

Pharmaceuticals and Digital Health: Evidence from Data-driven Insights on the Insulin Market*

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Abstract

Digital health technologies, such as Continuous Glucose Monitors (CGMs), are transforming the availability of patient-level data, potentially influencing other healthcare markets. This paper examines how CGMs influence the insulin market, shedding light on the impact of digital health technologies on pharmaceutical demand, pricing, and innovation incentives. I develop and estimate a tractable model of supply and demand for insulin, embedding: (i) patient-specific learning about treatment performance through CGMs, (ii) physician-level learning about new insulin products from patient experiences, and (iii) price bargaining between pharmaceutical companies and the regulator. Using medical claims data from France, I find that CGMs' patient-specific information steered insulin demand toward newer products, with limited spillover to nonusers. Manufacturers of drugs that benefited from higher perceived quality could negotiate higher prices. My findings indicate that introducing these newly observable product attributes into pharmaceutical demand shifts the relative profitability of drug innovation strategies, thereby shaping the direction of future pharmaceutical innovation.

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1 Introduction

From smartphone step counters to smartwatches, digital devices that generate high-frequency health data are now widely available, transforming the landscape of individual-level information for decision-making. These data are compelling for pharmaceutical markets 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. Therefore, by generating timely information, digital technologies can affect markets for other healthcare products.

This paper investigates the impact of Continuous Glucose Monitors (CGMs) on insulin choice in diabetes treatment. By delivering continuous glucose readings, CGMs enhance the information available to evaluate insulin treatments, highlighting the limitations of traditional measures that conceal critical glucose control variations. Key questions arise: How do CGMs’ insights influence insulin choices for technology users? To what extent do these insights guide physicians’ decisions for other patients? What are the implications for drug price negotiations between manufacturers and regulators? How do CGMs impact pharmaceutical innovation incentives?

I address these questions leveraging comprehensive medical claims data for France, which provides a unique setup to assess the impacts of CGMs. This dataset is especially valuable due to the French centralized universal insurance system, recording prescription reimbursements for the entire population. Additionally, a policy change that expanded glucose sensor coverage boosted adoption among insulin-dependent diabetic patients. This policy shift, along with the device’s technological characteristics, allows for inferring technology adoption and attrition from claims data. I use these data to show that new patient-drug information from CGMs steers insulin demand toward newer, less familiar drugs, fostering physicians’ learning about these products’ real-life performance. By influencing how physicians perceive drugs’ clinical match values, CGMs enable manufacturers of drugs that perform well on the new *observable* attributes to negotiate higher prices, ultimately impacting the profitability of the pharmaceutical innovation strategies toward drugs with different characteristics.

This paper sheds light on how digital health technologies shape pharmaceutical markets, disentangling two mechanisms. First, high-frequency data can speed up physicians’ learning about the performance of treatments. Second, CGMs provide detailed patient-specific insights, broadening the attributes observable for evaluating

the effectiveness of drugs. This distinction matters: faster learning upon market entry mitigates the barriers to new drug adoption without changing the perceived differentiation of drugs after the initial uncertainty resolves. In contrast, new attributes for evaluating drug performance change the information available to physicians when choosing treatments beyond market entry. By reshaping physicians' preferences for treatments, the attributes observed thanks to these new technologies may not only impact competition between existing products but also affect pharmaceutical innovation incentives. I develop an empirical framework of demand and supply for insulin, accounting for: (i) patient-specific match value components revealed by CGMs, (ii) physician-level learning about new drugs upon market entry, and (iii) price responses from bargaining with the regulator. Using claims data from 2015 to 2021 — a period marked by new insulin entries and increased CGM adoption — I identify (i) the impact of CGM-generated patient-specific information by comparing insulin choices for similar patients with and without CGMs and (ii) the impact of CGMs on physicians' speed of learning about new drugs through variations in prescription patterns as they gain experience with drugs from similar patients with and without CGMs.

The descriptive analysis provides three empirical facts highlighting the interaction between glucose sensors and insulin demand. First, CGM users are 35 to 55% more likely to switch treatments shortly after technology adoption compared to nonusers. These switches are not random and involve new insulin products with different characteristics. Second, these switches are not driven by a change in switching costs or reverse causality from patients' selection into technology adoption. Third, physicians learn the real-life performance of new drugs across patients: as they gain experience with a product, they become more likely to switch additional patients to that drug.

The insulin market changed, regardless of CGMs, due to new product entries before and after the CGM insurance coverage decision. A structural model is necessary to disentangle the effect of new product entries separately from CGM adoption and pinpoint the impact of patient-specific information from physician-level learning. On the demand side, physicians treating heterogeneous patients select the most cost-effective insulin. They face imperfect information about the patient-product clinical match value — especially for new drugs — affecting choices. Physician learning occurs through direct patient experience ([Coscelli and Shum \(2004\)](#)) but remains incomplete without patient-specific CGM data. The device generates unique insights about the patient's glucose profile, which can be informative about (i) the patient, independent

of the medication; (ii) the drug, independent of the patient; or (iii) the patient-drug combination. However, only the latter two channels affect pharmaceutical demand, implying that some complementarity between the technology insights and the drug’s mechanism of action is crucial in influencing demand. In the 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 accounting for perceived product differentiation. CGMs potentially influence equilibrium insulin prices through these channels.

I estimate the demand model via simulated maximum likelihood to account for unobserved patient experience. To address patient selection into CGM, I use a flexible specification of patient-product match values that controls for product-specific unobserved heterogeneity common across patients with similar characteristics. The remaining within-group heterogeneity is assumed independent of CGM adoption. Physicians learn about the common component of match values across patients within a group, while the within-group idiosyncratic component is observed when the patient uses a glucose sensor. The estimates suggest pessimistic beliefs about new products at entry, consistent with [Coscelli and Shum \(2004\)](#) for anti-ulcer drugs in Italy. CGM affects insulin choice through the idiosyncratic match value component revealed by sensor use, which accounts for 40% of the match value on average. The device only marginally improves the precision of visit-level experience signals about new drugs, potentially limiting information spillovers to nonusers. The pricing model estimation highlights that, in line with low prices despite quasi-inelastic demand, most bargaining weight can be attributed to the regulator, which maximizes consumer surplus.¹

Finally, I use the demand and supply estimates to compute two counterfactuals illustrating how glucose sensors affect pharmaceutical markets. First, I assess the short-term impact by simulating the market equilibrium without CGMs, fixing the set of products. Second, I study long-term implications for pharmaceutical innovation by simulating the entry of alternative drugs under different technological environments.

The first counterfactual shows that most short-term consumer welfare gains from CGMs go to device users, with the benefits to nonusers being ten times smaller. By revealing previously unobserved attributes that steer user demand toward newer drugs, CGMs allow physicians to learn 4.4% faster, on average, about their real-

¹Insulin product prices are significantly higher in countries without price controls, such as the US.

world performance. However, learning about drugs that appear less attractive on CGM-observable attributes is only 0.5% faster, driven by a fixed number of learning opportunities and the limited effect of CGMs on the precision of experience signals extrapolated to nonusers. The information generated by CGMs contributed heterogeneously to new drug adoption, ranging from a 0.5 percentage point decrease in market share for the entering bioequivalent drug to a four percentage point increase (+18%) in 2021. The drug benefiting most from CGM adoption triggers low overnight glucose levels — a feature more complicated to detect without the technology. Turning to negotiated insulin prices, the new observable attributes affect the perceived quality of products. The manufacturers of drugs that perform better on these new attributes bargain slightly higher prices — up to +4.4% in 2021 — suggesting a limited effect of market power on prices in a regulated setting. For most products, demand and supply forces reinforce each other, with profits changing from -17% to +23%.

The second counterfactual highlights the implications of cross-market complementarities between medical devices and pharmaceuticals for innovation. Considering a pharmaceutical company’s product design decision, I compare the profit-maximizing product in environments with and without CGMs, where CGMs help physicians match patients to products.² When considering the entry of a hypothetical new drug with relatively strong performance on attributes unobservable without the CGM technology, the manufacturer’s profits would be 5% lower than profits from the actual market entrant in an environment without CGMs. However, in an environment where CGMs are widely used, the profitability of this potential entrant significantly increases, becoming 30% higher than that of the actual market entrant. This increase in profitability comes with a 25% rise in consumer welfare gains relative to the welfare generated by the current market entrant. This result indicates that the most profitable pharmaceutical innovation strategy can shift depending on the technological environment in which insulin choices are made. It implies that devices like CGMs, which introduce new observable attributes for evaluating drug performance, can shape the direction of pharmaceutical innovation. Overall, these findings illustrate how new measurement technologies can reshape market outcomes by expanding the set of observable dimensions relevant for decision making.

Related literature. By providing an empirical framework to analyze how dig-

²I abstract away from the extensive margin of innovation and strategic responses of other drug manufacturers.

ital technologies help overcome demand-side information frictions and affect market outcomes, this paper contributes to several strands of the existing literature. It builds primarily on research analyzing demand-side learning in healthcare markets, emphasizing that information frictions regarding drugs’ clinical match values arise upon market entry and initial diagnosis (Coscelli and Shum (2004), Crawford and Shum (2005), Ching (2010a), Currie and MacLeod (2020)). These frictions decrease as physicians gain direct and indirect experience with the drug (Coscelli and Shum (2004), Chintagunta et al. (2009), 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 (Erdem and Keane (1996)), my work is closely related to Crawford and Shum (2005), who focus on treatment experimentation and learning upon initial patient diagnosis. This paper studies learning about new products upon market entry, focusing on patients already diagnosed with the disease. Physicians learn dynamically about the drugs’ clinical match values across their patient population, drawing on experiences of heterogeneous qualities depending on patients’ monitoring technology.³

When consumers learn dynamically about products, 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 empirical literature to focus on demand-side mechanisms with the exceptions of Ching (2010a) and Ching (2010b) for pharmaceuticals. My paper relies on its institutional context to build a tractable framework in which learning is internalized by the pharmaceutical companies and the regulator when bargaining over treatment prices.

This paper also contributes to the literature on the impact of information frictions on market outcomes. Previous work documents 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)). I focus on the impact of consumer-level data on the demand side to overcome information frictions. While consumer-level data from monitoring technologies can mitigate information asymmetries in insurance markets (Jin and Vasserman (2025)), I focus on a monitoring technology reducing

³Unlike Crawford and Shum (2005), I assume physicians are myopic at the time of treatment decision, limiting the scope for physicians’ experimentation within and across patients over time. Beyond learning, this work adds to the literature on the sources of inertia in demand (Dubé et al. (2010)). I disentangle switching costs from learning as sources of inertia in a chronic disease relying on institutional features.

demand-side information frictions.⁴ This paper also builds on the literature developed in empirical industrial organization, assessing the value of new goods (Trajtenberg (1989), Petrin (2002)). Igami et al. (2024) measure the welfare gains from product and process innovations. This paper links 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.

This work explores complementarities across markets and how innovations in one market can shape outcomes in another. While earlier studies document the impact of upstream innovation in vertically related markets (Eizenberg (2014)), Bresnahan and Trajtenberg (1995) highlight that complementary innovations may be needed to fully exploit new technologies. My paper emphasizes the complementarity between medical device innovation and new pharmaceuticals in a context where adoption of the complementary technology is the consumer’s choice. I show how medical device innovations alter pharmaceutical product shares and can shape the product offering.⁵ In this regard, my paper relates to literature on personalized medicine, where pharmaceutical products are approved with companion diagnostics. While Philipson (2018) notes that the lack of IP on companion diagnostics may deter innovation, I find that CGM increases pharmaceutical innovation appropriability.

Finally, this paper contributes to the literature on information technology adoption in healthcare. Earlier empirical works focus on electronic medical records (Agha (2014), Dranove et al. (2014), Lee et al. (2013), McCullough et al. (2016)) and, more recently, telemedicine (Zeltzer et al. (2024), Dahlstrand (2024)) and 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. I extend this literature by documenting the channels through which wearable devices generating high-frequency health data affect treatment market outcomes.

The paper proceeds as follows. Section 2 describes the empirical setting and data. Section 3 documents the impact of CGM adoption on insulin choice. Section 4 develops a demand and pricing model for insulin, with some patients using digital devices. Section 5 estimates the primitives of the model. Section 6 presents the counterfactual scenarios, and Section 7 concludes.

⁴By studying how markets react to monitoring technologies, this paper relates to Baker and Hubbard (2003).

⁵Previous work by Dranove et al. (2022) highlights that demand shocks can incentivize R&D, favoring follow-up innovations in the case of Medicare Part D. Hamilton et al. (2021) also studies how consumer demand affects the direction of pharmaceutical innovation.

2 Context and Data

2.1 Diabetes treatment in France

Diabetes is characterized by high blood sugar levels and its management aims to stabilize blood glucose within a target range. As of 2021, about 22% of diabetic adults in France relied on insulin. This project studies the choice of long-acting insulin — hereafter insulin choice — stabilizing glucose over 24 hours through daily injections.⁶ Products primarily differ in their theoretical duration of action, and their *effective* duration varies across patients due to demographics, time since diagnosis, and metabolism, so clinical benefits are heterogeneous.⁷ Managing diabetes also requires patients to monitor glucose levels to avoid adverse events. Before 2017, monitoring was burdensome because each measurement required a finger-prick. Physicians assessed diabetes control using three-month average glucose levels (A1c), finger-pricked measurements, and patient-reported events, with the laboratory-measured A1c considered as the gold standard for assessing good versus poor diabetes management.

Between 2015 and 2021, significant changes occurred in the insulin product space and the glucose monitoring technologies, which impacted the information available to physicians to evaluate treatment efficacy. On the glucose monitoring side, Continuous Glucose Monitors provide glucose readings every 5 to 15 minutes through a sensor, contrasting with the unique snapshot provided by strip tests (Supplemental Appendix Figure A2). In France, CGMs were widely adopted by patients following the Health Technology Agency (HTA) coverage decision in mid-2017.⁸ 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 insulin units reimbursed (Supplemental Appendix Figure A3). Between 2016 and 2018, four new products entered the market, including a biosimilar for the 24-hour drug and three longer-acting drugs. In particular, the 42-hour drug targets patients with low overnight glucose levels.

Physicians learn about the new insulins' performance outside the controlled en-

⁶It is often combined with short-acting insulin injected at mealtimes to manage food intake. Because these products serve different roles, they can be studied separately. The European Medicines Agency approved the first once-weekly long-acting insulin in 2024.

⁷Adjusting insulin dosage has limited impact on duration and changes glucose levels throughout the action period. Choosing the right product for each patient is therefore a key decision margin.

⁸The coverage decision targeted around 68% of diabetic patients taking long-acting insulin. The decrease in daily glucose monitoring burden thanks to CGMs drove a broad and fast device adoption.

vironment of clinical trials across a heterogeneous patient population from patients' experience. CGMs expand the observable attributes for evaluating insulin treatment by providing detailed measurements of the daily glucose profile, including overnight levels. They complement traditional metrics, as the three-month average 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 (Supplemental Appendix Figure A1).⁹ 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. With new products entering the market, the impact of digital devices on insulin choice can be twofold: (i) identifying poor patient-product clinical matches (Shields and Sankaranarayanan (2016)), and (ii) gathering information about the real-life performance of new drugs (Seaquist et al. (2017)). Throughout the paper, I refer to products by their duration, '24-hour Biosimilar' for Abasaglar, 'Type 2' for Xultophy and 'Human' and 'Mix' for 12-hour products.

2.2 Data

I rely on rich claims data from the French health insurance system. Owing to the centralized universal healthcare system, the data is exhaustive of the French population and includes all medical claims to a 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 prescriber's medical specialty, the dates of the prescription and pharmacy visit, and the drug characteristics at the package level. The data covers all insulin reimbursements to a given patient and all prescriptions written by a physician.¹⁰

⁹Concerns about over-treatment have emerged recently: physicians may overestimate the benefits of low average glucose levels while under-weighting the hypoglycemia risk underlying glucose variability. <https://www.reuters.com/investigates/special-report/usa-diabetes-overtreatment/>

¹⁰Purchasing 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 nonadherence. I assume that patients always comply with their physician's prescription. Patients under insulin therapy must inject insulin every day, limiting the scope for nonadherence.

2.2.2 CGM adoption and attrition

Observing patients adopting and dropping out of continuous glucose monitoring is a crucial component of this project. CGMs are registered medical devices whose insurance coverage was enacted in France in June 2017. As a result, CGM use is inferred from pharmaceutical claims data. As for insulin reimbursements, I observe the patient and prescriber IDs, the prescription and pharmacy visit dates, and the device characteristics. I assume the patient starts wearing the sensor from the pharmacy visit date and stops using CGM at the expiration of the last sensor reimbursed to the patient.¹¹ Mismeasurement in CGM adoption can arise for patients purchasing the technology out-of-pocket; Supplemental Appendix B.3 addresses these concerns.

2.2.3 Patient-level demographics and medical conditions

Patient demographics are necessary to capture sufficient heterogeneity inherent in the diabetes population. The data includes the patient’s age, gender, and residential area at the municipality level. Low-income individuals are identified because they benefit from free public complementary health insurance. Annual patient registries, constructed from all medical claims for a patient, report information on the type of diabetes and chronic conditions, including anxiety, cancer, cardiovascular disease, dialysis, depression, hypercholesterolemia, hypertension, obesity, etc.

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, I assess diabetes management using information on inpatient care and Emergency Room (ER) visits. The data includes all ER visits, but diagnoses are available only for ER visits leading to an inpatient stay.

2.3 Sample selection

This study examines insulin prescriptions of diabetes specialists between 2015 and 2021 for patients aged 18-75 who were already using long-acting insulin before 2016.

¹¹The 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.

This sample and period present several advantages. First, they capture both the entry of new drugs (from 2016) and CGM coverage (from 2017). Second, prior insulin users — ‘incumbents’ — were already familiar with injections and glucose monitoring before CGMs were introduced.¹² Third, restricting the sample to adults under 75 increases the likelihood that patients self-administer insulin. Finally, although diabetes specialists generate only 25% of all prescriptions, General Practitioners renew their prescriptions such that specialists have a considerable impact on insulin prescribing.¹³ Supplemental Appendix B provides details on the data and sample construction.

The final sample includes 330k patients, 28% with Type 1 diabetes and 39% with Type 2 diabetes using short and long-acting insulin. 68% of the sample was eligible for CGM reimbursement. Patients are, on average, 57 years old, and fewer than half are women. Around 65% of eligible patients ever used a CGM, with adoption being staggered over time and attrition remaining rare (Supplemental Appendix Table A1 and Figure A4). Among physicians, I focus on diabetes specialists and hospital services who account for 74% of treatment switches. 97% of specialists encountered patients wearing a CGM between 2017 and 2021 (Supplemental Appendix Table A2).

3 Descriptive evidence

This section documents the interaction between glucose sensor adoption and insulin demand. Patients are temporarily more likely to switch insulin products after starting CGM, typically toward new products with different characteristics. These switches cannot be explained by lower switching costs, and there is no evidence of reverse causality. Physician-level learning about new drugs suggests potential spillovers.

3.1 CGM adoption and potential patient-insulin mismatch

This section examines how CGM adoption affects insulin choices for technology users. I first analyze whether patient-physician pairs switch a patient’s insulin treatment following CGM adoption, comparing decisions for patients using a CGM with those for similar patients not using one. Focusing on the decision made by the patient i -

¹²Hence, the analysis does not reflect learning about insulin initiation (Crawford and Shum (2005)). Patients using insulin pumps are excluded because they do not use long-acting insulin.

