mathbf{d}^m, \mathbf{a}^m) - W_{ikt}(\mathbf{p}^0, \mathbf{d}^0, \mathbf{a}^0)\big)$$

where $W_{ikt}(\mathbf{p}^m, \mathbf{d}^m, \mathbf{a}^m)$ correspond to consumer welfare in scenario m and $W_{ikt}(\mathbf{p}^0, \mathbf{d}^0, \mathbf{a}^0)$ correspond to consumer welfare without the technology.

relevant insights (Siamashvili et al. (2021)).

Next, I assess the impact on physician learning. Figure 11 compares the difference between $\hat{\theta}_{nj}$ and $\hat{\theta}^{V_k}_{nkj}$, the partial information clinical match value and the end-of-period physician-level prior mean. This difference is a proxy for belief accuracy, where a smaller difference indicates a more accurate belief about product j. It is computed for each physician, k, patient group, n, and new product j. The figure plots belief accuracy without the device (horizontal axis) against its value when the technology is available (vertical axis).[44] Points above (below) the 45-degree line indicate more (less) accurate belief about product j when the device is available. Interestingly, while CGMs accelerated learning about some products (e.g., the 42-hour product), they did not enhance learning for others (e.g. the 24-hour biosimilar). It is likely due to two factors: (i) physicians face a limited number of opportunities to gain experience with new drugs such that products *compete* over these opportunities, and (ii) the experience signal from CGM users about θ_{nj} are equally precise as the ones received from regular patients. Consequently, learning about some products may come at the expense of others, and not all new products benefit equally from CGM insights.

At the market level, Table 8 shows the market shares for 2021, while Figure 12 tracks their evolution over time. Figure 13 presents manufacturers' profits. In 2021, the 42-hour product saw a 16.5% increase in market share due to CGM adoption, while the 36-hour product experienced only a temporary increase in market share, which nearly vanished by the end of 2021. Similarly, profits for the 42-hour product rose by 23%, driven primarily by the demand response to CGM (+18%). These results suggest that CGMs unevenly favored new products' adoption at the expense of older ones, particularly the 24-hour products.

In summary, this counterfactual analysis shows that the introduction of CGMs (i) primarily benefited CGM users with limited spillovers to non-users, (ii) accelerated physician learning about certain products, and (iii) was sufficient to affect market shares and insulin manufacturers' profits.

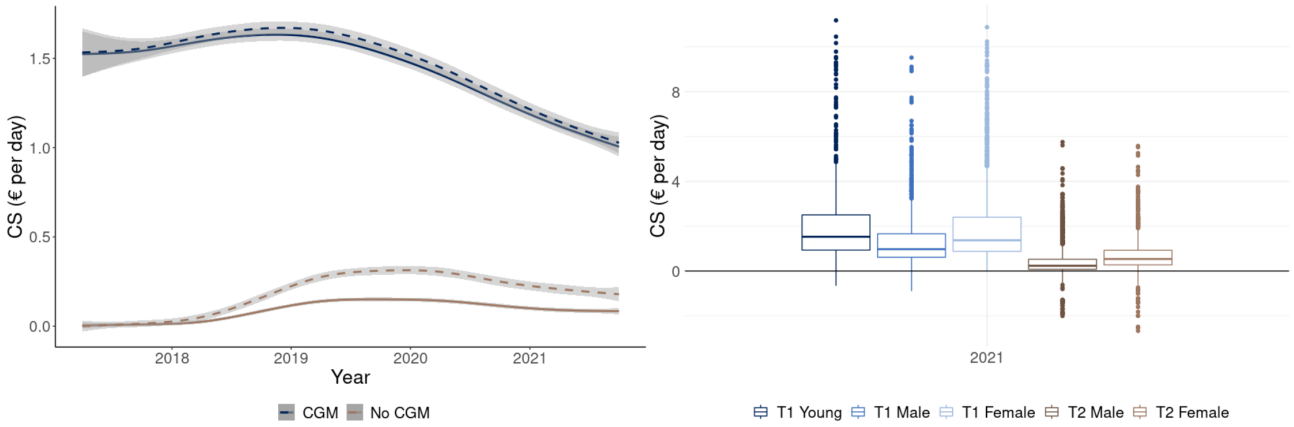
The limited spillovers to non-users may be influenced by the unequal propensity of physicians to see CGM patients (Table 1).[45] To explore this further, I conduct a counterfactual reallocation of CGM sensors among eligible patients, accounting for patient demographics that may correlate with adoption (detail in Appendix E). Figure A16 shows that reallocating sen-

[44] In this context, prior beliefs are not consistent with the true partial information match value. The results from the estimation suggests pessimistic prior beliefs as $\widehat{\theta}^0_j < \widehat{\theta}_{nj}$ for each new drug j and patient group n.

[45] In the extreme case where all patients in the same cluster are either adopting or not at a physician practice, spillovers cannot arise.

sors does not increase spillovers to non-users. It indicates that the variation in CGM adoption across physicians is not the primary driver of limited spillovers. However, this counterfactual does not address how spillovers could be enhanced by allocating sensors to patients with *different* demographic characteristics.

Figure 10: Consumer welfare

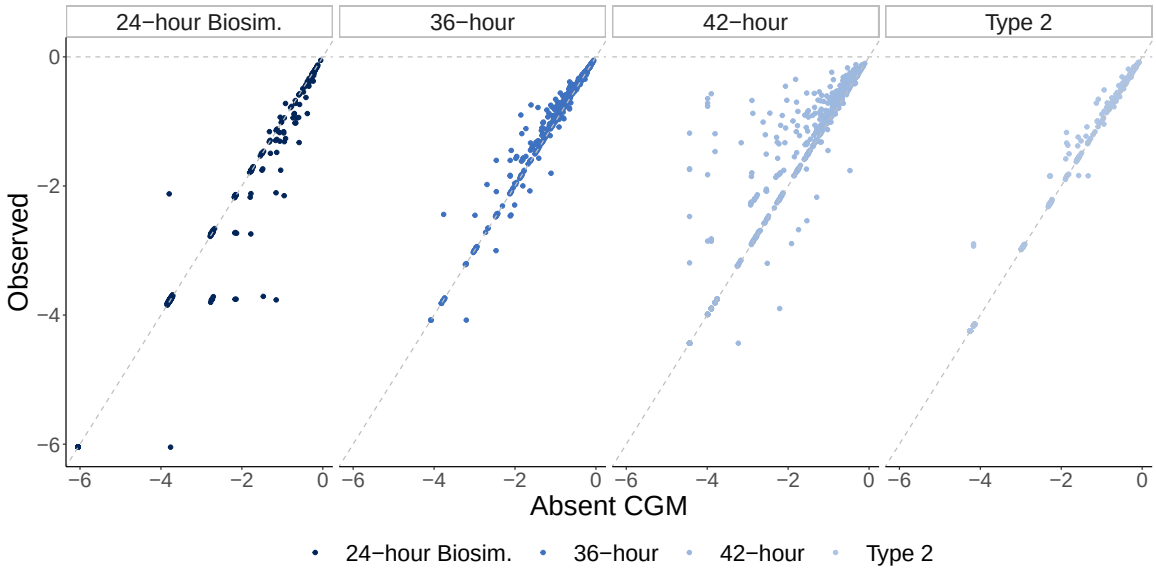


(a) Average over time

(b) Distribution across patient types

Note: Figure 10a presents the compensating variation (vertical axis), in euro per day, following a prescription happening in period t (horizontal axis). The average consumer welfare is presented for patients with CGM (blue curve) and without (brown curve). Dashed lines focus on the consumers eligible for the device. Figure 10b presents the compensating variation distribution (vertical axis) across different eligible patient types (horizontal axis) in 2021 for CGM users. Ineligible clusters are not represented here as the effect is negligible.

Figure 11: Learning rate about the partial clinical match value, $\hat{\theta}_{nj}$, with and without CGM



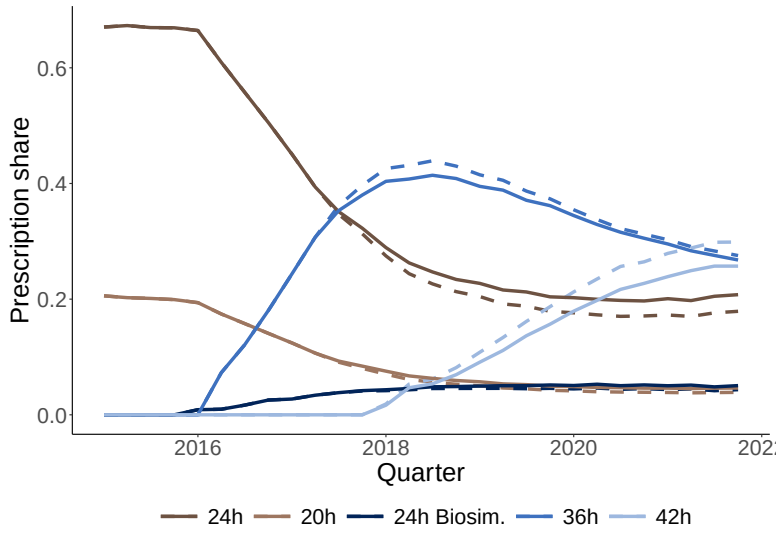
Note: This figure plots the difference between $\hat{\theta}_{nj}$ and $\hat{\theta}^{V_k}_{nkj}$, the partial information clinical match value and the end-of-period physician-level prior mean in an environment with CGM (vertical axis) against its value in an environment without CGM (horizontal axis). One observation per physician, patient type among types eligible for the technology and product. Points above the 45-degree lines suggest more accurate belief at the end of the period when the technology is available.

Table 8: Market shares with vs without CGM in 2021

Scenario	24-hour	20-hour	24-hour Bios.	36-hour	42-hout
Base (no CGM)	0.203	0.046	0.050	0.281	0.250
Demand-response	0.174	0.038	0.044	0.287	0.292
+ Supply response	0.174	0.038	0.043	0.289	0.291

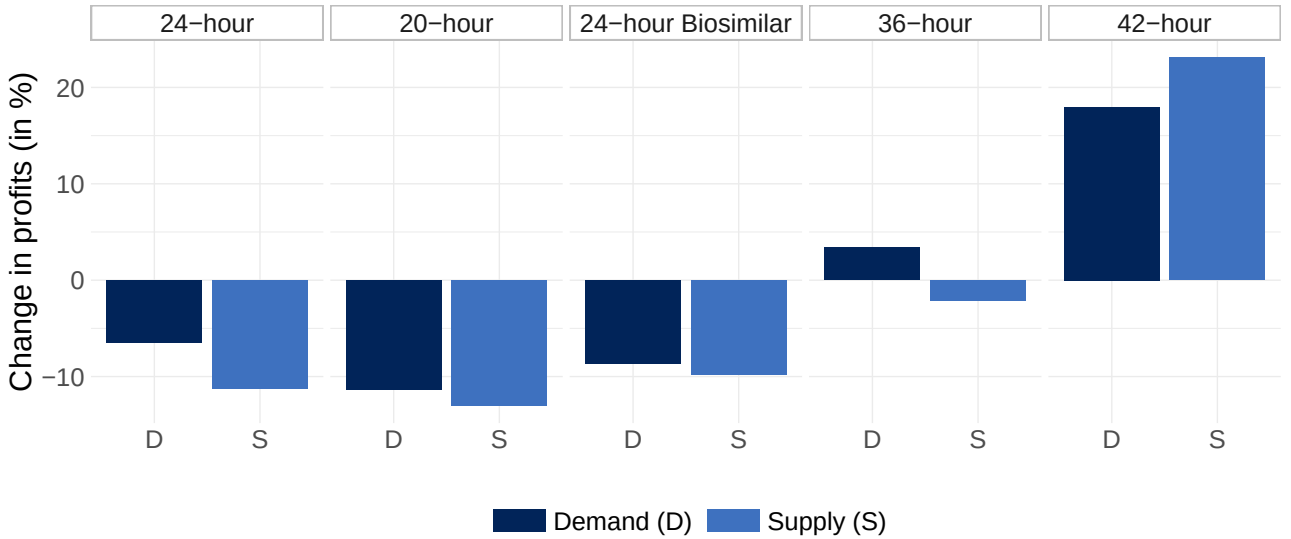
Note: The first row corresponds to the predicted 2021 market share, absent the technology. The second row takes into account the demand response to CGM information. The third row allows prices to respond to changes in demand and correspond to the predicted 2021 market shares, given the observed adoption pattern. Insulin mixes (including Type II product) and human insulin are not represented.

Figure 12: Market shares without vs with (dashed) CGM over time



Note: This figure plots the choice probabilities absent CGM (plain lines) and their counterpart as CGM became available (dashed lines) over time. Insulin mixes (including the new Type II product) and human insulin shares are not represented.

Figure 13: Impact of CGM on drug manufacturer's profits across 2017-2021



Note: Change in profits due to the introduction of CGM over the 2017-2021 period for each product. The profits without CGM are normalized to 100 for each product, and each scenario is compared to this baseline. For each product, the first bar corresponds to changes in profits due to CGM affecting the demand curve and the second bar accounts for prices to react to the change in demand.

