Pharmaceuticals and Digital Health: How Data-driven Insights May Reshape 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 comprehensive medical claims data from France, I find that CGMs' patient-specific information steered insulin demand toward newer products, with limited information spillover to nonusers. Manufacturers of drugs that benefited from higher perceived quality could negotiate higher prices. My findings indicate that the introduction of these newly *observable* product attributes into pharmaceutical demand shifts the relative profitability of drug innovation strategies, thereby shaping the direction of future pharmaceutical innovation.

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.[1] 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 may conceal critical variations in glucose control (Figure A1). Key questions arise: How do CGMs' insights influence insulin choices for technology users? To what extent do these insights guide physicians' prescriptions for other patients? What are the implications for pharmaceutical price negotiations between manufacturers and regulators? Finally, how do CGMs impact incentives for pharmaceutical innovation?

To address these questions, I leverage comprehensive medical claims data from the French health insurance system, which provides a unique setup to assess the impacts of CGMs. This dataset is particularly valuable due to France's universal, centralized insurance system, which provides comprehensive records of 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.[2] I use claims data to estimate a tractable demand and pricing model for insulin 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 set higher prices, ultimately impacting the profitability of the pharmaceutical innovation strategies.

This paper sheds light on how digital health technologies shape pharmaceutical markets,

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

[2]The adoption date for patients paying for CGMs out-of-pocket before the coverage decision can be inferred from claims for alternative glucose measurement technologies. The current technology relies on disposable sensors that must be replaced every 14 days.

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 dampens 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 the direction of future pharmaceutical innovations. 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.

In a descriptive analysis, I provide three empirical facts highlighting the interaction between glucose sensors and insulin demand. First, CGM users are 35 to 55% more likely to switch treatment shortly after 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 are learning about the real-life performance of new drugs across patients. As they see more patients using new drugs in real-life conditions, they are more likely to switch more patients to that treatment.

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. Motivated by the empirical facts, I develop a tractable framework in which, on the demand side, physicians facing heterogeneous patients choose the most cost-effective insulin. Physicians 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 CGM insights and the drug's mechanism of action is crucial in influencing demand. In my empirical model, insights from CGMs affect insulin demand from users and alter physicians' dynamic learning about new products' performance. On the supply side, the regulator and insulin manufacturers bargain over price, internalizing demand-side learning and perceived product differentiation. CGMs potentially influence equilibrium insulin prices by impacting new drug learning and perceived product differentiation.

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 for the patient-product match values, controlling for product-specific unobserved heterogeneity common across patients with similar characteristics. The remaining within-group patient-product heterogeneity is assumed to be independent of the drivers of CGM adoption. Physicians learn about the common component of the match value across patients within a group. The within-group patient-product idiosyncratic component is observed when the patient starts using a glucose sensor. The estimates suggest pessimistic beliefs about the performance of new products upon entry, similar to the findings of Coscelli and Shum (2004) for the anti-ulcer drugs market in Italy. CGM influences insulin choice through the idiosyncratic match value component observed when using a sensor, which accounts for one third of the match value on average. The device does not increase or decrease the precision of the experience signal about new drugs' quality , suggesting limited information spillovers to nonusers. The pricing model is estimated using GMM. As equilibrium prices remain relatively low despite quasi-inelastic insulin demand, most bargaining weight can be attributed to the regulator, which maximizes consumer surplus.[3]

Finally, I use the demand and supply framework estimates to compute two counterfactuals that illustrate how digital devices affect pharmaceutical markets. First, I assess the short-term impact of CGMs on market outcomes by simulating the equilibrium prices and market shares in the absence of CGMs, while holding the product set constant. Second, I explore the potential long-term implications of CGMs on the direction of pharmaceutical innovation by simulating

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

the entry of alternative drugs under different technological environments — both with and without CGMs.

The first counterfactual analysis 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 and steering demand toward newer drugs, CGMs provide opportunities for physicians to learn 2.7% faster on average about the performance of these drugs in real-life as users share their experiences with the new product with their physician. However, learning about new drugs that are less attractive on the attributes observable thanks to CGMs is slightly slower, -0.7%, driven by a fixed total number of learning opportunities and the limited effect of CGMs on the precision of experience signals that are extrapolated to nonusers. The information generated by CGMs contributed heterogeneously to new drug adoption, ranging from a one percentage point decrease in market share for the entering bioequivalent drug to a four percentage point increase (+16%) 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 attributes observed thanks to the device affect the perceived relative quality of products, which matters for the regulator who maximizes expected consumer welfare. As a result, the manufacturers of drugs that perform better on these new attributes bargain slightly higher prices, up to +4.4% in 2021. For most products, demand and supply forces reinforce each other, and the overall impact on product-level profits ranges from a 13% decrease to a 23% increase.

The second counterfactual highlights the implications of cross-market complementarities between medical device and pharmaceutical innovations. I focus on the unilateral product design decision of a pharmaceutical firm considering the launch of a new insulin product. I abstract away from the extensive margin of whether to innovate and from the strategic responses of other drug manufacturers. I compare the profit-maximizing product in environments with and without CGMs, where CGMs help physicians match patients to products thanks to otherwise unobservable attributes. Specifically, 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 10% 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 64% higher than that of the actual market entrant. This increase in profitability comes with a 15% rise in consumer welfare 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 techno-

logical 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.

Related literature The primary contribution of this paper is to develop an empirical framework to understand how digital technologies help overcome demand-side information frictions. In this context, it contributes to several strands of the existing literature. Primarily, it builds on research analyzing demand-side learning in healthcare markets. The existing literature emphasizes that information frictions regarding drugs' clinical match values arise upon market entry and initial diagnosis (Coscelli and Shum (2004), Crawford and Shum (2005), Currie and MacLeod (2020)). These frictions decrease as physicians gain direct and indirect experience with the drug — such experience can come from drug manufacturers' detailing, scientific information, clinical trials, etc. (Chintagunta et al. (2009), Coscelli and Shum (2004), Zhu (2023), Dickstein (2021), Grennan et al. (2024), Dubois and Tunçel (2021), Alsan et al. (2024)). Building on structural modeling of demand-side learning from experience (Roberts and Urban (1988), Erdem and Keane (1996)), my work is closely related to Crawford and Shum (2005), who focus on treatment experimentation and learning upon initial patient diagnosis. In this paper, I study learning about new products upon market entry, focusing on patients *already* diagnosed with the disease at the time of entry. I assume physicians are myopic at the time of treatment decision, and they learn dynamically about the drugs' clinical match values across their patient population, drawing on experiences of heterogeneous qualities depending on patients' monitoring technology. Under these assumptions, the scope for physicians' experimentation within and across patients over time is limited.[4]

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

This project also contributes to the literature on the impact of information frictions on

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

market outcomes. On the demand side, previous works document how consumer choice under imperfect information affects product offerings (Brown and Jeon (2024)) and how information provision to consumers can shift the market equilibrium (Jin and Leslie (2003), Handel and Kolstad (2015), Barahona et al. (2023)). On the supply side, incomplete information about the demand curve affects firms' behavior beyond insurance markets (Hitsch (2006), Handel and Misra (2015), Doraszelski et al. (2018)). I focus on the impact of consumer-level data to overcome information frictions. In the auto insurance market, consumer-level data generated by monitoring technologies can mitigate information asymmetries (Jin and Vasserman (2021)). Instead, I focus on demand-side information frictions and data-driven insights from a monitoring technology that informs consumers about their effective preferences for alternative products.[5]

I add to the literature on assessing the value of innovative pharmaceutical drugs and medical devices, drawing on the method developed in the empirical industrial organization literature (Trajtenberg (1989), Petrin (2002)). Igami et al. (2024) measure the welfare gains from product and process innovations. In this paper, I link the last two literatures by studying how new information technologies producing insights available for decision-making can enhance the value of pharmaceutical innovation for consumers.

This work also explores complementarities across markets and how innovations in one market may shape outcomes in another. While earlier work documents the impact of upstream innovation in vertically related markets (Eizenberg (2014)), Bresnahan and Trajtenberg (1995) highlight that complementary technologies may be necessary to fully exploit the potential of new technologies. My paper emphasizes the complementarity between medical device innovation and the diffusion of new pharmaceuticals in a context where the adoption of the complementary technology is the consumer's choice. I show how innovations in the medical device market alter pharmaceutical product shares and can shape the product offering.[6]

Finally, this paper contributes to the literature on information technology adoption in healthcare. Earlier empirical works focus on the impact of electronic medical records on healthcare costs and hospital productivity (Agha (2014), Dranove et al. (2014), Lee et al. (2013), McCullough et al. (2016)) and, more recently, telemedicine (Zeltzer et al. (2024), Dahlstrand (2024)) or artificial intelligence (Agarwal et al. (2023)). Handel and Kolstad (2017) highlight the potential for wearable devices to overcome the lack of data on critical outcomes. Yet, to

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[5]By studying how markets react to monitoring technologies, this paper is also related to Hubbard (2000) and Baker and Hubbard (2003).

[6]Previous work by Dranove et al. (2022) highlight that demand shocks can incentivize firms to undertake R&D activities. However, in the context of Medicare Part D, the effect favors follow-up rather than breakthrough innovations. Hamilton et al. (2021) also studies how consumer demand affects the direction of pharmaceutical innovation.

the best of my knowledge, the literature studying how new information technologies impact healthcare markets is scarce. I extend this literature by documenting the channels through which wearable devices generating high-frequency health data affect treatment choices.

The paper proceeds as follows. Section 2 provides background information on diabetes treatment in France and describes the 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 demand and pricing model. Section 6 presents the counterfactual scenarios, and Section 7 concludes.

2 Context and Data

2.1 Diabetes treatment in France

Diabetes is a major chronic condition affecting 1 in 10 adults worldwide.[7] The disease is characterized by high blood sugar levels, which can arise as the pancreas stops producing insulin (Type 1 Diabetes) or as the insulin produced loses its efficacy (Type 2 Diabetes). Both high and low glucose levels can lead to severe complications, including blindness, amputation, stroke, heart attack, and kidney failure. The primary goal of diabetes management for the patient (he) and the physician (she) is to stabilize blood glucose within a targeted range.

As of 2021, approximately 22% of diabetic adults in France were dependent on insulin. This project focuses on the choice of long-acting insulin, referred to throughout the paper as *insulin choice*. Long-acting insulin stabilizes the glucose level over a 24-hour period. It is often combined with short-acting insulin products, injected around mealtimes to manage food intake. Since long and short-acting products serve different functions, they can be studied independently. Long-acting insulins are primarily differentiated by their theoretical duration of action and must be injected daily.[8] However, the effective duration of each product varies across patients, depending on demographics, time since diagnosis, and individual metabolism. Hence, the clinical benefit of a product is heterogeneous across patients.[9] Part of daily diabetes management requires patients to monitor their glucose levels; the objective is to adjust short-acting insulin doses and avoid adverse events. Before 2017, glucose monitoring represented a

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

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

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

significant burden as one must prick one's finger for each glucose measurement.[10] Physicians evaluate diabetes control by relying on the three-month average glucose level (A1c), glucose measurements from strips and patient-reported adverse events. In particular, the laboratory-measured A1c level was 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, impacting 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 (Figure A2). In France, CGMs became widely used by patients following the Health Technology Agency (HTA) coverage decision in mid-2017. The 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 in the population. The cost of monitoring glucose increased by 67% between 2014 and 2023 (Figure A3).[11] Indeed, CGMs rely on a 14-day disposable sensor, making this form of monitoring substantially more expensive. 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 (Figure A4a). Between 2016 and 2018, four new products entered the market (Figure 1). These new insulins include a bioequivalent drug for the 24-hour insulin ('Biosimilar') and three products with an extended duration. These latter target patients for whom the effective duration of the 24-hour product is less than a day, and the 42-hour product specifically targets patients with a low overnight glucose level.

As prescription drugs are experience goods, physicians are initially uncertain about the patient-drug match values. They learn about the new insulins' performance outside the controlled environment of clinical trials across a heterogeneous patient population. CGMs expand the attributes observable for evaluating insulin treatment by providing detailed measurements of the daily glucose profile, including overnight levels. They complement traditional metrics, as the laboratory-measured average glucose (A1c) does not capture the (i) within-day variation or (ii) day-to-day fluctuations in glucose levels and can obscure important heterogeneity in glucose control (Figure A1).[12] By providing insights into the glucose profile, CGMs generate some information that (i) was previously unavailable and (ii) matters when evaluating the performance

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[10]Regular glucose monitoring involves placing a drop of blood on a disposable test strip in a glucose meter.

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

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

of insulin therapy. In a market where new products are entering, the impact of digital devices on insulin choice can be twofold: (i) identifying poor patient-product clinical matches (Shields and Sankaranarayanan (2016)) and (ii) gathering information about the real-life performance of new drugs (Seaquist et al. (2017)). In the remainder of the paper, I will refer to products by their duration of action, '24-hour Biosimilar' for Abasaglar, Type 2 for Xultophy and 'Human' and 'Mix' for 12-hour products.

Figure 1: New products entry timeline, 2016-2019
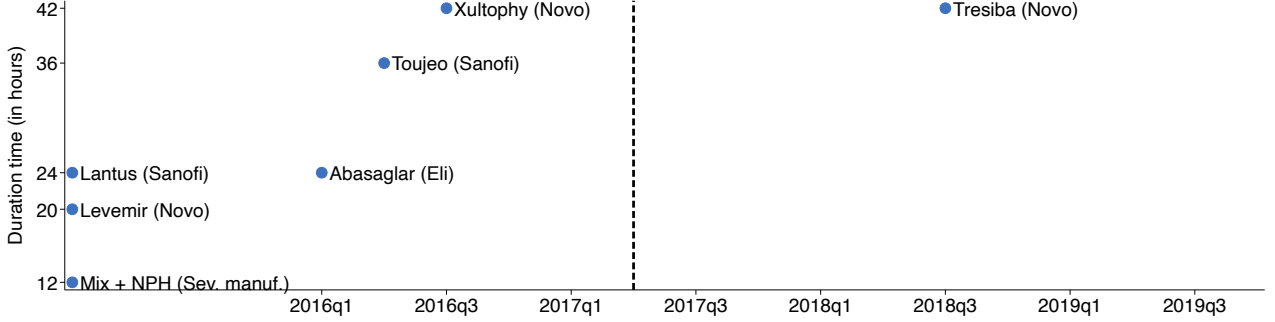
Notes: The horizontal axis corresponds to the entry date for new products. The vertical axis corresponds to the theoretical duration of each insulin. Each dot corresponds to one product, except for the 12-hour products. The dashed line corresponds to the first reimbursement of glucose sensors.

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 care reimbursements to a given patient and all care prescribed by a physician.

2.2.1 Insulin prescriptions

The data on insulin prescriptions comes from pharmaceutical claims from 2015 to 2021. For each reimbursement flow, I observe the patient and prescriber IDs, the medical specialty of the prescriber, the date of the prescription, the date of the claim (i.e. the date of the 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.[13] The prescription date allows for separating distinct visits from pharmacy refills.

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[13]Purchasing insulin requires a medical prescription. I observe all prescriptions filled by the patient. In practice, the prescription is written by the physician and purchased by the patient, leaving scope for 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. Like insulin reimbursements, I observe the patient and prescriber IDs, the prescription date, the pharmacy visit date, and the device characteristics. I assume the patient starts wearing the sensor on the day it is claimed at the pharmacy and stops using CGM at the expiration of the last sensor reimbursed to the patient.[14] Mismeasurement in CGM adoption can arise for patients purchasing the technology out-of-pocket (i) before June 2017 or (ii) because they are not eligible for coverage from the health insurance system.[15] In Appendix B.2, I describe how I overcome these limitations.

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 report information on the type of diabetes and chronic conditions. These files are built by the health ministry from all drugs and care reimbursements to a patient over a year. They report information about anxiety, cancer, cardiovascular disease, dialysis, depression, hypercholesterolemia, hypertension, obesity, etc. Claims data register laboratory tests' occurrences, but not their results.

2.2.4 Inpatient care/Emergency Room visits

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

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

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

2.3 Sample selection

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

Table A1 provides summary statistics on incumbent patients followed by diabetes specialists. The final sample includes 330k patients, 28% with Type I diabetes and 39% with Type II patients 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 13% benefited from the low-income complementary insurance during 2015-2022, and they live in less favored areas than the average French individual. Type II patients are more likely to take treatments for other chronic conditions such as hypertension and hypercholesterolemia. Around 65% of eligible patients ever used a CGM, with adoption being staggered over time and attrition remaining rare (Figure A6).

Table A2 provides summary statistics for physicians involved in the diabetes treatment for my patient sample. It suggests significant heterogeneity across physicians involved in insulin prescription. Most appointments happen with GPs, who represent 90% of distinct entities and 72% of visits. I focus on diabetes specialists and hospital services who see more patients and write more prescriptions at a given practice than GPs. While they represent 25% of prescriptions, they account for 74% of treatment switches. 97% of specialists and 58% of GPs encountered patients wearing a CGM between 2017 and 2021.

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[16]The results will not capture CGMs' benefits to learn about insulin injection therapy and diagnosis matching upon treatment initiation (Crawford and Shum (2005)). Diabetes patients using an insulin pump are excluded as they do not use long-acting insulin.