¹³Specialists are more likely to make an active choice at each visit. Moreover, focusing on specialists who prescribed insulin before 2016 also limits physician heterogeneity, particularly regarding indirect learning channels such as pharmaceutical detailing or scientific publications (Supplemental Appendix C.2.)

physician k pair during appointment v , I consider

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

$Switch_{ikv}$ equals one if patient i 's treatment at visit v , j_{iv} , differs from that at the previous visit, j_{iv-1} . CGM_{iv} equals one for patients wearing a CGM at v , and $First_{iv}$ equals one for the first specialist visit after CGM adoption. Because switching may be occasional, I allow heterogeneous effects between the first CGM visit ($\beta_0 + \beta_1$) and subsequent visits (β_0). I control for demographics and chronic conditions (D_i), the physician's information set at visit v (X_{kv} , proxied by prior patients using new products), physician fixed effects (λ_k), and a quadratic time trend ($\delta_{t(v)}$). The model is estimated by OLS. Table 1, Columns (1)-(3), shows a positive short-run correlation between CGM use and insulin switching. Physicians are 36-56% more likely to switch treatment at the first post-adoption visit. Afterward, the effect vanishes and turns negative, indicating no persistent impact, similar to the findings by [Tang et al. \(2023\)](#) for Remote Patient Monitoring and hypertension treatment. Physicians appear to respond to CGM insights by switching treatments for some patients.

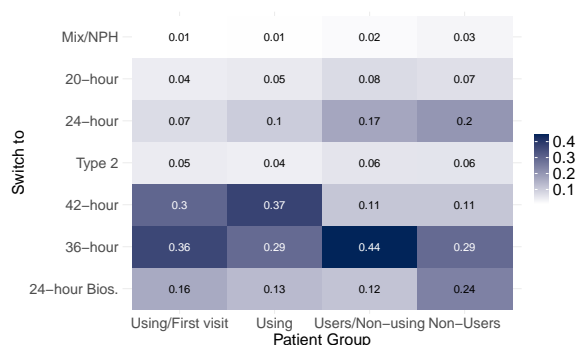
Then, I examine the products involved in those switches. CGMs provide detailed information about the patient-product match value, potentially allowing physicians to better match patients with treatments. If so, 'CGM-induced' switches should be less likely to involve equivalent products and more likely to address previously unobserved mismatches. Figure 1 shows the distribution of switches with and without CGMs. CGM users are more likely to switch to the 36- and 42-hour products — new drugs with different characteristics — and less likely to switch to the 24-hour biosimilar. Notably, some patients switch to the 36-hour product at the first post-adoption visit, although it was available before CGM coverage. The figure does not control for product entry or growing physician experience, but these two pieces of evidence are consistent with a patient-insulin mismatch, which the device reveals to the physician.

Alternative explanations could remain: CGMs may lower switching costs, affecting supply-side responses ([Dubé et al. \(2010\)](#)), or be prescribed to patients poorly matched to their treatment, generating reverse causality and undermining the idea that CGMs provide information to physicians. The next section presents evidence against these alternative mechanisms.

Table 1: Pr(Switching) estimates

	(1)		(2)		(3)		(4)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
$CGM_{iv} \times First_{iv}$	0.1181	0.0035	0.0630	0.0024	0.0638	0.0024	0.0720	0.0427
CGM_{iv}	-0.0451	0.0025	-0.0164	0.0016	-0.0308	0.0019	-0.0201	0.0761
$CGM User_i$					0.0282	0.0013		
Patient demographics			✓		✓		✓	
Patient \times Physician			✓		✓		✓	
Physician information set			✓		✓		✓	
$Switch_{iv}$				0.1310				
First Stage F-Stat							50,102.06	

Notes: The sample is restricted to patients eligible for CGM coverage. All regressions contain physician fixed-effects and a quadratic time trend. ‘Patient \times Physician’ controls for the time since the last interaction between the two. Columns (1)-(3) are estimated via OLS, while column (4) is estimated via 2SLS where $CGM_{iv} \times First_{iv}$ and CGM_{iv} are instrumented using glucose sensor adoption at the department level, by patients followed by a different physician. Standard errors are clustered at the physician level.

Figure 1: Switching patterns with/without glucose sensors

Notes: Conditional on switching, the figure shows the product the patient is switched to (vertical axis) by glucose sensor use at the visit (horizontal axis). ‘Nonusers’ are eligible patients who do not adopt sensors. Labels report the conditional probability of switching to product j , so each column sums to one. Insulin mixes and the 20- and 24-hour products are entering before 2016; the other four enter from 2016 onward. Supplemental Appendix Figure A8 shows switching matrices conditional on the pre-visit product.

3.2 Ruling out alternative mechanisms and reverse causality

The post-adoption switching patterns are inconsistent with lower switching costs, as this channel would raise the switching probability at any visit — an effect not supported by the estimates for β_0 (Table 1). Switching costs should matter most for switches between equivalent products. Yet, Figure 1 shows that CGM users are less likely than nonusers to switch to a bioequivalent treatment. Supplemental Appendix C.3 rejects the hypothesis of lower switching costs for CGM users.¹⁴

¹⁴Appendix C.3 estimates switching costs using the relative choice between the 24-hour branded drug and its biosimilar, both for first-in-line prescriptions and existing patients.

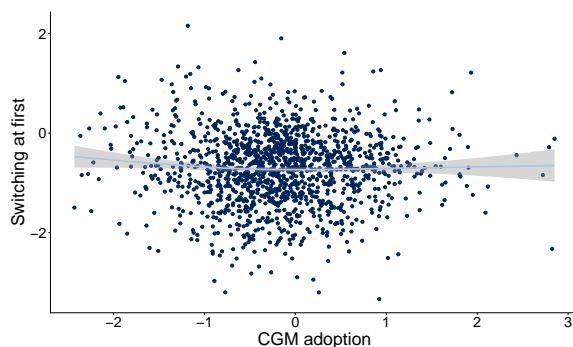
Reverse causality can affect the extensive margin of CGM adoption — if sensor users are in poorer condition *ex-ante* — and the timing of adoption — if patients are prescribed CGMs after their condition worsens. However, convenience is the primary motivation for adopting a sensor as it significantly reduces the burden of glucose monitoring compared to disposable strips.¹⁵ I provide two additional pieces of evidence to support this point. First, I re-estimate the correlation presented in Equation (1), instrumenting for glucose sensor adoption with the adoption by patients living in the same geographical area, treated by a different physician. Adoption by patients followed by other physicians in the same local area increases exposure to the technology and thus the likelihood of adoption, while not directly affecting your physician’s switching decision. The results, presented in Table 1 Column (4), indicate that the positive correlation between CGM adoption and insulin switching persists. Second, I examine whether physicians more likely to treat CGM users also switch treatment more often on the first post-adoption visit as a positive correlation would suggest they prescribe CGMs to patients they see as poorly matched to treatment. Figure 2 plots, at the physician level, the switching propensity (vertical axis) against the propensity to treat CGM users (horizontal axis), showing no correlation. Finally, I examine the timing of CGM adoption by estimating the correlation between CGM uptake and prior diabetes-related ER visits. Table 2 reports the results of logistic regressions of CGM adoption on prior ER visits. The negative correlation suggests that severe diabetes-related events are unlikely to drive adoption.

3.3 Physician-level learning and limited experimentation

Prescription drugs are experience goods: physicians are uncertain about real-world performance of new drugs upon market entry and learn from patients’ experience. Section 3.1 shows that CGM adoption correlates with switching toward newer drugs (Figure 1). As physicians are less familiar with these products, CGM-induced switches create learning opportunities as patients return, generating mechanical information externalities for nonusers if physicians extrapolate information across patients.

I test this by examining whether physicians’ prescribing of new products correlates with their product-level experience. For each physician k , product j , and quarter q , I

¹⁵Supplemental Appendix Table A3 presents the drivers of CGM adoption. Patient demographics (age and gender), and diabetes type explain most of the variation in CGM adoption, followed by physician fixed effects. Environmental factors, the medical condition, and hospitalizations prior to 2017 contribute little.

Figure 2: Physician-level heterogeneity

Notes: This figure plots physicians’ propensity to see CGM patients (horizontal axis) against their propensity to switch insulin at the first post-adoption visit (vertical axis). Each value corresponds to the estimated physician fixed effect from a logistic regression — predicting CGM adoption (x-axis) or switching at the first CGM visit (y-axis) — that controls for patient characteristics.

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			✓		✓		✓	
CGM_i	0.6206		0.6206		0.6206		0.6206	
ER_i	0.1127		0.1127		0.0929		0.4661	
Bandwidth (days)	365		365		180		365	

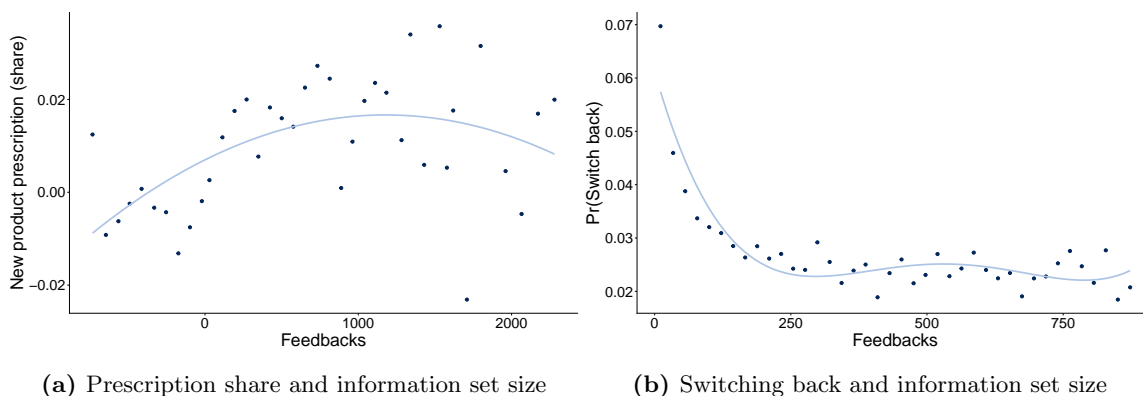
Notes: The model is estimated by logistic regression on patients eligible for the technology, with standard errors clustered at the physician level. For adopters, I count visits in the 365 days before their first CGM prescription; for non-adopters, the maximum in any 365-day window from June 2017 to January 2020. Controls include demographics (age, gender, diabetes type), environmental factors (city size, area deprivation index, low-income status), chronic conditions (listed in Supplemental Appendix Table A1), and glucose strip use in 2015-2016. Columns (1)-(3) examine diabetes-related ER visits leading to inpatient stays, while column (4) considers all ER visits resulting in inpatient stays, regardless of diagnosis.

compute the prescription share of j among patients not already using it. The physician’s information set is proxied by the cumulative number of visits up to $q - 1$ in which patients arrived already using j . Figure 3a shows a binned scatter of prescription shares (vertical axis) against the information set size (horizontal axis). The bell-shaped pattern indicates a positive correlation between product-level experience and prescribing to other patients, consistent with learning across patients and leaving scope for spillovers from CGM users to nonusers. Supplemental Appendix C.4 examines whether the type of information (with or without CGM) matters.

Learning may also induce experimentation: forward-looking physicians might prescribe new, potentially dominated, products to learn about their match values and

switch patients back after learning. While ethical concerns may limit such behavior, this would imply a non-monotonic relationship between the information set size and switching back. In contrast, myopic physicians would switch patients back only after making mistakes, implying a monotonic decline in the switching-back probability as experience accumulates. Figure 3b plots the probability of switching back against the physician’s information set size and shows a monotonic decrease, suggesting limited experimentation. I thus assume physicians are myopic moving forward.

Figure 3: Physician-level learning and experimentation



Notes: Figure 3a presents a binscatter of product j ’s prescription share among j -naive patients (vertical axis) against physician feedback from prior real-world experience (horizontal axis), residualized for physician fixed effects, product-quarter fixed effects, and average patient demographics. The sample includes diabetes specialists, with feedback measured at the hospital level when applicable, and excludes the new Type 2 product. Supplemental Appendix Figure A9(a) focuses on physicians outside hospitals. Figure 3b shows the probability of switching back to a previous treatment (vertical axis) versus cumulative product-level feedback, excluding the top 5% by information size (horizontal axis). Supplemental Appendix Figure A9(b) restricts to treatment spells initiated with minimal prior product information.

4 Insulin demand and pricing model

Building on the evidence presented in the previous section, this section develops a demand and pricing model for insulin products, analyzing how digital device information influences prescription drug choices and prices. The model recovers preferences for insulin products, consumer surplus, and firm profits. Section 5 estimates its primitives using micro-level pharmaceutical claims data, which are then used in Section 6 to quantify the impact of digital device information on the insulin market.

The model describes the behavior of physicians, insulin manufacturers, and the regulator. Insulin manufacturers and the regulator negotiate insulin product prices.

Physicians prescribe an insulin product to their patients, which aggregates to drug-level demand. The entry of new drugs and the adoption of CGMs are assumed to be exogenous. The timing is as follows. At the beginning of each year, the insulin manufacturers and the regulator agree on the price of each product for the upcoming year. Throughout the year, myopic physicians face a sequence of medical appointments during which they make treatment decisions, leading to a static decision problem. Insulin manufacturers and the regulator form rational expectations about the upcoming annual demand. Physicians face uncertainty about the match value of a given insulin product for a particular patient, and they learn about clinical match values from patients' experience signals generated with or without a CGM. On the pricing side, insulin manufacturers aim to maximize profits from prescription drug sales, while the regulator considers consumer surplus. On the demand side, physicians maximize their current expected indirect utility at each appointment. Despite making static choices, they accumulate experience signals over time and can use the information they receive from one patient to inform their decisions for other patients. This structure enables a two-step approach. In Section 4.1, I model static prescription decisions within each year, which aggregate to the annual demand for each insulin product. In Section 4.2, the annual demand and consumer surplus for each product are used as inputs to the annual insulin price negotiation between drug manufacturers and the regulator.

4.1 Insulin demand

4.1.1 Setting

Consider a patient i (he) followed by a physician k (she), who chooses the treatment. Medical appointments at which an insulin prescription is written, within physician k 's practice, are indexed by $v \in \{0, \dots, V_k\}$. Physicians differ in the number of patients they see, V_k , and in the characteristics of their patient population, both taken as given. At appointment v , the physician prescribes an insulin product $j \in \mathcal{J}_v$ to patient i . Patients differ in their glucose monitoring technology, denoted a_{iv} , and their clinical match value with product j , denoted $\Theta_{ij} \in \mathbb{R}$. $a_{iv} \in \{0, 1\}$ indicates digital device adoption: $a_{iv} = 1$ if the patient uses a CGM, and 0 otherwise. The physician observes a_{iv} and glucose sensor data when $a_{iv} = 1$. She faces uncertainty about Θ_{ij} and forms prior beliefs based on clinical trial evidence, updating them through experience signals generated by patients using product j . Considering a physician k , at each visit v

1. **Patient arrival:** Patient i arrives for an insulin prescription using monitoring device a_{iv} . The patient’s identity, technology, and choice set are taken as given.
2. **Belief updating:** The physician observes the last product used by patient i , $j_{i,v-1}$, and its effect on glucose levels. This generates an experience signal the physician uses to update her beliefs about the clinical benefit of $j_{i,v-1}$ for *any* patient. The signal enters the information set of physician k at time v , $\mathcal{I}_{kv}^{a_{iv}}$, which summarizes the stock of information accumulated up to visit v .¹⁶
3. **Treatment choice:** Given $\mathcal{I}_{kv}^{a_{iv}}$, physician k chooses the treatment $j \in \mathcal{J}_v$ that maximizes her expected payoff.

Physicians prescribe the most cost-effective treatment. The true indirect utility of the patient i -physician k pair when choosing product j is

$$U_{ikjv} = \Theta_{ij} - \alpha p_{jv} + f(\text{age}_{jv}) + \varepsilon_{ikjv} \quad (2)$$

p_{jv} is the price of product j , age_{jv} is the time since drug j entered the market, and ε_{ikjv} is an idiosyncratic preference shock. $f(\text{age}_{jv})$ captures physicians’ learning through channels other than patient experience such as word of mouth, scientific conferences/articles, or pharmaceutical detailing. Θ_{ij} , the true clinical match value between patient i and drug j , is assumed independent of the glucose monitoring technology. I assume $\Theta_{ij} = \mu_{ij} + \nu_{ij}$ where μ_{ij} denotes the preference for the drug’s effect on the average glucose level, and ν_{ij} the preference for the drug’s effect on the glucose profile.¹⁷ The physician maximizes the expected indirect utility. Given the monitoring device, a_{iv} , her information set, $\mathcal{I}_{kv}^{a_{iv}}$, the treatment choice satisfies

$$\max_{j \in \mathcal{J}_v} \mathbb{E}_k(U_{ikjv} | \mathcal{I}_{kv}^{a_{iv}}) = \max_{j \in \mathcal{J}_v} \{ \mathbb{E}_k(\Theta_{ij} | \mathcal{I}_{kv}^{a_{iv}}) - \alpha p_{jv} + f(\text{age}_{jv}) + \varepsilon_{ikjv} \} \quad (3)$$

where $\mathcal{J}_v = \mathcal{J}^{Old} \cup \mathcal{J}_v^{New}$ and \mathcal{J}_v^{New} denotes insulins entering after 2015 available at visit v (Supplemental Appendix Figure A7). Diabetes is a chronic disease so there is no outside option. Given $\mathcal{I}_{kv}^{a_{iv}}$, and product j , I assume the physician’s expectation

¹⁶The physician receives an experience signal only during a medical appointment linked to an insulin prescription. Given the large number of patients and appointments to a given physician, Section 5 will impose some restrictions on the extent of learning across patients.

¹⁷Each argument combines the attribute value and the utility weight for that attribute.

of Θ_{ij} is

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

The following paragraphs provide details on Equation (4).

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

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

For each drug $j \in \mathcal{J}^{Old}$ and each patient, physicians know the drug's effect on the average glucose level, μ_{ij} . The physician does not observe the drug's effect on the glucose profile, ν_{ij} , because the detailed patient glucose profile is unavailable without a sensor. The physician's expectation about ν_{ij} remains equal to her initial belief, which I assume is $\mathbb{E}_k(\nu_{ij}|\mathcal{I}_{kv}^0) = 0$. Without the sensor, for product $j \in \mathcal{J}^{Old}$,

$$\mathbb{E}_k(\Theta_{ij}|\mathcal{I}_{kv}^0) = \mu_{ij} + \mathbb{E}_k(\nu_{ij}|\mathcal{I}_{kv}^0) = \mu_{ij} \quad (5)$$

μ_{ij} is independent of the physician k and visit v because all physicians have already learned about this value for old drugs. The lack of information about the glucose profile, ν_{ij} , without glucose sensors, prevents the physician from learning the full match value and her belief about Θ_{ij} remains biased.¹⁸

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

For new treatments, physicians initially have no experience, and therefore imperfect information about μ_{ij} . At $v = 0$, the physician forms a prior belief about μ_{ij} and ν_{ij} . Following Erdem and Keane (1996), beliefs about μ_{ij} satisfy $\mu_{ij} \sim \mathcal{N}(\mu_{ij}^0, V_{ij}^0)$, allowing nonrational initial expectations ($\mu_{ij}^0 \neq \mu_{ij}$). The physician is Bayesian and updates her belief about μ_{ij} using patients' experience when he returns to her practice while using product j . She learns *across* patients, using patient i 's experience signal to update her beliefs for any patient i' . Signals $e_{ii'kj}^v$ are assumed to be unbiased but noisy: $e_{ii'kj}^v \sim \mathcal{N}(\mu_{i'j}, \sigma_{ii'v}^2)$ where $\sigma_{ii'v}^2$ corresponds to the noise of the signal provided

¹⁸Alternatively, one can assume that physicians learn partially about ν_{ij} without a CGM.

by patient i in v when extrapolated to patient i' . The signal enters the information set of k at $v' \geq v$, $\mathcal{I}_{kv'}$. Without a glucose sensor, the physician does not learn ν_{ij} , so

$$\mathbb{E}_k(\Theta_{ij}|\mathcal{I}_{kv}^0) = \mathbb{E}_k(\mu_{ij} + \nu_{ij}|\mathcal{I}_{kv}^0) = \mathbb{E}_k(\mu_{ij}|\mathcal{I}_{kv}^0) \quad (6)$$

which varies over time as physicians accumulate experience and across physicians due to different patient populations.¹⁹

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

Glucose sensors generate detailed reports about the effectiveness of insulin treatments throughout the day. I assume the benefits from CGM data are two-fold:

1. **Comprehensive measurement of the glucose profile:** The sensor reveals the patient's glucose profile, and I assume physicians observe ν_{ij} for all j . Thus, $\mathbb{E}_k(\nu_{ij}|\mathcal{I}_{kv}^1) = \nu_{ij}$. These insights are patient-specific.
2. **Experience signal about μ_{ij} :** The glucose sensor data generated while using product j produces an experience signal about μ_{ij} . This signal is also unbiased but may differ in precision from signals observed without a CGM.