6.3 Cost from relying on partial information about the clinical match value

By generating continuous data, the digital device emphasizes the inefficiencies arising from incomplete learning in prescription drug choice. Observing the choice for patients under complete learning helps quantify the costs of relying solely on partial information, in terms of market shares, foregone profits and consumer welfare. In this section, I extrapolate the results from device users to non-users to measure the losses from incomplete learning and assess how much of this gap is bridged by providing broad access to CGM.

I begin by considering the complete information scenario in which every patient uses a CGM as the "frictionless" solution. In this case, physicians access each patient's true clinical match values, Θ_{ij}. I then compare this market outcome to two scenarios where (i) the technology was never available and (ii) CGM coverage is available, but some patients do not adopt the device, reflecting the current situation. Comparing the frictionless case to the first scenario, in which choices rely exclusively on partial information, emphasizes the losses from incomplete learning in terms of industry profits and consumer welfare. To abstract away from the uncertainty about new drugs' performance upon market entry, I focus on the steady-state choice probabilities that prevail once this friction is resolved. The steady-state choice probabilities are obtained

by assuming physicians receive a precise signal from patients about the performance of new drugs ($\sigma_0 = 0.001$ and $\sigma_1 = 0$) and restrict my attention to the last year of the data, over 36 months after the last product entered the market.[46] The new equilibrium prices are computed for each drug under each scenario. Table 9 shows each product's steady-state shares and Figure 14 presents the profits. Comparing the first two rows highlights the products winning (older drugs) and those losing out (new products) due to incomplete learning. Measuring these losses in terms of consumer welfare, partial information accounts for -0.36€/per day on average across prescriptions — 8 times less than the daily cost of Continuous Glucose Monitoring. Providing broad CGM coverage for patients closes 54.8% of this gap, slightly above the adoption rate, since patients using CGM experience larger losses from partial information (Figure 15).

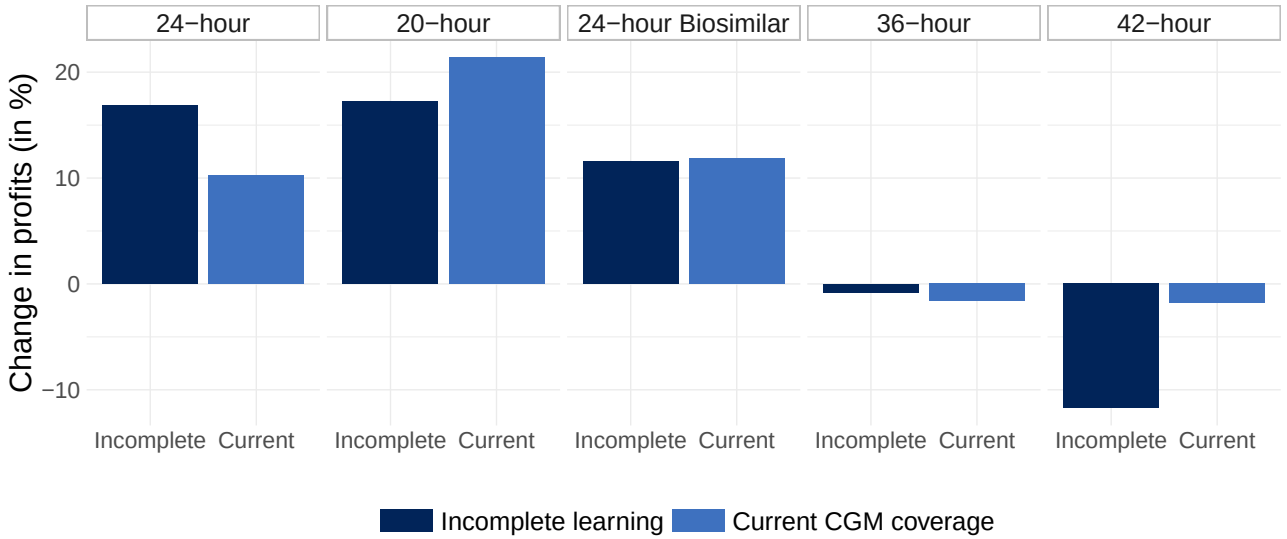
Table 9: Steady state market shares in 2021, complete vs partial information

Information	Product				
Complete	24h	20h	24-h Bios.	36h	42h
✓	0.095	0.020	0.076	0.271	0.383
No	0.122	0.028	0.095	0.264	0.332
Users	0.106	0.024	0.085	0.267	0.363

Note: This table presents market shares for each product once the uncertainty about the value of θ_{nj} for new products is resolved. Each row differs by the set of patients using CGMs daily. Insulin mix (including the Type 2 product), human insulin are not represented as their price are held fixed in counterfactuals.

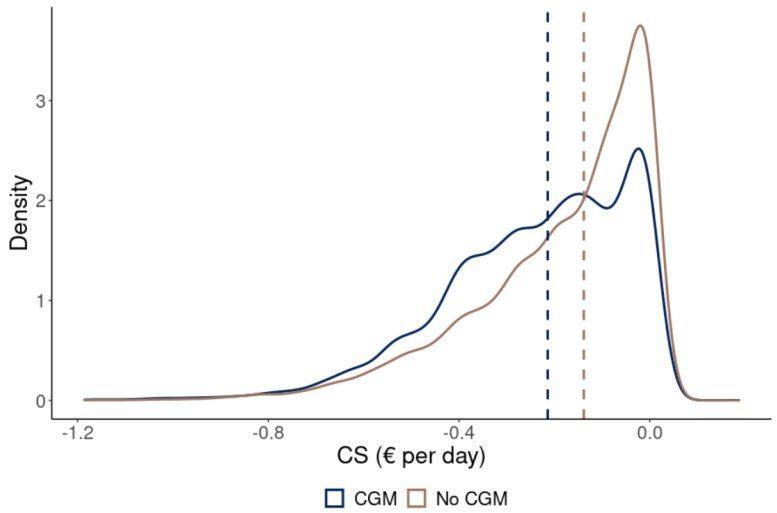
[46] Given the initial prior variance and the signal precision presented in Table 4, the uncertainty level becomes negligible after a physician receives the first feedback.

Figure 14: Changes in profits due to incomplete learning



Note: Change in profits for 2021 compared to the 'frictionless' case where choice is made under complete learning for each patient. The profits in the 'frictionless' case are normalized to 100 for each product, and each scenario is compared to this baseline. Bars above (below) zero suggest higher (lower) profits than if the choice was made under complete learning for all patients. For each product, the first bar corresponds to changes in profits in the absence of CGM, and the second bar corresponds to the changes in profits under the current coverage and adoption decisions.

Figure 15: Losses from partial information



Note: The figure plots the distribution of compensating variations between the frictionless case and relying exclusively on partial information across patients. Distributions are plotted separately for patients who adopted the technology in the observed coverage scheme (blue curve) and those who did not (brown curve). The top and bottom 2.5% are not represented here for clarity. The vertical dashed line corresponds to the median loss for each patient population.

6.4 Cross-market complementarities

The results from the previous section indicate that the introduction of CGM did not benefit all treatments equally. In 2021, the market share of the 42-hour product was 16.2% higher thanks to the insights generated by CGM, compared to only 3% for the 36-hour product. This result suggests that CGM helps better exploit the potential of certain new drugs. Hence, this section aims to quantify the welfare gains generated by the complementarity between data insights and the clinical benefit of insulins.

To measure this, I simulate market outcomes without CGM, assuming each new product had not entered while keeping competitors' price and entry decisions unchanged. I consider unilateral deviations in the entry decision for the 36 and 42-hour products, both in environments with and without CGMs.[47] For each product j and patient i, I denote $\Delta CS_{ij}^{e,a}$ as the change in consumer welfare in situations where the product enters or not, $e \in \{1, 0\}$, and whether or not the technology is available, $a_{it} \in \{1, 0\}$.[48] I consider the following decomposition:

$$\Delta CS_{ij}^{1,1} = \Delta CS_{ij}^{1,0} + \Delta CS_{ij}^{0,1} + \Gamma_{ij} \tag{26}$$

where $\Delta CS_{ij}^{1,1}$ captures the welfare gains from the entry of drug j alongside CGM, $\Delta CS_{ij}^{1,0}$ represents the gains from product j, had CGM not been available, and $\Delta CS_{ij}^{0,1}$ the gains generated by CGM, had drug j not entered.[49] The term Γ_{ij} measures the difference between the welfare gains from the two innovations and the unilateral contribution of each innovation, absent the other. A positive Γ_{ij} suggests that the welfare gains from product j and CGM entries together are higher than the sum of the gains from product j and those from CGM unilateral decision, indicating synergies between the two innovations.

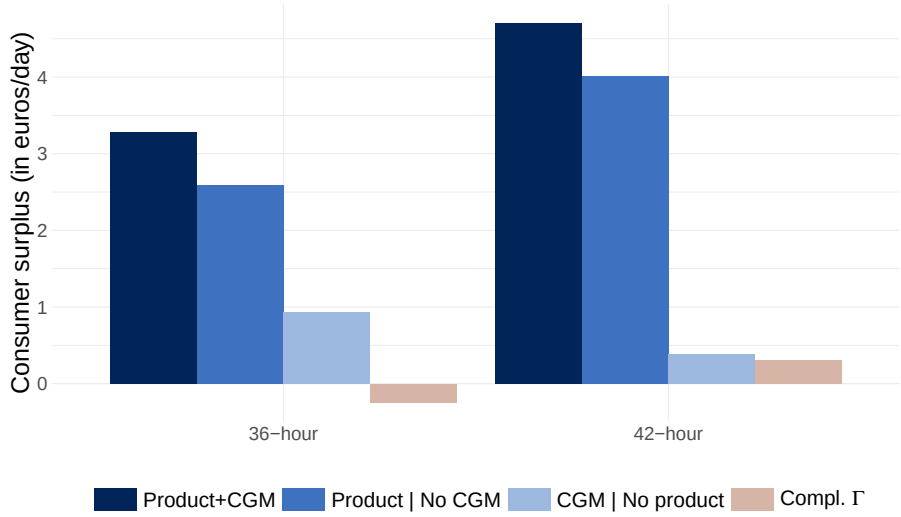
Figure 16 presents the average welfare gains across prescriptions from 2019 to 2021 and computes the average differential gains, $\overline{\Gamma}_j$ for the 36-hour and 42-hour products. The positive $\overline{\Gamma}_j$ for the 42-hour product suggests that the availability of CGM amplifies the welfare gains from this innovation. In contrast, $\overline{\Gamma}_j$ is negative for the 36-hour product, indicating that the technology does not similarly enhance its gains.

[47] The price of competing products is fixed to abstract away from the consumer welfare induced by the competitive pressure of having one more alternative in the market. New equilibrium prices for products still on the market can be computed from the Nash bargaining first-order conditions.

[48] In each case, the consumer surplus is computed using the welfare without entry ($e = 0$) and without CGM ($a = 0$) as benchmark.

[49] CGMs still affect insulin demand absent new drugs entry from $\Delta\nu_{ij}$.

Figure 16: Daily consumer surplus, 2019-2021



Note: Each bar corresponds to the average consumer surplus in euros per day. For each product (horizontal axis), the first bar corresponds to the average consumer surplus from the joint entry of the product and CGM, $\Delta CS_j^{1,1}$, the second bar corresponds to the average surplus from the product entry, absent CGM, $\Delta CS_j^{1,0}$, the third bar is the average benefit from CGM absent this product, $\Delta CS_j^{0,1}$ and the last bar is the average of the difference between the first bar and the sum of the last two, Γ_j.

6.5 Towards product design

To explore the potential impact of CGMs on the profitability of pharmaceutical innovations, I simulate the entry of a different product in 2018 — replacing the 42-hour option — and compare the potential profits from each new drug from the perspective of the insulin manufacturer. This scenario assumes the manufacturer forecasts the availability of CGMs and technology adoption in the population during product development. Table 10 outlines the characteristics of the alternative entering product, called the '72-hour' drug. This product is designed to appear more or less appealing under incomplete and complete learning.[50] The marginal cost of the molecule (net of the cost shock, ζ_{jt}) is assumed to be 15% higher than that of the 42-hour product. I compute the market clearing prices with and without CGM and compare manufacturers' profits and consumer surplus in each scenario.

Figure 17 presents each scenario's market share and firm profits. The ranking of market shares and profits across products shifts depending on whether CGM is available. Without

[50]The '72-hour' product features are designed to resemble the characteristics of the once-weekly insulin approved by the EMA in April 2024. Clinical trial outcomes are used to set partial-information clinical match values, θ_{nj}. However, the duration is 72 hours instead of 7 days to reduce the extent of out-of-sample extrapolation. In particular, the demand model does not capture the convenience of injecting insulin once a week against once a day. Hence, the 72-hour product is assumed to be injected once a day, similar to other available products. https://www.ema.europa.eu/en/medicines/human/EPAR/awiqli

CGM, the 42-hour product captures a larger market share and is more profitable for the manufacturer than the 72-hour version. However, when CGM is introduced (and adopted by patients), the market share of the 72-hour version increases by 40%, and it becomes more profitable for the firm to launch the 72-hour product rather than the 42-hour one.