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

3 Descriptive evidence

This section presents motivating evidence that the adoption of glucose sensors by diabetic patients interacts with insulin demand. First, patients are temporarily more likely to switch insulin products right after they start wearing a CGM. These switches are not random and tend to be toward new insulin products with different characteristics. Second, these switches are inconsistent with lower switching costs with the digital device, and there is no evidence of reverse causality. Finally, evidence of physician-level learning about new drugs leaves scope for spillovers. These facts motivate the features of the structural model presented in Section 4.

3.1 CGM adoption and potential patient-insulin mismatch

This section documents how the adoption of CGM affects insulin choices. To that end, I consider first the decision by patient-physician pairs to switch the insulin treatment of the patient: prescribing a product j_v in a given appointment v different from the one used before the visit, j_{v-1}. I compare the decision to switch products for patients using CGM to the choice made for similar patients not wearing a glucose sensor. Considering the decision by the patient i–physician k pair in appointment v,

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

$Switch_{ikv}$ equals one when patient i's treatment in appointment v, j_{iv}, differs from patient i's treatment in his previous appointment, j_{iv-1}, zero otherwise. CGM_{iv} equals one when the patient is wearing a CGM at the time of the visit, and $First_{iv}$ equals one only for patient i's first visit to a specialist after adopting a CGM. $Switch_{ikv}$, the outcome of interest, may be occasional; hence, I consider heterogeneous effects between the first appointment while wearing the device ($\beta_0 + \beta_1$) and subsequent appointments (β_0). D_i includes patient demographics and chronic conditions. X_{kv} proxies the physician's information set during appointment v, counting the number of visits with patients already using new products. λ_k and $\delta_{t(v)}$ are respectively a physician fixed effect and a quadratic time trend. The model is estimated by OLS. Table 1 Columns (1)-(3) present the results. The estimates suggest a positive correlation between wearing a CGM and changing insulin product in the short run. Physicians are between 36 and 56% more likely to switch the patient's insulin treatment during the first appointment after the patient adopts a CGM. Beyond the first appointment, the positive correlation disappears and the coefficient becomes negative, suggesting no persistent impact on switching. This finding

aligns with Tang et al. (2023), who show a positive impact of Remote Patient Monitoring on hypertension medication adjustments for Medicare beneficiaries. The physician seems to react to the insights generated by CGM by switching their treatment for some patients while sticking to the former treatment for others.

Then I consider 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 this is true, treatment switches induced by the technology should be less likely to involve equivalent products and potentially be directed toward products that trigger features of the patient-product mismatch that were previously unobserved by the physician. To document this pattern, I consider the distribution of products involved in treatment switches. Figure 2 plots the distribution of switches with and without CGMs. This figure suggests that patients wearing a CGM are more likely to switch to the 36 and 42-hour product — new products with different characteristics — and less likely to switch to the 24-hour biosimilar. Importantly, some patients switch to the 36-hour product at the first appointment after adoption, even though the product was available before the CGM coverage decision. This figure presents several caveats as it does not control for new products entering over time and physicians' experience with new drugs increasing. Detailed switching matrices are presented in Figure A12. Altogether, these two pieces of evidence are consistent with a patient-insulin mismatch, which the technology revealed to the physician.

The positive correlation between CGM use and insulin switching documented in the previous paragraphs could alternatively arise from lower switching costs thanks to the technology or reverse causality where physicians prescribe CGMs to patients they know are less well treated *ex-ante*. The first confounding factor matters when considering the supply-side responses to CGMs (Dubé et al. (2010)). Reverse causality would lead to overestimating the correlation between adoption and switching patterns and undermine the idea that CGMs provide information to physicians.

3.2 Ruling out alternative mechanisms and reverse causality

This paragraph provides evidence ruling out lower switching costs and reverse causality as alternative mechanisms to explain the correlation between CGM adoption and insulin switches documented in the previous section. In particular, it documents whether physicians prescribe glucose sensors to patients they *already know* have a poor match value with their current treatment.

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		
Physician FE	✓		✓		✓		✓	
Time trend	✓		✓		✓		✓	
Patient demographics			✓		✓		✓	
Patient × Physician			✓		✓		✓	
Physician information set			✓		✓		✓	
$\overline{Switch}_{iv}$				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 × 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.

First, the switching patterns following CGM adoption presented in the previous paragraph are inconsistent with a reduction in switching costs. Indeed, lower switching costs would increase the probability of switching insulin at any appointment, which is ruled out by the estimates for β_0 in Table 1. Second, switching costs are particularly salient when considering switches between equivalent products. Figure 2 suggests that CGM users are *less* likely to switch to a bioequivalent treatment than non-users. In Appendix C.3, I formally rule out lower costs for CGM users.[18]

Second, reverse causality can affect both the extensive margin of CGM adoption if glucose sensor users are in worse condition *ex-ante* and the timing of adoption if patients are prescribed CGMs as a result of a worsening of their condition. Importantly, convenience is the primary motivation for adopting a glucose sensor as it significantly reduces the burden of glucose monitoring compared to disposable strips. Table A3 presents the drivers of CGM adoption, measuring the pseudo-R^2 of a logit model explaining CGM adoption with different sets of covariates. Patient demographics such as age, 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 very little.

To strengthen this point, I provide two additional pieces of evidence. First, I re-estimate the correlation between glucose sensor adoption and treatment switch (Equation 1), instrumenting for glucose sensor adoption with the adoption by patients living in the same geographical area

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[18]I rely on the relative choice between the 24-hour branded drug and its biosimilar to estimate switching costs. I compare the choice probabilities for existing patients who face both information frictions and switching costs, to the first-intention treatment choice made for 'new' insulin patients, who are only subject to information frictions.

Figure 2: Switching patterns with/without glucose sensors
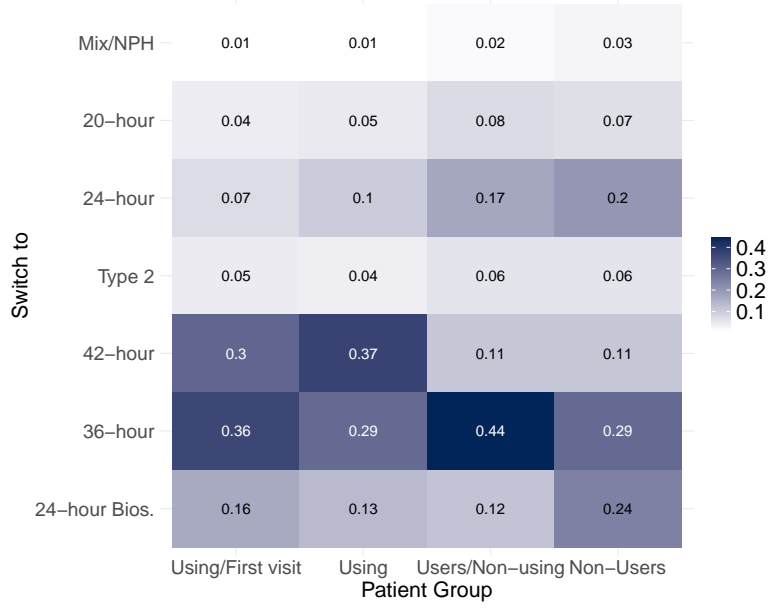
Notes: Conditional on switching treatment, the vertical axis corresponds to the product the patient is switched to, depending on whether patients are wearing a glucose sensor at the time of the appointment (horizontal axis). 'Non-users' include patients eligible for glucose sensor coverage not adopting the technology. The label corresponds to the conditional probability of switching to product j such that each column sums to one. Insulin mixes, the 20-hour and the 24-hour products are old products, entering the market before 2016. The remaining four products enter from 2016 onwards (Figure 1). Figure A12 presents switching matrices conditional on the product used before the appointment for each patient group.

(at the department level), treated by a different physician. The results, presented in Table 1 Column (4), indicate that the positive correlation between CGM adoption and insulin switching persists. Second, I consider the correlation between the physician's propensity to face patients wearing a glucose sensor and her propensity to switch the insulin treatment of CGM patients during the first appointment after patient adoption. If physicians prescribe CGMs to patients they know are poorly treated, one expects a positive correlation between these two dimensions. Figure 3 presents a scatter plot of the physician-level propensity to switch the treatment of a patient the first time he returns while wearing a glucose sensor (vertical axis) and her propensity to treat patients wearing a glucose sensor (horizontal axis). The figure displays no correlation.

Finally, I focus on the timing of technology adoption and study the correlation between CGM adoption and the occurrence of diabetes-related ER visits before the adoption date. For patients adopting a CGM, I consider the number of ER visits occurring in a bandwidth of 365 days before the first CGM prescription. For patients not adopting a CGM, I consider the maximum number of diabetes-related ER visits the patient faces in 365 days from June 2017 to January 2020.[19] Table 2 presents the results of logistic regressions of CGM adoption on the number of ER visits. The results indicate a negative correlation between the two variables, suggesting that severe

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

Figure 3: Physician-level heterogeneity
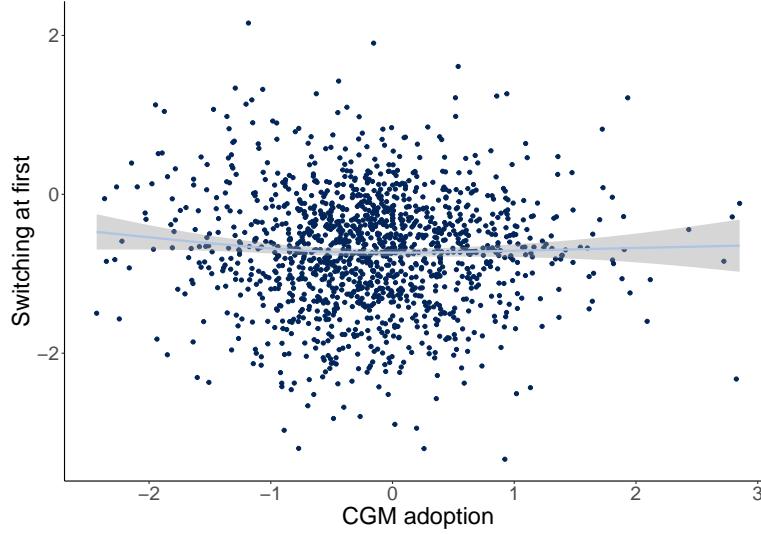
Notes: This figure presents the physician-level propensity to see patients with CGMs (horizontal axis) against her propensity to switch patients in the first appointment after they adopted CGMs (vertical axis). Each propensity corresponds to the parameter of a logistic regression where the outcome variable is 'CGM adoption' (horizontal axis) and 'Switching insulin in the first appointment with CGM' (vertical axis), and patients' characteristics are included as controls. One point corresponds to one physician. The fitted line corresponds to a flexible non-parametric smoothing of the data with a 95% confidence interval.

adverse events related to diabetes are unlikely to drive technology adoption.

Table 2: CGM adoption and prior ER visits

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

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

3.3 Physician-level learning and limited experimentation

Prescription drugs are experience goods: physicians are initially uncertain about the real-life performance of products upon market entry and learn about it from patients' experience. Section 3.1 documents treatment switches following the digital device adoption toward newer drugs (Figure 2). Being less familiar with these products, physicians encounter more learning opportunities thanks to CGMs — as sensor users return to their physicians after switching to a

new product. In this context, if physicians extrapolate experience across patients, information externalities for non-users arise mechanically thanks to the switches. This paragraph documents learning across patients for a given physician, examining the correlation between a physician's prescribing behavior toward new products and her prior product experience.

For each physician k, new product j, and quarter q, I compute the product-level prescription share among the patients not already using product j at the time of the appointment. The physician's information set for product j at q is proxied by the total number of appointments up to $q-1$ where the patient arrived while using j. Figure 4 presents a binned scatter plot of a product's prescription share to 'new' patients (vertical axis) against the physician's information set (horizontal axis). The bell-shaped relationship provides evidence of a positive correlation between the physician's information set for patients' experience with product j and her propensity to prescribe the product to other patients. This evidence suggests physicians extrapolate information across patients, leaving scope for information spillovers between CGM users and non-users. In Appendix C.4, I document whether the composition of the information set (between patients providing feedback with or without the technology) impacts the strength of the correlation.

Physicians learning from patients' experience with new drugs could lead forward-looking physicians to experiment within and/or across patients — prescribing new products to learn about the match values. By prescribing 'dominated' products, forward-looking physicians will switch patients back to a former product after learning. Myopic physicians will switch back patients mistakenly switched in the first place, suggesting a monotonic relationship between switching back and the physician's information set, as physicians are less likely to make mistakes as they learn. On the contrary, forward-looking physicians will also start switching back patients once the value of information becomes small, leading to a non-monotonic relationship between the information set size and switching back. In Figure 5, I consider the probability of switching back to a former treatment (vertical axis) as a function of the physician's information set (horizontal axis). This figure displays a monotonically decreasing relationship between the two variables, suggesting that experimentation by physicians is limited. I assume physicians are myopic moving forward.

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, considering how digital device information influences

Figure 4: Physician-level prescription share and information set size
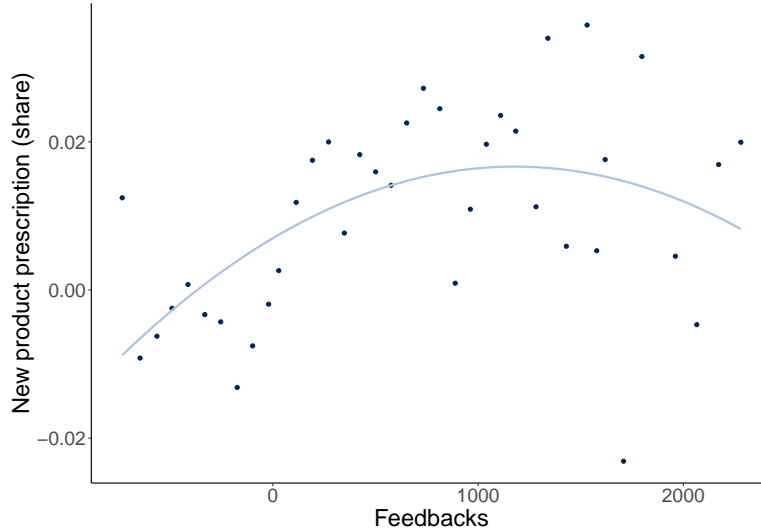
Notes: The vertical axis corresponds to product j prescription share for patients not using the product before the appointment. The horizontal axis corresponds to the amount of feedback from real-life experience with the new product j received by the physician up to the previous period. For each variable, I consider the residuals from a linear model controlling for physician fixed effects, product-specific quarter fixed effects, and the average demographics of the patient visiting physician k in a given period. The figure focuses on prescriptions by diabetes specialists and excludes the new Type 2 product directed toward a subset of patients. The information set proxy (horizontal axis) is computed at the hospital level for specialists working in the hospital. Figure A13 focuses on individual physicians working outside the hospital.

prescription drug choices and prices. The model recovers preferences for insulin products, consumer surplus, and firm profits. Its primitives are estimated in Section 5 using micro-level pharmaceutical claims data, which I use in Section 6 to quantify the impact of digital device information on the insulin market.

The model explains the behavior of physicians, insulin manufacturers, and the regulator. Insulin manufacturers and the regulator negotiate the price of insulin products. Physicians prescribe an insulin product to their diabetic patients, which aggregate up to the demand for each drug. The entry of new drugs and the adoption of CGMs are assumed to be exogenous. The timing of the game 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, each physician (she) faces a sequence of medical appointments with diabetic patients for whom she makes a treatment decision. Insulin manufacturers and the regulator form rational expectations about the upcoming annual demand. Physicians face uncertainty about the idiosyncratic 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 when bargaining over drug prices. On the demand side, physicians are assumed to be myopic when choosing the insulin product

Figure 5: Probability of switching back and physician-level information set size
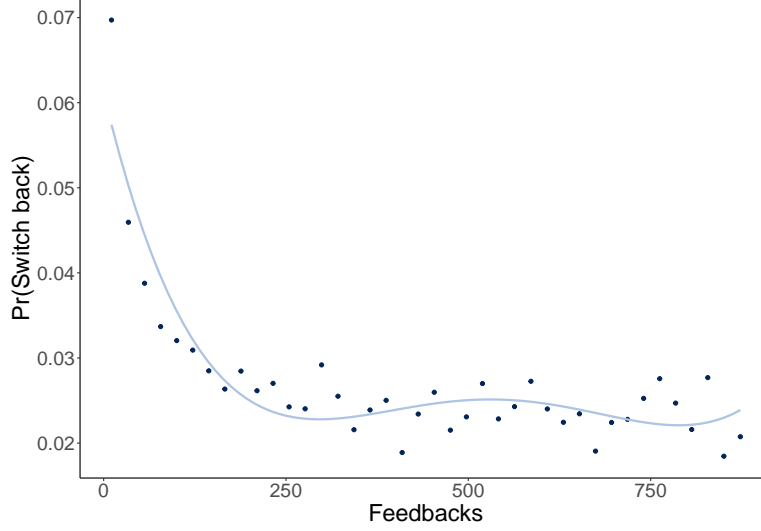
Notes: The vertical axis corresponds to the probability of switching back to a former treatment for patients who previously switched to a new product. The horizontal axis corresponds to the amount of product-level feedback from patients received by the physician up to (and including) the current appointment. The top 5% of observations by information set size (horizontal axis) are omitted. Figure A14 focuses on treatment spells that were initiated when the physician had very little information about the product.

for each patient, leading to a static decision problem at each appointment. Yet, physicians accumulate experience signals over time and can use the information they receive about the real-life performance of products from one patient to inform their decisions for other patients, generating spillovers. This structure enables a two-step approach. In Section 4.1, I model static prescription decisions within each year, aggregating up to the annual demand for each insulin product. In Section 4.2, the aggregate annual demand and consumer surplus for each product are used as inputs to the annual insulin price negotiation between insulin manufacturers and the regulator.