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

Thanks to the glucose sensor, the physician observes ν_{ij} for patient i . Since μ_{ij} is known for old drugs,

$$\mathbb{E}_k(\Theta_{ij}|\mathcal{I}_{kv}^1) = \mathbb{E}_k(\mu_{ij}|\mathcal{I}_{kv}^1) + \mathbb{E}_k(\nu_{ij}|\mathcal{I}_{kv}^1) = \mu_{ij} + \nu_{ij} = \Theta_{ij} \quad (7)$$

Hence, learning about the match value with old drugs becomes complete for device users. The insights about ν_{ij} from CGMs are uninformative for nonusers who keep facing Equation (5). As a result, pharmaceutical demand is affected by the monitoring technology if ν_{ij} differs across alternatives: the newly observable attributes make certain treatments appear relatively more appropriate — even in the absence of new products. As these insights are assumed to be patient-specific, the magnitude of this effect at the market level strongly depends on device adoption. When insights from glucose sensor data do not emphasize differences across products, for example,

¹⁹Physician sees many patients such that the size of the information set is large. Section 5.1.1 presents the empirical specification and the restrictions assumed to keep the dimension of the information set tractable.

when $\nu_{ij} = \nu_i \forall j \in \mathcal{J}^{Old}$, pharmaceutical demand in markets without product entry remains unaffected.

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

For new treatments, CGM data have two impacts: revealing ν_{ij} and potentially changing the quality of the experience signal about μ_{ij} . I assume these signals remain normally distributed and unbiased, but may differ in variance. Whether CGM signals are more, less, or equally informative about μ_{ij} than signals received when the patient is not wearing a CGM remains an empirical question.²⁰ Thus, for products $j \in \mathcal{J}_v^{New}$,

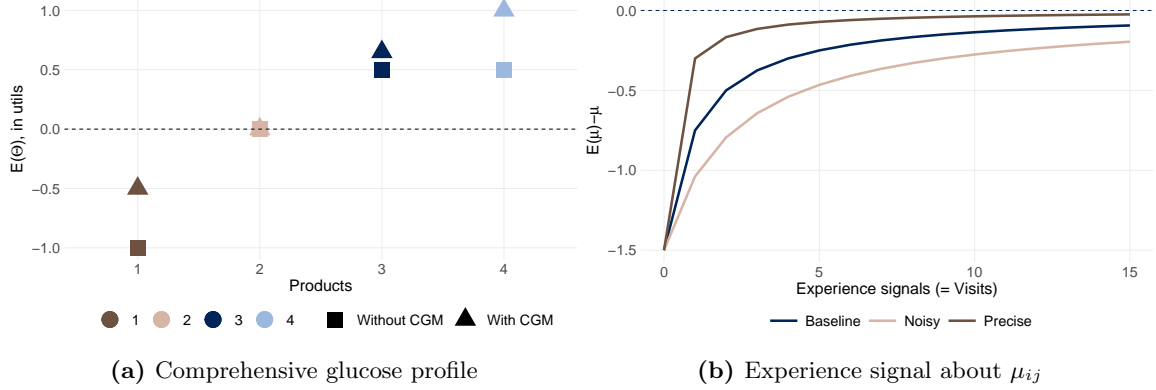
$$\mathbb{E}_k(\Theta_{ij}|\mathcal{I}_{kv}^1) = \mathbb{E}_k(\mu_{ij}|\mathcal{I}_{kv}^1) + \nu_{ij} \quad (8)$$

where $\mathbb{E}_k(\mu_{ij}|\mathcal{I}_{kv}^1)$ can differ from $\mathbb{E}_k(\mu_{ij}|\mathcal{I}_{kv}^0)$ in Equation (6).

Figure 4 summarizes the two effects of CGMs on physicians' expectations about the clinical match value, Θ_{ij} . Figure 4a illustrates the impact of observing the glucose profile, abstracting from learning dynamics upon product entry, with the vertical axis showing expected match values, $\mathbb{E}_k(\Theta_{ij})$, with (triangle) and without (square) CGM insights across drugs with different μ_{ij} and ν_{ij} (on the horizontal axis). Without CGM information on ν_{ij} the physician is indifferent between products 3 and 4 for patient i (*ceteris paribus*), but with a glucose sensor she observes ν_{ij} in addition to μ_{ij} so product 4 yields a higher expected match value and may trigger switching. Given that Θ_{ij} is independent of the glucose monitoring technology, the sensor only affects physicians' perceptions of match values, altering *perceived* differentiation. Figure 4b illustrates the learning dynamics of μ_{ij} upon entry, showing how the physician's expectation about the drug's effect on average glucose, μ_{ij} (vertical axis), evolves as she accumulates experience signals (horizontal axis), with more precise signals reducing the gap between beliefs and the true value for a given number of signals and thus enabling faster learning about μ_{ij} . The distinction between Figures 4a and 4b matters: conditional on \mathcal{J} , signal precision affects learning temporarily, whereas new observable attributes (Figure 4a) affect demand persistently.

²⁰Observing a patient's drug performance using the digital device ($a_{iv} = 1$) may provide more precise information about μ_{ij} than observation without the technology ($a_{iv} = 0$). While I do not assume complete learning about μ_{ij} , CGM insights can generate a very precise signal, leading to more accurate and precise posterior beliefs about μ_{ij} after receiving CGM information.

Figure 4: Impact of CGMs on the perceived match value



Notes: Figure 4a plots physicians’ expectations of Θ_{ij} (vertical axis) across products (horizontal axis), with (▲) and without (■) CGM insights, abstracting from learning about μ_{ij} . Figure 4b shows how beliefs about μ_{ij} evolve (vertical axis) with experience signals from returning patients — one per visit (horizontal axis). The figure assumes pessimistic normal priors and unbiased but noisy signals (σ), either precise ($\sigma = 1$) or noisy ($\sigma = 3$) relative to baseline ($\sigma = 2$).

4.1.4 Consumer welfare

In this setting, the decision utility diverges from the utility experienced by the patient: uncertainty and incomplete learning distort the decision utility, whereas the underlying experienced utility relies on Θ_{ij} , the true clinical match value. Following Equations (2), (3) and (4), the experience utility from product j is

$$U_{ikjv} = \Theta_{ij} - \alpha p_{jv} + f(\text{age}_{jv}) + \varepsilon_{ikjv} \equiv \mathbb{E}_k(U_{ikjv} | \mathcal{I}_{kv}^{a_{iv}}) - [\mathbb{E}_k(\mu_{ij} | \mathcal{I}_{kv}^{a_{iv}}) - \mu_{ij} + \nu_{ij}(a_{iv} - 1)]$$

Following Dubois et al. (2018) and letting $j^* = \arg \max_j \mathbb{E}_k(U_{ikjv} | \mathcal{I}_{kv}^{a_{iv}})$, the expected experienced utility for the patient i -physician k pair from the choice at v is

$$W_{ikv} = \mathbb{E}_\varepsilon \left[\max_j \{ \mathbb{E}_k(U_{ikjv} | \mathcal{I}_{kv}^{a_{iv}}) \} \right] - \mathbb{E}_\varepsilon \left[\mathbb{E}_k(\mu_{ij^*} | \mathcal{I}_{kv}^{a_{iv}}) - \mu_{ij^*} + \nu_{ij^*}(a_{iv} - 1) \right] \quad (9)$$

The second term captures the gap between the realized and expected match value.

4.1.5 Discussion

This framework relies on several assumptions regarding physician and patient behavior. First, the patient-product clinical match value is not affected by the digital device. The information generated by CGMs does not affect the effect of insulin j

on the average or profile of glucose levels for patient i .²¹ Second, focusing on patients diagnosed before new product entry, it is assumed that physicians know the preference for the drug’s effect on the average glucose level, μ_{ij} , among old alternatives. This feature circumvents the initial conditions problem that arises in a dynamic setting. Third, physicians are altruistic as they choose the treatment to maximize a weighted sum of the expected patient-level clinical benefit and treatment prices. Last, physicians are myopic, limiting exploration (as discussed in Section 3.3).

4.2 Drug price setting model

This paragraph presents the insulin price-setting model, considering the pricing responses of drug manufacturers and the regulator to medical device information. Motivated by the timeline and uncertainty around drug and device development, I consider the arrival of innovations in drugs and devices as given.

I assume that prices are set every year by static bilateral Nash bargaining between each drug manufacturer and the regulator (Tunçel (2024)). A demand system for experience goods presents dynamic features, even when decision-makers are myopic. Modeling price setting in markets with dynamic demand is inherently complex, as firms have incentives to leverage this feature and set their prices in a forward-looking manner (Shapiro (1983), Bergemann and Välimäki (2006)). In France, the price for prescription drugs, determined through negotiations, is established upon entry for an extended period and is renegotiated over time. Price increases are difficult to negotiate, preventing manufacturers from taking advantage of the demand dynamics by setting a low price upon introduction to raise it in later periods in the spirit of Shapiro (1983). Hence, I assume static pricing in each period.

In pharmaceutical markets, each branded drug is often produced by a single firm, and I treat the 24-hour biosimilar and its branded version as separate products.²² Unlike other pharmaceuticals, the insulin market is concentrated, with three firms providing the complete range of products in France. I assume bargaining takes place at the drug portfolio level for each manufacturer. The profits for firm f offering products $j \in \mathcal{J}_{ft}$ in year t is

²¹The average and profile of the glucose levels can be affected by the device owing to the better fine-tuning of short-acting insulin but the effect must be independent of the long-acting product.

²²These products are not ‘interchangeable’ at the pharmacy: the physician writes a prescription for one version, and the pharmacist must provide the prescribed drug.

$$\pi_{ft}(\mathbf{p}_t) = \sum_{\forall j \in \mathcal{J}_{ft}} (p_{jt} - c_{jt})q_{jt}(\mathbf{p}_t) \quad (10)$$

where $q_{jt}(\mathbf{p}_t)$ is the total demand for drug j across appointments v occurring in year t , derived from the sum of individual choice probabilities, $s_{ikjv}(\mathbf{p}_t|\mathcal{I}_{kv})$, derived from Equation (3). This profit function assumes that manufacturers have rational expectations about demand realizations in a given year, including physicians' learning, CGM insurance coverage, adoption, and the impact on insulin demand.

When bargaining with firm f , the regulator is assumed to maximize the expected *ex-ante* consumer surplus generated by the portfolio of drugs offered by firm f in year t , $\Delta_{ft}CS(\mathbf{p}_t)$, given by

$$\Delta_{ft}CS(\mathbf{p}_t) = \frac{1}{\alpha} \sum_{\forall i,k,v \in t} \mathbb{E}_\varepsilon \left(\max_{j \in \mathcal{J}_v} \mathbb{E}_k(U_{ikjt}|\mathcal{I}_{kv}^{aiv}) \right) - \frac{1}{\alpha} \sum_{\forall i,k,v \in t} \mathbb{E}_\varepsilon \left(\max_{j' \in \mathcal{J}_v \setminus \mathcal{J}_{ft}} \mathbb{E}_k(U_{ikj't}|\mathcal{I}_{kv}^{aiv}) \right) \quad (11)$$

where $\mathbb{E}_k(U_{ikjt}|\mathcal{I}_{kv}^{aiv})$ follows from Equation (3).²³ I assume the regulator knows the firm's marginal costs and also forms rational expectations about the adoption of the digital device and its impact on demand and consumer surplus. Equation (11) assumes that the consumer surplus the regulator considers when setting drug prices ignores the discrepancy between the decision and experience utility (Equation (9)).

Denoting b_{ft} the bargaining weight of firm f in year t , the Nash-in-Nash equilibrium prices maximize the Nash product for the manufacturer's profits and the regulator surplus, taking the prices of other products as given:

$$\max_{\mathbf{p}_{jt}, j \in \mathcal{J}_{ft}} [\pi_{ft}(\mathbf{p}_t)]^{b_{ft}} [\Delta_{ft}CS(\mathbf{p}_t)]^{1-b_{ft}} \quad (12)$$

where the disagreement profits for the pharmaceutical company are zero. The portfolio of each pharmaceutical company, \mathcal{J}_{ft} , is treated as an exogenously given indivisible block. I do not consider bargaining over a subset of products. The first-order condition with respect to the price of drug $j \in \mathcal{J}_{ft}$ in year t is given by

$$b_{ft} \frac{\partial \pi_{ft}(\mathbf{p}_t) / \partial p_{jt}}{\pi_{ft}(\mathbf{p}_t)} + (1 - b_{ft}) \frac{\partial \Delta_{ft}CS(\mathbf{p}_t) / \partial p_{jt}}{\Delta_{ft}CS(\mathbf{p}_t)} = 0 \quad (13)$$

²³Consumer surplus is scaled using the demand price-sensitivity parameter α . This normalization is without loss of generality: although a regulator may in practice use a different scaling from utils to euros, this would not affect the first-order conditions.

When a firm offers two products, j and j' , the first-order conditions yield the following pricing equation:

$$p_{jt} = c_{jt} - \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t) / \partial p_{jt}}{q_{jt}(\mathbf{p}_t)} + \left(\beta_{ft} h_{j't} + \frac{\partial q_{j't}(\mathbf{p}_t) / \partial p_{jt}}{q_{j't}(\mathbf{p}_t)} \right) \frac{\left(q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} \right)}{\left(q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} \right)} \right]^{-1} \quad (14)$$

where $h_{jt} = \frac{\partial \Delta_{ft} CS(\mathbf{p}_t) / \partial p_{jt}}{\Delta_{ft} CS(\mathbf{p}_t)} < 0$, $\beta_{ft} = \frac{1-b_{ft}}{b_{ft}}$ and the last term collapses to zero for single-product firms. The details for the first-order condition computation are provided in Supplemental Appendix D.

5 Empirical specification and estimation

5.1 Demand model

This section focuses on estimating the demand model presented in Section 4.1. The expected indirect utility from insulin j by the patient i -physician k pair at visit v is

$$\begin{aligned} \mathbb{E}_k(U_{ikjv} | \mathcal{I}_{kv}^{a_{iv}}) &= \mathbb{E}_k(\mu_{ij} | \mathcal{I}_{kv}^{a_{iv}}) + \nu_{ij} a_{iv} - \alpha p_{jv} + f(\text{age}_{jv}) + \varepsilon_{ikjv} \\ &\equiv u_{ikjv}(\mathcal{I}_{kv}^{a_{iv}}) + \varepsilon_{ikjv} \end{aligned} \quad (15)$$

where $u_{ikjv}(\mathcal{I}_{kv}^{a_{iv}})$ denotes the deterministic part and ε_{ikjv} is the unobserved idiosyncratic shock, *i.i.d.* and distributed Type-I extreme value. p_{jv} is the price of insulin j at time v , and $\mathbb{E}_k(\mu_{ij} | \mathcal{I}_{kv}^{a_{iv}}) + \nu_{ij} a_{iv}$ is the expected patient-drug clinical match value, following Equation (4). age_{jv} is the time since product j became available; it enters quadratically to approximate learning from indirect experience.

5.1.1 Empirical specification

Heterogeneity in patient-drug clinical match value. The patient-insulin clinical match value, Θ_{ij} , varies from one patient to another on the basis of physiologic and metabolic factors. I assumed 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 drug's effect on the glucose profile, ν_{ij} . Physicians learn dynamically about μ_{ij} from patients' direct experiences, which are summarized in their information set, $\mathcal{I}_{kv}^{a_{iv}}$, hence the dimension of $\mathcal{I}_{kv}^{a_{iv}}$ is large. To accommodate the heterogeneity in μ_{ij} while maintaining the model's tractability, I assume that patients can be classified, *ex-ante*, into N distinct

groups, $n \in \{1, \dots, N\}$. Within a cluster, n , μ_{ij} is constant and denoted μ_{nj} . Each physician holds a prior belief about μ_{nj} , common to all patients in group n , limiting the dimension of the state. Physicians know which group each existing patient belongs to.²⁴ They form beliefs about μ_{nj} upon drug j 's entry, which evolves as the physician gathers more direct patient experience.²⁵

The classification of patients into N groups is performed in two steps. First, I categorize patients into three groups based on their diabetes type and insulin therapy. Second, I apply k-means clustering within each group to classify patients into subgroups, resulting in a total of six clusters. Details are provided in Supplemental Appendix E. Within each cluster, the preference for the drug's effect on the average glucose level, μ_{nj} , is represented by a group-specific product fixed effect, allowing preferences for specific products to vary across groups on the basis of factors observed by the physician during treatment decisions but not observed by the econometrician.

The preference for drug j 's effect on the glucose profile for patient i , ν_{ij} , is proxied by the patient's sensitivity to the insulin duration of action d_j in the econometric model. To accommodate patient-level heterogeneity and nonlinearities, $\nu_{ij} = \beta_1(x_i)d_j + \beta_2(x_i)d_j^2$ where x_i includes observable demographics and chronic conditions.

New products' learning dynamics. Upon market entry, the physician forms beliefs about the preference for drug j 's performance on the average and the profile of glucose levels for patient i , μ_{ij} , and ν_{ij} . She holds a common belief about μ_{ij} for patients in the same cluster n . Each physician's prior belief about μ_{nj} and ν_{ij} is summarized by the following distributions:

$$\begin{aligned} \mu_{nj} &\sim \mathcal{N}(\mu_j^0, V_j^0) \\ \nu_{ij} &\sim F(\nu_{ij}) \text{ where } \mathbb{E}_k(\nu_{ij} | \mathcal{I}_{kv}^0) = 0 \end{aligned} \tag{16}$$

where $F(\cdot)$ is the cumulative distribution function of the beliefs about ν_{ij} . Physicians' prior beliefs about μ_{nj} are characterized at market entry by an initial mean μ_j^0 and variance V_j^0 , both assumed to be constant across physicians.²⁶ When learning about μ_{nj} from the experience signals of patients, I assume that physicians do not

²⁴For newly diagnosed patients, the physician may not be able to identify i 's type directly, leading to diagnosis matching, and experimentation (Crawford and Shum (2005)). The structural model abstracts away from these considerations by focusing on existing diabetes patients.

²⁵ μ_{nj} is assumed equal for bioequivalent drugs. Physicians might hold inaccurate beliefs regarding bioequivalence, and the learning process also pertains to the entering biosimilar (Maini et al. (2022)).

²⁶The prior beliefs could be heterogeneous, influenced by the sources of indirect learning. The model is

learn across clusters, which limits the scope of information spillovers. Considering a patient i in group n , previously prescribed insulin product $j \in \mathcal{J}_v^{New}$, who visits physician k during medical appointment v , with glucose measurement technology a_{iv} , the experience signal is drawn from

$$e_{ikj}^v \sim \mathcal{N}(\mu_{nj}, \sigma_{a_{iv}}^2) \quad (17)$$

After receiving e_{ikj}^v , physician k 's posterior belief mean, $\mathbb{E}_k(\mu_{ij} | \mathcal{I}_{kv}^{a_{iv}}) \equiv \mu_{nkj}^v$, are updated using Bayes' rule. The signal's noise when the patient uses a CGM ($a_{iv} = 1$) affects how quickly physicians learn. If σ_1 is high, CGM insights are uninformative about μ_{nj} , so physicians cannot be misled. Whether CGM signals are more, less, or equally informative compared with traditional tools depends on σ_1 and σ_0 (Figure 4b). The specification assumes $\sigma_{a_{iv}} = \sigma_{cst} + \sigma_{A1c}A1c_i + \sigma_{strips}Strips_i$ if $a_{iv} = 0$ and $\sigma_{a_{iv}} = \sigma_{cst} + \sigma_{cgm}$ if $a_{iv} = 1$ where $A1c_i$ and $Strips_i$ are measured from 2015 claims.