Figure 18, similar to Figure 16, presents the decomposition of consumer surplus using Equation (26). The consumer surplus from the 72-hour product combined with CGM is 24% higher than that of the 42-hour product, driven by the 52% increase in consumer surplus thanks to the joint entry of the drug and CGM, as measured by Γ_j.

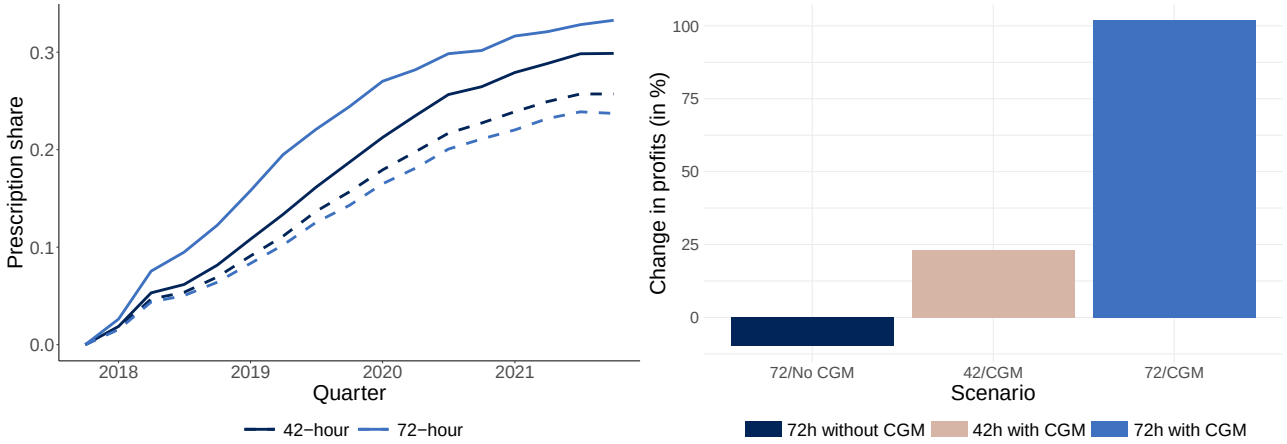
This last result suggests that the most profitable pharmaceutical innovation can shift based on the technological environment in which demand occurs. Complementary technologies, like CGM, can change the relative appeal of different drugs by introducing new criteria for evaluating drug performance, potentially affecting future pharmaceutical innovations.

Table 10: Product features

	Supply		Priors		θ_{nj}						
	mc_j	Duration	θ_{0j}	σ_{0j}	θ_{1j}	θ_{2j}	θ_{3j}	θ_{4j}	θ_{5j}	θ_{6j}	θ_{7j}
42-hour (Obs)	mc_{42}	1.75	-3.49	2.65	0.94	0.5	0.40	0.26	0.31	0.77	0.47
72-hour	$1.15 \times mc_{42}$	3	-3.57	2.70	$0.5\theta_{n,42}$			0.25		$1.1\theta_{n,42}$	

Note: The 72-hour product is inspired by the clinical trial outcomes for insulin icodec, approved by the EMA in April 2024. The marginal cost is assumed to be 15% higher than the 42h version.

Figure 17: 42-hour vs 72-hour product entry

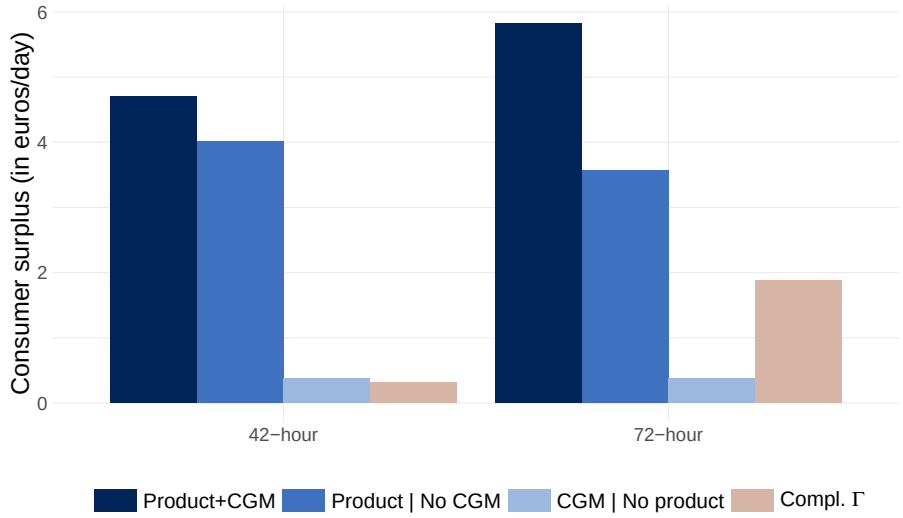


(a) Market shares, with vs without (dashed) CGM

(b) Firm's profit from product entry

Note: Figure 17a compares the average choice probabilities for each product over time following entry. The dashed lines correspond to product shares in a market that does not provide access to CGM, while the plain lines consider CGM's availability for patients. Figure 17b plots the changes in profits compared to the profits from the entry of the 42-hour product in an environment without CGM. The first bar corresponds to the difference in profits if the 72-hour product enters an environment without CGM. The second bar corresponds to the profits difference if the 42-hour product enters an environment with CGM, and the third bar corresponds if the 72-hour product enters an environment with CGM.

Figure 18: Daily consumer surplus, 2019-2021



Note: Each bar corresponds to a measure of average consumer surplus, in euros per day. For each product (horizontal axis), the first bar corresponds to the average consumer surplus from the joint entry of the product and CGM, $\Delta CS_j^{1,1}$, the second bar corresponds to the average surplus from the product entry, absent CGM, $\Delta CS_j^{1,0}$, the third bar is the average benefit from CGM absent this product, $\Delta CS_j^{0,1}$ and the last bar is the average of the difference between the first bar and the sum of the last two, Γ_j.

7 Conclusion

This paper studies how digital medical devices affect pharmaceutical demand in the context of CGM insights for insulin choice. To that end, I develop a tractable model of demand and supply for insulin embedding: (i) patient-specific learning about treatment performance through the CGM, (ii) dynamic physician-level learning about new drugs from patient experiences and (iii) price setting by pharmaceutical companies and the regulator both internalizing demand-side learning. The model is estimated using medical claims data from France that records insulin prescriptions by diabetes specialists.

The results from the structural estimation highlight how the insights from digital health data reshaped physicians' preferences when prescribing insulin to diabetic patients. Despite significant information frictions about new products, affecting both CGM users and non-users initially, consumer welfare gains mostly accrued to patients using the device, and non-users did not benefit much from the insights generated by CGMs. The technology had a heterogeneous effect across new products. Physicians learn faster about new drugs that present features relevant to overcoming the flaws of existing drugs revealed by the technology. By inducing CGM users to switch treatment away from old molecules to these new drugs, the device generated opportunities to learn about the quality of the drug that would not have occurred absent the technology. As CGM did not improve the quality of experience signals received by physicians about new drugs and the number of learning opportunities remained fixed, physicians would have learned more about some products absent the device. Assuming CGMs provide complete learning about the patient-insulin clinical match values, this framework enables measuring the costs, in terms of foregone profits and consumer welfare, from relying on partial information when deciding on treatment. It also highlights the cross-market complementarities between medical devices and pharmaceuticals, exploring the potential long-term effect of CGMs on the insulin market. Specifically, the most profitable pharmaceutical innovation strategy can vary depending on the technological environment in which insulin choices are made, as CGMs introduce new criteria for evaluating drug performance that enters pharmaceutical demand.

This study opens up several important avenues for future research. First, estimating the patient-product clinical match values does not separately identify the preference for the effects on the average and glucose profile from their level as they remain unobserved in claims data. Further separating these would shed light on whether old criteria are phased out by the new criteria generated from CGM. Second, the analysis focuses on CGM's impact on existing insulin

patients. It does not account for the potential benefits for new insulin users, such as improved diagnosis matching by physicians at therapy initiation (Crawford and Shum (2005)). Third, the framework is estimated for France, where the regulator bargains the price of prescription drugs with insulin manufacturers and provides complete coverage for insulin and CGM expenses through the universal health insurance scheme. It leads to low prices and inelastic demand. CGM's impact may vary in environments where prices adjust more freely, and cost differences influence insulin choices. Last, this project focuses on cross-market externalities, and a complete welfare analysis of CGM is beyond its scope. Since CGM increases monitoring costs relative to traditional devices, broad coverage significantly raises healthcare expenses. Identifying which patients benefit most from CGM data and how they benefit would be crucial for designing an optimal coverage strategy (Chandra and Skinner (2012), Conner et al. (2024)).Their impact on the organization of care also presents important avenues for research that could inform policy debates, as healthcare systems like the NHS in the UK consider adopting these technologies to support system reform.[51]

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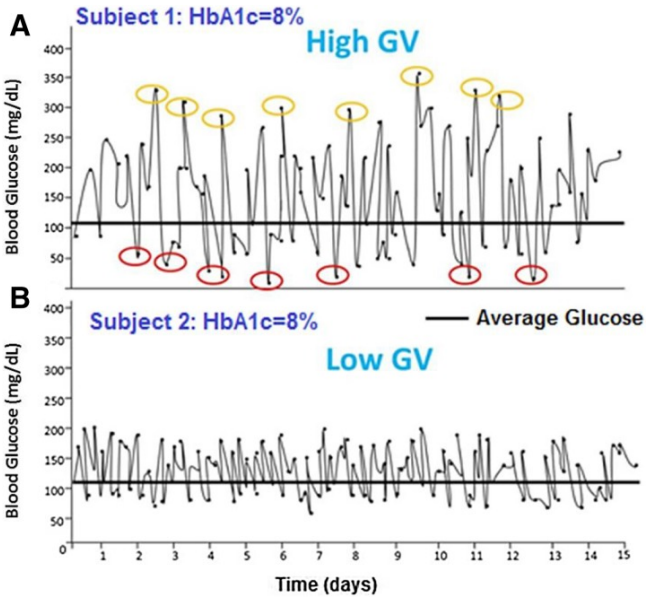
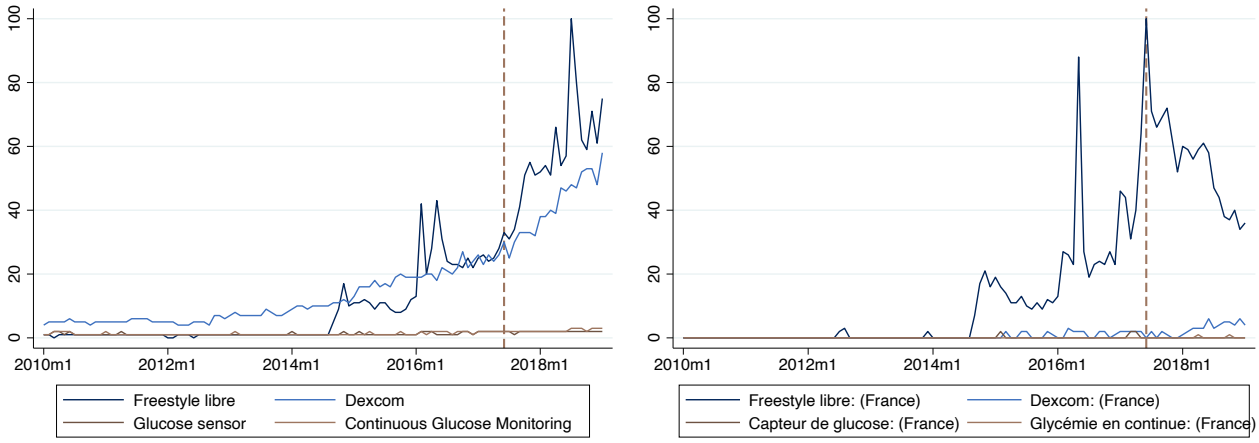
A Additional figures and tables

Figure A1: Glucose variability



Note: Different patterns of glycemic variability (GV) in two patients with same hemoglobin A1C (HbA1c). 15-day glucose traces of two patients who had identical HbA1c of 8.0% but different degrees of GV. High GV in patient 1 was reflected by numerous episodes of both hypo- and hyperglycemia (a), whereas low GV in subject 2 resulted in no such episodes (b). Patient 1 (a) had visibly higher glucose fluctuations than patient 2 (b) that resulted in seven episodes of moderate hypoglycemia ($\leq$ 50mg/dL) and eight episodes of moderate hyperglycemia ($\geq$ 350mg/dL). Reproduced from Chehregosha et al. (2019) under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/). No changes were made to the original figure.