4.1 Insulin demand

4.1.1 Setting

Consider a patient (he), indexed by i, followed by a physician k (she), the expert who decides on the treatment. The flow of medical appointments leading to an insulin prescription at a given physician practice is indexed by $v \in \{0, \ldots, V_k\}$. Physicians differ in the number of patients they see, V_k, and the characteristics of their patient population, which are taken as given. The physician prescribes an insulin product $j \in \mathcal{J}_v$ to patient i during a medical appointment. Patients differ in their glucose monitoring technology, denoted a_{iv}, and their true clinical match value with product j, denoted $\Theta_{ij} \in \mathbb{R}$. $a_{iv} \in \{0, 1\}$ denotes the adoption of the digital device, where $a_{iv} = 1$ if the patient uses a CGM, and 0 otherwise. The physician observes a_{iv} and the

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data generated by the glucose sensor when $a_{iv} = 1$. The physician faces uncertainty regarding Θ_{ij}. She forms prior beliefs about Θ_{ij} based on clinical trial information and learns about Θ_{ij} through experience signals generated by the direct use of product j. Considering the flow of appointments to physician k, at each visit v,

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

2. **Belief updating:** The physician observes the last product used by patient i until v, $j_{i,v-1}$, and its effect on i's glucose levels. This information generates an experience signal the physician uses to update her beliefs about the clinical benefit of $j_{i,v-1}$ for *any* patient. The experience signal enters the information set of physician k at time v, denoted $\mathcal{I}_{kv}$. $\mathcal{I}_{kv}$ represents the stock of information about insulin products' performance received by physician k up to appointment v (included).[20]

3. **Treatment choice:** Given her information set at appointment v, $\mathcal{I}_{kv}$, the physician, k, chooses the treatment $j \in \mathcal{J}_v$ that maximizes her expected payoff.

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

$$U_{ikjv} = \Theta_{ij} - \alpha p_{jv} + \delta f(age_{jv}) + \varepsilon_{ikjv} \tag{2}$$

p_{jv} is the price of product j, age_{jv} is the time since drug j has been on the market at appointment v and ε_{ikjv} is an idiosyncratic preference shock. α measures the price sensitivity of the patient-physician pair, and $f(age_{jv})$ approximates physicians' learning about drugs, other than through patients' direct experience. Θ_{ij} is the true clinical match value between patient i and drug j. The match value Θ_{ij} is assumed to be independent of the patient's glucose monitoring technology a_{iv}. I further assume that Θ_{ij} depends on the preference for the drug's effect on the average glucose level, denoted μ_{ij}, the preference for the drug's effect on the glucose profile, denoted ν_{ij}, and that $\Theta_{ij} = \mu_{ij} + \nu_{ij}$.[21] I assume each physician is myopic when selecting the treatment for patients i at appointment v, maximizing the expected indirect utility from drug j consumption by patient i at appointment v. Given the physician information set, $\mathcal{I}_{kv}$, the

---

[20]The 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, the empirical specification will impose some restrictions on the extent of learning across patients.

[21]Each argument combines the value of the attribute and the utility weight for that attribute.

monitoring device, a_{iv}, the choice of treatment is made according to

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

where $\mathcal{J}_v = \mathcal{J}^{Old} \cup \mathcal{J}_v^{New}$. $\mathcal{J}_v^{New}$ corresponds to the set of insulins entering after 2015 available at the time of appointment v (Figure 1). Given the chronic nature of the disease, there is no outside option, and the physician must prescribe one of the available treatment options. Given the information set, $\mathcal{I}_{kv}$, monitoring choice, a_{iv}, and product j, I assume the physician's expectation of the true value for Θ_{ij} is as follows:

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

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

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

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

I assume physicians know the drug's effect on the average glucose level, μ_{ij}, for each drug $j \in \mathcal{J}^{Old}$ and each existing diabetes patient. However, the physician has no information about the drug's effect on the glucose profile, ν_{ij}, as the exact patient profile i remains unobserved without a glucose sensor. The physician's expectation about ν_{ij} remains equal to her initial belief upon drug entry, which I assume is $\mathbb{E}(\nu_{ij}|\mathcal{I}_{kv}; a_{iv} = 0) = 0$. Without the technology, for product $j \in \mathcal{J}^{Old}$,

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

μ_{ij} is independent of the physician k and medical appointment v because all physicians have already learned about this value for old drugs. As patients are not using glucose sensors, information about the glucose profile is unavailable to physicians when considering the expected match value between patient i and drug j. As a result, learning about the patient-product clinical match value, Θ_{ij}, cannot be complete without the information produced by CGMs and

the physician's belief about Θ_{ij} remains biased.[22]

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

For new treatments upon entry, unlike Equation (5), the physician has no prior experience, and hence imperfect information about the drug's effect on the mean glucose level, μ_{ij}. At $v = 0$, the physician forms a prior belief about μ_{ij} and ν_{ij}. I follow Erdem and Keane (1996) in assuming beliefs about μ_{ij} are normally distributed such that $\mu_{ij} \sim \mathcal{N}(\mu_{ij}^0, V_{ij}^0)$. The physician may have nonrational expectations about new drugs' performance on the average glucose level upon entry such that it is possible that $\mu_{ij}^0 \neq \mu_{ij}$. The physician is Bayesian and updates her belief about μ_{ij} on the basis of the patient's experience signals when he returns to her practice at time v using the new product j. She learns *across* patients, using the signal produced by patient i to update the prior belief for any patient i'. These signals, denoted $e_{ii'kj}^v$, are assumed to be unbiased with respect to $\mu_{i'j}$ but noisy. They are drawn from a normal distribution, $e_{ii'kj}^v \sim \mathcal{N}(\mu_{i'j}, \sigma_{ii'v}^2)$ where $\sigma_{ii'v}^2$ corresponds to the noise of the signal provided by patient i in appointment v when extrapolated to patient i'. The signal enters the information set of physician k at $v' \geq v$, $\mathcal{I}_{kv'}$. The physician's belief about the preference for the drug's effect on the glucose profile, ν_{ij}, satisfies $\mathbb{E}(\nu_{ij}|\mathcal{I}_{kv}; a_{iv} = 0) = 0$. Without a glucose sensor, she cannot learn about its realization for patient i. Without the digital device, for $j \in \mathcal{J}_v^{New}$,

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

where $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}; a_{iv} = 0)$ is the mean of physician k's belief about μ_{ij} at time v given that $a_{iv} = 0$. This expectation varies (i) over time as a physician gathers more experience and (ii) across physicians as they see different patient populations. As a physician sees many patients, the size of the information set is large. Section 5.1.1 presents the empirical specification for the learning process and the restrictions keeping the dimension of the information set tractable.

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

Glucose sensors generate detailed reports about the effectiveness of insulin treatments throughout the day. The analysis of retrospective CGM data by physicians is informative about insulin products' match values. I assume the benefits from CGM data are two-fold:

1. **Comprehensive measurement of the glucose profile:** The sensor generates precise information about the glucose profile of the patient. I assume learning about $\boldsymbol{\nu}_i$

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[22]Alternatively, one can assume that physicians learn *partially* about ν_{ij} without a CGM.

is complete and immediate once a patient uses the device. The physician observes the realization of ν_{ij} for all j for patient i such that $\mathbb{E}(\nu_{ij}|\mathcal{I}_{kv}; a_{iv} = 1) = \nu_{ij}$. These insights are patient-specific and uninformative for nonusers.

2. **Experience signal about μ_{ij}:** The glucose sensor data generated when the patient was using product j produces an experience signal about μ_{ij}, the preference for the performance of the drug on the average glucose level. This signal is also unbiased with respect to μ_{ij} but may be more or less precise than the signal provided without a CGM.

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

Thanks to the glucose sensor, the realization of ν_{ij} for patient i is observed by the physician such that $\mathbb{E}(\nu_{ij}|\mathcal{I}_{kv}; a_{iv} = 1) = \nu_{ij}$. Given $a_{iv} = 1$, for drug $j \in \mathcal{J}^{Old}$,

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

Since there is no uncertainty about μ_{ij} for old drugs, $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) = \mu_{ij}$. The insights about ν_{ij} from CGMs are uninformative for nonusers who keep facing Equation (5). Owing to the digital device, learning about the performance of old treatments for patient i is complete as the physician now knows Θ_{ij}. Since there is no outside option, pharmaceutical demand is affected by the monitoring technology only if ν_{ij} differs across alternatives.

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

Despite the lack of product entry, the digital device can affect insulin demand among device users. This impact is driven by the availability of the patient's glucose profile, a newly observable attribute that makes certain treatments more appropriate. These insights are assumed to be patient-specific. Hence, 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, when $\nu_{ij} = \nu_i \ \forall j \in \mathcal{J}^{Old}$, demand for existing pharmaceutical alternatives remains unaffected.

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

For new treatments, the impact of CGM data is twofold. First, it allows the effect of treatments on the glucose profile, ν_{ij}, to be inferred. Second, it can affect the quality of the experience

signal about μ_{ij} when the patient returns to his physician while using product j, compared to the signal provided without a glucose sensor. I assume these signals are also normally distributed, unbiased, yet of different precisions. Whether they are more, less, or equally informative about μ_{ij} than signals received when the patient is not wearing a CGM remains an empirical question.[23] For new treatments $j \in \mathcal{J}_v^{New}$,

$$\mathbb{E}(\Theta_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) = \mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1) + \nu_{ij} \tag{8}$$

where $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1)$ can differ from $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 0)$ in Equation (6) for the product the patient was using when coming to the physician visit at time v.

Figure 6 summarizes the two effects of CGMs on physicians' expectations about the clinical match value, Θ_{ij}. Figure 6a abstracts away from dynamic learning about new drugs and presents the impact of comprehensive glucose profile measurement when considering alternative products for a patient. The vertical axis corresponds to the physician's expected clinical match values, $\mathbb{E}(\Theta_{ij})$, both with (triangle) and without (square) the device, across various drugs represented on the horizontal axis. Without CGM insights about ν_{ij}, the physician is indifferent between prescribing products 3 and 4 for patient i, *ceteris paribus.* With a glucose sensor, the physician observes the performance of each insulin product j on patient i's glucose profile, ν_{ij}, in addition to μ_{ij}. The expected match value from product 4 dominates that from product 3, and the gap between products 1 and 2 narrows. The technology increases the *perceived* differentiation between products 2, 3, and 4, whereas it decreases between products 1 and 2 such that it may induce a treatment switch from product 3 to product 4. Given that the true match value between patient i and product j, Θ_{ij}, is independent of the glucose monitoring technology, the glucose sensor only affects the physicians' *perceptions* of the match values.

Figure 6b focuses on the learning dynamics of μ_{ij} for new drugs. It illustrates the impact of experience signals generated by patients who return to their physicians with new drug j while wearing a CGM during their appointment v when CGMs affect the noise of the experience signal. The figure represents the evolution of the physician's expectation about the preference for the drug's effect on the average glucose level, μ_{ij}, (vertical axis) as she accumulates experience signals (horizontal axis), with (brown lines) or without CGM (navy line). If experience signals

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[23]Observing the performance of a new drug j for a patient i using the digital device, $a_{iv} = 1$, might provide information about μ_{ij} in a different fashion than had the patient come without the technology $a_{iv} = 0$. I do not assume the glucose sensor generates complete learning about μ_{ij}. However, if the insights from CGM provide precise information about the performance of drug j on the average glucose level for patient i, μ_{ij}, the noise of the experience signal received from glucose sensor will be very small and the belief of physician k after receiving CGM information, $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv} = 1)$, will be close to its true value and precise.

generated by CGMs are more precise (dark brown) than traditional signals (navy line), the gap between the physician's expectation, $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv})$, and the true value of μ_{ij} is smaller, for a given number of experience signals received (horizontal axis). The physician can learn faster about μ_{ij} thanks to CGMs. The distinction between Figure 6a and 6b matters. While the effect illustrated in Figure 6b is temporary, the new observable attributes presented in Figure 6a affect demand persistently, beyond the market entry of new products.

Figure 6: Impact of CGMs on the perceived match value

(a) Comprehensive glucose profile

(b) Experience signal about μ_{ij}
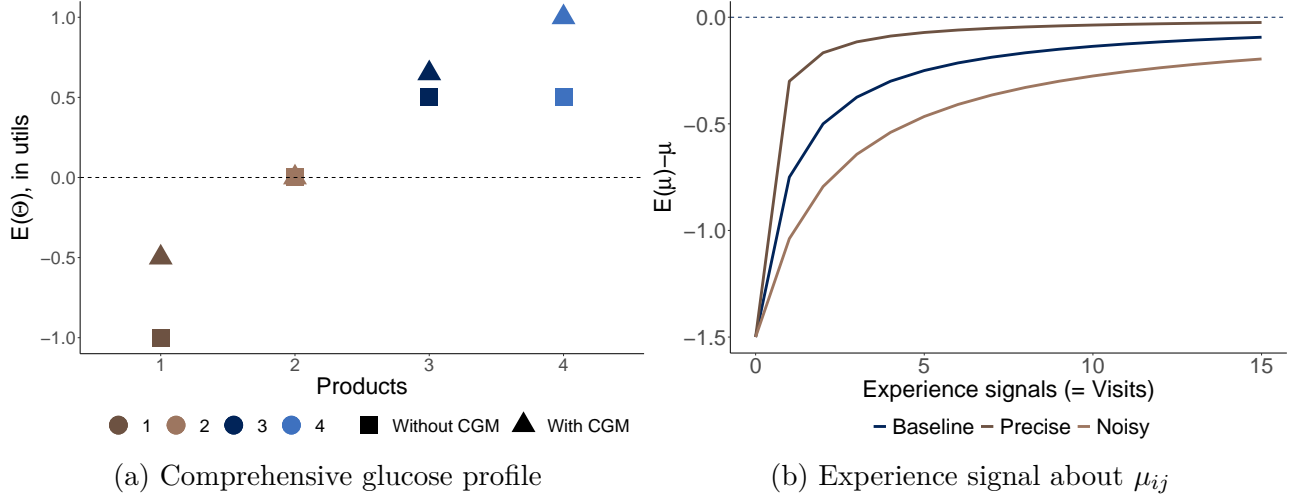
Notes: Figure 6a plots the physician's expectation about Θ_{ij} (vertical axis) for different products (horizontal axis), with (▲) and without (■) insights from CGMs. This example abstracts away from the dynamic learning about μ_{ij} for new drugs. Figure 6b shows the evolution of a physician's belief about μ_{ij} (vertical axis) as she receives more experience signals (horizontal axis) from patients who return to her practice while using new product j. One feedback corresponds to one visit where the patient shares his experience with product j. I assume that physicians form normally distributed priors about μ_{ij} at $v = 0$ and update their beliefs from normally distributed signals received from patients using product j. The signals are unbiased with respect to the true value, μ_{ij} but noisy, denoting the variance of the signal from patient i for patient i', $\sigma^2_{ii'v'}$. Here, a physician receives either precise ($\sigma_{ii'v'} = 1$) or noisy ($\sigma_{ii'v'} = 3$) signal compared with the baseline ($\sigma_{ii'v'} = 2$). For exposition purposes, this example assumes the noise is the same for signals received from $i' \neq i$.

4.1.4 Consumer welfare under imperfect information

In this setting, there exists a discrepancy between the decision utility and the utility experienced by the patient. Uncertainty and incomplete learning distort the decision utility, hence the demand for insulin, whereas the underlying experienced utility relies on Θ_{ij}, the true clinical match value. Following equations (2) and (3), the experience utility from patient i using product j is

$$U_{ikjv} = \Theta_{ij} - \alpha p_{jv} + \delta f(age_{jv}) + \varepsilon_{ikjv} \equiv \mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv}) - \left[\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}, a_{iv}) - \mu_{ij} + \nu_{ij}(a_{iv} - 1)\right]$$

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

$$
\begin{aligned}
W_{ikv} &= \mathbb{E}_\varepsilon[U_{ikj^*v}] \\
&= \mathbb{E}_\varepsilon\Big[\max_j\{\mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv})\}\Big] - \mathbb{E}_\varepsilon\Big[\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}; a_{iv}) - \mu_{ij} + \nu_{ij}(a_{iv} - 1)\Big]
\end{aligned}
\tag{9}
$$

where the second term accounts for the difference 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.[24] 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}, for these patients among old alternatives. This feature circumvents the initial conditions problem that arises in a dynamic setting. Third, physicians are altruistic and myopic. They are altruistic as they choose the treatment to maximize a weighted sum of the expected patient-level clinical benefit and treatment prices. As physicians' altruism and price sensitivity cannot be separately identified, a low α can be driven by a low sensitivity to price and a high level of altruism. Physicians are assumed to be myopic, which excludes exploration by physicians who could prescribe a less valuable treatment to learn about the clinical match value of new drugs. This assumption is discussed in the last paragraph of Section 3.3. Physicians may be reluctant to prescribe treatments for which the outcome is more uncertain. I approximate this feature in the econometric model by allowing for pessimistic initial priors, capturing the reluctance to switch patients to new treatments.