The learning framework relies on several assumptions and restrictions. First, learning across physicians arises through the product's time on the market, age_{jv} , and through patients who see multiple physicians.²⁷ Second, there is no learning across different patient types or time discounting for old signals. Finally, direct experience serves as the only source of physician-specific learning. Physicians are considered homogeneous regarding indirect sources of information, such as detailing. Supplemental Appendix C.2 provides suggestive evidence that there is limited variation in the physicians' likelihood of being detailed by insulin manufacturers.

5.1.2 Identification

The set of parameters to estimate includes the price sensitivity parameter, α , and the drug's age coefficients, δ_1 and δ_2 , the match value components, μ_{nj} , $\beta_1(x_i)$ and $\beta_2(x_i)$, and the dynamic learning parameters, μ_j^0 , V_j^0 , σ_{cst} , σ_{A1c} , σ_{strips} , and σ_{cgm} . The patient-product-visit-specific taste shock, ε_{ikjv} , is assumed to be uncorrelated with the price of each insulin p_{jv} and the entry of the new drugs. The endogeneity of insulin prices is unlikely in this context since drug prices are set at the national level,

estimated using a subset of diabetes specialists working outside the hospital. I assume they receive similar information about new products upon entry.

²⁷Supplemental Appendix Figure A5 provides evidence about the limited practice size for diabetes specialists working outside the hospital, limiting concerns about spillovers within a practice.

and the empirical specification includes product fixed effects.

The match value parameters, μ_{nj} , $\beta_1(x_i)$ and $\beta_2(x_i)$, are identified from the choice probabilities of each insulin product j for different patient groups. The preference for the drug’s effect on the average glucose level, μ_{nj} , is identified from within-group choice probabilities for patients without the technology. I normalize μ_{nj} for the 24-hour product to zero for each patient group. The sensitivity to insulin duration parameters, $\beta_1(x_i)$ and $\beta_2(x_i)$, are identified from the choice probabilities for patients using CGMs and their deviation compared with nonusers within a group. The causal impact of the digital device on insulin choice can be retrieved if ε_{ikjv} is uncorrelated with CGM adoption, a_{iv} , which I discuss below.

The remaining parameters characterize the evolution of physicians’ beliefs and encompass the initial prior mean and variance, μ_j^0 and V_j^0 , along with the experience signals noise parameters, σ_{cst} , σ_{A1c} , σ_{strips} , and σ_{cgm} . These parameters are identified by leveraging the sequence of prescriptions written by a physician for patients in the same cluster as she gathers more experience signals from patients in that group (Supplemental Appendix Figure A10). Prescriptions made without prior experience identify the initial prior mean, while the product-specific variance parameters are identified from the increasing propensity to prescribe as experience accumulates.

I assume that the adoption of the digital device is exogenous to the choice of long-acting insulin, and identifying 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 identification arises from unobserved patient-level characteristics that may vary over time. First, as noted in Section 4.1.3, only unobserved components that lead to differences in product-level clinical match value are relevant. Second, the cluster-level product fixed effect accounts for product-level unobserved heterogeneity across patient groups. The remaining threats lie in within-group product-specific unobservables that correlate with adoption, which I cannot address. For example, physicians strategically offering CGMs to diabetic patients whom they suspect have poor glucose control with their current long-acting insulin would affect the validity of the estimates. This argument is discussed in Section 3.2.

5.1.3 Estimation

Following Equation (15), the likelihood of observing choice j by physician k for patient i , \mathcal{L}_{ikjv} , using a_{iv} , in appointment v is given by

$$\mathcal{L}_{ikjv} = \frac{\exp(u_{ikjv}(\mathcal{I}_{kv}^{a_{iv}}))}{\sum_{\forall j'} \exp(u_{ikj'v}(\mathcal{I}_{kv}^{a_{iv}}))}$$

While physicians observe the realization of the signal, e_{ikj}^v , entering into $\mathcal{I}_{kv}^{a_{iv}}$, the econometrician does not. Therefore, the likelihood for a given sequence of choices made by physician k must integrate over the distribution of unobserved signals. Given that $y_{ikj}^v = 1$ for the chosen alternative and 0 otherwise, the individual likelihood for physician k is expressed as

$$\mathcal{L}_k = \int_{-\infty}^{\infty} \left[\prod_{v=0}^{V^k} \prod_{\forall j} \left(\frac{\exp(u_{ikjv}(\mathcal{I}_{kv}^{a_{iv}}(\vec{e}_k)))}{\sum_{\forall j'} \exp(u_{ikj'v}(\mathcal{I}_{kv}^{a_{iv}}(\vec{e}_k)))} \right)^{y_{ikj}^v} \right] dF(\vec{e}_k)$$

where $\vec{e}_k = \{e_{ikj}^1, \dots, e_{ikj}^{V^k}\}$, is the vector of signals observed by physician k . I simulate $M = 200$ Halton draws from a normal distribution to approximate the integral. Given the number of physicians, \mathcal{K} , the demand model parameters can be estimated via simulated maximum likelihood by taking the simulated log-likelihood of the sample.²⁸

$$\log L = \frac{1}{\mathcal{K}} \sum_{\forall k} \log \frac{1}{M} \sum_{\forall m} \left[\prod_{v=0}^{V^k} \prod_{\forall j} \left(\frac{\exp(u_{ikjv}(\mathcal{I}_{kv}^{a_{iv}}(\vec{e}_k^m)))}{\sum_{\forall j'} \exp(u_{ikj'v}(\mathcal{I}_{kv}^{a_{iv}}(\vec{e}_k^m)))} \right)^{y_{ikjv}} \right] \quad (18)$$

In practice, maximizing the simulated log-likelihood in Equation (18) is computationally challenging because it requires simulating the joint probability of long physician choice sequences. With a finite number of draws, the simulation error increases with the sequence length, resulting in a noisy objective function. Therefore, I use a simulated pseudolikelihood constructed at the visit level, which improves numerical stability while leaving the model's structure and identification argument unchanged.

²⁸The draws are generated once and used across iterations. Without spillovers within a physician, across patient types, n , the likelihood function can be written at the cluster-physician level.

5.1.4 Estimation results and model fit

Table 3 reports the estimated parameters, excluding the match values μ_{nj} , $\beta_1(x_i)$, and $\beta_2(x_i)$. First, the price sensitivity is small, leading to an average elasticity of -0.31, indicating inelastic demand, consistent with prior literature.²⁹ The second part of Table 3 shows physicians’ prior beliefs, μ_j^0 and V_j^0 . Initial means $\hat{\mu}_j^0$ are significantly below true values $\hat{\mu}_{nj}$ (Figure 5), indicating reluctance to switch patients to new drugs. Estimates reveal heterogeneity: the 24-hour biosimilar has a low prior mean with high uncertainty, whereas the 36-hour product has higher prior means and lower variance, consistent with prior experience with the same molecule and firm.³⁰ Comparing prior variance \hat{V}_j^0 , and signal precision $\hat{\sigma}$, the results suggest that signals are imprecise: it takes 4 to 14 signals without a CGM to resolve over half the gap between the prior mean and true μ_{nj} . CGM-generated signals are only slightly more precise.³¹

Figure 5 shows expected match values $\mathbb{E}(\Theta_{ij})$ with (triangles) and without (squares) a glucose sensor, normalizing product duration $\tilde{d}_j = d_j - d_{24h}$. The difference corresponds to ν_{ij} relative to the 24-hour product. The estimated match values $\hat{\mu}_{nj}$ (squares), suggest that new drugs (except for the 24-hour biosimilar) are perceived to slightly outperform the 24-hour treatment without CGMs, after resolving initial uncertainty (detailed in Supplemental Appendix Table A4). Detailed estimates for $\beta_1(x_i)$ and $\beta_2(x_i)$, in Supplemental Appendix Table A5, are jointly significant. On average, ν_{ij} accounts for 41% of Θ_{ij} and represents a substantial share of match value dispersion: 77% of the variation across patients within a product and 21% of the variation across products within a patient (Table 4).

Robustness. I estimate the demand model under two alternative specifications. The first includes switching costs as a source of inertia, adding SC_{ijv} , the willingness to pay to remain on the same treatment at time v , as a separate regressor in Equation (15) (Supplemental Appendix C.3). The second addresses potential endogeneity of CGM adoption using a control function: predicted residuals from a regression of CGM_{iv} on the number of other adopters followed by other physicians in the patient’s geographic area are interacted with insulin duration d_j and included in Equation (15).

²⁹It is comparable to insulin estimates for elderly U.S. patients by Einav et al. (2018) (-0.02) and reflecting France’s full insurance coverage for diabetes.

³⁰Physicians have long observed cardiovascular outcomes of the 24-hour drug since the early 2000s.

³¹This empirical finding can suggest that the drug’s performance on average glucose levels is accurately approximated by the three-month average glucose level measured in the lab.

Table 3: Demand model estimates

	Coef.	s.e.
A. General		
Price (α)	0.58	(0.22)
Age (δ_1)	-0.56	(0.07)
Age ² (δ_2)	0.04	(0.00)
B. Priors		
24-hour biosimilar (Mean)	-6.10	(0.29)
36-hour (Mean)	-3.40	(0.35)
42-hour (Mean)	-3.70	(0.40)
Type 2 (Mean)	-4.27	(0.38)
24-hour biosimilar (sd)	2.67	(0.62)
36-hour (sd)	1.41	(0.40)
42-hour (sd)	2.10	(0.56)
Type 2 (sd)	2.17	(0.56)
C. Signals		
σ_{cst}	5.23	(1.65)
σ_{strips}	0.01	(0.05)
σ_{A1c}	-0.04	(0.06)
σ_{cgm}	-0.46	(0.25)
N	145,029	

Notes: Standard errors clustered at the physician level and computed from the average of the score. The model is estimated on a sample of 150 diabetes specialists working outside of the hospital.

Table 4: Demand model estimates - match values heterogeneity

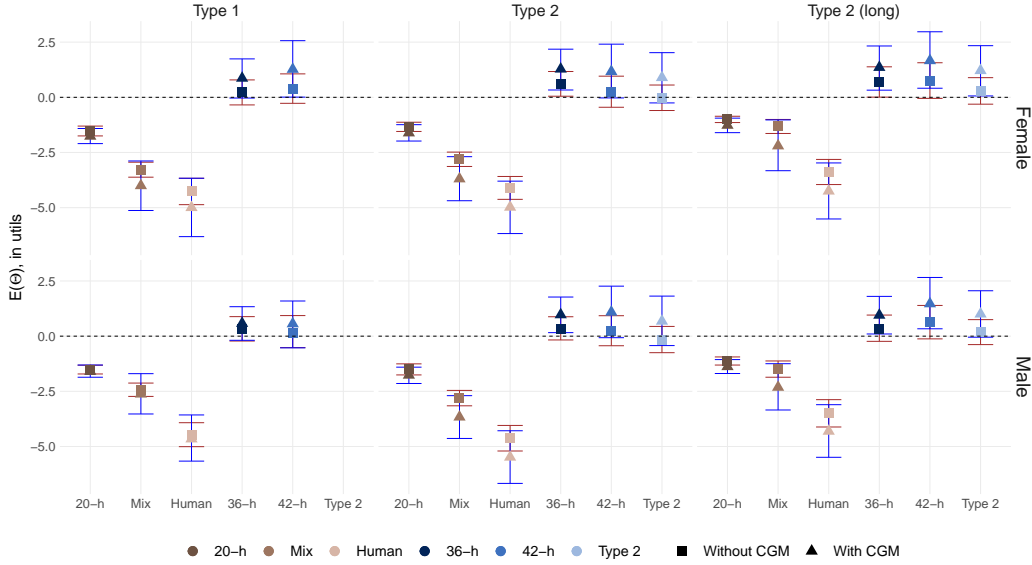
	(1)		(2)		(3)	
	Within patient		Within product		Patient \times Product	
	Av.	CI	Av.	CI	Av.	CI
$Var(\Theta)$	5.05	[2.36 ; 9.92]	0.44	[0.31 ; 1.01]	4.48	[2.11 ; 8.76]
$(Var(\nu) + Cov(\mu, \nu))/Var(\Theta)$	0.21	[-0.04 ; 0.40]	0.77	[0.63 ; 0.90]	0.31	[0.12 ; 0.49]

Notes: The first row displays the variance in patient-drug match values. This variance is computed across products for each patient and then averaged across patients in Column (1); across patients for each product and then averaged across products in Column (2); and across patients and products in Column (3). The second row displays the contribution of ν_{ij} to the overall variance in Θ_{ij} , $(var(\nu_{ij}) + cov(\mu_{ij}, \nu_{ij}))/var(\Theta_{ij})$. Confidence Intervals at the 5% level are computed using 1,000 draws from the asymptotic normal distribution of the parameter estimates, with variance given by the physician-level clustered variance-covariance matrix.

Estimates are similar to the baseline, so I rely on the baseline results (Supplemental Appendix Tables A6, A7, A8, and A9).

Model fit. The demand model's fit is evaluated using predicted choice probabilities. For each patient i , visit v , physician k , and product j , I compute $\hat{s}_{ikjv} =$

Figure 5: Perceived match value with/without a CGM



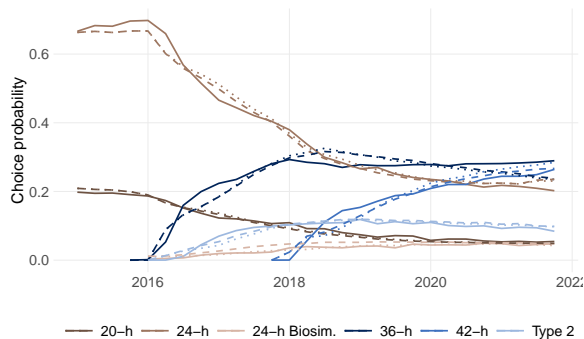
Notes: This figure shows the perceived match value, $E(\Theta_{ij})$, without the technology (■) and with a CGM (▲), in utils (vertical axis) across products (horizontal axis), by cluster, abstracting from post-entry uncertainty. Without CGMs, $E(\Theta_{ij}) = \mu_{nj}$; with CGMs, $E(\Theta_{ij}) = \mu_{nj} + \nu_{ij}$. Confidence intervals are computed using 1,000 draws from the asymptotic normal distribution of the parameter estimates, with variance given by the physician-level clustered variance-covariance matrix. The 24-hour product is the normalized good in each group. ‘Mix’ refers to insulin mixes, ‘Human’ to human insulins, and ‘Type 2’ to long-acting insulin combined with another molecule. New drugs are shown in blue and older products in brown.

$\frac{1}{M} \sum_m \hat{s}_{ikjv}(\mathcal{I}_{kv}^{aiv}(\bar{e}_k^m))$ where $\hat{s}_{ikjv}(\mathcal{I}_{kv}^{aiv}(\bar{e}_k^m))$ is the predicted choice probability in simulation m . Predictions are computed either (i) fixing past choices to observed ones or (ii) updating them at each visit based on the prediction. Figure 6 compares empirical insulin shares (solid) with predicted probabilities per quarter, keeping past choices fixed (dotted) or updating them (dashed). The model fits reasonably well: 90% of predictions are within 2.5 percentage points of actual choices. It slightly overestimates the 36-hour product in late 2018 at the expense of the 42-hour drug, but captures new drugs’ diffusion accurately. Cluster-level and technology-choice probabilities are also reasonably well matched (Supplemental Appendix Tables A10 and A11).

5.2 Price setting model

Following Equation (14), the price of insulin product j at time t , p_{jt} , is determined by the marginal cost, c_{jt} , and the markup which depends on the bargaining weight of the drug manufacturer, b_{ft} , both of which are unknown. These primitives must be recovered to compute the equilibrium insulin prices under alternative scenarios.

Figure 6: Model fit for product shares



Notes: Figure 6 compares each product’s actual and predicted choice probabilities over time. For clarity, insulin mixes and human insulins are not represented.

Yet, the first-order conditions lead to an identification challenge common in the Nash bargaining literature (Grennan (2013)).

5.2.1 Empirical specification and identification

To overcome this, I combine restrictions with external data on molecule-level production costs. First, I assume $c_{jt} = \gamma mc_j + \zeta_{jt}$ where mc_j are molecule-level costs of production for a daily dose using the estimates from Barber et al. (2024), and ζ_{jt} is an unobserved cost shock.³² Second, the bargaining weights are assumed to be firm-specific and constant over time, denoting $\beta_f \equiv \frac{1-b_{ft}}{b_{ft}}$. I combine Equation (14) with these two restrictions and rely on traditional instruments that are correlated with price but uncorrelated with the idiosyncratic cost shock, such as the number of competing products. By including firm fixed effects and mc_j in the set of exogenous variables, I can estimate the bargaining weights and marginal cost parameter from GMM using the corresponding moment conditions, $E[\zeta_{jt}|Z_{jt}] = 0$.

5.2.2 Results

The results are shown in Table 5. Insulin mixes (including the new Type 2 drug) and human insulins are excluded, with their prices held fixed in the counterfactuals. Estimated manufacturer bargaining weights range from 0.29 to 0.32 — lower than

³²Barber et al. (2024) estimates the cost of production per formulation relying on customs data for raw molecules and excipients’ quantities and prices. I rely on the ‘competitive’ estimates for insulin pens, which are the most common injection devices in France.

estimates for other prescription drugs in Canada by [Dubois et al. \(2022\)](#) and significantly lower than for antidepressants in France ([Tunçel \(2024\)](#)). With demand being rather inelastic to prices, this likely reflects strong regulatory control, which limits excessively high prices.³³ The model implies average per-product margins of 60-85%.

Table 5: Pricing model estimates

	Coef.	S.E.	b
Firm 1	2.48	(0.59)	0.29
Firm 2	2.49	(1.39)	0.29
Firm 3	2.12	(0.46)	0.32
γ	1.16	(0.90)	
N		30	

Notes: One-step GMM estimates with Jackknife standard errors. The estimation excludes insulin mixes, human insulin, and the Type 2 product, whose prices are held fixed in counterfactuals.

6 Data-driven insights, physician learning, and cross-market complementarities

This section evaluates how digital wearables’ insights affect pharmaceutical markets using counterfactual scenarios based on the demand and supply model. It examines (i) the impact of information on insulin demand and pricing, and (ii) how CGM data can influence pharmaceutical innovation. For each scenario, new equilibrium prices are computed using the price-setting and demand models.

6.1 Defining relevant market outcomes

To describe the impact of a new technology, such as CGMs, on pharmaceutical market outcomes, I rely on three indicators of market dynamics that capture the changes in outcomes: (i) firms’ profits, (ii) physician-level learning, and (iii) consumer welfare.

Firms’ profits are straightforward to compute from the predicted choice probabilities and equilibrium prices. Physician-level learning is studied through the accuracy of physicians’ end-of-period beliefs about μ_{nj} , denoted $\mu_{nkj}^{V_k}$. I use the difference between the estimated preference for drug j ’s effect on the average glucose level for patient group n , $\hat{\mu}_{nj}$, and an approximation of physician k ’s belief about $\mu_{nkj}^{V_k}$,

³³In the US, where the government does not intervene, insulin prices for the same products are much higher.

$\hat{\mu}_{nkj}^{V_k} = \frac{1}{M} \sum_m \hat{\mu}_{nkj}^{m, V_k}$, where a smaller difference suggests a more accurate belief about product j .³⁴ Consumer welfare must account for the discrepancy between the decision and experienced utility (Equation (9)). I denote $W_{ikv}(\mathbf{p}, \tilde{\mathbf{d}}, \mathbf{a})$ the expected utility for patient i from the choice made on his behalf by physician k at time v , given prices \mathbf{p} , the vector of product durations relative to the normalized good ($\tilde{d}_j = d_j - d_{24h}$), $\tilde{\mathbf{d}}$, and CGM usage \mathbf{a} in the patient population and use the compensating variation (CV) to measure the change in consumer welfare, converted to euros using the estimated price sensitivity of demand. To isolate welfare gains arising from improved matching rather than level shifts, I use the relative durations of products, \tilde{d}_j , ensuring CGMs add value only through drug ranking and allocation changes. The welfare induced by the device for patients is beyond what this project measures, as I restrict my attention to the long-acting insulin market.