Figure A2: Google trends for Continuous Glucose Monitoring, 2010-2019

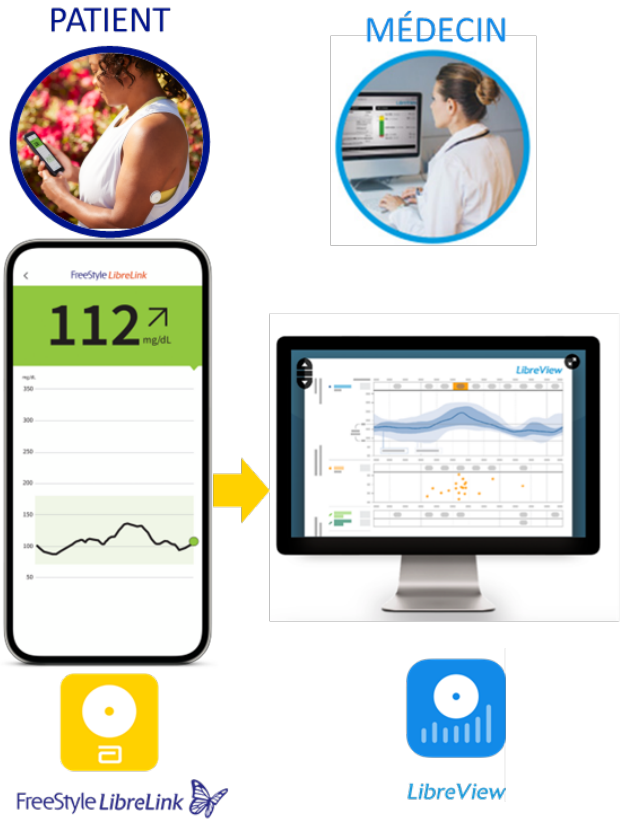


(a) All countries

(b) France

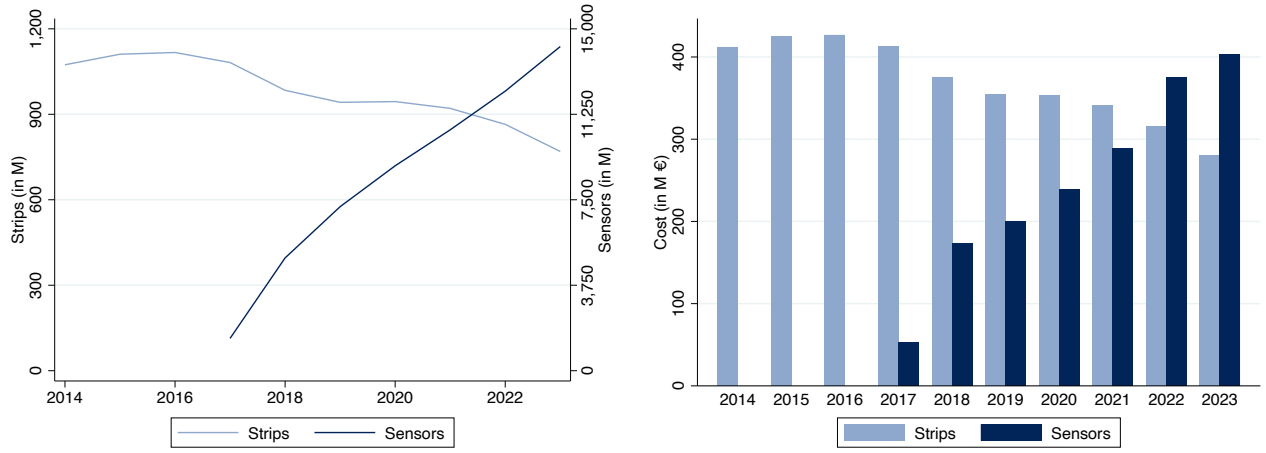
Note: In each figure, the legend corresponds to the keywords. In Figure A2b, 'Capteur de glucose' means 'glucose sensor' and 'Glycémie en continue' corresponds to 'Continuous glucose monitoring'. Freestyle Libre is the technology developed by Abbott in 2014. The former technology developed by Abbott - Freestyle Navigator II (not displayed) - faced a low index for the whole time it was available. Dexcom is also developing CGM.

Figure A3: Continuous Glucose Monitoring



Note: L'application FreeStyle LibreLink permet, si vous le souhaitez, le partage automatique et à distance de vos données de glucose avec votre médecin à travers la plateforme d'analyse en ligne sécurisée LibreView. Ce partage automatique nécessite que vous ayez au préalable créé un compte LibreView, puis que vous vous connectiez au cabinet de votre médecin.Avec un compte LibreView, vous pouvez : (1) Partager automatiquement vos données de glucose avec votre médecin. (2) Votre médecin pourra ainsi accéder à vos données de glucose depuis son compte LibreView, sans que vous ayez besoin de vous rendre à son cabinet. (3) Retrouver des rapports synthétiques et intuitifs qui mettent en évidence votre profil et vos tendances de variation de vos taux de glucose. (4) Accéder à tout moment à toutes vos données, stockées en toute sécurité sur LibreView. Illustration from Abbott's website, used in accordance with Abbott's copyright policy for non-commercial purposes. Source: Abbott website accessed on October 10th, 2024.

Figure A4: Glucose monitoring volumes and value in France, 2014-2023

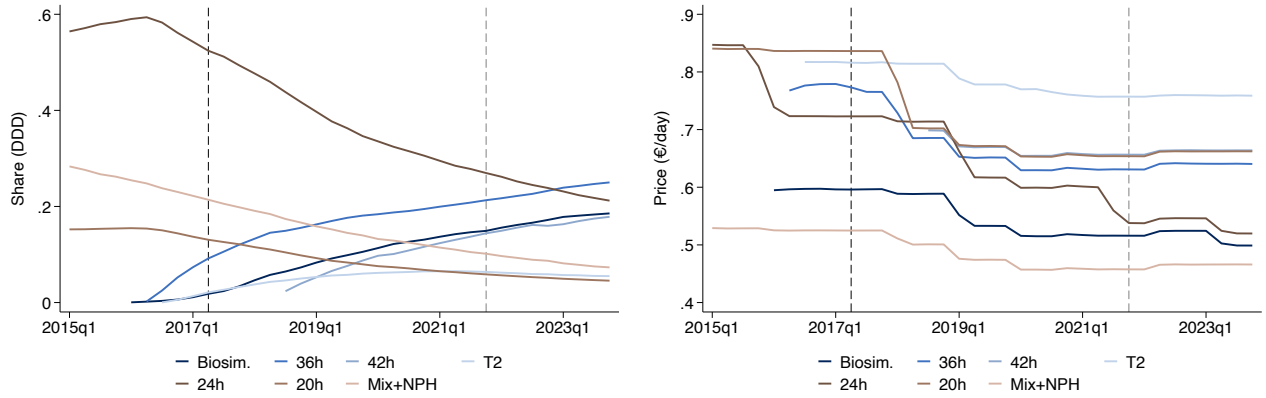


(a) Number of tests, in million

(b) Value, in million euros

Note: Test volume and value for all patients in France. In Figure A4a, the number of tests performed via sensors is computed from the number of sensors and frequency of automatic measurement. In Figure A4b, strip costs do not include the lancing device cost. Source: Open LPP.

Figure A5: Aggregate insulin sales and prices, 2015-2023

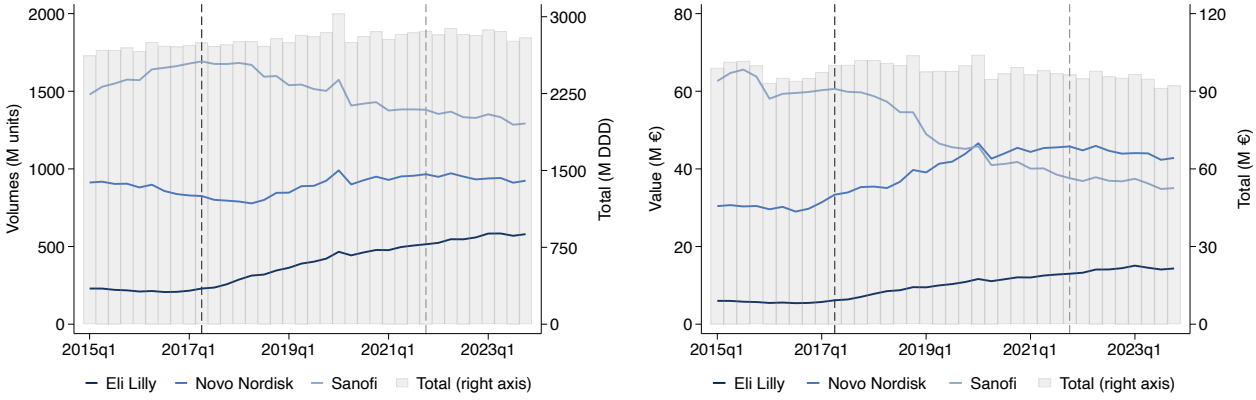


(a) Units reimbursed

(b) Price per daily consumption

Note: The first vertical line represents the start of CGM coverage. The second line corresponds to the end of the period considered in the analysis. Figure A5a plots the share for each product over time as a percentage of all insulin units reimbursed. Figure A5b plots the daily price, assuming 20 units per day. The 36h daily dose price is adjusted to account for the increased units required when switching from the regular 24h.

Figure A6: Sales volume and value, by manufacturer, 2015-2023

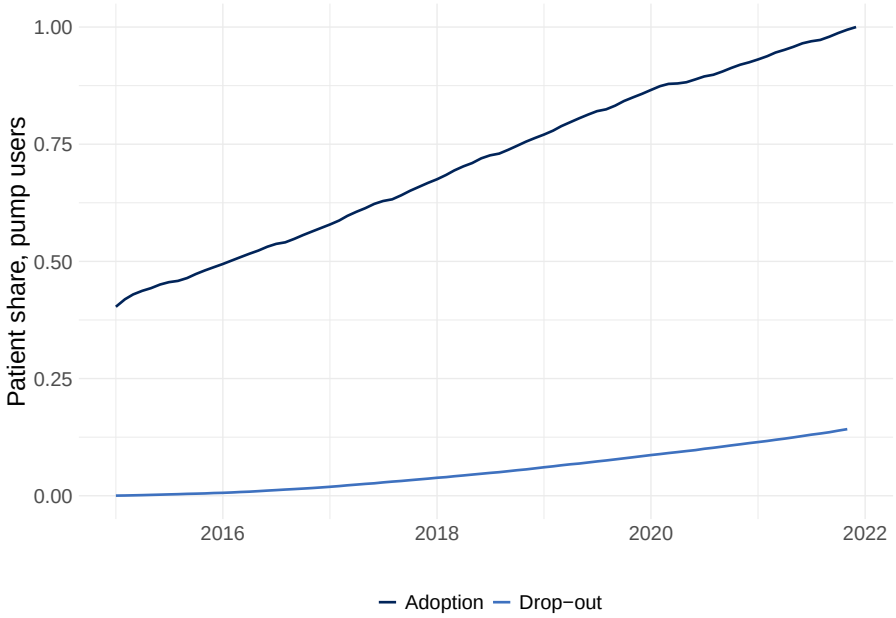


(a) Units reimbursed, million units

(b) Sales value, million €

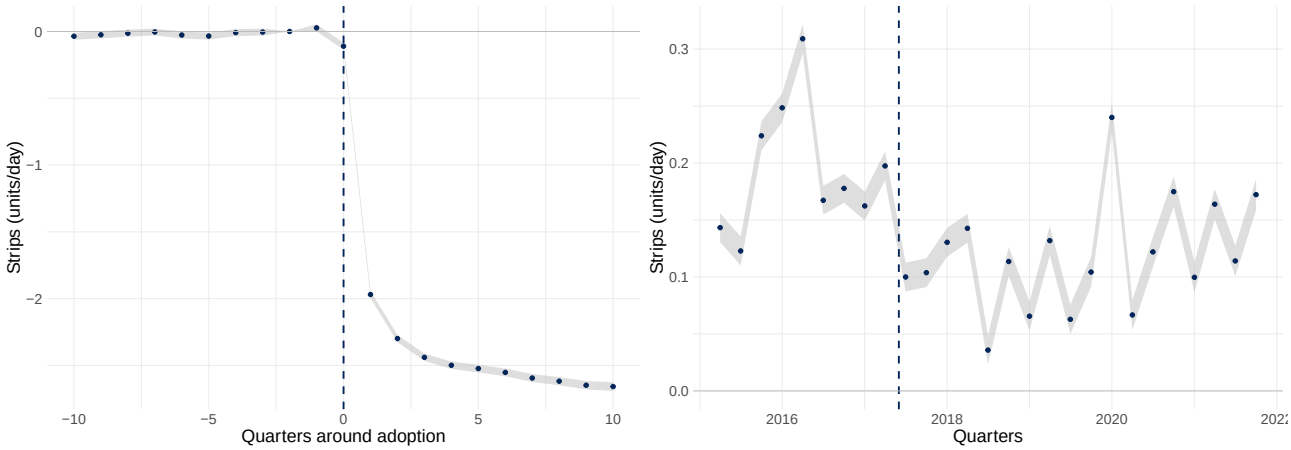
Note: The first vertical line represents the start of CGM coverage. The second line corresponds to the end of the period considered in the analysis.