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 of drug and device development, I consider the arrival of innovations in drugs and devices as

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[24]Under this assumption, the average and profile of the glucose levels for patient i can still be affected by the technology owing to the better fine-tuning of short-acting insulin around mealtime. Yet, the effect must be independent of the long-acting insulin product choice, j.

given.[25]

I assume that prices are set every year by static bilateral Nash bargaining between each drug manufacturer and the regulator, similar to 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)). I rely on the characteristics of the institutional setting to assume static pricing in each period. Indeed, in France, the price for prescription drugs is determined through negotiations between drug manufacturers and the regulator. The price 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 market dynamics by setting a low price upon introduction to raise it in later periods in the spirit of Shapiro (1983).

In pharmaceutical markets, each branded insulin product is produced by a single manufacturer, and I treat the 24-hour biosimilar and its branded version as separate products.[26] Unlike other pharmaceuticals, the insulin market is concentrated, with three companies 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

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

where $q_{jt}(\mathbf{p}_t) = \sum_{\forall i,k} \sum_{\forall v \in t} s_{ikjv}(\mathbf{p}_t)$ is the total demand for drug j across appointments v occurring in year t and individual choice probabilities, $s_{ikjv}(\mathbf{p}_t)$, are derived from Equation (3). This profit function assumes that manufacturers have rational expectations about demand realizations in a given year. The manufacturer correctly forecasts physicians' learning upon product entry, 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, given by

$$\Delta_{ft} CS(\mathbf{p}_t) = \frac{1}{\lambda} \sum_{\forall i,k} \sum_{\forall v \in t} \mathbb{E}_\varepsilon \big(\max_{j \in \mathcal{J}_v} \mathbb{E}(U_{ikjt} | \mathcal{I}_{kv}; a_{iv}) \big) - \frac{1}{\lambda} \sum_{\forall i,k} \sum_{\forall v \in t} \mathbb{E}_\varepsilon \big(\max_{j' \in \mathcal{J}_v \setminus \mathcal{J}_{ft}} \mathbb{E}(U_{ikj't} | \mathcal{I}_{kv}; a_{iv}) \big) \tag{11}$$

where $\mathbb{E}(U_{ikjt})$ follows from Equation (3). The parameter λ corresponds to the scaling factor for consumer surplus from the regulator's perspective. λ can differ from α, allowing the price

---

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

[26]These products are not 'interchangeable' by pharmacists in France during my sample period. The physician writes a different prescription for each molecule version, and the pharmacist must provide the prescribed product.

sensitivity of physicians, estimated from the demand model, to fail to accurately convert utils into euros for the regulator. Under Nash bargaining, both parties have symmetric information. The regulator knows the firm's marginal costs and also forms rational expectations about the adoption of the digital device and its impact on consumer surplus. In Equation (11), I assume that the consumer surplus the regulator considers when setting drug prices does not account for the difference between the decision and experience utility, similar to Grennan and Town (2020). Under these assumptions, access to the digital device affects equilibrium prices through profits and the *ex-ante* consumer surplus generated by the reimbursement of certain products.

Denoting b_{ft} the bargaining ability 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:

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

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

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

The scaling factor of the consumer surplus, λ, does not affect the equilibrium outcome, whereas the price sensitivity of demand matters. When a firm offers two products, j and j', the first-order conditions yield the following pricing equation:

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

where $h_{jt} = \frac{\partial \Delta_{ft} CS(\mathbf{p}_t)/\partial p_{jt}}{\Delta_{ft} CS(\mathbf{p}_t)} < 0$ and $\beta_{ft} = \frac{1-b_{ft}}{b_{ft}}$. For single-product firms,

$$p_{jt} = c_{jt} - \left[\beta_{ft} h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)} \right]^{-1} \tag{15}$$

The details for the first-order condition computation are provided in 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 for the choice of insulin j by physician k for patient i arriving at v is:

$$
\begin{aligned}
\mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv}) &= \mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}; a_{iv}) + \nu_{ij}a_{iv} - \alpha p_{jv} + \delta f(age_{jv}) + \varepsilon_{ikjv} \\
&\equiv u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}) + \varepsilon_{ikjv}
\end{aligned}
\tag{16}
$$

where $u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv})$ denotes the deterministic part and ε_{ikjv} is the idiosyncratic shock, unobserved by the econometrician, assumed to be *i.i.d.* and distributed Type-I extreme value. p_{jv} is the daily price of insulin j at time v, age_{jv} is the time since product j became available, and $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}; a_{iv}) + \nu_{ij}a_{iv}$ is the expected patient-drug clinical match value, following Equation (4). age_{jv} approximates physician learning from indirect experiences such as word of mouth, scientific conferences/articles, or pharmaceutical detailing by entering quadratically. Physician learning from these alternative sources is assumed to be constant across physicians and products at a given age.

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. In Section 4.1, I assume Θ_{ij} is the sum of: (i) the preference for the drug's effect on the average glucose level, μ_{ij}, and (ii) 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, $\mathcal{I}_{kv}$. The dimension of $\mathcal{I}_{kv}$ is large as physicians see many patients. 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, $n \in \{1, ..., N\}$. Within a cluster, n, μ_{ij} is constant and denoted μ_{nj}. μ_{nj} is assumed to be equal for bioequivalent products. Each physician holds a prior belief about μ_{nj}, common to all patients in group n, limiting the dimension of the physician's information set. Physicians know which group each existing patient belongs to.[27] They form beliefs about μ_{nj} upon drug j's entry which can be inaccurate initially such that $\mathbb{E}(\mu_{nj}|\mathcal{I}_{k0}; a_{iv}) = \mu_{ikj}^0 \neq \mu_{nj}$. This belief evolves as the physician gathers

---

[27]For newly diagnosed patients, the physician may not be able to identify i's type directly, leading to diagnosis matching, experimentation, and exploration (Crawford and Shum (2005)). The structural estimation of the model avoids these considerations by focusing on existing diabetes patients.

more direct patient experience. $\mathbb{E}(\mu_{nj}|\mathcal{I}_{kv}; a_{iv})$ varies over time and across physicians who see different patients.[28]

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 I diabetic patients', 'Type II diabetic patients using both long and short-acting insulins', and 'Type II diabetic patients using only long-acting insulin'. Second, I apply a k-means algorithm within each group to classify patients into two to three subgroups, resulting in a total of seven clusters. The variables used to create the clusters include patients' demographics, environment, chronic conditions, diabetes management, and health status prior to the availability of continuous glucose monitors. 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. This flexible parameterization allows preferences for specific insulin products to vary across groups on the basis of factors observed by the physician during treatment decisions but not captured in the data.

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. I assume the digital device 'reveals' the patient's sensitivity to the duration of action of the insulin products. 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}. The physician learns about each component, as presented in Section 4.1. The physician 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:

$$
\begin{aligned}
\mu_{nj} &\sim \mathcal{N}(\mu_j^0, V_j^0) \\
\nu_{ij} &\sim F(\nu_{ij}) \text{ where } \mathbb{E}(\nu_{ij}|\mathcal{I}_{kv}, a_{iv} = 0) = 0
\end{aligned}
\tag{17}
$$

where $F(.)$ is the cumulative distribution function of the beliefs about ν_{ij}. Each physician holds a normally distributed prior belief about μ_{nj}, characterized upon market entry by an initial mean μ_j^0 and a variance V_j^0, assumed to be constant across physicians.[29] Physicians are

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[28]Physicians might hold inaccurate beliefs regarding bioequivalence, indicating that the learning process also pertains to the entering biosimilar (Maini et al. (2022)).

[29]Initial prior beliefs could be influenced by the sources of indirect learning, such as clinical trials, medical conferences, and detailing. The model is estimated using a subset of diabetes specialists working outside the hospital. Hence, they are assumed to receive similar information about new products upon entry. In Figure

Bayesian and learn about μ_{nj} from the experience signals received from patients who return to their physicians using product j, regardless of whether they are wearing a glucose sensor. I assume that physicians do not learn across clusters, which limits the scope of information spillovers. Consider 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 or without a CGM, a_{iv}. A medical appointment generates an experience signal, drawn from the following distribution:

$$e_{ikj}^v \sim \mathcal{N}(\mu_{nj}, (\sigma_0 + \sigma_1 a_{iv})^2) \tag{18}$$

where the technology affects the signal's precision. Given the normally distributed prior beliefs and signals, physician k's posterior belief mean, $\mathbb{E}(\mu_{ij}|\mathcal{I}_{kv}; a_{iv}) \equiv \mu_{nkj}^v$, after receiving i's experience, e_{ikj}^v, and given the prior belief, μ_{nkj}^{v-1}, is given by:

$$\mu_{nkj}^v = \begin{cases} \mu_{nkj}^{v-1} \frac{\sigma_0^2}{\sigma_0^2 + V_{nkj}^{v-1}} + e_{ikj}^v \frac{V_{nkj}^{v-1}}{\sigma_0^2 + V_{nkj}^{v-1}} & \text{if } a_{iv} = 0 \\ \mu_{nkj}^{v-1} \frac{(\sigma_0+\sigma_1)^2}{(\sigma_0+\sigma_1)^2 + V_{nkj}^{v-1}} + e_{ikj}^v \frac{V_{nkj}^{v-1}}{(\sigma_0+\sigma_1)^2 + V_{nkj}^{v-1}} & \text{if } a_{iv} = 1 \end{cases} \tag{19}$$

The signal's noise when the patient is using a CGM ($a_{iv} = 1$) influences how quickly physicians learn from CGMs. If σ_1 is high, the insights from glucose sensors provide an uninformative signal about μ_{nj}. Physicians cannot be misled about μ_{nj} by the CGM readings. Whether signals from CGMs are more, less, or equally informative about μ_{nj} compared with signals from traditional tools depends on the sign of σ_1 (Figure 6b).

Discussion 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.[30] 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. In Appendix A11, I provide suggestive evidence that there is limited variation in the physicians' likelihood of being detailed by insulin manufacturers. Each insulin manufacturer has detailed the majority of diabetes specialists since at least 2014.

A11, I provide evidence that most diabetes specialists interact with the three pharmaceutical companies. The interactions occur on average once per year.

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

5.1.2 Identification

The set of parameters to estimate includes the price sensitivity parameter and the drug's age coefficient, α and δ, 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_0 and σ_1. The patient and 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, 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, since there is no outside option. 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_0 and σ_1. 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. Figure 7 presents the average of the physician's belief about μ_{nj} (vertical axis) as she accumulates experience signals (horizontal axis), for different levels of prior mean, μ_j^0, and variance, V_j^0. The extent of prescriptions made without experience identifies the initial prior mean. The product-specific variance parameters are identified by the increase in the propensity to prescribe a product as the physician accumulates experience signals.

Endogenous CGM adoption 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. Any individual and time-specific component that does not vary across drug choice alternatives cancels out in the logit specification. Second, the cluster-level product fixed effect accounts for product-level unobserved heterogeneity across patient groups. As a result, 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 concern is addressed in Section 3.2.

Figure 7: Identification of beliefs
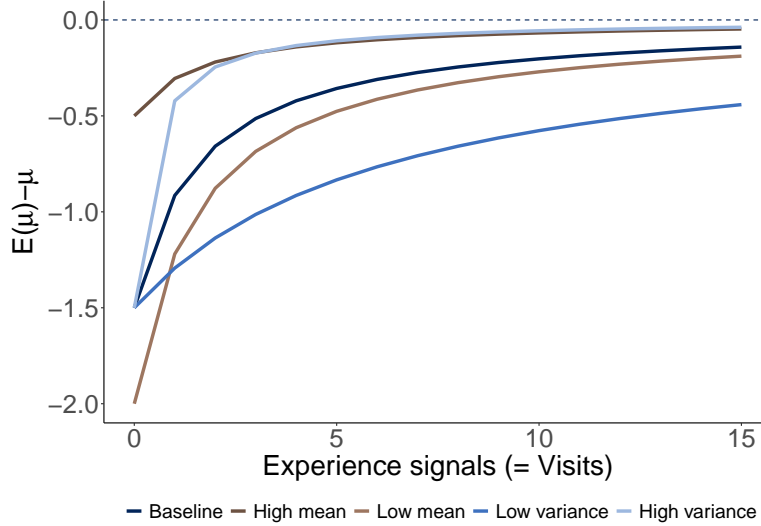
Notes: This figure illustrates the evolution of the physician's beliefs about μ_{nj} (vertical axis) as she accumulates experience signals (horizontal axis) from patients who return to her practice while using the new product j. Each piece of feedback corresponds to one visit where the patient shares their experience with product j. Physicians are assumed to form normally distributed priors regarding the drug's effect on the average glucose level, μ_{nj} at $t = 0$, and update their beliefs from the Bayes rule based on normally distributed signals. Here, $\mu_{nj} = 0$, and the figure depicts alternative updating of beliefs over time for varying prior means (in brown) and varying prior variances (in blue).

5.1.3   Estimation

Given Equation (16) and the distribution of ε_{ikjv}, the likelihood of observing choice j by physician k for patient i, $\mathcal{L}_{ikjv}$, using a_{iv}, in appointment v is given by

$$
\begin{aligned}
\mathcal{L}_{ikjv} &= \Pr(\mathbb{E}(U_{ikjv}|\mathcal{I}_{kv}; a_{iv}) > \mathbb{E}(U_{ikj'v}|\mathcal{I}_{kv}; a_{iv}) \; \forall j' \neq j) \\
&= \frac{\exp(u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}))}{\sum_{\forall j'} \exp(u_{ikj'v}(p_{j'v}, d_{j'}, a_{iv}|\mathcal{I}_{kv}))}
\end{aligned}
\tag{20}
$$

While physicians observe the realization of the signal, e_{ikj}^v, entering into $\mathcal{I}_{kv}$, 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

$$
\mathcal{L}_k = \int_{-\infty}^{\infty} \left[\prod_{v=0}^{V^k} \prod_{\forall j} \left(\frac{\exp(u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}))}{\sum_{\forall j'} \exp(u_{ikj'v}(p_{j'v}, d_{j'}, a_{iv}|\mathcal{I}_{kv}))} \right)^{y_{ikj}^v} |\vec{e}_k \right] dF(\vec{e}_k)
\tag{21}
$$

where $\vec{e}_k = \{e^1_{ikj}, ..., e^{V_k}_{ikj}\}$, 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 are estimated via simulated maximum likelihood by taking the simulated log-likelihood of the sample.[31]

$$\log L = \frac{1}{\mathcal{K}} \sum_{\forall k} \log \frac{1}{M} \sum_{\forall m} \left[\prod_{v=0}^{V^k} \prod_{\forall j} \left(\frac{\exp(u_{ikjv}(p_{jv}, d_j, a_{iv}|\mathcal{I}_{kv}))}{\sum_{\forall j'} \exp(u_{ikj'v}(p_{j'v}, d_{j'}, a_{iv}|\mathcal{I}_{kv}))} \right)^{y_{ikjv}} |\vec{e}^m_k \right] \tag{22}$$

5.1.4 Results

Estimates Table 3 presents the estimated parameters, excluding the match value components, μ_{nj}, $\beta_1(x_i)$, and $\beta_2(x_i)$. The price sensitivity of demand is small, negative, and not statistically significant. Table 4 provides the corresponding mean own and cross-price elasticities of demand for each product, indicating that demand is very inelastic. This finding is consistent with the literature on pharmaceutical demand, closely aligns with the estimates for insulins reported by Einav et al. (2018) for elderly individuals in the U.S. (-0.02), and is not surprising given the French mandated health insurance full coverage of diabetes treatments.

The second part of Table 3 presents the parameter estimates of the physicians' prior beliefs, μ^0_j and V^0_j. The initial prior means, $\widehat{\mu}^0_j$, are significantly negative and lower than their true value, $\widehat{\mu}_{nj}$ (displayed in Table 5), indicating that physicians are initially reluctant to switch existing patients to new products. The estimates display heterogeneity in μ^0_j and V^0_j. Physicians' beliefs regarding the 24-hour biosimilar seem particularly pessimistic and uncertain. In contrast, the 36-hour product exhibits a higher prior mean and a lower variance, which aligns with the characteristics of this new product. This product is indeed derived from the same molecule and produced by the same manufacturer as the 24-hour drug already on the market, for which physicians have accumulated significant experience.[32]

The speed at which physicians learn about μ_{nj} is influenced by the estimated initial prior mean, $\widehat{\mu}^0_j$, the true value, $\widehat{\mu}_{nj}$, the prior variance, $\widehat{V}^0_j$, and the precision of experience signals, $\widehat{\sigma}_0$ and $\widehat{\sigma}_1$. The experience signals are notably imprecise — their magnitude ranges from 1.6 to 3.8 times that of the initial level of uncertainty — and signals generated by CGMs are neither more nor less precise as $\widehat{\sigma}_1$ is small and not statistically significant.[33] It takes approximately four experience signals for physicians to resolve more than half of the difference between the

---

[31]The 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.