6.2 Digital device adoption and the insulin market

This section uses the model estimates to evaluate the impact of CGMs on the short-run insulin market equilibrium, taking the product characteristics and patient sensor adoption as given. I simulate a scenario where CGMs are not used, setting $a_{iv} = 0$ for all patients, and compare the market equilibrium with and without CGM adoption.

Figure 7 shows the change in consumer welfare from CGM introduction. Figure 7a plots the compensating variation in euros/day (vertical axis) by prescription quarter. Average effects are shown for CGM users (blue) and nonusers (brown), for all patients (solid lines) and those eligible for coverage (dashed lines). Three insights emerge. First, welfare gains for CGM users are about ten times larger than for nonusers (around €0.06/day for eligible nonusers), indicating limited spillovers.³⁵ Second, user gains are highest in the early months of coverage and decline over time, because CGM information is most valuable when physicians face greater uncertainty about new drugs. Abstracting from pricing responses, long-run gains remain positive due to information on glucose profiles, ν_{ij} . Third, gains for nonusers materialize more slowly, as physicians learn from CGM users. Over time, and absent pricing responses, these gains converge to zero. Figure 7b reports the distribution of welfare gains among CGM

³⁴Given that experience signals are unbiased, as the physician accumulates experience signals, the average of her belief approaches the true value.

³⁵This finding relates to Chintagunta et al. (2009): physicians are learning more within than across patients. My results suggest that CGMs do not help physicians learn more across patients.

users in 2021 by patient cluster (Diabetes Type 1 vs. Type 2 and demographics). Women — especially with Type 1 diabetes — benefit more, consistent with medical evidence that they are more prone to nocturnal hypoglycemia, a condition for which CGMs provide valuable insights (Siamashvili et al. (2021)).

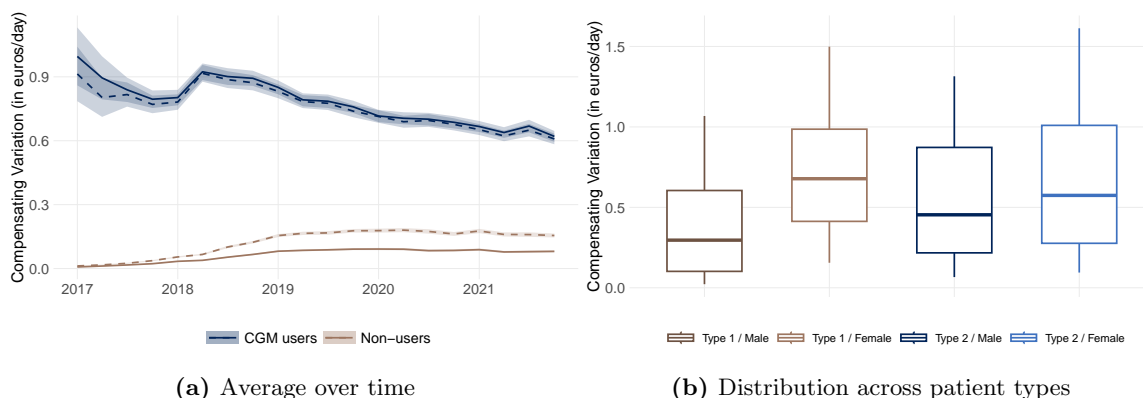
Considering physician learning, Figure 8 compares the difference between $\hat{\mu}_{nj}$ and $\hat{\mu}_{nkj}^{V_k}$ — the true preference for a drug’s effect on average glucose and the end-of-period physician prior — across settings with and without CGMs. For each physician k , patient group n , and drug j , the figure plots belief accuracy without CGMs (horizontal axis) against accuracy with CGMs (vertical axis). Points above the 45-degree line indicate more accurate beliefs when CGMs are available.³⁶ The results show heterogeneous effects. CGMs accelerate learning for some products (e.g., the 42-hour drug) but not necessarily others (e.g., the 24-hour biosimilar). Three features explain this pattern. First, the contribution of ν_{ij} to match value Θ_{ij} varies across drugs; longer-acting products benefit more from the additional information generated by sensors. Second, physicians have limited opportunities to gain experience with new drugs, so products compete for learning opportunities. Third, experience signals with CGMs are not much more precise than without the device ($\hat{\sigma}_{cgm}$ is negative but small). By revealing new observable attributes — such as overnight glucose performance — CGMs shift demand toward drugs that perform well on these dimensions, many of which are new. Physicians then learn about μ_{nj} through follow-up visits with these patients. However, because the number of learning opportunities is fixed and signal precision does not increase, learning about some products comes at the expense of others. As a result, CGMs do not uniformly enhance learning across all new drugs.

Figure 9 shows the impact of CGMs on manufacturer profits from 2017 to 2021. Effects are heterogeneous, even among new drugs. Profits for the 42-hour product increase by 24%, mainly due to higher demand (+21%) and, to a lesser extent, higher prices, whereas profits for the 24-hour biosimilar fall by 9%. In most cases, demand and pricing effects reinforce each other, except for the 36-hour product, driven by higher disagreement payoffs for the regulator. CGMs slightly reduce average markups, suggesting limited effects on price competition, in line with the regulator’s role in France. This counterfactual indicates that CGMs primarily benefit users, with limited spillovers, accelerate physician learning for certain drugs, and alter firms’ profits.³⁷

³⁶The estimation results suggest pessimistic prior beliefs since $\hat{\mu}_j^0 < \hat{\mu}_{nj}$ for all j and n .

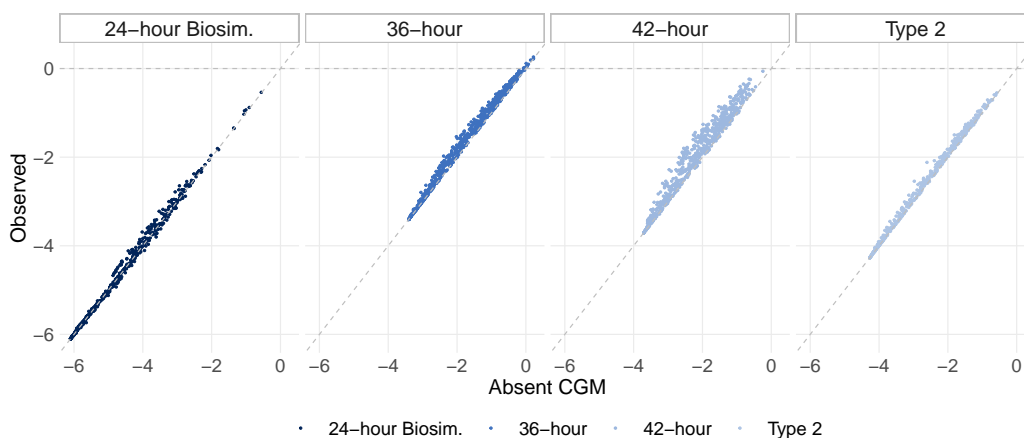
³⁷Limited spillovers to nonusers may reflect unequal physician exposure to CGM patients (Supplemental

Figure 7: Glucose sensors and consumer welfare



Notes: Figure 7a plots compensating variation (euros per day) after a prescription in period t , comparing patients with CGMs (blue) and without CGMs (brown). Dashed lines restrict the sample to device-eligible patients. Figure 7b shows the distribution of compensating variation across eligible patient types in 2021 for CGM users; ineligible groups are omitted due to negligible effects.

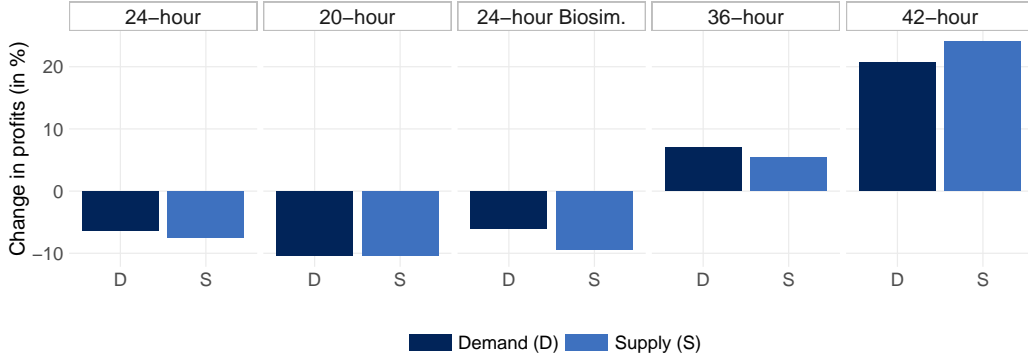
Figure 8: Glucose sensors and physician-level learning



Notes: This figure plots the difference between $\hat{\mu}_{nj}$ and $\hat{\mu}_{nkj}^{V_k}$ — the true preference for a drug’s effect on average glucose and the physician’s end-of-period prior — with CGMs (vertical axis) against without CGMs (horizontal axis). Each observation corresponds to a physician-eligible patient type-product combination. Points above the 45-degree line indicate more accurate end-of-period beliefs when CGMs are available.

Appendix Table A3). In the extreme case where all patients within a cluster either adopt or not within a practice, spillovers cannot arise in the model. A counterfactual reallocation of sensors across eligible patients, accounting for demographics, shows no increase in spillovers (Supplemental Appendix F). Thus, variation in physician-level adoption does not drive the limited spillovers, though this exercise does not assess alternative demographic targeting.

Figure 9: Glucose sensors and drug manufacturers’ profits from 2017-2021



Notes: Change in profits due to the introduction of CGMs from 2017 to 2021 for each product. The profits without CGMs 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 CGMs affecting the demand curve, and the second bar accounts for prices to react to the change in demand.

6.3 Cross-market complementarities

The previous results show that CGMs did not benefit all drugs equally: profits rose by 24% for the 42-hour product but only 5% for the 36-hour product, suggesting that CGMs better leverage some innovations. This section examines how medical devices that reveal new drug attributes affect the value of pharmaceutical innovations. It quantifies the complementarity between CGM insights and insulin characteristics, and, following [Petrin \(2002\)](#), evaluates new products’ value using consumer welfare.

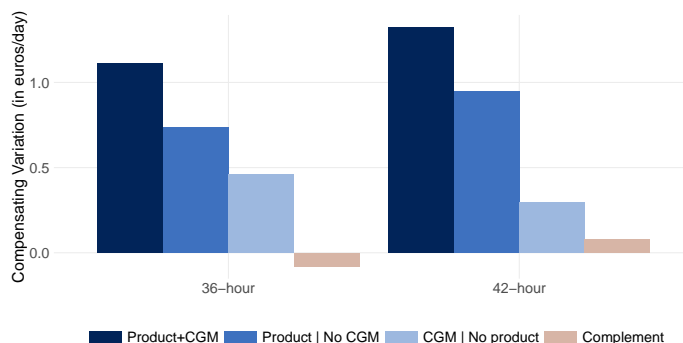
For each new product, I simulate a baseline in which the product does not enter, and CGMs are unavailable, holding competitors’ entry fixed. I then consider unilateral deviations in drug entry and CGM availability, focusing on the 36-hour and 42-hour products. Let $CV_j^{e,a}$ denote the average compensating variation depending on j ’s entry ($e \in \{0, 1\}$) and CGMs availability ($a \in \{0, 1\}$), relative to the baseline ($e = 0$, $a = 0$). When $a = 1$, CGM adoption matches observed levels. I decompose changes in welfare as:

$$CV_j^{1,1} = CV_j^{1,0} + CV_j^{0,1} + \Gamma_j \quad (19)$$

where $CV_j^{1,1}$ is the welfare gain from joint entry, $CV_j^{1,0}$ the gain from the drug alone, and $CV_j^{0,1}$ the gain from CGMs alone. The term Γ_j captures complementarities: a positive value indicates that joint entry generates welfare gains exceeding the sum of individual effects. [Figure 10](#) reports average consumer welfare gains (in euros per day) from 2019-2021 and the differential gains, Γ_j , for the 36-hour and 42-hour products.

A positive Γ_j for the 42-hour drug indicates that CGMs amplify its welfare gains. In contrast, Γ_j is negative for the 36-hour drug, meaning CGMs do not enhance its value. This negative effect reflects interactions with competing innovations — especially the 42-hour product. The welfare gains from CGMs alone ($CV_j^{0,1}$) are 55% larger when the 36-hour drug is absent than when the 42-hour drug is absent.

Figure 10: Consumer surplus and cross-market complementarities, 2019-2021



Notes: Each bar shows average compensating variation (euros per day). For each product, the first bar reports surplus from joint entry with CGMs ($CV_j^{1,1}$); the second shows surplus from the product alone ($CV_j^{1,0}$); the third shows the benefit from CGMs without the product ($CV_j^{0,1}$); and the fourth reports the differential gain, Γ_j , equal to the first bar minus the sum of the second and third.

6.4 Implications for innovation incentives

The previous sections show that digital medical devices influence both manufacturer profits and consumer welfare from new drugs that perform well on new observable attributes. This section considers the implications for pharmaceutical innovation, focusing on the private appropriability of surplus and the direction of innovation.³⁸

6.4.1 Impact on the appropriability of pharmaceutical innovation

By influencing physicians’ prescriptions, CGM insights affect both the social value of pharmaceutical innovations and manufacturers’ profits. Private innovators capture only part of the welfare gains — as effects on consumer surplus, competitors’ profits, and insurer costs are not fully internalized — leading to suboptimal private R&D (Jones and Williams (2000)). This section examines whether CGMs help better “reward innovation” by increasing the private share of total welfare gains.³⁹

³⁸France is a small market unlikely to drive innovation, which I discuss at the end of the section.

³⁹I thank Kyle Myers for suggesting this analysis.

Using the demand and pricing estimates, I compute the total surplus from introducing a new drug j and analyze the profit increases documented in Section 6.2 in terms of (i) the change in total surplus and (ii) the share captured by the manufacturer — i.e., private appropriability. The effect of CGMs on manufacturer profits from drug j can be decomposed into the change in total surplus, $TS_j^{e,a}$, and the change in the manufacturer’s share:

$$\log(\Delta\pi_f^{1,1}) - \log(\Delta\pi_f^{1,0}) = \underbrace{\log(TS_j^{1,1}) - \log(TS_j^{1,0})}_{\text{Innovation value}} + \underbrace{\log\left(\frac{\Delta\pi_f^{1,1}}{TS_j^{1,1}}\right) - \log\left(\frac{\Delta\pi_f^{1,0}}{TS_j^{1,0}}\right)}_{\text{Private surplus share}} \quad (20)$$

The first term captures CGMs’ effect on the social value of the innovation, while the second shows how the technology alters the alignment of private and social incentives. The net impact is ambiguous: CGMs improve patient-drug matching potentially, raising social value, but also influence competition and insurer costs. Figure 11 shows the decomposition of CGMs’ impact on profits for the 36- and 42-hour products using Equation (20). Manufacturer profits and total welfare are computed from entry to 2021 with a 0.9 annual discount rate.⁴⁰ Both drugs generate higher profit increases with CGMs for the innovator, consistent with Figure 9. For the 36-hour product, total surplus is lower with CGMs due to smaller gains in consumer surplus and industry profits, yet the manufacturer captures a larger share of the surplus. For the 42-hour product, both the social value and the profit increase rise with CGMs, with the manufacturer’s share of total surplus increasing by 12%. In both cases, CGMs boost private appropriability, more effectively rewarding innovation.

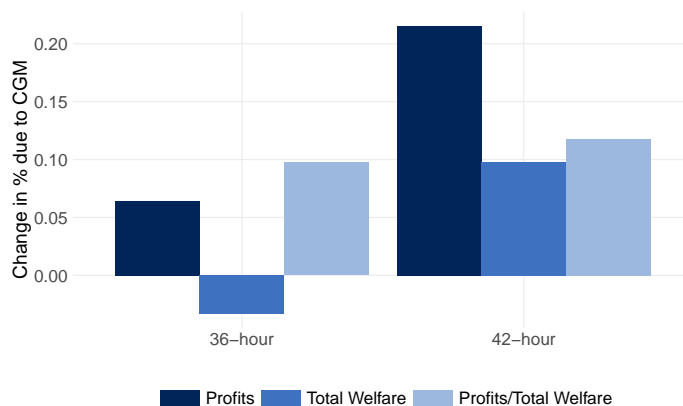
6.4.2 Toward product design

Finally, this section examines how digital medical devices, by revealing new drug attributes, influence the direction of pharmaceutical innovation — steering firms’ R&D incentives toward drugs with different characteristics.

A manufacturer f chooses which new drug to bring to the market from a set of potential products $j \in \tilde{\mathcal{J}}_f$, each defined by match values Θ_j and marginal costs c_j . At stage 0, the firm anticipates future demand and CGM adoption and selects the

⁴⁰Profits exclude R&D costs. For products outside the pricing model, I use costs from Barber et al. (2024) and draw a cost shock, ζ_{jt} , from the estimates distribution.

Figure 11: Impact of CGM on social value and appropriability of innovation



Notes: Figure 11 shows the percentage change in innovator profits, total welfare, and appropriability for the 36- and 42-hour products from a no-CGM to a CGM environment. Profits are calculated from market entry to 2021 with a 0.9 annual discount rate, and decomposed into changes in total surplus and the manufacturer’s share, following Equation (20).

product that maximizes expected profits: $j^* = \arg \max_{j \in \tilde{\mathcal{J}}_f} \mathbb{E}(\pi_f^j(\mathbf{p}, \mathbf{a}; \Theta))$.⁴¹

I compare two products: the 42-hour drug that entered in 2018 and a hypothetical 72-hour product designed to vary in μ_{ij} and ν_{ij} dimensions (Supplemental Appendix Table A12).⁴² Profits are restricted to 2018-2021 and discounted at 0.9 annually. I compare j^* in an environment with and without CGMs.⁴³ Figure 12 presents the firm’s profits and consumer surplus under each scenario. It shows that without CGMs, the 42-hour product is 5% more profitable than the 72-hour drug. With CGMs, the 72-hour product becomes 29% more profitable. Hence, the ranking of products based on profits changes depending on whether CGMs are available. This reordering of innovation profitability also benefits consumers. Consumer surplus rises 24%, driven in part by the joint entry of the drug and CGMs — Γ_j represents 17% of the welfare gains. These results indicate that complementary technologies — by introducing new observable product attributes that affect demand — can shift the most profitable drug candidate and, hence, influence the direction of pharmaceutical innovation.

Discussion Pharmaceutical innovation depends on global profits, and France

⁴¹I abstract from (i) strategic interactions, (ii) multiple-product development, and (iii) regulatory approval and assume equal fixed costs and time to market across products.