Figure A7: Insulin pump usage, CDF



Note: This figure plots the cumulative distribution function of the first and last pump reimbursement date for patients relying on an insulin pump between 2015 and 2021. These distributions present no discontinuity/change in trends after the CGM coverage decision.

Figure A8: Strips reimbursement per patient

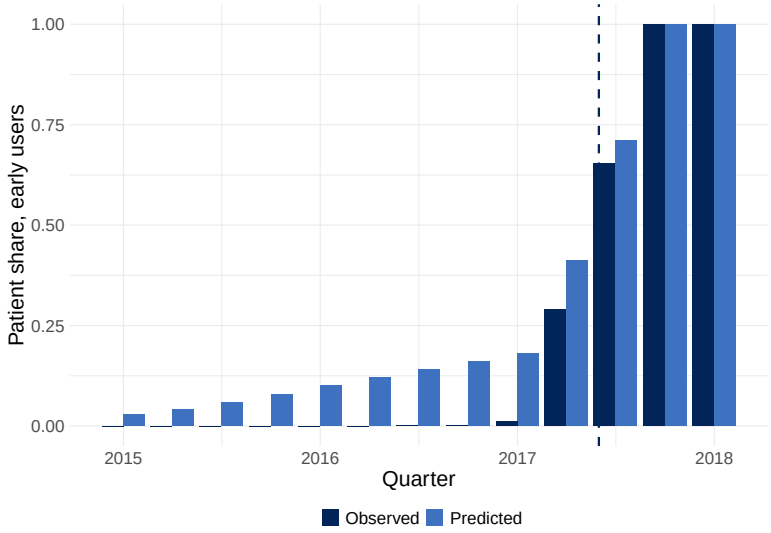


(a) Before-after CGM adoption

(b) Non-users over time

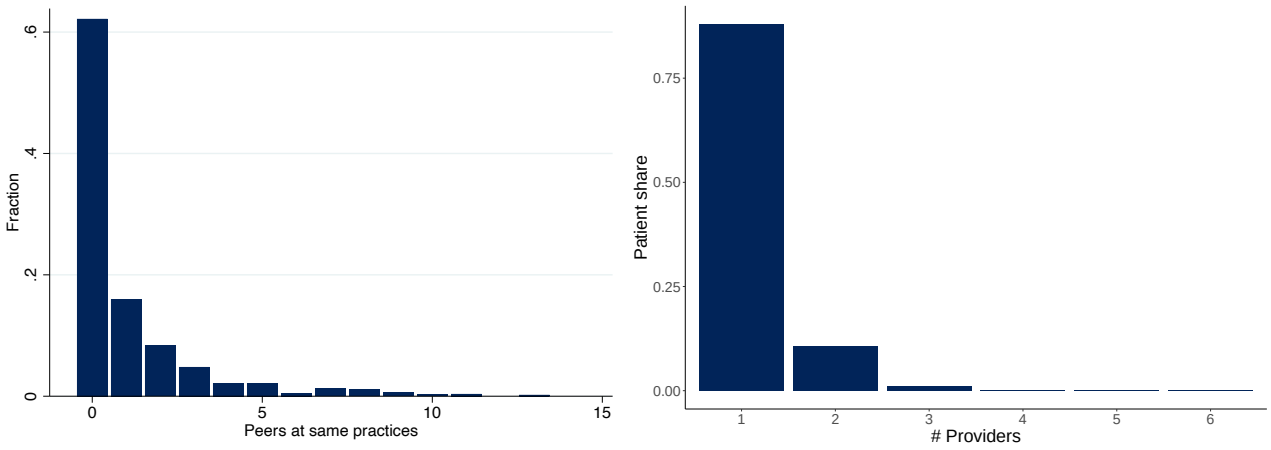
Note: Figure A8a presents the estimates from an event study model considering the number of strips reimbursed in the quarters around CGM adoption. CGM adoption is identified from a patient's first prescription of a CGM. The regression includes patient fixed-effects and focuses on patients with their first CGM prescription from January 2018 onwards. Figure A8b plots the linear regression coefficients of strip reimbursement over time for non-users.

Figure A9: Observed and predicted CGM adoption date for 'early' users



Note: Figure A9 compares the first CGM prescription date observed in the data to the one predicted by the model summarized in Table A3 for 'early adopters'. 'Early adopters' are patients whose first CGM reimbursement happens before January 2018 such that the first CGM prescription may not coincide with their adoption date. 40k patients are adopting before January 2018, among which 7k face a predicted adoption date different from their observed date.

Figure A10: Diabetes specialists outside of hospital practices

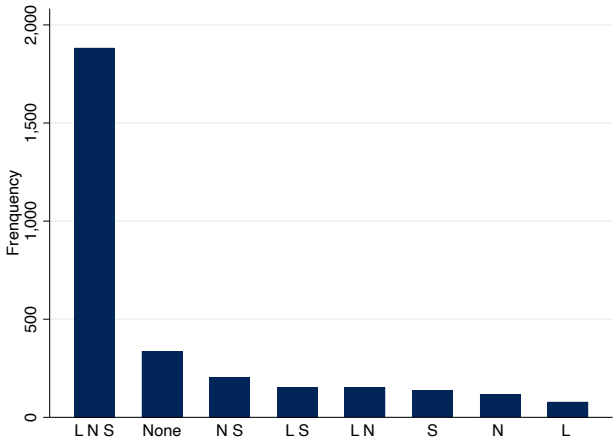


(a) Number of "peers"

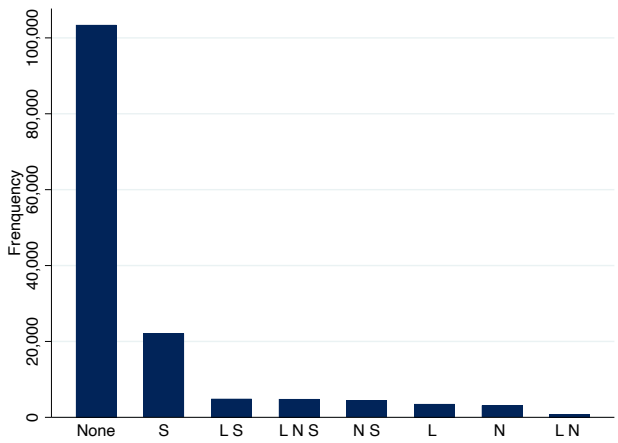
(b) Number of practitioners by patient

Note: Figure A10a represents the number of "peers" working at the same practice for diabetes specialists working outside the hospital. 62% are working in an environment without any other diabetes specialist, 78% with at most one peer. Figure A10a uses data from the practionners directory in France available at https://annuaire.sante.fr/web/site-pro/extractions-publiques. Figure A10b plots the number of diabetes specialists working outside the hospital by patient.

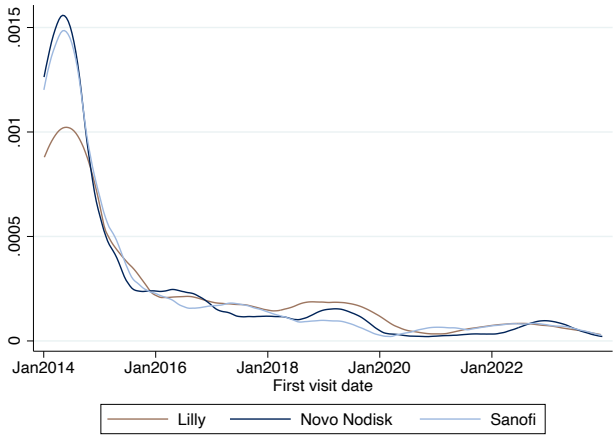
Figure A11: Insulin manufacturer detailing to physicians, 2014-2023



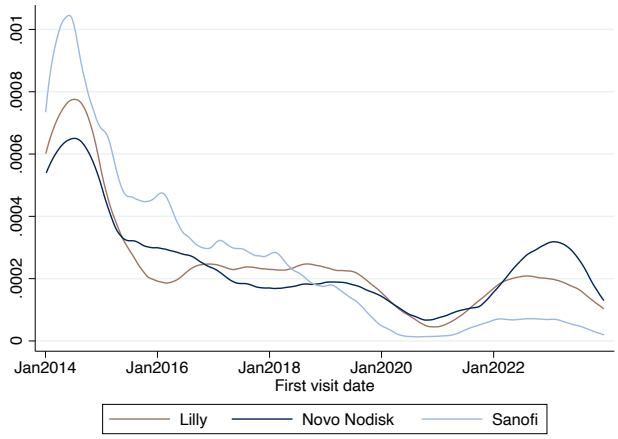
(a) Specialists and manufacturers interactions



(b) GPs and manufacturers interactions



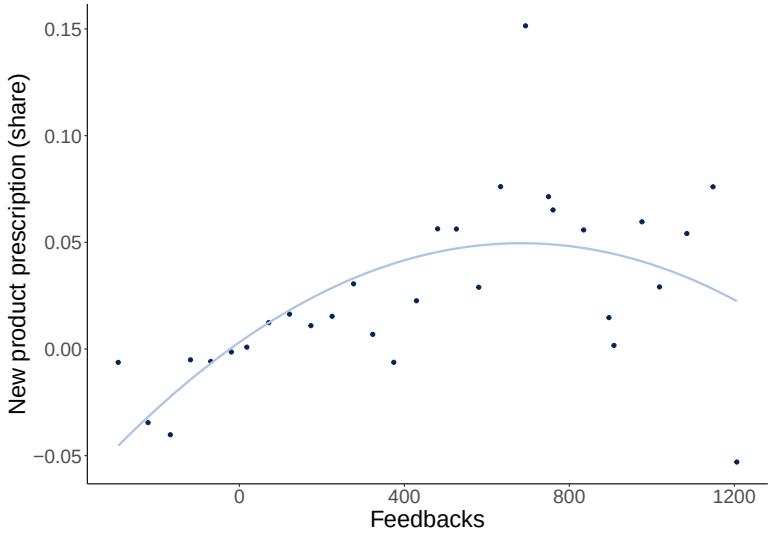
(c) First detailing to specialists



(d) First detailing to GPs

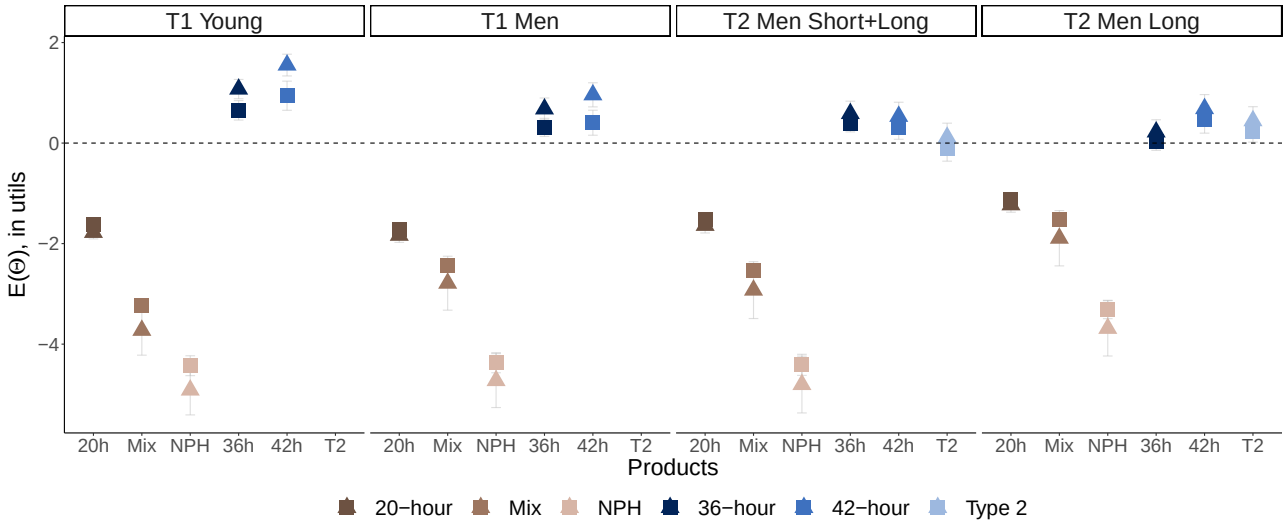
Note: Descriptive evidence of pharmaceutical detailing by insulin manufacturers from 2014 to 2023 are provided in Figure A11. Diabetes specialists are more likely to interact with insulin manufacturers than GPs. Over the period, 90% of specialists interacted at least once with a pharmaceutical company, and 60% of them can be linked to the three manufacturers. They interact on average once per year and, in most cases, since the beginning of my sample period. On the other hand, 70% of GPs never interacted with either one of these companies. While 25% interacted with Sanofi, the manufacturer with the most diverse prescription drug portfolio, less than 10% interacted with Eli Lilly and/or Novo Nordisk, which have a less diverse portfolio.