[32]For example, the effects of the existing 24-hour drug on cardiovascular outcomes are well known by physicians who have been prescribing this insulin product since the early 2000s.

[33]This 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.

prior mean and the true value for μ_{nj}.

Table 5 displays the estimated match values derived from the estimates for μ_{nj}, reflecting the physicians' beliefs about Θ_{ij} for patients without a glucose sensor after resolving the initial level of uncertainty regarding μ_{nj}. In most instances, $\widehat{\mu}_{nj}$ is significantly greater than zero for new drugs other than the 24-hour biosimilar, indicating that newly introduced products slightly outperform the 24-hour treatment in this regard once uncertainty is resolved.[34]

Figure 8 displays the physician's match value expectations, $\mathbb{E}(\Theta_{ij})$, with (triangles) and without (squares) a glucose sensor. The difference between the average expected match value with and without the sensor corresponds to the average ν_{ij} for the corresponding product j within a group, compared with the (reference) 24-hour product. On average, ν_{ij} accounts for 34% of the clinical match value, Θ_{ij}. The figure highlights that the contribution of the preference for the drug's effect on the glucose profile is heterogeneous across products and patient groups. On average, the difference with the reference good increases for insulin products with a duration of action exceeding 24 hours. The *perceived* match value of these new products improves due to the information generated by the glucose sensor, allowing these products to benefit from the data about the glucose profile provided by the device.

Table 3: Dynamic parameters

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

Notes: Standard errors are computed from the average of the score. The model is estimated using a sample of 150 diabetes specialists who work outside of hospital settings.

Model fit To document the fit of the demand model estimates with the data, I use the parameter estimates to simulate the choices and choice probabilities for each product at every medical appointment v. The sets of medical appointments assigned to a particular physician k, the identity of the patient i, and the choice of glucose monitoring technology, a_{iv}, are kept constant. I also fix the previous insulin product choices, $j_{i,v-1}$, to update physicians' prior

---

[34]For the 24-hour biosimilar, μ_{nj} is assumed to be equal to the value of the branded version.

Table 4: Own and cross-price elasticities

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

Notes: Average across patients.

Table 5: Preference for the drug's effect on average glucose level, μ_{nj}

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

Notes: Standard errors are computed from the average of the score. 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').
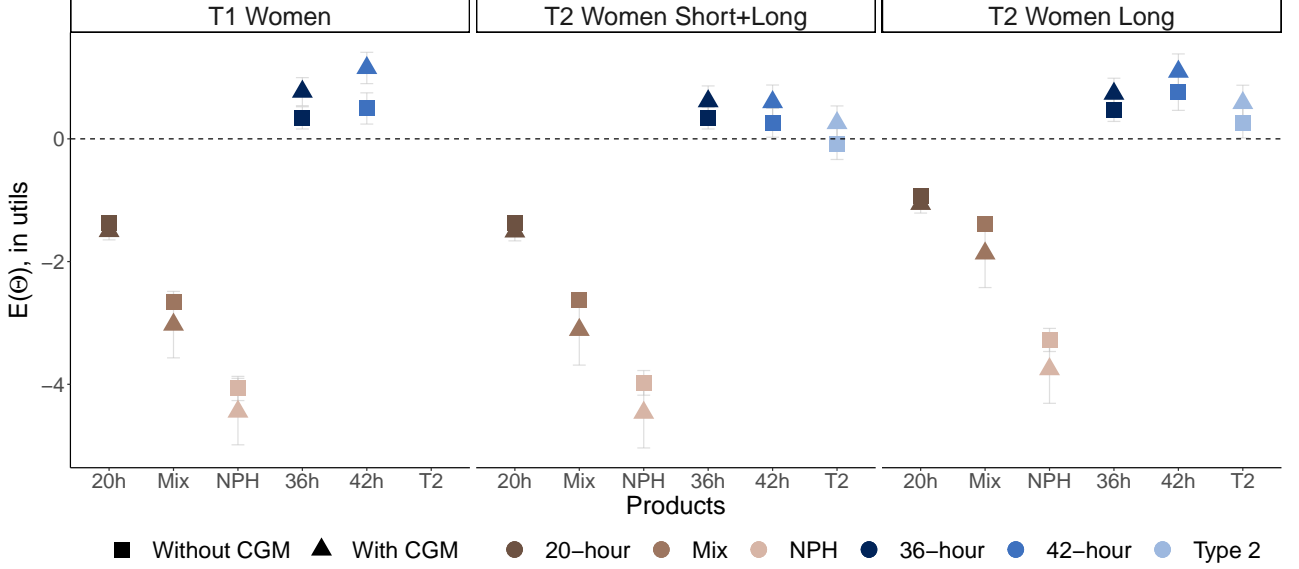
beliefs. I also compute the average predicted choice probabilities in an environment where the predicted choice at v influences future prescription learning, to illustrate the empirical model's capability to reproduce the diffusion pattern observed in the data.

Figure 9 displays the average predicted choice probabilities per product per quarter, along with the empirical insulin product shares, and the fully simulated average choice probabilities. The parameters generally overestimate prescriptions for the 36-hour product compared to the actual choices made by physicians during the years immediately following the product's introduction. To a lesser degree, the model slightly overestimates prescriptions for the 42-hour drug from 2019 to 2021. Figure A16 compares realized and predicted choices, while Table A4 shows the frequency of accurate predictions across years and patient groups. The accuracy rates range from 31% to 82%, similar to those reported in Dickstein (2021), who estimates a demand model with learning for antidepressants in the U.S.

5.2 Price setting model

The unknowns in the Nash bargaining first-order conditions are the marginal costs, c_{jt}, and the bargaining parameters, b_{ft}, as the remaining elements are observed or can be computed from the estimates of the demand system (Equation 14). These unknown primitives must be recovered to compute the equilibrium insulin prices under alternative scenarios. Yet, the first-order conditions generate a system of $\mathcal{J}_{ft}$ equations and $\mathcal{J}_{ft} + 1$ unknowns, leading to an

Figure 8: Perceived match value with/without a CGM

Notes: This figure presents the perceived match value, $E(\Theta_{ij})$, both without the technology (■) and with a CGM (▲) in utils (vertical axis) for each product (horizontal axis). The expectation assumes that $\mathbb{E}(\mu_{ij}) = \mu_{nj}$ for patient i in group n, resolving the initial uncertainty surrounding μ_{ij} for new drugs. The perceived match value without the technology corresponds to μ_{nj}. In contrast, the perceived match value with the technology is $\mu_{nj} + \nu_{nj}$, where ν_{nj} is the average across patients within a cluster. The 24-hour product (not shown) corresponds to the normalized good in each group. 'Mix' refers to insulin mixes, 'NPH' denotes human insulins, and 'Type 2' designates the combination of long-acting insulin and another molecule, meant exclusively for type 2 diabetes patients. New drugs are represented in blue, while old products are in brown. Only three clusters out of seven patient groups are displayed. The remaining clusters are presented in Figure A15.

identification challenge common in the Nash bargaining literature (Grennan (2013)).

### 5.2.1 Empirical specification and identification

To overcome this identification challenge, 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 in 2016, using the estimates from Gotham et al. (2018), and ζ_{jt} is an unobserved cost shock.[35] Second, the bargaining weights are assumed to be firm-specific and constant over time, denoting $\beta_f \equiv \frac{1-b_{ft}}{b_{ft}}$. Combining these two restrictions with Equation (14), we obtain:

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

The above equation underscores the common endogeneity concern that arises on the supply side between the price and the marginal cost shock. I rely on traditional instruments that are

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

Figure 9: Model fit for product shares
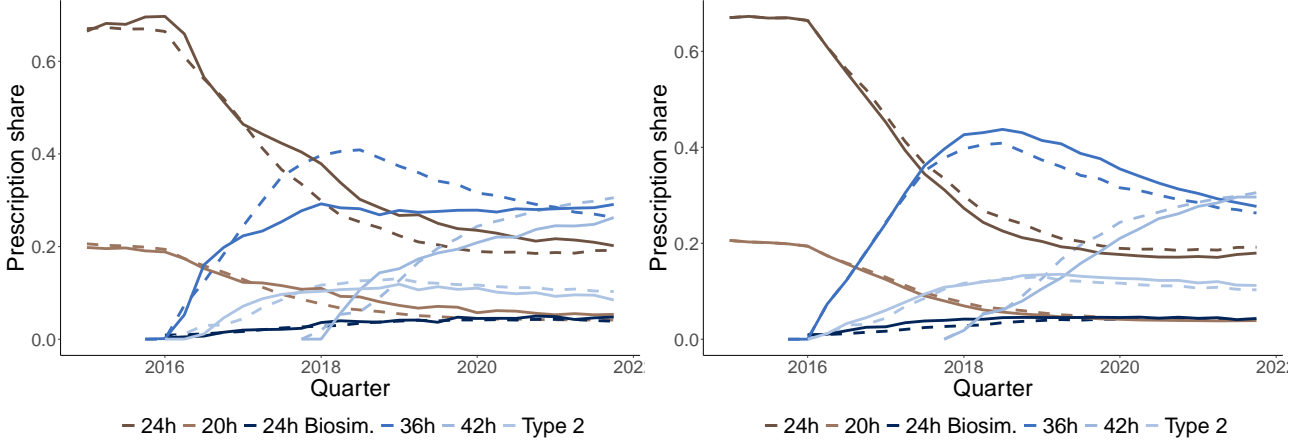
(a) Realized and predicted (dashed) shares (b) Fully simulated and predicted (dashed) shares

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

correlated with price but uncorrelated with the idiosyncratic cost shock, such as the number of competing products. By including firm fixed effects and marginal costs in the set of exogenous variables, I can estimate the bargaining weights and marginal cost parameter via GMM using the following moment conditions:

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

In the main specification, the coefficient for production costs, γ, is set to $\gamma^* = 1.3$ as it is difficult to estimate precisely both marginal costs and firm-specific bargaining weights. γ^* is determined by estimating the model for $\gamma \in [1, 2]$, and choosing γ minimizing the value of the GMM objective function.[36]

5.2.2 Results

The results are presented in Table 6. Insulin mixes (including the new Type II drug) and human insulins are excluded from the estimation, keeping their prices fixed in the counterfactuals. The bargaining weights reflect the drug manufacturer's ability to set a price above its marginal cost when negotiating with the regulator. The estimated manufacturer-level bargaining weights range from 5 to 7%. These figures are significantly lower than those estimated for various prescription drugs by Dubois et al. (2022) in Canada and Tunçel (2024) in France regarding the antidepressant market. This discrepancy may be driven by differences in the price elasticity

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[36]An alternative specification could assume that $\gamma = 1$; however, several reasons rationalize $\gamma > 1$. I rely on the 'competitive' estimates from Gotham et al. (2018). This can also be explained by the cost of the injection device, which is not included in the current estimate, and distribution costs. Indeed, most patients in France rely on insulin pens to inject their insulin, while the current estimates are calculated for vials. Robustness checks can be conducted to account for the cost of the injection device.

of demand, and the specificity of diabetes treatment insurance coverage. With demand being nearly inelastic to prices, the regulator serves as the primary force preventing pharmaceutical companies from setting excessively high prices.[37] The average per-product margin implied by the model lies between 53 and 85%.

Table 6: Bargaining weights estimates

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

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

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

In this section, the estimates from the demand and supply model are used to assess the impact of the insights generated by digital wearables on pharmaceutical demand through various counterfactual scenarios. The framework aims to understand: (i) the effect of information provision on insulin product demand and pricing; and (ii) how CGM information can affect pharmaceutical innovation. In each counterfactual scenario, I compute the new equilibrium drug prices using the price-setting model and the realization of demand.

6.1 Defining relevant market outcomes

Before implementing and comparing counterfactual scenarios, I define the relevant indicators to understand whether and how the market dynamics have shifted owing to the digital device. This section focuses on three key indicators of market 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 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, $\widehat{\mu}_{nj}$, and the average of physician k's

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

belief about μ_{nj} at her last appointment, V_k, denoted $\hat{\mu}_{nkj}^{V_k}$, as a proxy for the accuracy of physicians' beliefs at the end of the sample period.[38] A smaller difference indicates a more accurate belief about product j. Consumer welfare must account for the discrepancy that exists between decision and experienced utility (Section 4.1.4). Denoting $\mathbf{p}$ the equilibrium prices, $\mathbf{d}$ the vector of product durations, d_j, and $\mathbf{a}$ the vector of CGM usage in the patient population, the expected indirect utility for patient i from the choice made on his behalf by physician k at time v is:

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

where $s_{ikjv}(\mathbf{p},\mathbf{d},\mathbf{a})$ denotes the choice probability, given by Equation (20). This expression allows for a comparison of consumer welfare under alternative market outcomes, m, using the compensating variation.[39] Note that the welfare induced by the digital device for patients is beyond what is measured in this project, as I restrict my attention to the impact of the device on the long-acting insulin market.

6.2 Digital device adoption and the insulin market

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

Figure 10 illustrates consumer welfare induced by the introduction of CGMs. Figure 10a shows the compensating variation (vertical axis) in euros per day following a prescription occurring in period t (horizontal axis). The average consumer welfare is presented for patients with a CGM (blue curve) and those without (brown curve). The average is computed by including all patients (solid lines) and by restricting to patients eligible for CGM insurance coverage (dashed lines). Three insights emerge. First, the average welfare gains for CGM users are nearly ten

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

[39]The compensating variation is computed as

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

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

times greater than those for nonusers, indicating limited information spillovers between the two groups. Second, among CGM users, welfare gains are greater in the early months of CGM coverage and decline over time. The information generated by the technology is most valuable for patients shortly after drug entry, when physicians face greater uncertainty about the performance of new products on real-life patients. CGMs should continue generating positive consumer welfare gains for users in the long run — as physicians gather sufficient experience with new drugs — due to the information about the glucose profile, ν_{ij}. Third, for nonusers, the welfare gains take longer to materialize. Physicians must observe the performance of new drugs from patients with the device for the information to benefit nonusers. Nonuser gains should converge to zero as physicians accumulate enough knowledge about new drugs. Figure 10b displays the distribution of consumer welfare gains across patients using CGM, distinguishing between individuals with Type I and Type II diabetes and with different demographic characteristics. Patients with Type I diabetes benefit more than those with Type II diabetes do, and women tend to benefit more than men within each diabetes type. These findings align with the medical literature, which suggests that patients with a long history of diabetes and women are more prone to low overnight glucose levels, a condition for which CGMs provide relevant insights (Siamashvili et al. (2021)) and which is triggered by some insulin products already on the market.

Considering physician learning, Figure 11 compares the difference between $\hat{\mu}_{nj}$ and $\hat{\mu}_{nkj}^{V_k}$, that is, the preference for the drug's effect on the average glucose level, and the end-of-period physician-level prior mean. This difference is computed for each physician, k, patient group, n, and new product j. The figure plots belief 'accuracy' without the device (horizontal axis) against its value when the technology is available (vertical axis).[40] Points above (below) the 45-degree line indicate more (less) accurate beliefs about product j when the device is available. Interestingly, while CGMs accelerated learning about some products (e.g., the 42-hour product), they did not enhance learning for others (e.g., the 24-hour biosimilar). Three factors drive this heterogeneous impact: (i) the contribution of ν_{ij} to the match value, Θ_{ij}, is heterogeneous across insulin products and new drugs with a duration of action exceeding 24 hours have a higher perceived match value owing to the information generated by glucose sensors; (ii) physicians face a limited number of opportunities to gain experience with new drugs such that products compete over these opportunities; and (iii) the experience signals from CGM users about μ_{nj} are as precise as those received from regular patients. By generating new observable

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[40]In this context, prior beliefs are inaccurate relative to the true partial information match value. The results from the estimation suggest pessimistic prior beliefs since $\hat{\mu}_j^0 < \hat{\mu}_{nj}$ for each new drug j and patient group n.

drug attributes, such as a drug's performance regarding overnight glucose levels, for both old and new products, glucose sensors direct insulin demand for CGM users toward drugs that excel in these dimensions. These products are also new to the market. As patients return to their physician while using the new product, the physician learns about μ_{nj} from their experience. This opportunity to learn about μ_{nj} would not have arisen if the patient had not been switched to that drug based on the information provided by his sensor (ν_{ij}). However, because the number of appointments fixes the number of learning opportunities and experience signals from CGM users are not more precise than those from patients without the device, the physician learns slightly more slowly about new drugs that do not excel in these new observable attributes. Consequently, learning about some products may come at the expense of others, and not all new products benefit equally from CGMs' insights.