⁴²The ‘72-hour’ product is designed to resemble the once-weekly insulin approved by the EMA in 2024. Clinical trial outcomes are used to set μ_{nj} . The duration is 72 hours instead of 7 days to reduce the extent of out-of-sample extrapolation since the demand model does not capture the convenience of weekly injections. <https://www.ema.europa.eu/en/medicines/human/EPAR/awiqli>

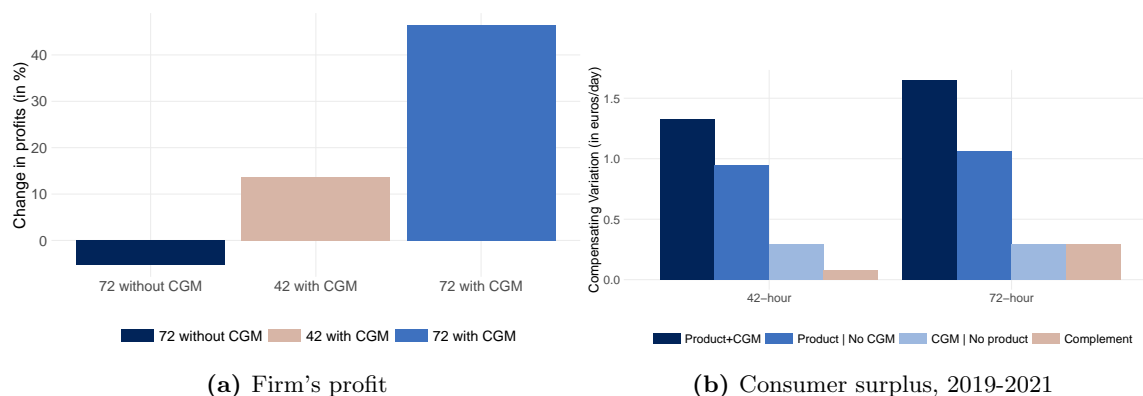
⁴³I compute the equilibrium prices with and without CGM and compare the firm’s profits.

alone does not drive R&D. The counterfactuals’ implications therefore rely on the external validity of my estimates for other geographical markets. On the demand side, CGMs generate new observable patient-specific attributes and limited spillovers to nonusers—patterns likely to extend beyond France. However, because the contribution of ν_{ij} varies across patients, the aggregate impact depends on its distribution and CGM adoption rates, so magnitudes may differ across settings.

On the supply side, the French regulator limits direct extrapolation to markets like the US, where manufacturers bargain with multiple insurers and disagreement payoffs shape prices. Still, insurers may also value drugs with higher match value. Yet, firms may set prices dynamically, internalizing demand responses across periods, and market power may have a stronger impact on drug prices.

Finally, CGM adoption is taken as given. Since social learning is limited and effects operate mainly through users’ demand, both the level and composition of adoption matter, though insurer coverage decisions for CGMs are beyond this paper’s scope.

Figure 12: Glucose sensors and product design



Notes: Figure 12a shows profit changes relative to the 42-hour product entering without CGMs. The first bar shows the 72-hour product without CGMs, the second the 42-hour product with CGMs, and the third the 72-hour product with CGMs. Figure 12b shows average consumer surplus (euros per day) using Equation (19): for each product, the first bar is surplus from joint entry with CGMs ($CV_j^{1,1}$), the second from the product alone ($CV_j^{1,0}$), the third from CGMs alone ($CV_j^{0,1}$), and the fourth is the differential gain, Γ_j .

7 Conclusion

This paper examines how digital medical devices affect pharmaceutical demand in the context of CGM insights for insulin choice. I develop a structural model of insulin demand and supply incorporating: (i) patient-specific learning via CGMs, (ii)

dynamic physician-level learning from patient experiences, and (iii) price setting by firms and the regulator, both accounting for demand-side learning. This framework can be applied to other settings where new measurement technologies reshape the information available for decision-making.

The results show that CGMs primarily influenced choices by revealing new drug attributes, altering perceived product differences, and firms' profits. The analysis emphasizes cross-market complementarities between medical devices and pharmaceuticals with implications for pharmaceutical innovation incentives: CGMs increased private appropriability and shifts the profitability of different innovation strategies, suggesting that digital technologies can influence the direction of pharmaceutical innovation.

Future research could extend these findings by: separating the preferences for the average glucose level and glucose profile from the attributes' value to better understand physician trade-offs; assessing CGM effects on diagnosis or new insulin users; incorporating regulatory approval constraints, which rely on predefined clinical endpoints and may limit incentives for products targeting CGM-observed attributes; and evaluating the full welfare impacts of CGMs, including which patients benefit most and optimal coverage strategies for digital technologies. Such insights could inform healthcare policy and the design of digital device interventions.

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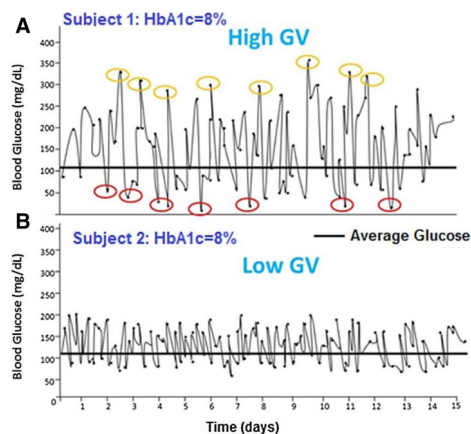
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Pharmaceuticals and Digital Health: Online Appendix

Léa Bignon*

A. Additional figures and tables

Figure A1: Glucose variability



Notes: Glucose traces for two patients with identical HbA1c (8.0%) but different glycemic variability. Source: [Chehregosha et al. \(2019\)](#), licensed under Creative Commons Attribution-NonCommercial 4.0 International License. No changes made.

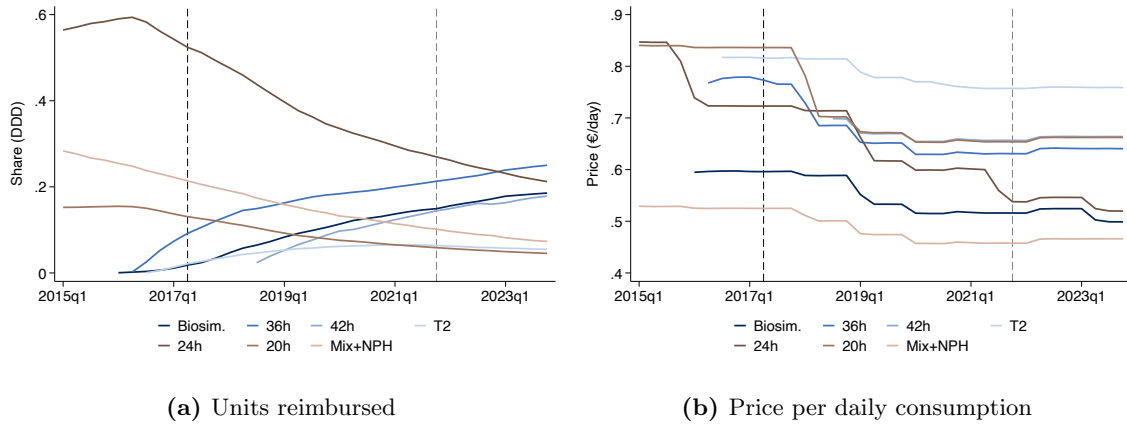
Figure A2: Continuous Glucose Monitoring



Notes: Illustration of glucose data sharing via LibreView. Source: [Abbott website](#) accessed on October 10th, 2024.

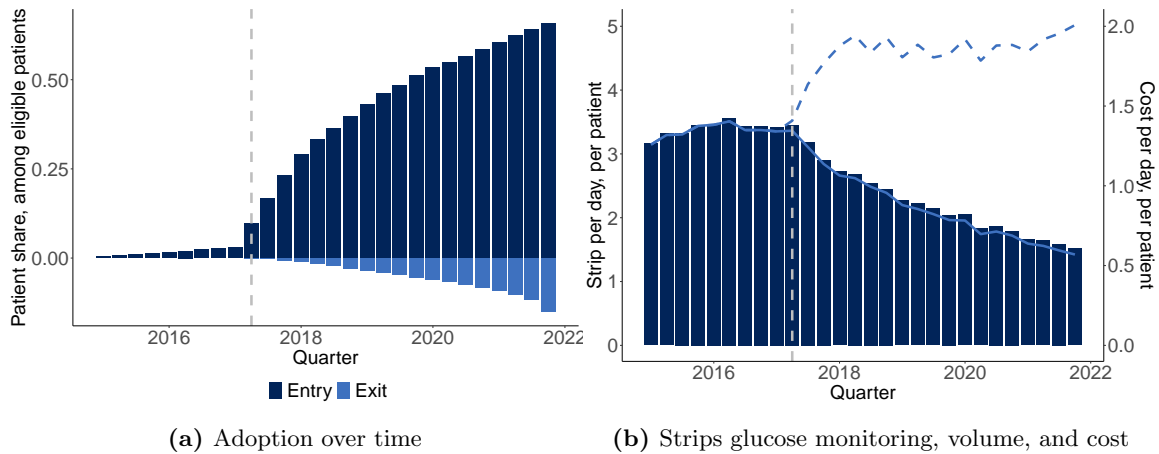
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Figure A3: Aggregate insulin sales and prices, 2015-2023



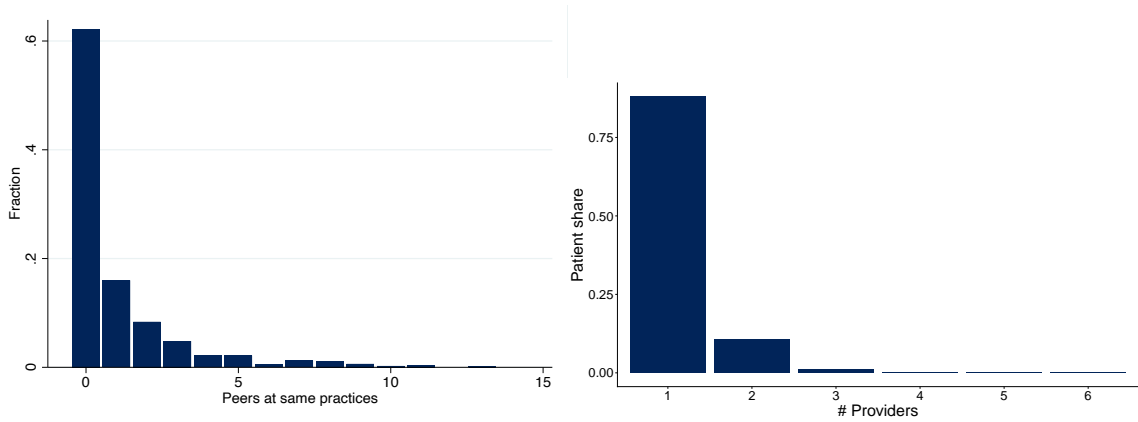
Notes: The first vertical line represents the start of CGM coverage (second quarter of 2017). The second line corresponds to the end of the period considered in the analysis (fourth quarter of 2021). Figure A3a plots the share for each product over time as a percentage of all insulin units reimbursed. Figure A3b 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 A4: Glucose sensor adoption among eligible patients, 2015-2021



Notes: In each figure, the vertical line represents the start of CGM coverage (second quarter of 2017). Figure A4a presents the stock of patients who ever adopted CGM and dropped out from continuous glucose monitoring over time among eligible patients. The adoption is inferred from the first CGM prescription date. For patients adopting before the coverage decision, the adoption date is identified from the decline in glucose strip reimbursements (Appendix B.3). The exit date corresponds to the expiration of the last sensor claimed at the pharmacy. Figure A4b represents, with bars, the average number of strips per patient among eligible individuals (left axis) and, with lines, 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 completely after adopting a CGM as they may need to confirm symptoms during adverse events.

Figure A5: Diabetes specialists outside of hospital practices in France

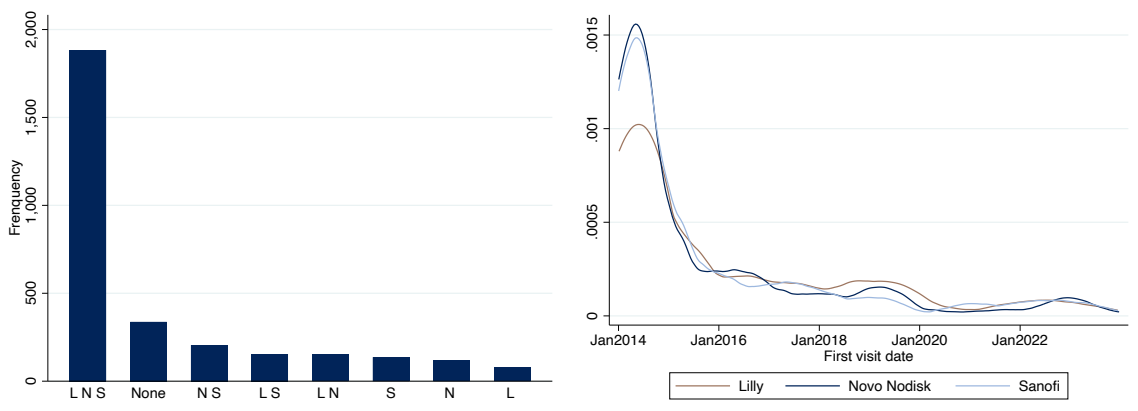


(a) Number of “peers”

(b) Number of practitioners by patient

Notes: Using data from the practitioners registry in France (available at <https://annuaire.sante.fr/web/site-pro/extractions-publiques>), Figure A5a represents the number of diabetes specialists working at the same practice for specialists working outside the hospital. 62% are working in an environment without any other diabetes specialist, 78% with at most one peer. Using the administrative claims data, Figure A5b plots the number of diabetes specialists working outside the hospital per patient.

Figure A6: Diabetes specialists detailing by insulin manufacturers, 2014-2023

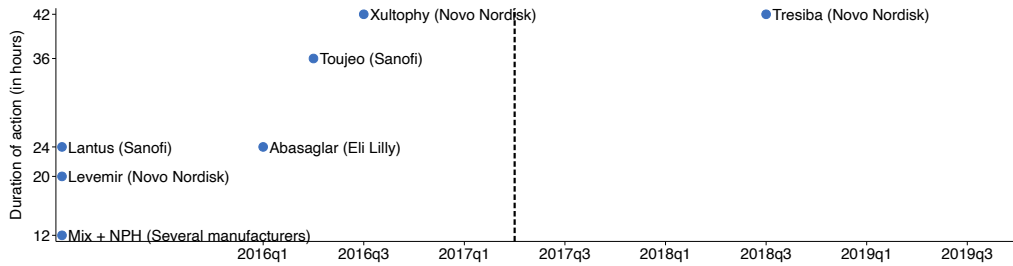


(a) By set of manufacturers

(b) First interaction by physician

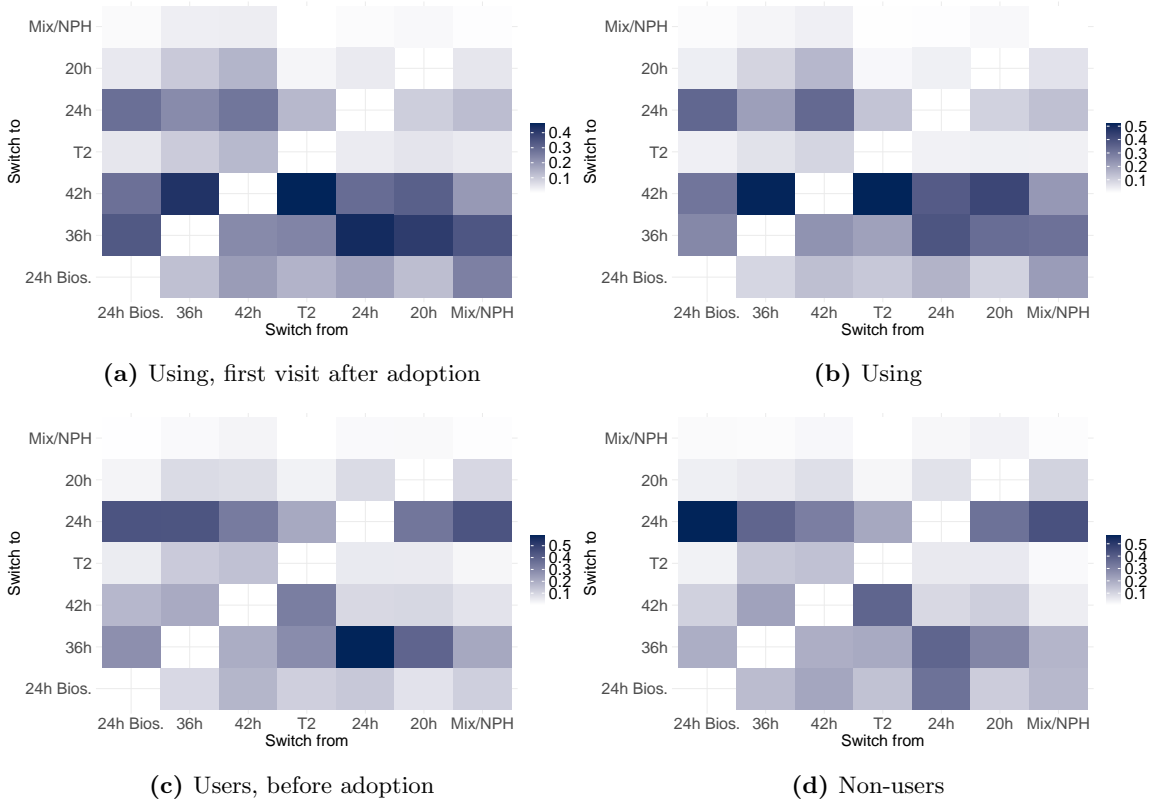
Notes: This figure provides descriptive evidence of pharmaceutical detailing by the three insulin manufacturers — Eli Lilly (L), Novo Nordisk (N) and Sanofi (S) — from 2014 to 2023. The data comes from the publicly available ‘Transparency in Healthcare’ database. Figure A6a plots the number of physicians interacting with each subset of manufacturers at least once over the period. Figure A6b plots the distribution of the first interaction between each physician-manufacturer pair.

Figure A7: New products entry timeline, 2016-2019



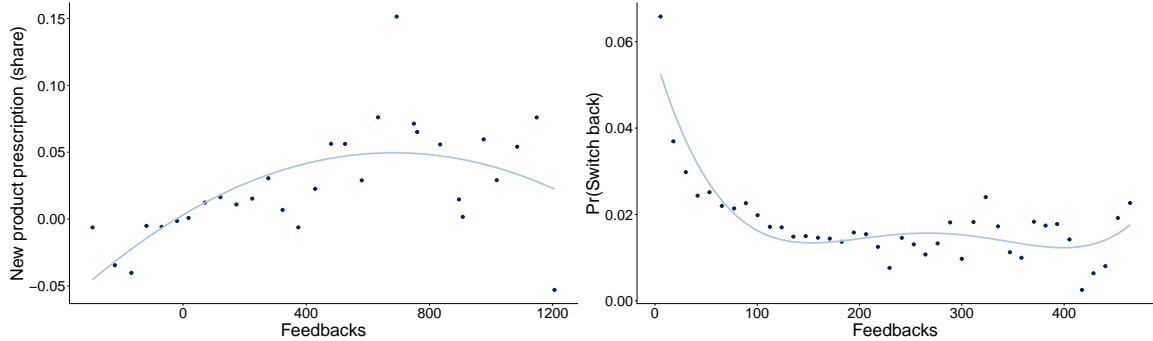
Notes: The vertical axis shows each insulin’s theoretical duration, and the horizontal axis shows product entry dates. Each dot represents a product (except the 12-hour drugs). The dashed line marks the first reimbursement of glucose sensors. Xultophy, targeted toward Type 2 diabetes, combines a long-acting insulin with another molecule, and its duration is determined by the insulin.

Figure A8: Switching matrices, by patient group



Notes: Focusing on treatment switches, each figure represents the probability of switching to a given product (vertical axis) conditional on the treatment used before switching (horizontal axis) such that each column sums to one. Figure A8a represents the switches that occurred the first appointment the patient is wearing a glucose sensor. Figure A8b represents the switches that occurred while the patient is wearing a glucose sensor. Figure A8c represents the switches for patients adopting a sensor, before they adopt. Figure A8d represents all switches that occurred to patients, eligible for glucose sensor coverage, who never adopted the technology. Insulin mixes, the 20-hour and 24-hour products are old products, entering the market before 2016. The remaining four products enter from 2016 onwards.