Figure A12: Physician prescription share and the information set size, city specialist



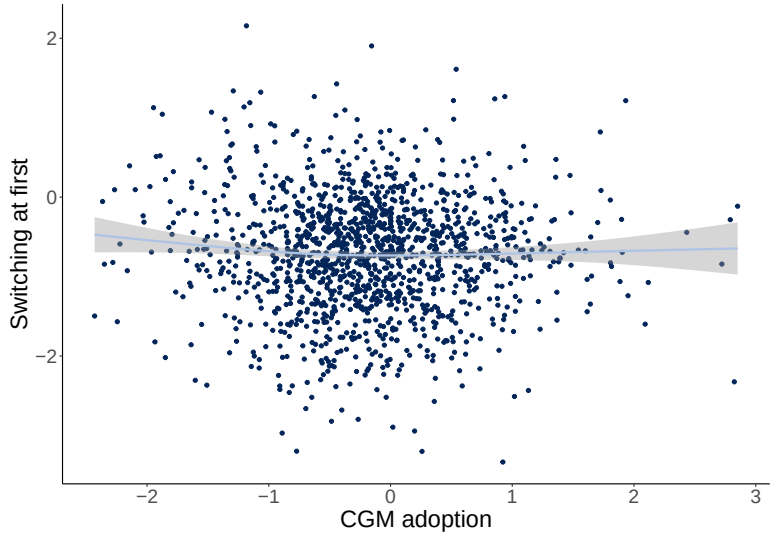
Note: The horizontal axis corresponds to the amount of feedback from real-life experience with the new product j received by the physician up to the previous period. The vertical axis corresponds to product j prescription share for patients not using the product before the appointment. For each variable, I consider the residuals from a linear model controlling for physician fixed effect, product-specific quarter fixed effect, and the average demographics of the patient visiting physician k in a given period. The figure focuses on prescriptions by diabetes specialists working outside the hospital and excludes the new Type 2 product directed towards a subset of patients.

Figure A14: Perceived match value with/without a CGM



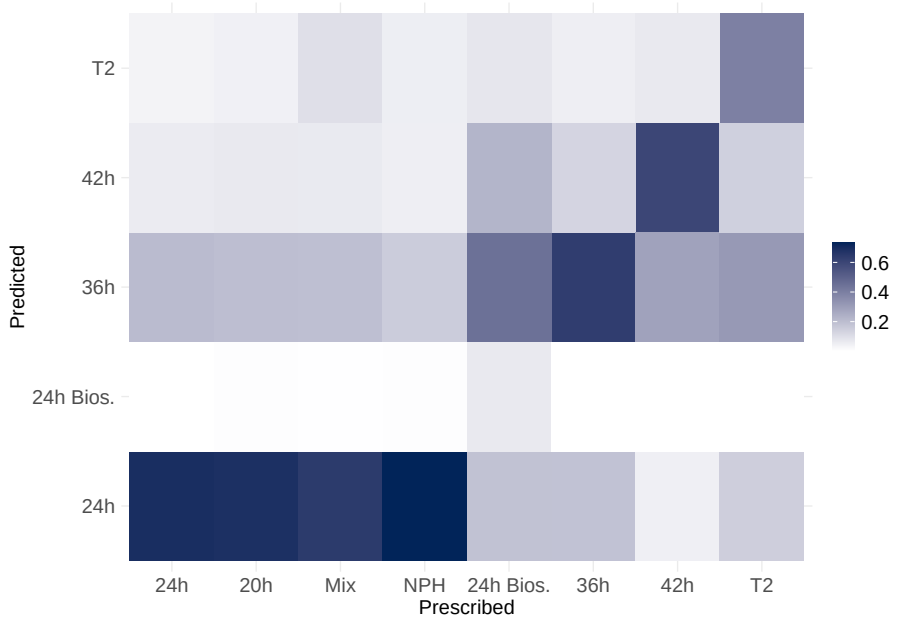
Note: This figure presents the perceived match value without the technology (squares) and with CGM (triangles) in utils (vertical axis) across products (horizontal axis). The perceived match value without the technology corresponds to θ_{nj} while the perceived match value with the technology is $\theta_{nj} + \Delta\nu_{nj}$ where $\Delta\nu_{nj}$ is the average across patients within a cluster.

Figure A13: Physician-level heterogeneity



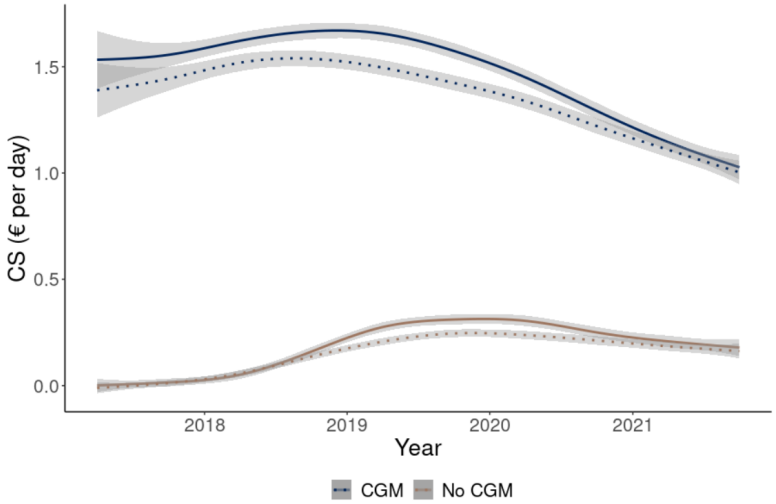
Note: This figure presents the physician-level propensity to see patients with CGMs (horizontal axis) against her propensity to switch patients in the first appointment after they adopted CGMs (vertical axis). Each propensity corresponds to the parameter of a logistic regression where the outcome variable is 'CGM adoption' (horizontal axis) and 'Switching insulin in the first appointment with CGM' (vertical axis), and patients' characteristics are included as controls. One point corresponds to one physician. The fitted line corresponds to a flexible non-parametric smoothing of the data with a 95% confidence interval.

Figure A15: Prescribed vs predicted treatment choice



Note: This figure compares the product prescribed in the actual data j^{obs} to $\hat{j} = \arg\max \hat{\hat{u}}_{ikjv}$. The idiosyncratic shock is excluded from the prediction. Note that $\hat{j}$ never corresponds to the 20-hour, insulin mixes nor human insulin treatments.

Figure A16: Consumer surplus under observed allocation and after sensor reallocation



Note: The figure presents the compensating variation (vertical axis), in euros per day, following a prescription happening in period t (horizontal axis). The average consumer welfare is presented for patients with CGM (blue curve) and without (brown curve). The plain line represents consumer welfare from the observed adoption pattern. Dotted lines present welfare after reallocating sensors across patients.

Table A1: Summary statistics, patient level

	(1)	(2)	(3)	(4)
	All	Type I	Type II	
			Long+short	Long only
N ('000)	333.4	94.2	133.4	105.8
Age	57	49	60	62
Female	0.434	0.405	0.449	0.440
Type 1	0.283	1.000	0.000	0.000
Low-income	0.126	0.135	0.126	0.117
Residential area				
Deprivation index	0.262	0.044	0.336	0.371
Population('000)	41.0	44.1	41.2	37.7
Chronic conditions				
Hypertension	0.692	0.442	0.783	0.799
Hypercholesterolemia	0.619	0.401	0.700	0.712
Analgesics	0.412	0.286	0.474	0.446
Obesity	0.324	0.169	0.412	0.351
Cardiovascular	0.318	0.205	0.382	0.338
Anxiolytics	0.174	0.143	0.193	0.177
Antidepressants	0.168	0.135	0.192	0.167
Respiratory	0.148	0.103	0.178	0.150
Hypnotics	0.108	0.078	0.127	0.110
Cancer	0.097	0.064	0.115	0.104
Neuroleptics	0.043	0.036	0.045	0.046
Dialyse	0.016	0.013	0.022	0.010
Prescriptions	7	8	8	5
CGM Users	0.449	0.728	0.531	0.096
CGM Temporary	0.073	0.050	0.080	0.174
Pump Users	0.067	0.171	0.041	0.008
Insulin switch	0.548	0.579	0.616	0.435
Nb switches	1.446	1.437	1.538	1.294

Note: The sample is restricted to patients between 18 and 75 in 2015 who had already used long-acting insulin in early 2016, who had gotten a prescription from a diabetes specialist, and who did not rely exclusively on an insulin pump over the sample period. The Deprivation index is computed based on 2015 measures of unemployment, blue-collar workers, high school graduates shares and the median income by consumption unit at the city level from the national statistic institute (INSEE). It is centered around zero, goes from -6.1 to 10.3, and the variance is 2.72. Negative values stand for more favorable areas. In 2015, the median individual in France lived in a 9,423 inhabitants city, and the deprivation index is around 0.116. The number of prescriptions is restricted to prescriptions written by diabetes specialists. The number of insulin switches is computed on the sample of patients who switched at least once. Appendix B.1 details the sample construction.

Table A2: Summary statistics, physician level

	(1) All	(2) Specialists	(3) Hospital	(4) GP	(5) Care Center	(6) Entering non-GP
N	108,542	845	1,022	99,244	7,062	369
N (Share)		0.008	0.009	0.914	0.065	0.003
Patients (#)	5	122	179	5	3	10
Prescriptions (#)	22	739	428	23	5	17
Prescriptions (Share)		0.089	0.164	0.715	0.028	0.004
Ever CGM (%)	0.581	0.946	0.994	0.577	0.526	0.691
CGM users	2	62	77	2	1	6
CGM prescription (#)	1	152	72.5	1	1	5
CGM (Share)		0.134	0.231	0.592	0.031	0.012
	A. Ever prescribed (%)					
All products	0.084	0.670	0.886	0.070	0.082	0.263
20-hour	0.485	0.983	0.994	0.482	0.389	0.566
24-hour	0.853	1.000	1.000	0.857	0.762	0.827
24-hour biosimilar	0.324	0.754	0.993	0.310	0.369	0.396
36-hour	0.516	0.954	0.994	0.512	0.449	0.629
42-hour	0.316	0.863	0.944	0.307	0.272	0.577
Type 2	0.290	0.856	0.934	0.283	0.220	0.477
	B. Switching behavior					
Ever switching	0.301	0.996	1.000	0.283	0.348	0.650
Switches (Share)		0.213	0.529	0.213	0.029	0.016
Switching × 24-hour biosimilar	0.122	0.574	0.952	0.104	0.192	0.233
Switching × 36-hour	0.144	0.910	0.900	0.129	0.141	0.461
Switching × 42-hour	0.068	0.811	0.830	0.051	0.081	0.466
Switching × Type 2	0.052	0.796	0.742	0.037	0.056	0.350

Note: Physician-level summary statistics. Patients, visits and prescriptions are restricted to patients in the sample of interest (Table A1). Patients, visits, CGM users and CGM visits correspond to the sample median.

Table A3: Predicted vs observed CGM adoption

		Observed	
		No	Yes
Predicted	No	0.8243	0.2463
	Yes	0.1757	0.7537

Note: Table A3 presents the accuracy of CGM adoption prediction for patients adopting the technology from January 2018. Adoption is predicted from individual demographics and the evolution of strip consumption over time for patients using the technology. Youden's index is used as a threshold to classify observations. The risks of Type I and Type II errors are 17.6% and 24.6%, respectively.

Table A4: Switching costs, CGM users vs non-users

	A. All		B. Specialists	
	coef.	s.e.	coef.	s.e.
α	-0.186	(0.039)	-0.232	(0.043)
c_1: Incumbent	-2.010	(0.039)	-2.195	(0.045)
c_2: Users	0.013	(0.053)	-0.091	(0.058)
c_3: Using CGM	0.024	(0.112)	0.082	(0.119)
N	621		414	

Note: Robust standard errors. The first column includes prescriptions from GPs, diabetes specialists and diabetes specialists working in the hospital. The second column focuses on specialists. Both specifications include a quadratic time trend.

Table A5: Information set and non-user switching behavior

	A. All non-users		B. Eligible		C. Non-eligible	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
$\mathbf{1}(F_{kt} > 0)$	0.548	(0.036)	0.243	(0.017)	0.306	(0.025)
F_{kt}	0.159	(0.016)	0.059	(0.009)	0.096	(0.011)
$(F_{kt})^2$	-0.003	(0.000)	-0.001	(0.000)	-0.002	(0.000)
F_{kt}^{CGM}	-0.081	(0.027)	-0.012	(0.015)	-0.061	(0.016)
$(F_{kt}^{CGM})^2$	0.001	(0.001)	-0.001	(0.001)	0.001	(0.001)
Obs.	7,568		7,434		7,497	
$\overline{Y}$	0.932		0.428		0.517	
$\overline{F}$	3.709		3.728		3.723	
$\overline{F}_{CGM}$	2.288		2.292		2.292	

Note: The information set is measured in $'0$ of visits. Standard errors clustered at the physician level. I restrict the sample to individual diabetes specialists and focus on the 42-hour product.