At the market level, Figure 12 presents the impact of CGMs on drug manufacturers' profits from 2017 to 2021. The effect is heterogeneous, even among new products. Profits for the 42-hour product rose by 23%, driven primarily by the demand response to CGMs (+18%) but also by higher prices, while profits for the biosimilar decreased by 10%. In summary, this counterfactual analysis shows that the introduction of CGMs (i) primarily benefited CGM users with limited spillovers to nonusers, (ii) accelerated physician learning about specific products, and (iii) affected insulin manufacturers' profits.[41]

6.3 Cross-market complementarities

The results from the previous section indicate that the introduction of CGMs did not benefit all drugs equally. The profits from the 42-hour product were 23% higher owing to the insights generated by CGMs, compared with 2% lower for the 36-hour product. This result suggests that CGMs better leverage the potential of certain new drugs. This section documents how innovation in medical devices, which provide new observable drug attributes, impacts the value of new products in pharmaceutical markets. This analysis quantifies the benefits derived from the complementarity between the data insights generated by the device and the characteristics of insulin products and examines how medical devices can affect the value of certain innovations. Following Petrin (2002), I assess the benefits of new products using consumer welfare.

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[41]The limited spillovers to nonusers may be influenced by the unequal propensity of physicians to see CGM patients (Table A3). In the extreme case where all patients in the same cluster are either adopting or not at a physician practice, spillovers cannot arise. To explore this further, I conduct a counterfactual reallocation of glucose sensors among eligible patients, accounting for patient demographics that may correlate with adoption (details in Appendix E.1). Figure A18 shows that reallocating sensors does not increase spillovers to nonusers. This finding indicates that the variation in CGM adoption across physicians is not the primary driver of limited spillovers. However, this counterfactual does not address how spillovers could be enhanced by allocating sensors to patients with *different* demographic characteristics.

Figure 10: Glucose sensors and consumer welfare

(a) Average over time

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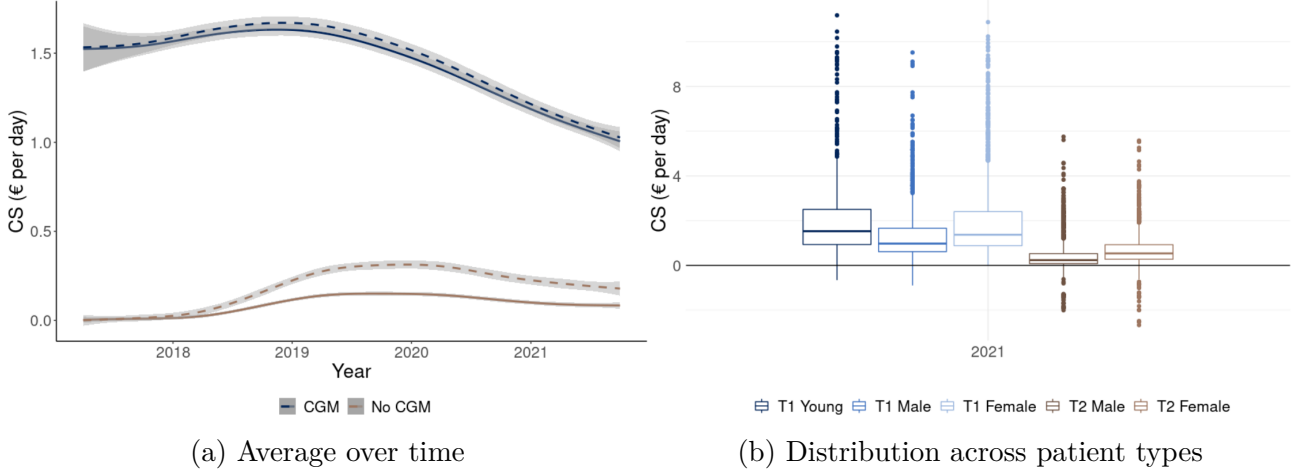
Notes: Figure 10a presents the compensating variation (vertical axis), in euros per day, following a prescription occurring in period t (horizontal axis). The average consumer welfare is presented for patients with CGMs (blue curve) and without CGMs (brown curve). The dashed lines focus on the consumers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

For each new product, I simulate market outcomes in which the new product has not entered and CGMs are unavailable while keeping competitors' price and entry decisions unchanged. From that baseline scenario, I consider unilateral deviations in the entry decision for the 36-hour and 42-hour products and in the availability of CGMs for diabetic patients.[42] For each product j and patient i, I denote $\Delta CS_{ij}^{e,a}$ as the change in consumer welfare in situations where the product enters or not, $e \in \{1, 0\}$, and whether or not the technology is available, $a \in \{1, 0\}$, compared with the baseline scenario where $e = 0$ and $a = 0$. When $a = 1$, the adoption of glucose sensors in the patient population is set to the observed one. I consider the following decomposition:

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

where $\Delta CS_{ij}^{1,1}$ captures the welfare gains from the entry of drug j alongside CGMs, $\Delta CS_{ij}^{1,0}$ represents the gains from product j had CGMs not been available, and $\Delta CS_{ij}^{0,1}$ represents the gains generated by CGMs had drug j not entered the market.[43] The term Γ_{ij} measures the difference between the welfare gains from the entry of two innovations (device + drug j) and the unilateral contribution of each innovation, absent the other. A positive Γ_{ij} suggests that the welfare gains from product j and CGM entries together are greater than the sum of the gains from product j and those from CGMs unilateral decision, indicating synergies between the two innovations.

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

[43]In the last case, CGMs still affect insulin demand absent new drugs entering the market through ν_{ij}.

Figure 11: Glucose sensors and physician-level learning
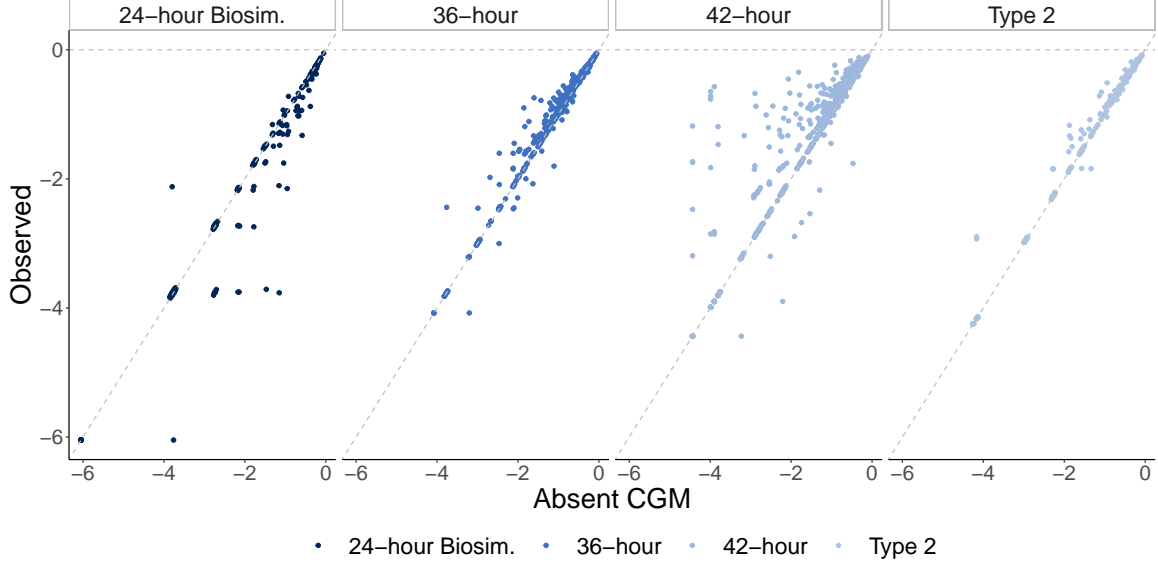
Notes: This figure plots the difference between $\hat{\mu}_{nj}$ and $\hat{\mu}_{nkj}^{V_k}$, the partial information clinical match value and the end-of-period physician-level prior mean in an environment with CGMs (vertical axis) against its value in an environment without CGMs (horizontal axis). One observation per physician, patient type among types eligible for the technology and product. Points above the 45-degree lines suggest a more accurate belief at the end of the period when the technology is available.

Figure 13 presents the average welfare gains across prescriptions from 2019 to 2021 and computes the average differential gains, $\overline{\Gamma}_j$ for the 36-hour and 42-hour products. The positive $\overline{\Gamma}_j$ for the 42-hour product suggests that the availability of CGMs amplifies the consumer welfare gains from this innovation. In contrast, $\overline{\Gamma}_j$ is negative for the 36-hour product, indicating that the technology does not similarly enhance its gains. The negative $\overline{\Gamma}_j$ for the 36-hour product is driven by the effect of the technology on competing pharmaceutical innovations and, in particular, the 42-hour product. Indeed, the average benefit from CGMs alone, $\overline{\Delta CS}_j^{0,1}$, is twice as high without the 36-hour drug than it is without the 42-hour product.

6.4 Toward product design

The previous sections provide evidence that the new information about drugs' performance provided by digital medical devices influences the consumer surplus and manufacturers' profits derived from the introduction of certain new drugs. This section documents how it can influence innovation incentives for insulin manufacturers. Specifically, I consider how new observable drug attributes on the demand side can affect the characteristics of new products developed by drug manufacturers, hence the direction of innovation. When considering drug development decisions by pharmaceutical companies, France is a small market unlikely to drive innovation on its own. This counterfactual assumes that the French market is representative of the global

Figure 12: Glucose sensors and drug manufacturers' profits from 2017-2021
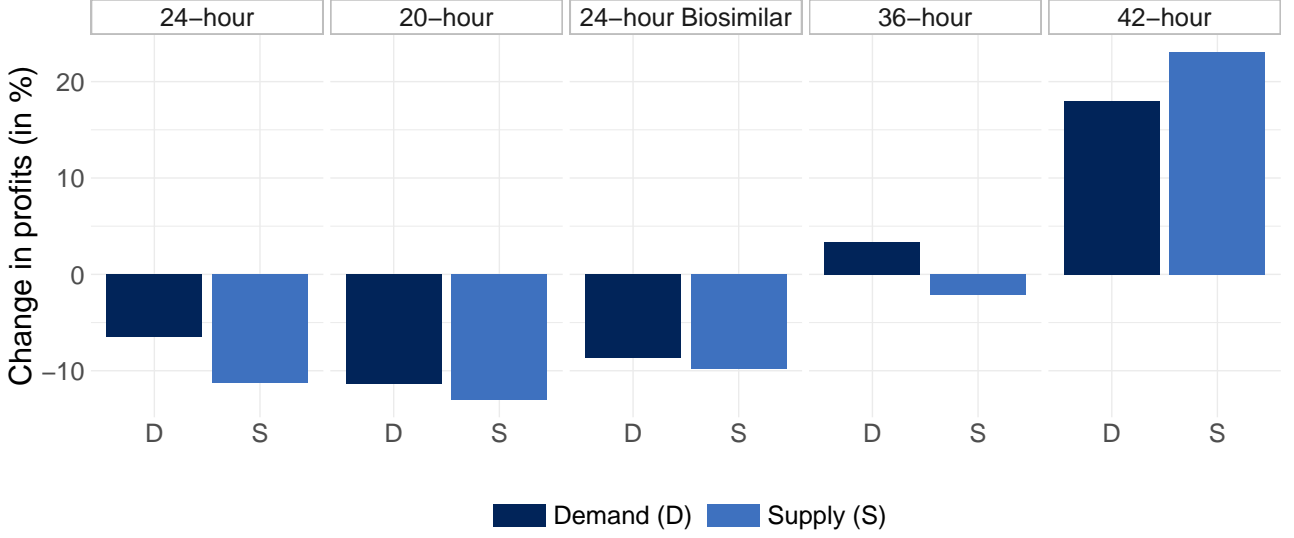
Notes: Change in profits due to the introduction of CGMs from 2017-2021 for each product. The profits without CGMs are normalized to 100 for each product, and each scenario is compared to this baseline. For each product, the first bar corresponds to changes in profits due to CGMs affecting the demand curve, and the second bar accounts for prices to react to the change in demand.

insulin market. I discuss this assumption at the end of the section.

I consider a drug manufacturer f with a set of potential products, $j \in \tilde{\mathcal{J}}_f$, characterized by their match values in the patient population, $\mathbf{\Theta}_j$ and marginal costs, $\boldsymbol{c}_j$. The manufacturer decides which new drug to bring to the market among $\tilde{\mathcal{J}}_f$ in stage 0. In subsequent periods, drug manufacturers and the regulator bargain over prices and demand is realized following the framework described in Section 4. Drug manufacturers have rational expectations about future demand, including CGM adoption, at the development stage. At stage 0, the expected profits from developing product j are denoted $\mathbb{E}(\pi_f^j(\mathbf{p}, \mathbf{a}; \mathbf{\Theta}))$. I assume that firm f develops the product that maximizes expected profits.[44]

$$j^* = \arg\max_{j \in \tilde{\mathcal{J}}_f} \mathbb{E}(\pi_f^j(\mathbf{p}, \mathbf{a}; \mathbf{\Theta})) \tag{27}$$

I assume that the fixed costs of development and time to market are the same across products. This hypothetical scenario considers two potential products: the 42-hour product that effectively entered the market in 2018 and an hypothetical product — the '72-hour' drug — whose characteristics are summarized in Table A6. The '72-hour' drug is designed to appear more or less appealing in the μ_{ij} and ν_{ij} dimensions.[45] I restrict the expected flow of profits to the

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[44]I abstract away from (i) strategic interactions across insulin manufacturers at the development stage, (ii) the decision to develop more than one product, and (iii) the drug approval process. I assume that all products in $\tilde{\mathcal{J}}_f$ would be approved by the regulator and postpone the discussion of this assumption to the conclusion.

[45]The '72-hour' product is designed to resemble the once-weekly insulin approved by the EMA in April 2024. Clinical trial outcomes are used to set μ_{nj}. However, the duration is 72 hours instead of 7 days to reduce the extent of out-of-sample extrapolation. The demand model does not capture the convenience of injecting insulin

Figure 13: Consumer surplus and cross-market complementarities, 2019-2021
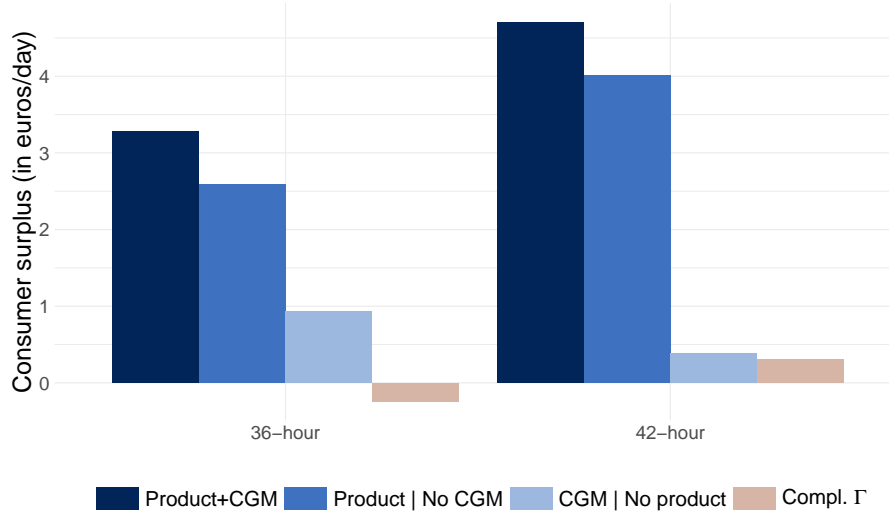
Notes: Each bar corresponds to the average consumer surplus in euros per day. For each product (horizontal axis), the first bar corresponds to the average consumer surplus from the joint entry of the product and CGMs, $\overline{\Delta CS}_j^{1,1}$; the second bar corresponds to the average surplus from the product entry, absent CGMs, $\overline{\Delta CS}_j^{1,0}$; the third bar is the average benefit from CGMs without this product, $\overline{\Delta CS}_j^{0,1}$; and the last bar is the average of the difference between the first bar and the sum of the last two, $\overline{\Gamma}_j$.

first four years following market entry (2018-2021) and compare j^* in an environment with and without CGMs.[46]

Figure 14 presents the firm's profits and consumer surplus under each scenario. Without CGMs, the 42-hour product yields higher profits than the 72-hour version. However, when CGMs are introduced (and adopted) on the demand side, the 72-hour product yields 64% higher profits than the 42-hour one, hence the ranking of profits across products shifts depending on whether CGMs are available. This reordering of innovation profitability also benefits consumers. The consumer surplus from the 72-hour product combined with CGMs is 24% greater than that of the 42-hour product, driven by the 52% increase in consumer surplus owing to the joint entry of the drug and CGMs, as measured by Γ_j. This last result suggests that the most profitable drug candidate can shift on the basis of the technological environment in which demand occurs. By introducing new observable attributes for evaluating drug performance, complementary technologies, such as CGMs, change the incentives for developing new products, potentially affecting the direction of pharmaceutical innovation.

Discussion Innovation in pharmaceutical markets is driven by global profits, and the French market is not large enough to drive innovation on its own. The insights from this counterfactual exercise rely on the external validity of my estimates across geographical markets, which I discuss briefly here. The econometric model estimates preferences for insulin products and

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once a week instead of once a day. Hence, the 72-hour product is assumed to be injected once a day, similar to other available products. https://www.ema.europa.eu/en/medicines/human/EPAR/awiqli

[46]I compute the equilibrium prices with and without CGM and compare the firm's profits in each scenario.

the primitives of the price-setting model. On the insulin demand side, given the adoption of glucose sensors, the results suggest that the device generates new observable patient-specific attributes and limited information spillovers to nonusers. This outcome is likely to hold in contexts beyond France. However, the contribution of ν_{ij} is heterogeneous across patients. The aggregate effect of observing ν_{ij} depends on its distribution in the whole patient population and among patients adopting the device. Hence, the magnitude of the effect may vary.