Figure A9: Physician-level learning and experimentation — Robustness

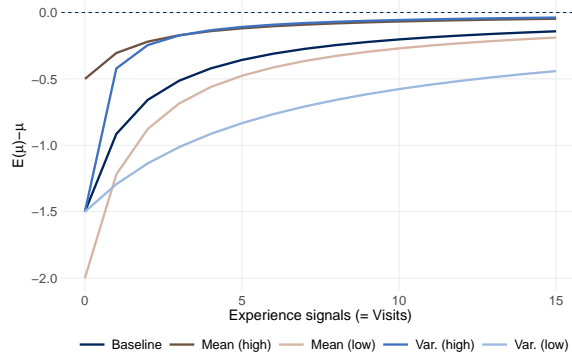


(a) Prescription share and information set size

(b) Switching back and information set size

Notes: Figure A9a presents a binscatter of product j 's prescription share among j -naive patients (vertical axis) against physician feedback from prior real-world experience (horizontal axis), residualized for physician fixed effects, product-quarter fixed effects, and average patient demographics. The sample includes diabetes specialists working outside the hospital. Figure A9b shows the probability of switching back to a previous treatment (vertical axis) versus cumulative product-level feedback, excluding the top 5% by information size (horizontal axis), focusing on treatment spells initiated with minimal product information (Feedback < 3).

Figure A10: Identification of beliefs



Notes: This figure shows how physicians' beliefs about μ_{nj} (vertical axis) evolve as they receive experience signals from returning patients using product j (horizontal axis). Each signal comes from one patient visit. Priors on μ_{nj} are normally distributed at $t = 0$, and pessimistic beliefs are updated via Bayes' rule using normally distributed signals. The figure illustrates belief updates over time for different prior means (brown) and prior variances (blue).

Table A1: Summary statistics, patient level

	(1)	(2)	(3)	(4)
	All	Type 1	Type 2	
			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
Dialysis	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

Notes: 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 by the national statistic institute (INSEE) based on 2015 measures of unemployment, blue-collar workers, high school graduates shares and the median income by consumption unit at the city level. 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.2 details the sample construction.

Table A2: Summary statistics, physician level

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Specialists	Hospital	GP	Care Center	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

Notes: Physician-level 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: Drivers of adoption

Variable	Df	AIC	Pseudo R^2
Model	1898	246,802.1995	0.1346
<i>Removing</i>			
- 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

Notes: The table presents pseudo- R^2 of logit models explaining CGM adoption with different sets of covariates 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 (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 A4: Preference for the drug’s effect on average glucose level, μ_{nj}

		20-hour	Mix	Human	36-hour	42-hour	Type 2
Type 1 / Male	Coef.	-1.52	-2.43	-4.46	0.33	0.16	
	s.e.	0.12	0.18	0.31	0.34	0.42	
Type 1 / Female	Coef.	-1.53	-3.27	-4.27	0.25	0.38	
	s.e.	0.13	0.19	0.34	0.36	0.40	
Type 2 / Male	Coef.	-1.51	-2.81	-4.63	0.34	0.23	-0.18
	s.e.	0.15	0.21	0.34	0.31	0.40	0.35
Type 2 / Female	Coef.	-1.34	-2.80	-4.09	0.61	0.24	-0.03
	s.e.	0.13	0.20	0.31	0.34	0.42	0.35
Type 2 (Long) / Female	Coef.	-1.00	-1.32	-3.37	0.69	0.75	0.30
	s.e.	0.09	0.19	0.34	0.43	0.49	0.35
Type 2 (Long) / Male	Coef.	-1.13	-1.49	-3.48	0.34	0.64	0.17
	s.e.	0.11	0.23	0.37	0.35	0.46	0.34

Notes: Standard errors are computed from the average of the score and clustered at the physician level. Type 1 and Type 2 refer to the patient’s type of diabetes. Type 1 patients must use both short-acting and long-acting insulins daily. Type 2 patients may depend on either short-acting and long-acting insulins (referred to as ‘short+long’) or long-acting insulin only (‘long’).

Table A5: Preference for the effect on the glucose profile, ν_{ij} — Detailed estimates

	Coef.	s.e.
A. d_j		
Constant	3.98	1.51
Age	-0.41	0.31
Age ²	-0.07	0.02
Cardiovascular	-1.73	1.02
Female	-0.31	0.63
Hypercholesterol	0.57	1.00
Hypertension	0.38	0.80
Obese	1.56	0.94
Type 1	-1.30	0.75
B. d_j^2		
Constant	-1.46	0.61
Age	0.26	0.12
Cardiovascular	0.69	0.40
Female	0.16	0.25
Hypercholesterol	-0.14	0.39
Hypertension	-0.10	0.32
Obese	-0.44	0.38
Type 1	0.65	0.30

Notes: Table A5 presents the estimates of the demand model for the preference for the effect on the glucose profile, ν_{ij} , as a function of patient demographics and health characteristics. $\nu_{ij} = \beta_1(x_i)d_j + \beta_2(x_i)d_j^2$ where d_j corresponds to product j theoretical duration of action and x_i is a vector of patient demographics and health characteristics. The standard errors are clustered at the physician level and computed from the average of the score. The model is estimated on a sample of 150 diabetes specialists working outside of the hospital. The parameters are jointly significant at the 1% level.

Table A6: Demand model estimates - Appendix

	(1)		(2)		(3)	
	Main		SC		CF	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
A. General						
Price (α)	0.58	(0.22)	2.22	(0.28)	0.58	(0.22)
Age (δ_1)	-0.56	(0.07)	-1.11	(0.06)	-0.56	(0.07)
Age ² (δ_2)	0.04	(0.00)	0.08	(0.00)	0.04	(0.01)
B. Priors						
24-hour biosimilar (Mean)	-6.10	(0.29)	-4.87	(0.33)	-6.17	(0.28)
36-hour (Mean)	-3.40	(0.35)	-1.77	(0.26)	-3.45	(0.32)
42-hour (Mean)	-3.70	(0.40)	-1.86	(0.29)	-3.83	(0.38)
Type 2 (Mean)	-4.27	(0.38)	-2.48	(0.26)	-4.37	(0.35)
24-hour biosimilar (sd)	2.67	(0.62)	2.91	(0.22)	2.49	(0.58)
36-hour (sd)	1.41	(0.40)	1.52	(0.14)	1.35	(0.37)
42-hour (sd)	2.10	(0.56)	1.70	(0.19)	2.23	(0.57)
Type 2 (sd)	2.17	(0.56)	2.52	(0.16)	2.23	(0.56)
C. Signals						
σ_{cst}	5.23	(1.65)	5.82	(0.56)	5.18	(1.59)
σ_{strips}	0.01	(0.05)	0.19	(0.13)	-0.03	(0.06)
σ_{A1c}	-0.04	(0.06)	-0.11	(0.11)	-0.04	(0.06)
σ_{cgm}	-0.46	(0.25)	-0.31	(0.49)	-0.53	(0.25)
δ_{SC}			6.05	(0.77)		
δ_{CF}					0.75	(0.36)

Notes: Standard errors clustered at the physician level and computed from the average of the score. The model is estimated on a sample of 150 diabetes specialists working outside of the hospital. The columns (Main), (SC) and (CF) report the estimates from the main model, the model with switching costs and the model with a control function, respectively. The model with switching cost uses the switching costs estimates from Table A15 in euros per day and includes it as a separate regressor for the past insulin choice — as $\delta_{SC}\alpha SC_{i,jv}$ where α is the price sensitivity. The control function model corrects for the potential endogeneity of CGM adoption, relying on CGM adoption rate in the physician’s geographical area, excluding the physician herself, see Section 3.2. The residuals from the first stage are included as a separate regressor interacted with insulin duration, d_j .

Table A7: Demand model estimates — μ_{nj} — Switching Costs

		20-h	Mix	Human	36-h	42-h	Type 2
Type 1 / Male	Coef.	-0.19	-1.86	-4.36	-0.28	-0.01	
	s.e.	0.10	0.28	0.34	0.29	0.34	
Type 1 / Female	Coef.	-0.19	-2.54	-4.16	-0.28	0.19	
	s.e.	0.13	0.33	0.35	0.32	0.29	
Type 2 / Male	Coef.	-0.22	-2.20	-4.52	-0.33	-0.18	-0.36
	s.e.	0.15	0.28	0.37	0.31	0.40	0.30
Type 2 / Female	Coef.	-0.34	-2.38	-4.17	-0.03	-0.02	-0.20
	s.e.	0.11	0.27	0.33	0.30	0.43	0.28
Type 2 (Long) / Female	Coef.	-0.27	-0.81	-3.58	0.28	0.57	-0.04
	s.e.	0.09	0.32	0.36	0.40	0.50	0.25
Type 2 (Long) / Male	Coef.	-0.32	-0.77	-3.57	-0.06	0.43	-0.24
	s.e.	0.11	0.45	0.39	0.32	0.53	0.25

Notes: Standard errors are computed from the average of the score and clustered at the physician level. Type 1 and Type 2 refer to the patient’s type of diabetes. Type 1 patients must use both short-acting and long-acting insulins daily. Type 2 patients may depend on either short-acting and long-acting insulins (referred to as ‘short+long’) or long-acting insulin only (‘long’).

Table A8: Demand model estimates — μ_{nj} — Control Function

		20-h	Mix	Human	36-h	42-h	Type 2
Type 1 / Male	Coef.	-1.55	-2.47	-4.42	0.42	0.14	
	s.e.	0.12	0.17	0.31	0.33	0.38	
Type 1 / Female	Coef.	-1.59	-3.47	-4.31	0.33	0.35	
	s.e.	0.13	0.18	0.34	0.35	0.37	
Type 2 / Male	Coef.	-1.54	-2.86	-4.67	0.40	0.22	-0.12
	s.e.	0.15	0.20	0.34	0.30	0.38	0.34
Type 2 / Female	Coef.	-1.39	-2.86	-4.10	0.72	0.23	-0.01
	s.e.	0.13	0.19	0.31	0.33	0.39	0.34
Type 2 (Long) / Female	Coef.	-1.01	-1.26	-3.22	0.88	0.78	0.29
	s.e.	0.09	0.19	0.36	0.42	0.45	0.32
Type 2 (Long) / Male	Coef.	-1.19	-1.36	-3.33	0.42	0.68	0.19
	s.e.	0.11	0.23	0.38	0.34	0.42	0.30

Notes: Standard errors are computed from the average of the score and clustered at the physician level. Type 1 and Type 2 refer to the patient’s type of diabetes. Type 1 patients must use both short-acting and long-acting insulins daily. Type 2 patients may depend on either short-acting and long-acting insulins (referred to as ‘short+long’) or long-acting insulin only (‘long’).

Table A9: Preference for the effect on the glucose profile, ν_{ij} — Detailed estimates

	(1)		(2)		(3)	
	Main		SC		CF	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
A. d_j						
Constant	3.98	1.51	3.81	2.12	3.85	1.57
Age	-0.41	0.31	-0.75	0.39	-0.57	0.32
Age ²	-0.07	0.02	-0.06	0.02	-0.08	0.02
Cardiovascular	-1.73	1.02	-1.75	1.51	-1.72	1.02
Female	-0.31	0.63	-0.36	0.92	-0.35	0.63
Hypercholesterol	0.57	1.00	0.54	1.21	0.53	1.00
Hypertension	0.38	0.80	0.35	0.91	0.35	0.80
Obese	1.56	0.94	1.55	1.18	1.53	0.93
Type 1	-1.30	0.75	-1.46	1.08	-1.29	0.75
B. d_j^2						
Constant	-1.46	0.61	-1.46	0.81	-1.65	0.61
Age	0.26	0.12	0.35	0.15	0.34	0.12
Cardiovascular	0.69	0.40	0.75	0.57	0.67	0.40
Female	0.16	0.25	0.10	0.35	0.15	0.25
Hypercholesterol	-0.14	0.39	-0.09	0.45	-0.13	0.39
Hypertension	-0.10	0.32	-0.03	0.35	-0.11	0.32
Obese	-0.44	0.38	-0.42	0.45	-0.44	0.38
Type 1	0.65	0.30	0.64	0.41	0.64	0.30

Notes: Table A9 presents the estimates of the demand model for the preference for the effect on the glucose profile, ν_{ij} , as a function of patient demographics and health characteristics. $\nu_{ij} = \beta_1(x_i)d_j + \beta_2(x_i)d_j^2$ where d_j corresponds to product j theoretical duration of action and x_i is a vector of patient demographics and health characteristics. The standard errors are clustered at the physician level and computed from the average of the score. The model is estimated on a sample of 150 diabetes specialists working outside of the hospital. Column (1) corresponds to the main specification presented in the paper. Column (2) accounts for switching costs. Column (3) corrects for the endogeneity of CGM adoption using a Control Function.

Table A10: Observed vs predicted product shares by patient group

Product	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5		Cluster 6	
	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.
24-hour (branded)	0.46	0.45	0.47	0.47	0.43	0.41	0.42	0.41	0.37	0.38	0.39	0.38
20-hour	0.10	0.10	0.10	0.10	0.09	0.09	0.11	0.11	0.14	0.14	0.13	0.13
Mix	0.05	0.05	0.02	0.02	0.03	0.03	0.03	0.03	0.13	0.13	0.12	0.11
Human	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.03	0.03
24-hour (biosimilar)	0.02	0.04	0.02	0.03	0.03	0.04	0.04	0.03	0.02	0.02	0.02	0.04
36-hour	0.24	0.23	0.24	0.23	0.24	0.22	0.22	0.21	0.13	0.15	0.14	0.16
42-hour	0.12	0.12	0.13	0.14	0.09	0.09	0.09	0.09	0.06	0.05	0.06	0.06
Type 2		0.00		0.00	0.07	0.11	0.08	0.11	0.12	0.09	0.11	0.10

Notes: Table A10 compares the observed and predicted product shares by patient cluster. The predicted shares are computed using the demand model estimates from Section 5.1.4 and the observed patient characteristics.

Table A11: Observed vs predicted product shares with/without CGM

Product	(1)		(2)	
	No CGM		CGM	
	Obs.	Pred.	Obs.	Pred.
24-hour (branded)	0.47	0.46	0.25	0.27
20-hour	0.13	0.13	0.07	0.05
Mix	0.08	0.08	0.02	0.02
Human	0.02	0.02	0.01	0.01
24-hour (biosimilar)	0.02	0.03	0.04	0.05
36-hour	0.15	0.16	0.34	0.31
42-hour	0.05	0.05	0.22	0.20
Type 2	0.07	0.07	0.05	0.08

Notes: Table A11 compares the observed and predicted product shares by CGM adoption status. The predicted shares are computed using the demand model estimates from Section 5.1.4 and the observed patient characteristics.

Table A12: Toward product design: product features

	Supply	Duration	Priors			μ_{nj}				
	mc_j		μ_{0j}	$(V_j^0)^{1/2}$	μ_{1j}	μ_{2j}	μ_{3j}	μ_{4j}	μ_{5j}	μ_{6j}
42-hour (Obs)	mc_{42}	1.75	-3.70	2.17	0.158	0.382	0.233	0.243	0.748	0.637
72-hour	$1.15 \times mc_{42}$	3	-3.80	2.14	$0.5\mu_{n,42}$		0.25		$1.1\mu_{n,42}$	

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

B. Data construction

B.1. Data coverage

I rely on exhaustive micro-level data for France from the *Système National des Données de Santé (SNDS)* covering all claims for the past 19 years. The data is exhaustive for the population, 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 approved the coverage. The mandatory health insurance system fully covers patients with diabetes for their expenditures as part of the Long-term care disease program.² For each claim, the data includes the patient and prescriber IDs, the product ID, the date of care prescription, date of treatment/service/procedure. The data also includes information about the patient’s demographics and comorbidities, as well as the prescriber’s specialty and practice location. Dates are available at the daily level, and the prescription date allows for separating doctor’s visits from pharmacy refills.

B.2. Sample selection

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.³ The prescriber ID corresponds to the hospital ID for physicians working at the hospital. Among patients, I focus on patients 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 1, 2016, and the last prescription was written after January 1, 2016; (ii) The time between the first and last prescription for a patient was at least 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 1, 2016;⁴

²The drug price still influences provider decisions via financial incentives and guidelines.

³I 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.

⁴The data also include insulin pump use, discussed in Appendix C.1. When a patient starts a pump, I exclude long-acting insulin prescriptions written during pump use.

(v) The patient was an adult, 74 or younger, in 2015. Among physicians, I consider (i) Diabetes specialists working in or out of the hospital; (ii) Prescribers with a first prescription to any patient before January 2016; (iii) 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 [A13](#) compares patients’ characteristics across samples. 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 intended treatment choice for new insulin patients is used to estimate switching costs separately from learning (Appendix [C.3](#)). (ii) The structural model is estimated on a random sample of 150 diabetes specialists working outside the hospital.

B.3. Risk of mis-measurement in CGM adoption

This section examines potential mismeasurement of CGM adoption in claims data for both insured and non-insured patients. For eligible individuals, sensors bought directly from manufacturers are not reimbursed; coverage is provided only with a prescription, limiting incentives to acquire devices outside claims data. Because reimbursement began 2.5 years after EU market entry, adoption dates may be left-censored; however, this concern is mitigated by low pre-coverage sales (about 40k sensors in 2015 per the HTA evaluation) and the gradual uptake observed in the data, with only a small share of first reimbursements occurring shortly after coverage (Figure [A4a](#)). The next paragraph describes how I recover adoption dates for early adopters. While discontinuation is a concern in wearable studies ([Patel et al. \(2015\)](#)), CGM’s reliance on 14-day disposable sensors allows discontinuation to be detected via non-renewal of prescriptions, though such cases are rare (Figure [A4](#)).

Among eligible patients, the timing of adoption matters as it determines the information available to physicians when prescribing insulin. Patients whose first CGM prescription occurs within seven months of the coverage decision may have adopted earlier out-of-pocket, so the first reimbursement in claims data may not reflect the true adoption date. To recover adoption timing for these “early users”, I exploit the substitutability between CGM and glucose test strips, whose consumption declines after CGM adoption (Figure [A11a](#)). I split CGM users into (i) “uncensored” patients whose first reimbursement occurs from 2018 onward and (ii) “censored” patients whose first reimbursement occurs before January 2018. I estimate the relationship

Table A13: Patient selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All, incl:	Final Sample	Infrequent	New Patients	No diabetes specialist	Old Age ≥ 75	Pump	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
Dialysis	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

Notes: The Deprivation index is computed by the national statistic institute (INSEE) based on 2015 measures of unemployment, blue-collar workers, high school graduates shares and the median income by consumption unit at the city level. 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.

between strip consumption and CGM adoption in the uncensored sample and use it to infer adoption timing in the censored sample. Specifically, I estimate

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

where $strips_{iq}$ is the average number of strips reimbursed per day in quarter q , and X_i includes diabetes type, gender and age. I then predict adoption in the censored sample and classify observations using Youden’s index. Table A14 reports Type I and Type II error rates of 17.6% and 24.6%, respectively. I assign adoption to quarter q when adoption is predicted for three consecutive quarters. The inferred adoption date differs from the first reimbursement date for about 18% of early users (7k patients).

Among patients treated with long-acting insulin, 32% are ineligible for CGM coverage (Table A1). Measurement error in adoption could arise if these patients purchase the device out-of-pocket. However, Guerci et al. (2023) note that patients outside the eligibility criteria could access the technology since no prior authorization was required. To assess potential off-claims adoption, I use reimbursements for glucose test strips, the alternative monitoring technology. Because strips and CGM are substitutes, strip consumption should decline if patients adopt CGM outside the insurance system. Figure A11 compares strip reimbursements for CGM users and nonusers over time. Figure A11a shows that strip consumption falls by about 2.5 strips per day after CGM adoption.⁵ By contrast, strip use among nonusers remains relatively stable across quarters, suggesting that off-claims CGM adoption is uncommon.