Table A6: Accurate prediction, per year and patient group

Cluster	2015	2016	2017	2018	2019	2020	2021
1	0.82	0.73	0.62	0.50	0.52	0.54	0.54
2	0.79	0.69	0.55	0.44	0.47	0.47	0.45
3	0.72	0.64	0.52	0.43	0.49	0.53	0.52
4	0.77	0.68	0.47	0.43	0.39	0.42	0.42
5	0.72	0.65	0.48	0.41	0.40	0.40	0.41
6	0.56	0.51	0.38	0.34	0.33	0.31	0.32
7	0.61	0.56	0.38	0.34	0.33	0.32	0.31

Note: This table compares the product prescribed in the actual data j^{obs} to $\hat{j} = \arg\max u_{ikjt}(p_{jt}, d_j, a_{it}|\mathcal{I}_{kt})$. The idiosyncratic shock is excluded from the prediction. The accurate prediction rates range from 31% to 82%.

Table A7: Patient selection

	(1) All, incl:	(2) Final Sample	(3) Infrequent	(4) New Patients	(5) No diabetes specialist	(6) Old Age≥ 75	(7) Pump	(8) Rest
N ('000)	1,423.0	333.4	54.3	335.0	91.9	408.7	48.3	151.5
Age	63	57	55	52	61	82	44	58
Female	0.483	0.434	0.491	0.474	0.425	0.558	0.560	0.420
Low income	0.103	0.126	0.156	0.162	0.122	0.018	0.105	0.135
Type 1	0.158	0.283	0.123	0.093	0.163	0.080	0.731	0.060
Death	0.003	0.002	0.005	0.001	0.001	0.007	0.000	0.002
Residential area								
Deprivation index	0.334	0.262	0.296	0.295	0.627	0.331	0.201	0.475
Population ('000)	38.3	41.0	43.8	42.2	31.8	34.6	32.2	37.5
Chronic conditions								
Hypertension	0.701	0.692	0.621	0.521	0.745	0.897	0.405	0.657
Hypercholesterolemia	0.550	0.619	0.453	0.415	0.649	0.616	0.370	0.527
Analgesics	0.429	0.412	0.459	0.335	0.419	0.544	0.272	0.389
Cardiovascular	0.358	0.318	0.440	0.205	0.249	0.577	0.171	0.264
Obesity	0.250	0.324	0.401	0.206	0.217	0.220	0.263	0.216
Anxiolytics	0.193	0.174	0.219	0.154	0.171	0.251	0.127	0.185
Antidepressant	0.178	0.168	0.180	0.139	0.145	0.230	0.161	0.163
Respiratory	0.158	0.148	0.227	0.128	0.126	0.196	0.109	0.150
Hypnotics	0.122	0.108	0.144	0.090	0.108	0.166	0.069	0.115
Cancer	0.137	0.097	0.260	0.089	0.087	0.217	0.056	0.125
Neuroleptics	0.047	0.043	0.060	0.044	0.041	0.055	0.019	0.055
Dialyse	0.013	0.016	0.048	0.005	0.004	0.016	0.006	0.007
Long-term care	0.842	0.927	0.691	0.746	0.930	0.845	0.939	0.828
Short-acting	0.556	0.744	0.610	0.512	0.474	0.491	0.982	0.313
Specialists	0.720	1.000	1.000	1.000	0.022	0.606	0.895	0.058
Prescriptions (Av.)	16	27	7	9	29	16	8	9
Specialist prescriptions (Av.)	3	7	3	3	0	2	4	0
CGM Users	0.226	0.449	0.023	0.214	0.125	0.081	0.930	0.065
CGM Temporary	0.091	0.073	0.364	0.128	0.136	0.138	0.018	0.188
Pump Users	0.051	0.067	0.000	0.000	0.000	0.004	1.000	0.000
Insulin switch	0.381	0.676	0.200	0.307	0.329	0.321	0.445	0.129
Nb switches	1.673	1.848	1.282	1.523	1.516	1.609	1.673	1.332

Note: The Deprivation index is computed based on 2015 measures of unemployment, blue-collar workers, high school graduates shares and the median income by consumption unit at the city level from the national statistic institute (INSEE). It is centered around zero, goes from -6.1 to 10.3, and the variance is 2.72. Negative values stand for more favorable areas. In 2015, the median individual in France lived in a 9,423 inhabitants city, and the deprivation index is around 0.116. The number of insulin switches is computed on the sample of patients who switched at least once. 'Infrequent' includes patients using insulin spontaneously over the sample period or who stopped before April 2016. 'New patients' have their first insulin prescription after March 2016. 'No diabetes specialist' refers to patients who have not seen a specialist already active in 2016. 'Old' patients were 75 or more in 2015. 'Pump' includes patients relying exclusively on insulin pumps. 'Rest' consists of the remaining patients prescribed insulin by new physicians or physicians who are not actively changing treatments.

B Data construction

B.1 Sample selection

I rely on exhaustive micro-level data for France from the *Système National des Données de Santé (SNDS)*. The data on the French population is exhaustive, thanks to the single-payer system. The Social Security system covers more than half of prescription drug expenditures and medical devices once the Health Technology Agency has enacted the coverage. The mandatory health insurance system fully covers patients with diabetes for their expenditures as part of the Long-term care disease program.[52] I build the sample of patients as follows.

First, I retrieve all the long-acting insulin reimbursement flows from 2015 to 2021. I extract the patient, prescriber, product IDs, and prescription date for each flow.[53] Note that the prescriber ID corresponds to the hospital ID for physicians working at the hospital. On the patient side, I focus on patients who were already familiar with insulin injections and glucose measurement before April 2016. I impose the following restrictions among patients: (i) The first long-acting insulin prescription was recorded before April 1st, 2016 and the last prescription was written after January 1st, 2016. (ii) The time between the first and last prescription was over three years. (iii) The patient received more than one prescription per year between his first and last prescription. (iv) I restrict my attention to patients not using an insulin pump or whose first pump reimbursement happened after January 1st, 2016.[54] (v) The patient was an adult, 74 or younger, in 2015. On the physician side, I consider (i) The diabetes specialists working in or out of the hospital. (ii) The prescribers with a first prescription to *any patient* before January 2016. (iii) The practitioners who wrote at least 24 prescriptions and switched a treatment at least once for *any patients in my sample* between 2016 and 2021. Table A7 compares the characteristics of patients in the final sample to the initial dataset. Focusing on the set of incumbent insulin patients, Table A2 provides summary statistics about the physicians involved in their therapy.

Most of the descriptive analysis relies on this sample. Note that (i) The first intention treatment choice for new insulin patients is used to estimate switching costs separately from

[52]The drug price still enters the care provider's decision through financial incentive schemes and guidelines.

[53]I focus on the following Anatomical Therapeutic Chemical (ATC) classes: A10AC, A10AD, A10AE. If two insulins in these classes are prescribed on the same day, I consider either (i) the new molecules when a new product is prescribed together with an old product or (ii) the 24-hour product when it is prescribed at the same time as insulin mixes. The remaining cases are dropped.

[54]The data also covers insulin pump coverage. Patients using a pump to stabilize their glucose level are prescribed long-acting insulin in case of a breakdown. They are not using it daily. When a patient starts using an insulin pump, I remove the long-acting insulin prescriptions written while using the pump.

learning (Section C.3). (ii) The structural model is estimated on a random sample of 150 diabetes specialists working outside the hospital.

B.2 Risk of mismeasurement in CGM adoption

This section documents the risk of mismeasurement in digital device adoption when relying on the claims data. It considers sequentially the risk for patients eligible for coverage and non-eligible for CGM coverage.

For individuals eligible for the technology, purchases of sensors directly from the device manufacturer are not reimbursed by the health insurance scheme. It is fully covered in the case of a prescription. These patients have no incentive to buy the technology outside the scope of my data. The coverage decision comes 2.5 years after the device was available in the EU, such that the adoption date imputed from the claims data is subject to left censoring. This concern is mitigated by the low sales volumes in 2015 for the most popular technology (40k sensors according to the HTA evaluation) and by the timing of adoption in the population according to claims data. The share of patients with a first sensor reimbursement in the first three months following the coverage decision remains limited (Figure 2a). In the descriptive analysis, I remove patients adopting CGM between June and August 2017 to account for the risk of mismeasurement in their adoption date. Individuals dropping out from using digital devices is an important issue when studying the impact of wearable technologies (Patel et al. (2015)). Technological features of the current device allow for overcoming this challenge. CGM relies on disposable sensors that must be replaced every 14 days. Patients not renewing their prescriptions are assumed to drop out from continuous monitoring. In practice, such cases are rare due to the comfort brought by the device to the patient.

Among patients treated with long-acting insulin, patients ineligible for coverage represent 32% of individuals (Table A1). In this case, measurement error in device adoption is possible. First, Guerci et al. (2023) suggest that patients outside of the eligibility criteria got access to the technology as no prior authorization was required. Second, the alternative glucose measurement system relies on disposable strips such that the number of strips reimbursed represents a good proxy for glucose testing intensity. If individuals were to adopt the technology outside the insurance system, strip reimbursement for these patients would decrease as measurement systems are substitutes to each other. I study the evolution of strip reimbursements for CGM users and non-users over time in Figure A8. Figure A8a plots the average daily number of

strips reimbursed before and after CGM adoption. Strip consumption decreases by 2.5 strips on average after adopting the technology.[55] The average for non-users stays relatively constant despite fluctuations across quarters. This suggests that the consumption of non-user glucose testing strips remains unaffected by the introduction of CGM. These descriptive facts do not rule out completely the adoption of the technology outside of the insurance scheme but suggest that it is uncommon.

In the structural analysis, the timing of adoption matters as it determines the information available to the physician when prescribing insulin. Patients whose first CGM prescription happens within the seven months following the coverage decision may have purchased the technology out-of-pocket before. As a result, their actual adoption date might not align with the first prescription recorded in the claims data. To accurately estimate the adoption date for these 'Early users', I leverage the substitutability between CGM and glucose test strips as strip consumption decreases once a patient adopts a CGM (Figure A8a). More precisely, I split the sample of CGM users into two distinct groups: (i) 'uncensored' eligible patients whose first CGM reimbursement occurs from 2018 onwards and (ii) 'censored' patients whose first reimbursement occurs before January 2018. I estimate the correlation between strip consumption and CGM adoption in the 'uncensored' population. I extrapolate these findings to the 'censored' population to infer their 'true' date of adoption. In particular, I estimate the following model, linking the number of test strips reimbursed to patient i in quarter q and CGM use:

$$CGM_{iq} = \alpha_0 strips_{iq} + \gamma \mathbf{1}(strips_{i,t+1})\mathbf{1}(strips_{i,t+2})strips_{i,2015} + \beta X_i + \varepsilon_{iq} \tag{27}$$

where $strips_{iq}$ measures the average number of strips reimbursed per day per quarter, and X_i includes diabetes type, gender and age. I use the estimates out-of-sample to predict the quarter of adoption in the 'censored' population, relying on Youden's index to classify observations based on their predicted probability. Table A3 reports the risks of Type I and Type II errors in the 'uncensored' sample, respectively 17.6% and 24.6%. I consider that a patient in the 'censored' sample adopted the technology at t if the model predicts adoption for three quarters in a row. Figure A9 plots the cumulative distributions of observed and predicted adoption quarters for early users. The CGM adoption quarter differs for approximately 18% of the patients.

[55] Patients keep consuming strips after CGM adoption to perform a regular test in case of an adverse event.

C Further descriptive evidence

C.1 Substitution towards insulin pump

Patients can use an insulin pump instead of the short-acting and long-acting insulin to stabilise their glucose levels. These patients rely exclusively on short-acting insulin and only get prescribed long-acting insulin in case of a pump breakdown. The long-acting insulins prescribed to pump users are excluded from the prescriptions physicians are learning from. Significant improvements in the pump technology have occurred over the past decade. The pump system is not in the physician's choice set in the main specification. This choice is motivated by two facts. First, the coverage for insulin pumps remains restricted in France. Second, while patients in my sample are increasingly relying on a pump system, there is no change in the pattern of pump adoption after the coverage of CGM (Figure A7), and the total number of patients remains limited (70k). There exists a discrepancy with the share of pump users displayed in Table A1, primarily because the table excludes patients relying on a pump system for the entire period and focuses on patients with long-acting insulin prescriptions, hence does not represent the share of pump users in the overall patient's population.

C.2 Detailing as an alternative source of learning

In this project, pharmaceutical detailing may matter as it represents an alternative source of learning about new products for patients and physicians (Grennan et al. (2024)). Direct-to-consumer advertising is forbidden for prescription drugs in France, and detailing to physicians is allowed but subject to transparency rules similar to the US Sunshine Act. Two caveats prevent me from precisely accounting for detailing to physicians. First, unlike the Sunshine Act data, the French publicly available data does not record the product mentioned during the meeting. The probability that the interaction mentioned insulins depends on the pharmaceutical companies' portfolio and the physician's medical speciality. Detailing to diabetes specialists is more likely to mention new insulins than interactions with GPs. The latter is even more uncertain as the company portfolio is diverse. Long-acting insulins account for around 8% of Sanofi's European sales in 2023. On the other hand, diabetes treatment represents 88% of Novo Nordisk sales in 2023, so its detailing strategy is likely to trigger diabetes. Second, the claims data cannot be linked to external sources, including the *Transparence Santé* registry. In Figure A11, I provide summary statistics about insulin manufacturer's detailing behavior towards diabetes specialists

and GPs separately.