Considering the price-setting model, the French regulator acts as a monopsony in a small country. This feature affects the external validity of my results for contexts like the US. In more fragmented settings where drug manufacturers bargain with insurers, the disagreement payoffs will affect equilibrium prices and the response of drug pricing to CGM information. Yet, the consumer surplus generated by a given prescription drug also matters for private insurers, who may also be inclined to pay higher prices for drugs that result in a higher match value. However, in contexts other than the French one, drug manufacturers may be able to set their price internalizing the demand-side dynamics across periods.

Last, I take CGM adoption as given. The results suggest little social learning, and the effect comes from insulin demand for glucose sensor users. Hence, the extent and composition of CGM adoption matter. Health insurers' decisions to cover CGMs and under which conditions are beyond the scope of this paper.

Figure 14: Glucose sensors and product design

(a) Product design and firm's profit

(b) Product design and consumer surplus, 2019-2021
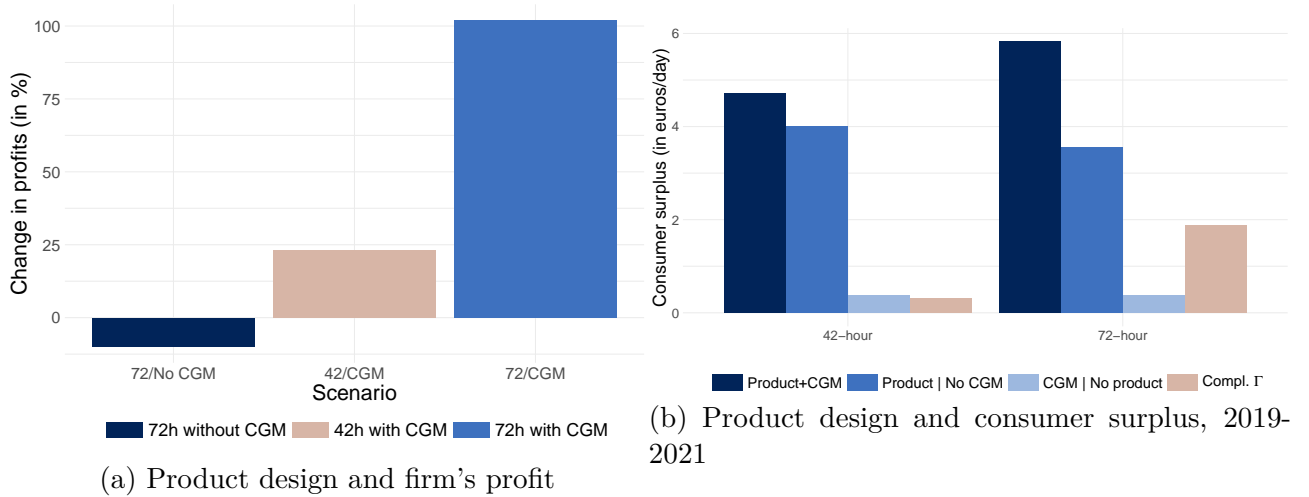
Notes: Figure 14a plots the changes in profits compared with the profits from the entry of the 42-hour product in an environment without CGMs. The first bar corresponds to the difference in profits if the 72-hour product enters an environment without CGMs. The second bar corresponds to the profit difference if the 42-hour product enters an environment with CGMs, and the third bar corresponds if the 72-hour product enters an environment with CGMs. Figure 14b plots the average consumer surplus in euros per day using the decomposition from Equation (26). For each product (horizontal axis), the first bar corresponds to the average consumer surplus from the joint entry of the product and CGMs, $\overline{\Delta CS}_j^{1,1}$; the second bar corresponds to the average surplus from the product entry, absent CGMs, $\overline{\Delta CS}_j^{1,0}$; the third bar is the average benefit from CGMs without this product, $\overline{\Delta CS}_j^{0,1}$; and the last bar is the average of the difference between the first bar and the sum of the last two, $\overline{\Gamma}_j$.

7 Conclusion

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

The results of the structural estimation highlight how insights from digital health data reshape physicians' preferences when prescribing insulin to diabetic patients. Despite significant information frictions about new products, affecting both CGM users and nonusers initially, consumer welfare gains mostly accrued to patients using the device, while the benefits to nonusers were ten times smaller. The technology had a heterogeneous effect across new products. Physicians learn faster about new drugs that present features relevant to overcoming the flaws of existing drugs revealed by the technology. By inducing CGM users to switch treatment away from old molecules to these new drugs, the device generated opportunities to learn about the quality of the drug that would not have occurred without the technology. As CGMs did not improve the quality of the experience signals received by physicians about new drugs and the number of learning opportunities remained fixed, physicians would have learned more about some products without the device. This paper highlights the cross-market complementarities between medical devices and pharmaceuticals, exploring the potential long-term effects of CGMs on the insulin market. Specifically, digital technologies that introduce new observable attributes into pharmaceutical demand can affect the direction of pharmaceutical innovation since the most profitable innovation strategy can vary depending on the technological environment in which insulin choices are made.

This study opens several important avenues for future research. First, estimating the patient-product clinical match values does not separately identify the preference for the effects on the average glucose level and the glucose profile from their level, as they remain unobserved in claims data. Further separating these criteria would shed light on how physicians trade off old and new product attributes. Second, the analysis focuses on the impact of CGMs on existing insulin patients. It does not account for the potential benefits for new insulin users, such as improved diagnosis matching by physicians at therapy initiation (Crawford and Shum (2005)). Third, in analyzing the impact of CGMs on pharmaceutical innovation, I assume

that each drug candidate would be approved by the regulator. In practice, regulatory approval is typically based on a predefined set of clinical endpoints, and new endpoints derived from digital devices may not be recognized. This gap introduces additional uncertainty for pharmaceutical companies during product development that may discourage investment in drugs targeting attributes observed through CGMs. The inefficiency resulting from the misalignment of regulatory agencies' criteria with clinical practice is an interesting avenue for future research. Finally, this project focuses on cross-market externalities, and a complete welfare analysis of CGMs is beyond its scope. Since CGMs increase monitoring costs relative to traditional devices, broad coverage significantly increases healthcare expenses. Identifying which patients benefit most from CGM data and how they benefit would be crucial for designing an optimal coverage strategy (Chandra and Skinner (2012), Conner et al. (2024)). Their impact on the organization of care also presents important avenues for research that could inform policy debates, as healthcare systems such as the NHS in the UK consider adopting these technologies to support system reform.[47]

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[47]https://www.independent.co.uk/news/uk/politics/nhs-smartwatches-diabetes-streeting-labour-b2632165.html accessed on October 25th, 2024.

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# A Additional figures and tables

Figure A1: Glucose variability
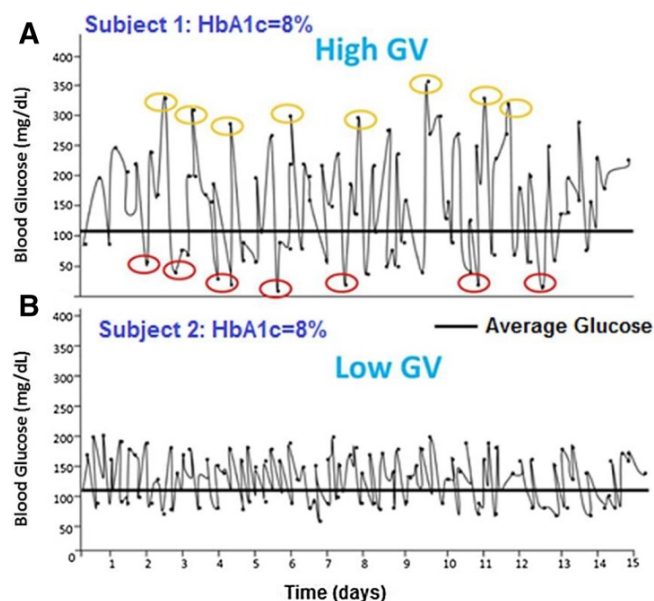
Notes: Different patterns of glycemic variability (GV) in two patients with same hemoglobin A1C (HbA1c). 15-day glucose traces of two patients who had identical HbA1c of 8.0% but different degrees of GV. High GV in patient 1 was reflected by numerous episodes of both hypo- and hyperglycemia (a), whereas low GV in subject 2 resulted in no such episodes (b). Patient 1 (a) had visibly higher glucose fluctuations than patient 2 (b) that resulted in seven episodes of moderate hypoglycemia ($\leq$ 50mg/dL) and eight episodes of moderate hyperglycemia ($\geq$ 350mg/dL). Reproduced from Chehregosha et al. (2019) under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/). No changes were made to the original figure.

Figure A2: Continuous Glucose Monitoring

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

Figure A3: Glucose monitoring volumes and value in France, 2014-2023

(a) Number of tests, in million

(b) Value, in million euros
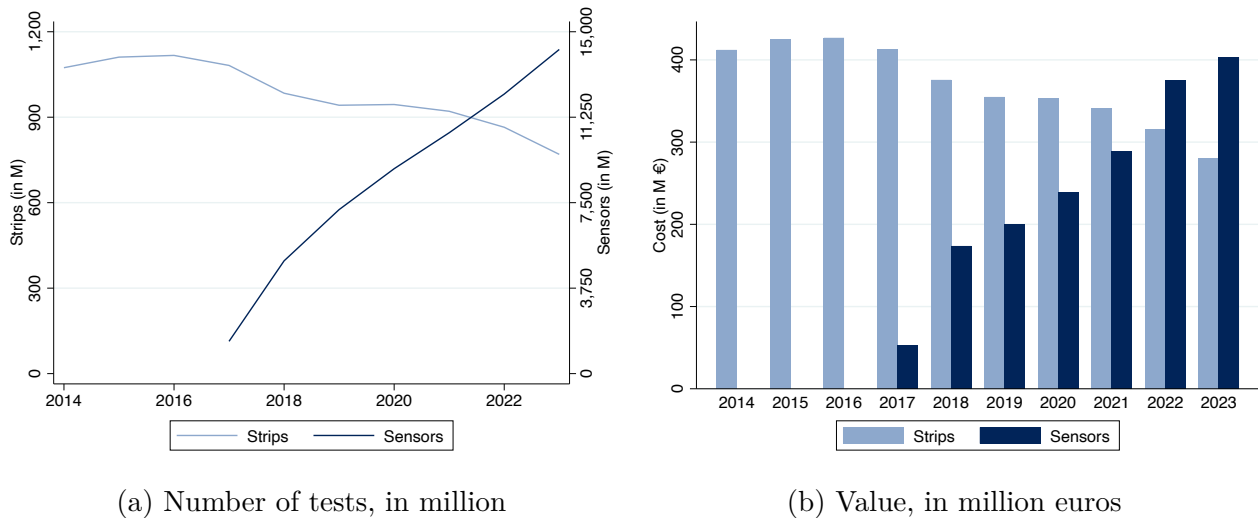
Notes: Test volume and value for all patients in France between 2014 and 2023. In Figure A3a, the number of tests performed via sensors is computed from the number of sensors and frequency of automatic measurement. In Figure A3b, strip costs do not include the cost of the lancing device. Source: Open LPP.

Figure A4: Aggregate insulin sales and prices, 2015-2023
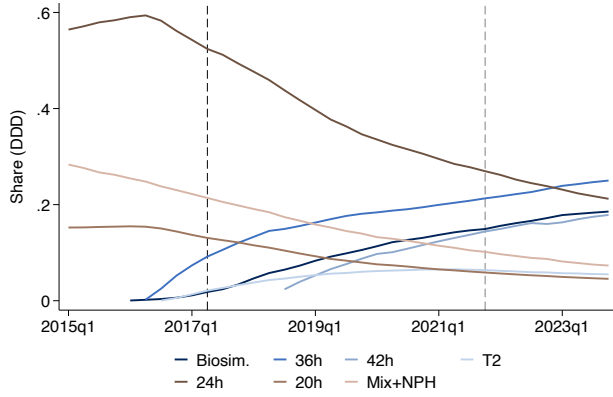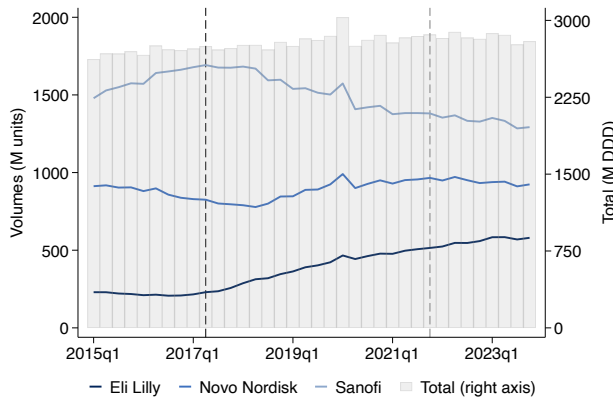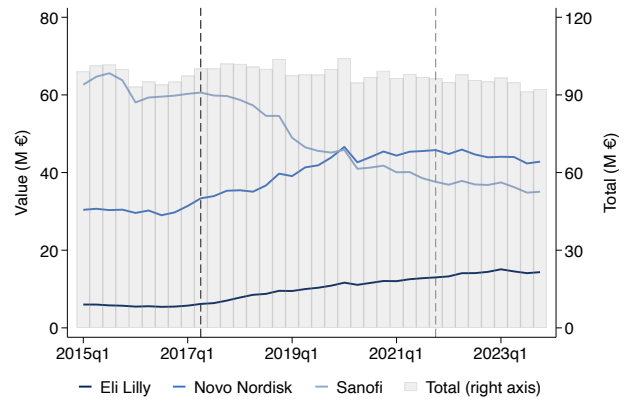

(a) Units reimbursed
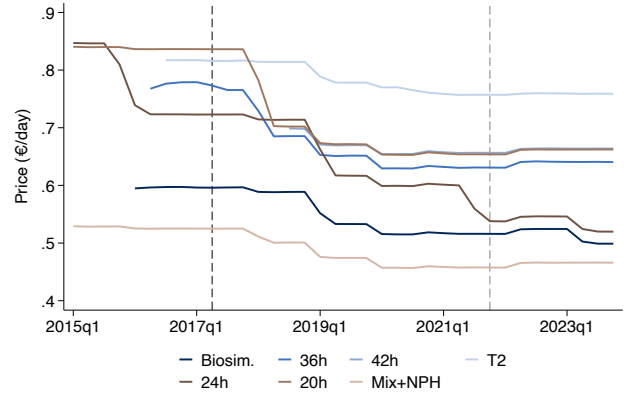
(b) Price per daily consumption

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 A4a plots the share for each product over time as a percentage of all insulin units reimbursed. Figure A4b 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 A5: Sales volume and value, by manufacturer, 2015-2023

(a) Units reimbursed, million units

(b) Sales value, million €

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 A6: Glucose sensor adoption among eligible patients, 2015-2021

(a) Adoption over time

(b) Strips glucose monitoring, volume and cost
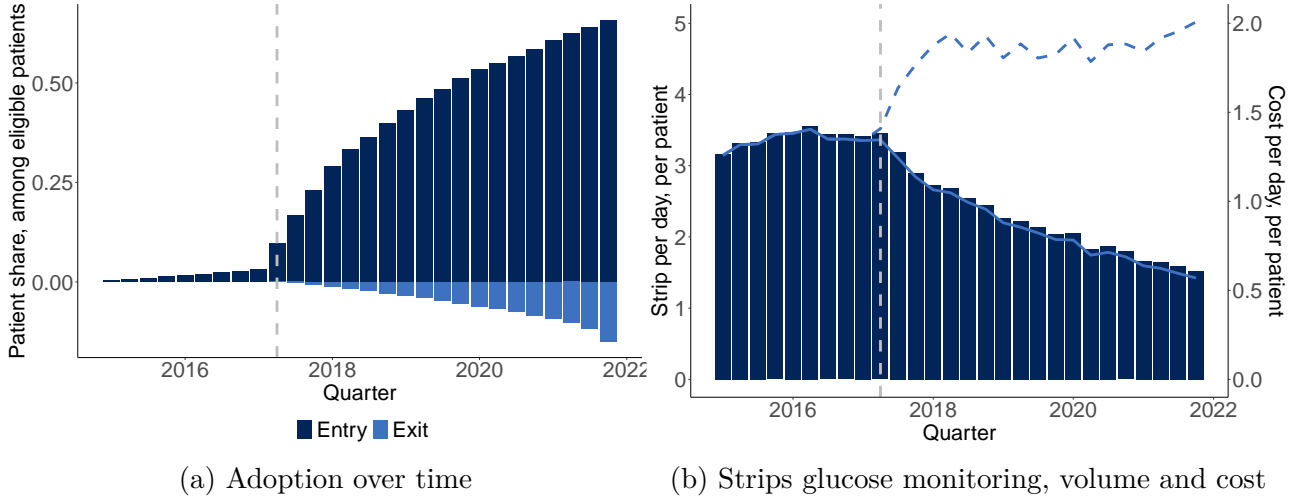
Notes: In each figure, the vertical line represents the start of CGM coverage (second quarter of 2017). Figure A6a presents the stock of patients who ever adopted CGM and dropped out from continuous glucose monitoring over time among eligible patients. The adoption is inferred from the first CGM prescription date. For patients adopting before the coverage decision, the adoption date is identified from the decline in glucose strip reimbursements (Appendix B.2). The exit date corresponds to the expiration of the last sensor claimed at the pharmacy. Figure A6b 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 A7: Insulin pump use among diabetic patients, 2015-2021
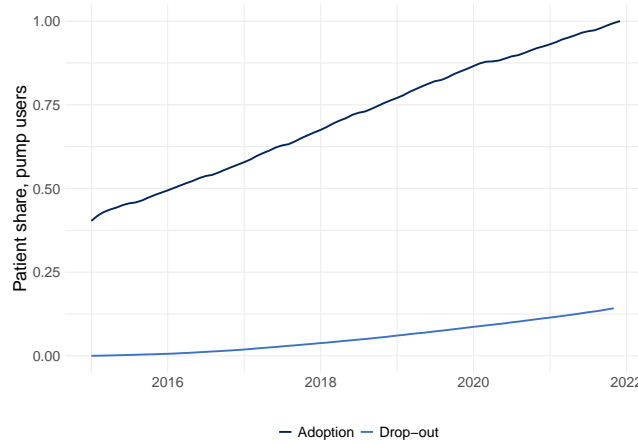
Notes: For each patient with an insulin pump insurance claim between 2015 and 2021, I consider the first and last claims for an insulin pump. The figure plots the cumulative distribution function of the first and last reimbursement dates among patients who use an insulin pump. There is no discontinuity in adoption or dropout after the CGM coverage decision.