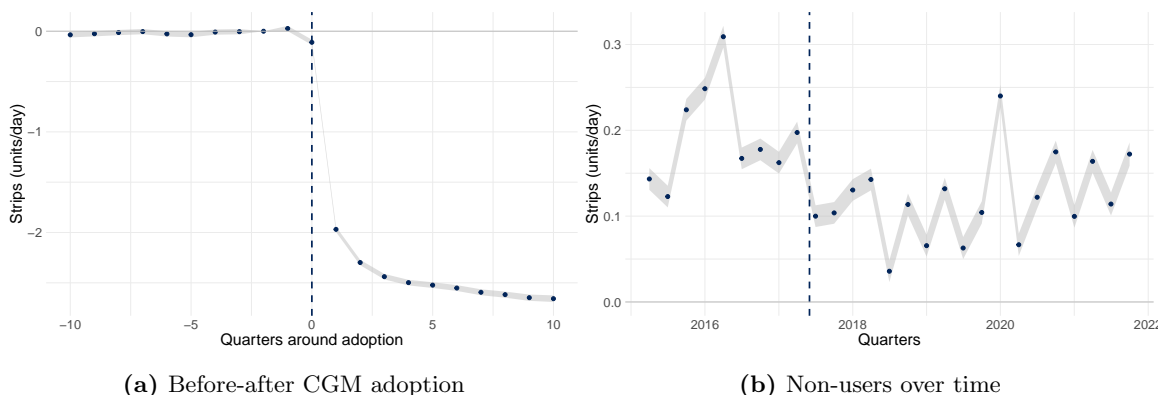
Table A14: Predicted vs observed CGM adoption

		Observed	
		No	Yes
Predicted	No	0.8243	0.2463
	Yes	0.1757	0.7537

Notes: This table 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. The details are presented in Appendix B.3. Youden’s index is used as a threshold to classify observations. The risks of Type I and Type II errors are respectively 17.6% and 24.6%.

⁵Patients continue to use strips occasionally after adoption, for example, following adverse events.

Figure A11: Glucose strips reimbursements



Notes: Figure A11a presents the estimates from an event study model that considers the number of strips reimbursed in the quarters before and after the adoption of a glucose sensor, where the adoption date is identified from a patient’s first prescription. The regression includes patient fixed effects and focuses on patients with their first CGM prescription from January 2018 onwards. Figure A11b plots the coefficients of a linear regression of strip reimbursements over time for patients who never use a glucose sensor between 2015 and 2021.

C. Further descriptive evidence

C.1. Substitution toward insulin pump

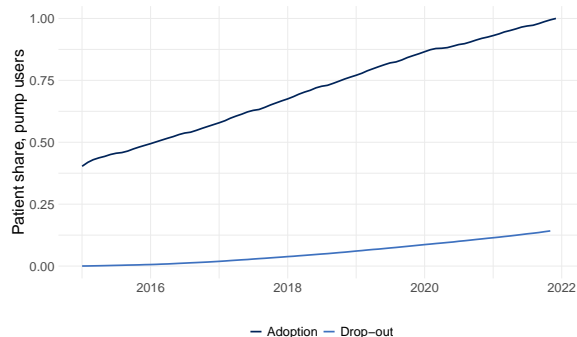
Patients can use an insulin pump — relying on continuous injection of short-acting insulin — instead of the short-acting and long-acting treatment scheme. While patients using a pump are largely using glucose sensors (Table A13), I do not include the insulin pumps in the physician’s choice set in the main specification. This choice is motivated by two facts. First, the coverage for insulin pumps remains restricted in France. Second, while patients are increasingly relying on a pump system, there is no change in the pattern of pump adoption after the coverage of CGM (Figure A12), and the total number of patients remains limited (70k).⁶

C.2. Detailing as an alternative source of learning

Pharmaceutical detailing represents an alternative source of learning about new products for patients and physicians (Grennan et al. (2024)). While direct-to-consumer advertising is forbidden for prescription drugs in France, detailing to physicians is

⁶There 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, and hence does not represent the share of pump users in the overall patient population.

Figure A12: Insulin pump use among diabetic patients, 2015-2021



Notes: For each patient with an insulin pump insurance claim between 2015 and 2021, I consider the first and last claims for an insulin pump. The figure plots the cumulative distribution function of the first and last reimbursement dates among patients who use an insulin pump. There is no discontinuity in adoption or dropout after the CGM coverage decision.

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 involved insulins depends on the pharmaceutical companies’ portfolio and the physician’s medical specialty. Yet, detailing to diabetes specialists is likely to mention new insulins. Second, I cannot link the claims data to external sources, including the *Transparence Santé* registry. Figure A6 provides summary statistics about insulin manufacturers’ detailing behavior toward diabetes specialists.

C.3. Switching cost estimation

To test whether switching costs differ across glucose monitoring systems, I estimate a reduced-form model comparing prescription shares for new and incumbent patients. While incumbent demand reflects both switching costs and post-entry learning, new patients — who have no prior experience with long-acting insulin — are affected only by learning. To limit heterogeneity in treatment needs, I compare choices between two bioequivalent products: the 24-hour branded product and its biosimilar (hereafter ‘generic’) entering in 2016.

I analyze prescriptions written by medical specialty m across three patient groups $I \in \{N, E^A, E^{\bar{A}}\}$: new patients N , existing patients adopting CGM, E^A , and existing patients not adopting CGM, $E^{\bar{A}}$. Let s_{jq}^{mI} denote the prescription share of product j ,

either Branded (B) or Generic (G), in period q . I estimate

$$\log(s_{Gq}^{mI}) - \log(s_{Bq}^{mI}) = \Delta\delta_q^m + \alpha\Delta p_q^m + c_1\mathbf{1}(I \in \{E^{\bar{A}}, E^A\}) + (c_2 + c_3CGMv_q^m)\mathbf{1}(I = E^A) + \Delta\xi_q \quad (2)$$

The dependent variable approximates the difference in mean utility between the Generic and Branded versions. $\Delta\delta_q^m$ is a time trend, capturing information frictions that affect all patient groups, and Δp_q^m is the price difference. $CGMv_q^m$ denotes the share of prescriptions for CGM users. The parameters c_1 , c_2 , and c_3 capture switching costs for incumbent patients. OLS estimates (Table A15) indicate positive switching costs ($\hat{c}_1 < 0$), but no heterogeneity across glucose measurement systems, as \hat{c}_2 and \hat{c}_3 are not statistically significant. The implied willingness to pay to remain on the branded version is approximately €9.47 per month.

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

This paragraph examines whether glucose sensors influence the quality of patient feedback that physicians use to evaluate new drug performance across patients, through the correlation between treatment switches and information set size. For each physician k and quarter q , 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 $q - 1$ where the patient was already using 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 q , Y_{kq} , is documented using a Poisson model:

$$E(Y_{kq}|X) = \exp\left(\alpha + \lambda_1\mathbf{1}(F_{kq} > 0) + f(F_{kq}) + \gamma X_k + \delta_q\right) \quad (3)$$

where $\mathbf{1}(F_{kq} > 0)$ captures the extensive margin and f is a quadratic function of F_{kq} , considering all feedbacks (F_{kq}) and those from patients wearing a sensor (F_{kq}^{CGM}). The model is estimated from physician-quarter combinations with more than 11 visits. The results, presented in Table A16, suggest that going from 10 experience feedbacks to 20 increases the occurrence of switches to the 42-hour product by 16.2%. The number of feedback provided through the sensor seems to dampen the spillover which could be driven by patient heterogeneity: feedbacks from CGM users are less informative for non-CGM users than traditional experience because patients are less

similar in terms of observable and unobservable characteristics. To test this hypothesis, I estimate the same model separately for eligible patients (more similar to CGM users) and non-eligible patients (less similar to CGM users) in specifications B and C. The results suggest that the spillover effect is not significantly different for eligible patients, while it is significantly weaker for non-eligible patients when the feedback comes from a CGM user. However, the absence of correlation between F_{kq}^{CGM} and switching for eligible patients suggests that CGMs may not provide more meaningful feedback for other patients.

Table A15: 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	

Notes: Robust standard errors. The table presents the estimates of the model presented in Appendix C.3. 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 A16: 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	
\bar{Y}	0.932		0.428		0.517	
\bar{F}	3.709		3.728		3.723	
\bar{F}_{CGM}	2.288		2.292		2.292	

Notes: The table presents the estimates from the analysis presented in Appendix C.4. 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.

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 and the objective of the regulator bargaining with firm f is to maximize the ex-ante expected consumer surplus (see Equations 10 and 11), which, assuming that ε_{ikjv} follows an i.i.d. Type I EV distribution, gives:

$$\Delta_{ft}CS(\mathbf{p}_t) = \frac{1}{\alpha} \sum_{\forall i,k;\forall v \in t} \ln \left(\sum_{\forall j \in \mathcal{J}_v} \exp(u_{ikjv}(\mathcal{I}_{kv})) \right) - \frac{1}{\alpha} \sum_{\forall i,k;\forall v \in t} \ln \left(\sum_{\forall j' \in \mathcal{J}_v \setminus \mathcal{J}_{ft}} \exp(u_{ikj'v}(\mathcal{I}_{kv})) \right) \quad (4)$$

where $u_{ikjv}(\mathcal{I}_{kv}) = \mathbb{E}(\Theta_{ij} | \mathcal{I}_{kv}; a_{iv}) - \alpha p_{jt} + f(\text{age}_{jv})$ and α corresponds to the price sensitivity of demand. The equilibrium prices maximize the Nash product. Considering the case where the firm bargain over two products, indexed by j and j' , the first order condition with respect to the price of product j , p_{jt} , is given by:

$$b_{ft} \frac{\partial \pi_{ft}(\mathbf{p}_t) / \partial p_{jt}}{\pi_{ft}(\mathbf{p}_t)} + (1 - b_{ft}) \frac{\partial \Delta_{ft}CS(\mathbf{p}_t) / \partial p_{jt}}{\Delta_{ft}CS(\mathbf{p}_t)} = 0 \quad (5)$$

where

$$\begin{aligned} \frac{\partial \pi_{ft}(\mathbf{p}_t)}{\partial p_{jt}} &= q_{jt}(\mathbf{p}_t) + (p_{jt} - c_{jt}) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + (p_{j't} - c_{j't}) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} \\ \frac{\partial \Delta_{ft}CS(\mathbf{p}_t) / \partial p_{jt}}{\Delta_{ft}CS(\mathbf{p}_t)} &= \frac{(1/\alpha) \frac{\partial}{\partial p_{jt}} \sum_{\forall i,k;\forall v \in t} \ln \sum_j \exp(u_{ikjv}(\mathcal{I}_{kv}))}{\Delta_{ft}CS(\mathbf{p}_t)} = \frac{\frac{\partial}{\partial p_{jt}} \sum_{\forall i,k;\forall v \in t} \ln \sum_j \exp(u_{ikjv}(\mathcal{I}_{kv}))}{\Delta_{ft}\widetilde{CS}(\mathbf{p}_t)} \end{aligned}$$

with $\Delta_{ft}\widetilde{CS}(\mathbf{p}_t) = \alpha \Delta_{ft}CS(\mathbf{p}_t)$. Denoting $h_{jt} = \frac{\partial \Delta_{ft}CS(\mathbf{p}_t) / \partial p_{jt}}{\Delta_{ft}CS(\mathbf{p}_t)}$ and $\beta_{ft} = \frac{1 - b_{ft}}{b_{ft}}$, combining the FOCs with respect to j and j' gives

$$\begin{aligned} (p_{jt} - c_{jt}) \left[\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft} h_{jt} \left(q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} \right) \right] - \\ \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft} h_{j't} \left(q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} \right) \Big] = \quad (6) \\ - \left(q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} \right) \end{aligned}$$

such that

$$c_{jt} = p_{jt} + \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t) / \partial p_{jt}}{q_{jt}(\mathbf{p}_t)} + \left(\beta_{ft} h_{j't} + \frac{\partial q_{j't}(\mathbf{p}_t) / \partial p_{jt}}{q_{jt}(\mathbf{p}_t)} \right) \frac{\left(q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} \right)}{\left(q_{jt}(\mathbf{p}_t) \frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t) \frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} \right)} \right]^{-1} \quad (7)$$

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

$$c_{jt} = p_{jt} + \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t) / \partial p_{jt}}{q_{jt}(\mathbf{p}_t)} \right]^{-1} \quad (8)$$

$q_{jt}(\mathbf{p}_t)$, $\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}}$, $\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}$, and h_{jt} are identified from the demand estimation. The remaining unobservable are marginal costs, c_{jt} , and bargaining weights, b_{ft} .

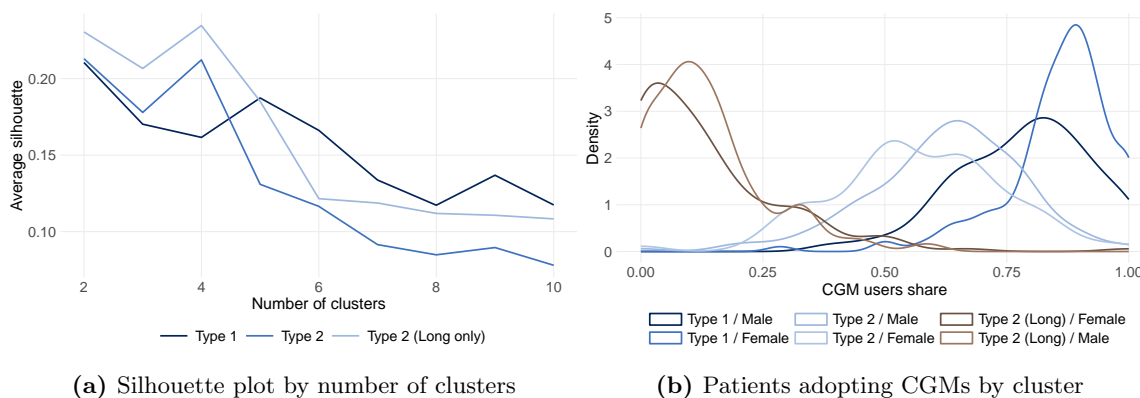
E. Estimation details: Patient clustering

The classification of patients into N groups is performed in two steps. First, I categorize patients into three groups based on their diabetes type and insulin therapy. I distinguish between ‘Type 1 diabetic patients’, ‘Type 2 diabetic patients using both long and short-acting insulins’, and ‘Type 2 diabetic patients using only long-acting insulin’. Second, for each patient, I construct a vector of individual characteristics as of 2015/2016 including demographics — the patient age, gender, whether he benefits from the low income complementary insurance —, indicator of diabetes management — years with diabetes, average number of glucose strips reimbursed per day, number of A1c tests, claims for dialysis care, hospitalization for diabetes, and diabetes-related complications —, indicators of other conditions — respiratory diseases, antalgics, cancer, cardiovascular disease, hypertension, hypercholesterolemia, obesity, depression, anxiolytics, hypnotics, neuroleptics —, and ER visits. In the clustering procedure, each variable has the same weight except for age which has a weight of 2 and discrete variables with an entropy score below 0.15 which have a weight of 0.5.⁷ The number of clusters within each group is chosen using average silhouette width, which measures the similarity of patients within a cluster relative to patients in other clusters. The number of clusters is chosen to maximize the average silhouette width across clusters and, the lowest number of clusters is kept in case of similar silhouette, resulting in a total of six clusters (Figure A13a). Table A17 presents the average patient char-

⁷Low income complementary insurance, respiratory disease, cancer, antidepressants, anxiolytics, hypnotics, neuroleptics, dialysis, ketoacidosis, indicator for ER visits and ER visits related to diabetes.

acteristics per cluster. Figure A13b shows the distribution of the share of patients adopting CGMs at a practice by cluster.

Figure A13: k-means clustering



Notes: Figure A13a plots the average silhouette width (vertical axis) by number of clusters (horizontal axis) for each subgroup of patients. The number of clusters is set to 2 for each subgroup based on the maximum silhouette width — considering the smallest number of clusters in case of a small difference. Figure A13b plots the share of patients adopting CGMs in each cluster within a practice.

F. Counterfactual scenarios: sensor reallocation

The counterfactual in Section 6.2 suggests that information spillovers from CGM users to nonusers are limited. Table A3 suggests that adoption is heterogeneous across physicians, such that the lack of spillovers could be driven by little variation in CGM adoption at the physician level. In the extreme case where all patients within a cluster-practice are either adopting or not, nonusers cannot benefit from the information generated by CGM users. To analyze whether this drives the lack of spillovers, I compute the equilibrium shares and the consumer surplus generated by glucose sensors under an alternative allocation of CGM, which eliminates differences across physicians. To that end, I predict patient device adoption in my sample of physicians using a model similar to the one presented in Table A3. I compute the predicted probability of adoption, net of the physician fixed effect for each patient, \hat{p}_i . I randomly select patients to adopt the technology using \hat{p}_i , fixing the number of users to the number observed in the data, and allocate adoption dates randomly. The compensating variation in consumer welfare is presented in Figure A14.

Table A17: Patient demographics by cluster

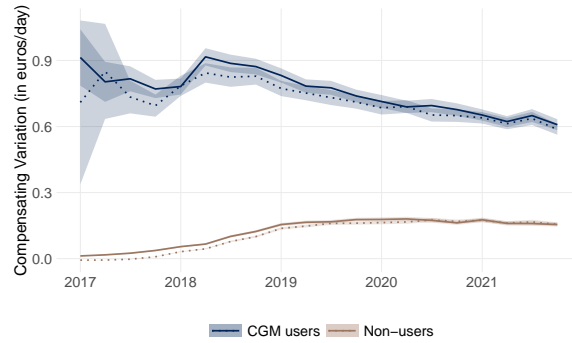
	(1)	(2)	(3)	(4)	(5)	(6)
	Type 1		Type 2		Type 2 (Long)	
	Male	Female	Male	Female	Female	Male
A. Demographics						
Type 1	1.000	1.000	0.000	0.000	0.000	0.000
Short + Long acting	0.983	0.989	1.000	1.000	0.000	0.000
Age	55.918	37.591	60.363	58.613	60.823	61.376
Years with diabetes	13.937	9.224	10.982	11.084	10.013	9.387
Female	0.239	0.628	0.000	1.000	1.000	0.000
Low Income insurance	0.089	0.104	0.075	0.126	0.111	0.068
B. Chronic conditions						
Respiratory disease	0.116	0.044	0.142	0.152	0.136	0.108
Antalgics	0.321	0.107	0.334	0.475	0.475	0.297
Cancer	0.084	0.024	0.110	0.099	0.091	0.094
Cardovascular	0.268	0.024	0.383	0.225	0.194	0.330
Hypertension	0.611	0.116	0.764	0.708	0.752	0.763
Hypercholesterolemia	0.608	0.090	0.722	0.621	0.669	0.744
Obesite	0.189	0.046	0.279	0.384	0.308	0.215
Antidepressant	0.172	0.066	0.136	0.225	0.190	0.104
Anxiolytics	0.172	0.059	0.133	0.211	0.191	0.104
Hypnotics	0.083	0.017	0.097	0.124	0.114	0.066
Neuroleptics	0.037	0.017	0.035	0.044	0.037	0.029
Dialysis	0.010	0.002	0.012	0.008	0.002	0.003
C. Diabetes management and complications						
Complications	0.016	0.064	0.007	0.011	0.005	0.004
Ketoacidosis	0.010	0.056	0.005	0.008	0.005	0.003
ER unit	0.171	0.158	0.224	0.194	0.135	0.158
ER diabetes	0.065	0.089	0.074	0.054	0.034	0.052
ER visit	0.259	0.385	0.279	0.324	0.283	0.244
ER visits (NB)	0.439	0.705	0.444	0.581	0.464	0.370
Glucose strips (daily av.)	3.857	4.056	2.728	3.255	2.388	1.777
A1c labs	2.823	2.537	3.218	3.450	3.552	3.238

Notes: Table A17 presents the descriptives of the six patient clusters. The clusters are defined based on the patient’s type of diabetes (Type 1, Type 2, or Type 2 with long-acting insulin only) and a k-means clustering of patients based on demographics and health characteristics within each subgroup. The table is organized in three panels of variables used to build the clusters: A. Demographics, B. Chronic conditions, and C. Diabetes management and complications.

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Figure A14: Consumer surplus after sensor reallocation across physicians



Notes: The figure presents the compensating variation (vertical axis), in euros per day, following a prescription happening in period t (horizontal axis). The figure focuses on patients eligible for CGM insurance coverage. 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. The dotted lines represent welfare after reallocating sensors among patients, eliminating differences in sensor adoption at the physician level.

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