C.3 Switching cost estimation

I consider separately the demand for the 24-hour product from physicians of medical speciality, m, for patients in group, $I \in \{N, E^A, E^{\bar{A}}\}$, among new patients, N, existing patients adopting, E^A, and not adopting CGM, $E^{\bar{A}}$. Denoting s_{jq}^{mI} the prescription share of Lantus (L) and its biosimilar (B) indexed by $j \in \{L, B\}$ and at time q, I estimate switching costs relying on the following model

$$log(s_{Bq}^{mI}) - log(s_{Lq}^{mI}) = \Delta\delta_q^m + \alpha\Delta p_q^m + c_1\mathbf{1}(I \in \{E^{\bar{A}}, E^A\}) + (c_2 + c_3 CGMv_q^m)\mathbf{1}(I = E^A) + \Delta\xi_q \tag{28}$$

$log(s_{Bq}^{mI}) - log(s_{Lq}^{mI})$ proxies the difference in mean utility between the biosimilar, B, and the branded version, Lantus, L. $\Delta\delta_q^m$ is a time trend which accounts for information frictions. Δp_q^m is the difference in prices.[56] $CGMv_q^m$ is the share of prescriptions to patients wearing a CGM. c_1, c_2, and c_3 arise only in the biosimilar demand for incumbent patients and proxy switching costs. The model is estimated by OLS, and the results are displayed in Table A4. $\widehat{c}_1 < 0$ suggesting positive switching costs, yet no heterogeneity across glucose measurement systems as $\widehat{c}_2$ and $\widehat{c}_3$ are not significant. From these estimates, the willingness to pay to stick to the treatment patients are familiar with lies around ~ 9.47€ per month.

C.4 Physician level-learning: qualitative effect of CGM information

For each physician k and quarter t, I count the number of switches to the 42-hour product for patients without a CGM. Physicians' information set, denoted F_{kq}, is approximated using the number of appointments up to $t-1$ where the patient already used the 42-hour product at the beginning of the visit. The correlation between F_{kq} and the number of switches to the 42-hour product in quarter t, Y_{kq}, is documented using a Poisson model:

$$E(Y_{kq}|X) = \exp\left(\alpha + \lambda_1\mathbf{1}(F_{kq} > 0) + f(F_{kq}) + \gamma X_k + \delta_q\right) \tag{29}$$

[56] Given the pricing scheme in France, the price coefficient is difficult to identify separately from the time trend. Here, it is identified by exploiting the introduction of a financial scheme for diabetes specialists working in the hospital, rewarding the biosimilar prescription over the branded 24-hour product. This variation is assumed to be uncorrelated with the error term.

f is a quadratic function of F_{kq}. $\mathbf{1}(F_{kq} > 0)$ captures the extensive margin. The model is estimated from physician-quarter combinations with more than 11 visits. Table A5 presents the results. Going from 10 experience feedbacks to 20 increases the occurrence of switches to the 42-hour product by 16.2%. Digital technology feedback seems to dampen the spillovers. Specifications B and C consider the correlation between the information set and switching eligible non-users and non-eligible patients separately. Eligible patients are more similar to CGM users in terms of observable and unobservable characteristics than non-eligible. For eligible individuals, receiving feedback from CGM against the traditional measurement system has no significant impact on the magnitude of the spillover effect. For non-eligible individuals, the spillover effect is significantly weaker if the feedback is received from a patient using a CGM. If physicians extrapolate based on patients ' similarities, this effect may be driven by patient heterogeneity (Alsan et al. (2024)).

D Multi-product bargaining

The regulator and the pharmaceutical company, f, are assumed to bargain over the full set of insulins offered by the manufacturer, $j \in \mathcal{J}_f$. The objective of the firm is to maximize its profits:

$$\pi_f(\mathbf{p}_t) = \sum_{\forall j \in \mathcal{J}_f} (p_{jt} - c_{jt}) q_{jt}(\mathbf{p}_t) \tag{30}$$

The objective of the regulator when bargaining with firm f is to maximise consumer surplus:

$$\Delta_f CS(\mathbf{p}_t) = \sum_{\forall i,k} \frac{1}{\lambda} \ln\Big(\sum_{\forall j \in \mathcal{J}} \exp(u_{ikjt}(p_{jt}, d_j, a_{it}|\mathcal{I}_{kt})\Big) - \sum_{\forall i,k} \frac{1}{\lambda} \ln\Big(\sum_{\forall j' \notin \mathcal{J}_f} \exp(u_{ikj't}(p_{j't}, d_{j'}, a_{it}|\mathcal{I}_{kt})\Big) \tag{31}$$

Where we allow λ to be different from α. The equilibrium prices maximize the Nash product:

$$\max_{\mathbf{p}_{ft}} [\pi_f(\mathbf{p}_t)]^{b_{ft}} [\Delta_f CS(\mathbf{p}_t)]^{1-b_{ft}} \tag{32}$$

Let's consider the case where the firm bargain over two products, indexed by j and j'. The FOC with respect to the price of product j, p_{jt}, is given by:

$$b_{ft} \frac{\partial \pi_f(\mathbf{p}_t)/\partial p_{jt}}{\pi_f(\mathbf{p}_t)} + (1 - b_{ft}) \frac{\partial \Delta_f CS(\mathbf{p}_t)/\partial p_{jt}}{\Delta_f CS(\mathbf{p}_t)} = 0 \tag{33}$$

where

$$\frac{\partial \pi_f(\mathbf{p}_t)}{\partial p_{jt}} = q_{jt}(\mathbf{p}_t) + (p_{jt} - c_{jt})\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + (p_{j't} - c_{j't})\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}$$

and

$$\frac{\partial \Delta_f CS(\mathbf{p}_t)/\partial p_{jt}}{\Delta_f CS(\mathbf{p}_t)} = \frac{-\alpha q_{jt}(\mathbf{p}_t)}{\Delta_f CS(\mathbf{p}_t)} = \frac{\sum -\alpha s_{ikjv}(\mathbf{p}_t)}{\Delta_f CS(\mathbf{p}_t)}$$

The scaling parameter, λ does not enter the FOC, hence has not impact on the equilibrium. Denoting $h_{jt} = \frac{\partial \Delta_f CS(\mathbf{p}_t)/\partial p_{jt}}{\Delta_f CS(\mathbf{p}_t)}$ and $\beta_{ft} = \frac{1-b_{ft}}{b_{ft}}$, the first order condition with respect to p_{jt} becomes

$$\begin{aligned}
&\frac{\partial \pi_f(\mathbf{p}_t)}{\partial p_{jjt}} + \beta_{ft} h_{jt} \pi_f(\mathbf{p}_t) = 0 \\
&q_{jt}(\mathbf{p}_t) + \Big(p_{jt} - c_{jt}\Big)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + \Big(p_{j't} - c_{j't}\Big)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt}\Bigg((p_{jt} - c_{jt})q_{jt}(\mathbf{p}_t) + (p_{j't} - c_{j't})q_{j't}(\mathbf{p}_t)\Bigg) = 0 \\
&(p_{jt} - c_{jt})\Bigg(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{jt}(\mathbf{p}_t)\Bigg) + (p_{j't} - c_{j't})\Bigg(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{j't}(\mathbf{p}_t)\Bigg) + q_{jt}(\mathbf{p}_t) = 0
\end{aligned} \tag{34}$$

By symmetry, the FOC with respect to $p_{j't}$ yields

$$\begin{aligned}
&(p_{j't} - c_{j't})\Bigg(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{j't}(\mathbf{p}_t)\Bigg) = -\Bigg[(p_{jt} - c_{jt})\Bigg(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{jt}(\mathbf{p}_t)\Bigg) + q_{j't}(\mathbf{p}_t)\Bigg] \\
&(p_{j't} - c_{j't}) = -\Bigg[(p_{jt} - c_{jt})\Bigg(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{jt}(\mathbf{p}_t)\Bigg) + q_{j't}(\mathbf{p}_t)\Bigg]\Bigg[\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{j't}(\mathbf{p}_t)\Bigg]^{-1}
\end{aligned} \tag{35}$$

Plugging Equation 35 into Equation 34,

$$\begin{aligned}
(p_{jt} - c_{jt})\Bigg[\Big(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{jt}(\mathbf{p}_t)\Big) - \Big(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{jt}(\mathbf{p}_t)\Big)\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{j't}(\mathbf{p}_t)\Big)^{-1}\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{j't}(\mathbf{p}_t)\Big)\Bigg] = \\
-q_{jt}(\mathbf{p}_t) + q_{j't}(\mathbf{p}_t)\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{j't}(\mathbf{p}_t)\Big)^{-1}\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{j't}(\mathbf{p}_t)\Big)
\end{aligned} \tag{36}$$

such that

$$\begin{aligned}
(p_{jt} - c_{jt})\Bigg[\Big(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{jt}(\mathbf{p}_t)\Big)\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{j't}(\mathbf{p}_t)\Big) - \Big(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{jt}(\mathbf{p}_t)\Big)\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{j't}(\mathbf{p}_t)\Big)\Bigg] = \\
-q_{jt}(\mathbf{p}_t)\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{j't} q_{j't}(\mathbf{p}_t)\Big) + q_{j't}(\mathbf{p}_t)\Big(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{jt} q_{j't}(\mathbf{p}_t)\Big)
\end{aligned} \tag{37}$$

Given $h_{jt} = \frac{-\alpha q_{jt}(\mathbf{p}_t)}{\Delta_f CS(p)}$,

$$\beta_{ft} h_{j't} q_{jt}(\mathbf{p}_t) = \beta_{ft} h_{jt} q_{j't}(\mathbf{p}_t)$$
$$\beta_{ft} h_{j't} q_{j't}(\mathbf{p}_t) q_{jt}(\mathbf{p}_t) = \beta_{ft} h_{jt} q_{j't}(\mathbf{p}_t) q_{j't}(\mathbf{p}_t)$$

the first order condition becomes,

$$\begin{aligned}(p_{jt} - c_{jt})\Bigg[\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}}\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{jt}\left(q_{jt}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}\right) - \\ \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{j't}\left(q_{j't}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}\right)\Bigg] = \\ -\left(q_{jt}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}\right)\end{aligned} \tag{38}$$

such that

$$c_{jt} = p_{jt} + \left[\beta_{ft} h_{jt} + \frac{\beta_{ft} h_{j't}\left(q_{j't}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}\right) + \left(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}}\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}\right)}{\left(q_{jt}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}\right)}\right]^{-1} \tag{39}$$

$$c_{jt} = p_{jt} + \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)} + \left(\beta_{ft} h_{j't} + \frac{\partial q_{j't}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)}\right)\frac{\left(q_{j't}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}\right)}{\left(q_{jt}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}\right)}\right]^{-1} \tag{40}$$

For single-product firms, the first-order condition boils down to

$$c_{jt} = p_{jt} + \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)}\right]^{-1} \tag{41}$$

Note that, due to the Type I extreme value error term,

$$\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} = \sum_{\forall i,k}\sum_{\forall v \in t} -\alpha s_{ikjv}(\mathbf{p}_t)(1 - s_{ikjv}(\mathbf{p}_t)) \tag{42}$$

and, for j and j', $j' \neq j$

$$\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} = \sum_{\forall i,k}\sum_{\forall v \in t} \alpha s_{ikjv}(\mathbf{p}_t) s_{ikj'v}(\mathbf{p}_t) \tag{43}$$

The remaining unobservable are marginal costs, c_{jt}, and bargaining weights, b_{ft} .

E Counterfactual scenario: sensor reallocation

The counterfactual in Section 6.2 suggests that information spillovers from CGM users to non-users are limited. The consumer surplus generated by the technology mostly accrued to patients using the device. As Table 1 suggests that adoption is heterogeneous across physicians, the lack of spillovers could be driven by little variation in CGM adoption within the set of patients followed by a given physician. Considering the extreme case where all patients within a cluster at a particular practice are either adopting or non-adopting, non-users cannot benefit from the information generated by CGM users. To analyze whether this phenomenon drives the lack of spillovers, I compute the equilibrium shares and the consumer surplus generated by spillovers under an alternative allocation of CGM, which removes the variation across physicians. To that end, first, I predict patient device adoption in my sample of physicians using a model similar to the one from Table 1. I compute the predicted probability of adoption, net of the physician fixed effect for each patient, $\hat{p}_i$. Two patients with similar characteristics have the same probability of adopting the device. I randomly select patients to adopt the technology, fixing the number of users to the number observed in the data and using the predicted probability of adoption, $\hat{p}_i$, as weights. Adoption dates are allocated randomly. I compute consumer welfare under this alternative allocation and present the results (against the allocation observed in the data) in Figure A16.