Figure A8: Glucose strips reimbursements

(a) Before-after CGM adoption

(b) Non-users over time
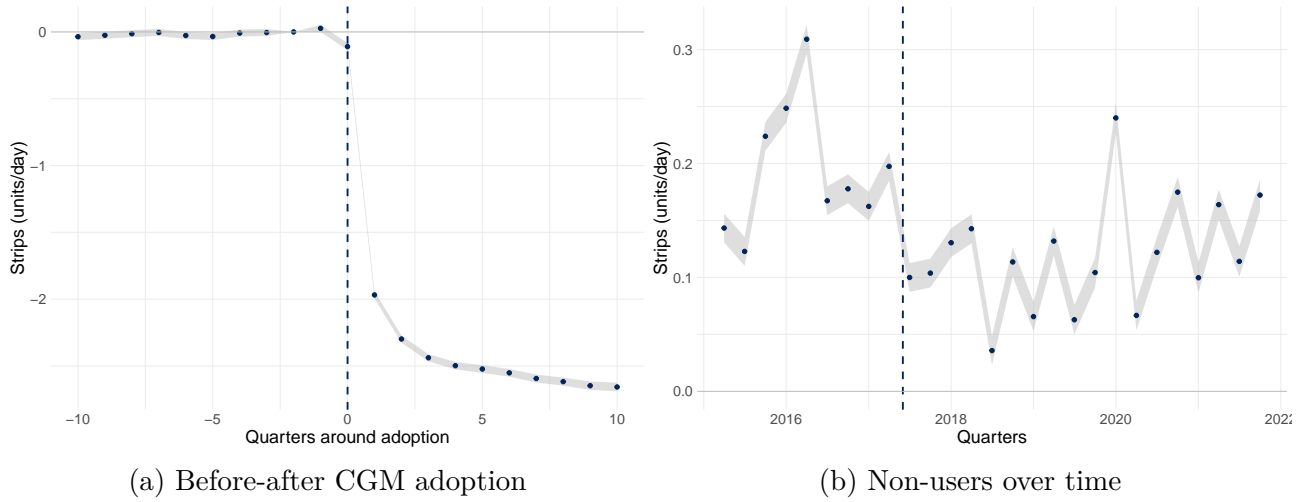
Notes: Figure A8a presents the estimates from an event study model that considers the number of strips reimbursed in the quarters before and after the adoption of a glucose sensor, where the adoption date is identified from a patient's first prescription. The regression includes patient fixed effects and focuses on patients with their first CGM prescription from January 2018 onwards. Figure A8b plots the coefficients of a linear regression of strip reimbursements over time for patients who never use a glucose sensor between 2015 and 2021.

Figure A9: Observed and predicted CGM adoption date for 'early' users
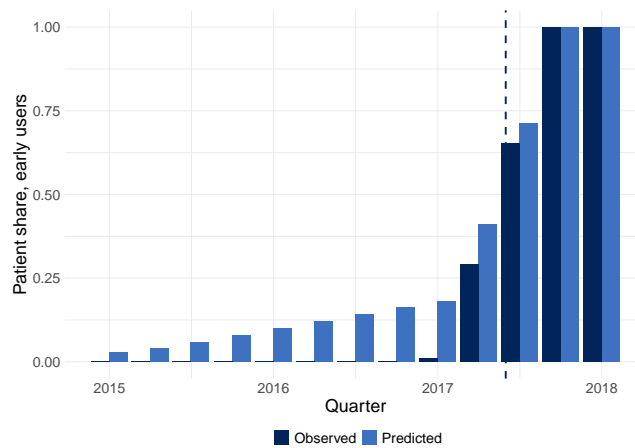
Notes: Figure A9 compares the first CGM prescription date observed in the data to the one predicted by the model presented in Section B.2, and summarized in Table A8 for 'early' users. 'Early' users are patients whose first CGM reimbursement occured before January 2018 such that the first CGM prescription may not coincide with their adoption date. Using patients whose first glucose sensor claim occurs from January 2018 onward, I estimate the discontinuity in glucose strips reimbursements — the alternative glucose measurement technology —- around sensor adoption. I use the estimates from this model to predict the adoption date for patients whose first sensor claim occured before January 2018. Forty thousand patients are adopting before January 2018, among which seven thousand have a predicted adoption date different from their observed date.

Figure A10: Diabetes specialists outside of hospital practices in France

(a) Number of "peers"

(b) Number of practitioners by patient
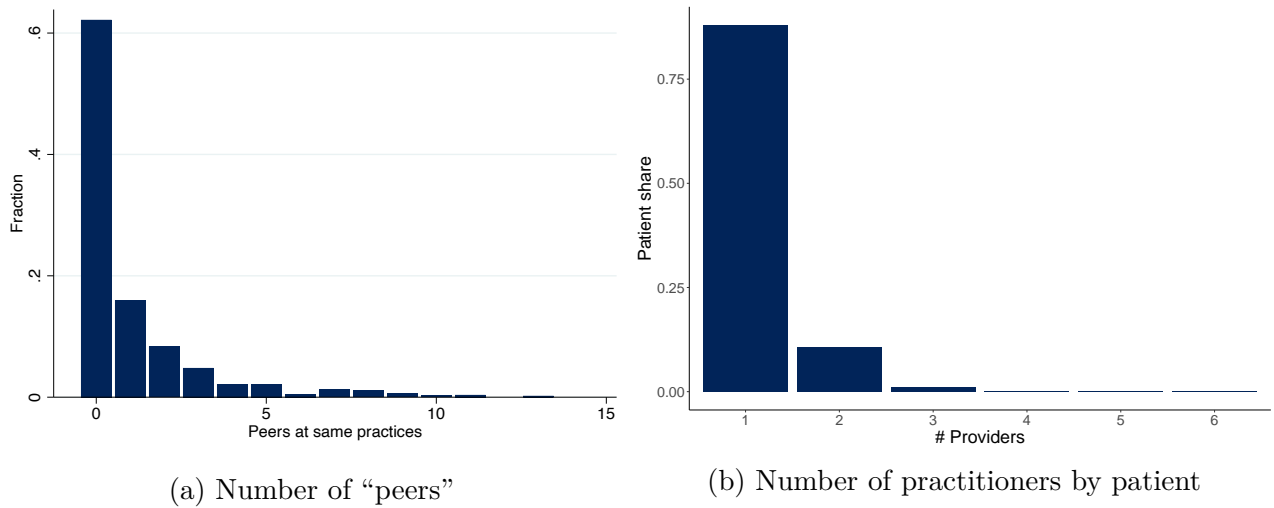
Notes: Using data from the practionners registry in France (available at https://annuaire.sante.fr/web/site-pro/extractions-publiques), Figure A10a represents the number of diabetes specialists working at the same practice for specialists working outside the hospital. 62% are working in an environment without any other diabetes specialist, 78% with at most one peer. Using the administrative claims data, Figure A10b plots the number of diabetes specialists working outside the hospital per patient.
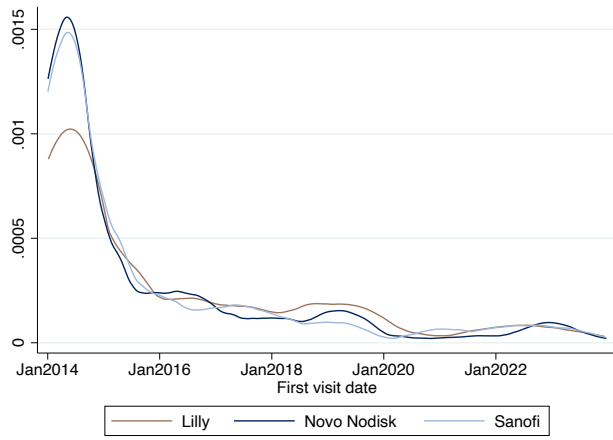
Figure A11: Physician detailing by insulin manufacturers, 2014–2023
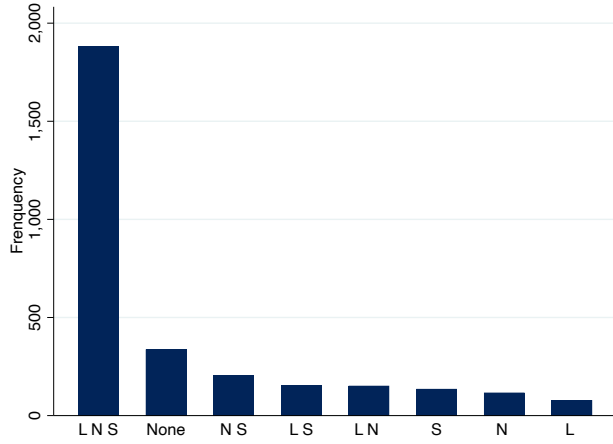
(a) Diabetes specialists interacting with manufacturers
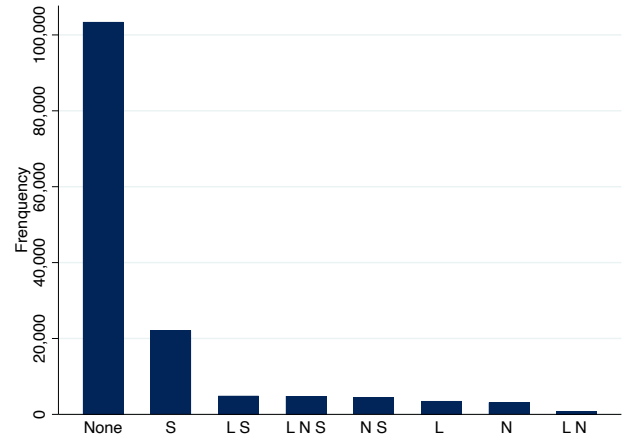
(b) GPs interacting with manufacturers

(c) First detailing to diabetes specialists
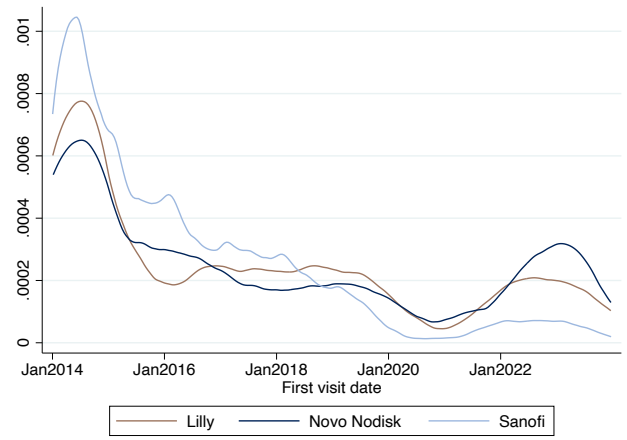
(d) First detailing to GPs

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. Figures A11a and A11b plot the number of physicians interacting with each subset of manufacturers at least once over the period. Figures A11c and A11d plot the distribution of the first interaction between each physician-manufacturer pair.

Figure A12: Switching matrices, by patient group

(a) Using, first visit after adoption

(b) Using

(c) Users, before adoption

(d) Non-users
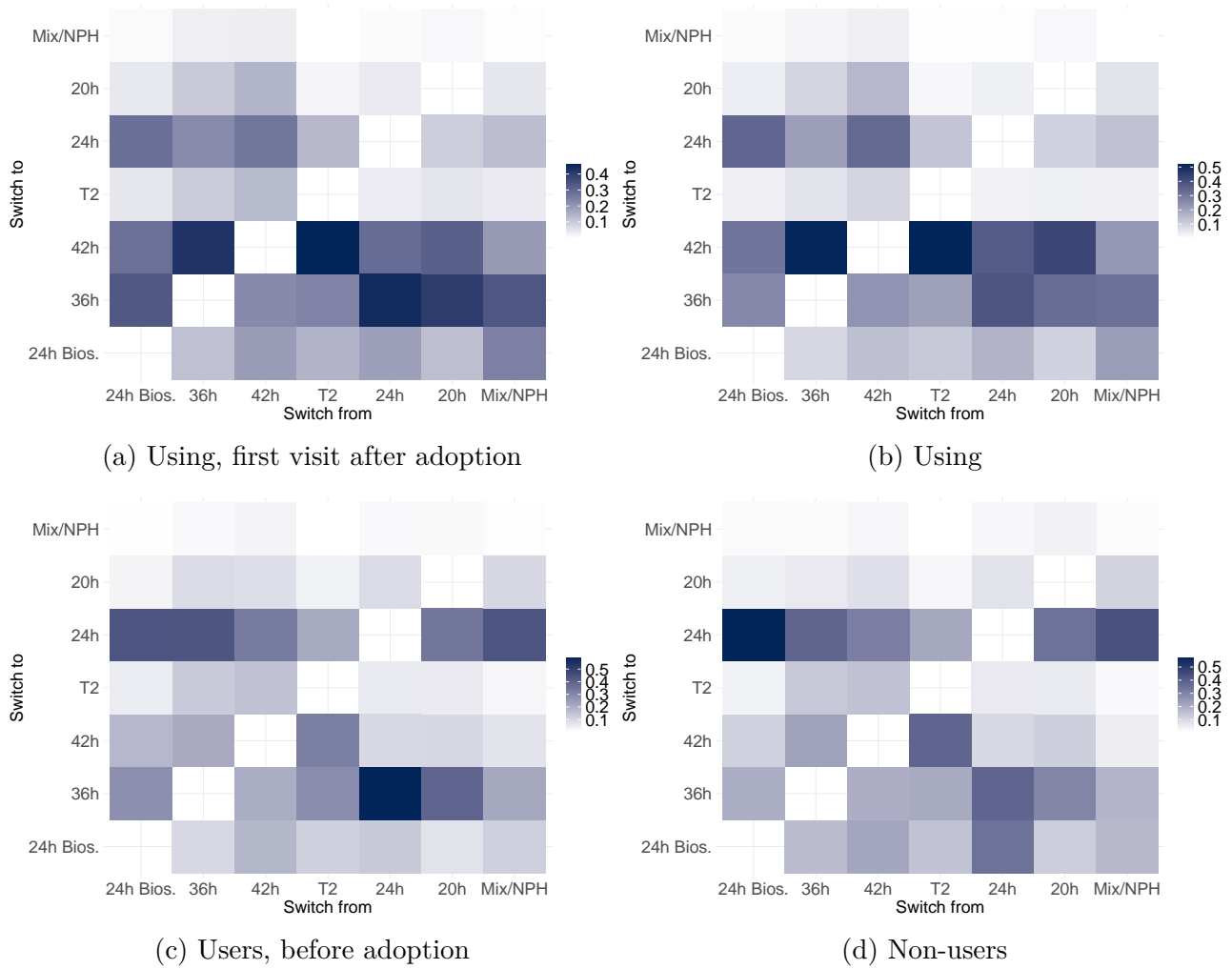
Notes: Focusing on treatment switches, each figure represents the probability of switching to a given product (vertical axis) conditional on the treatment used before switching (horizontal axis) such that each column sums to one. Figure A12a represents the switches that occured the first appointment the patient is wearing a glucose sensor. Figure A12b represents the switches that occured while the patient is wearing a glucose sensor. Figure A12c represents the switches for patients adopting a sensor, before they adopt. Figure A12d represents all switches that occured 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 1).

Figure A13: Physician-level prescription share and information set size, city specialists

Figure A14: Probability of switching back and physician-level information set size, low initial information

Figure A15: Perceived match value with/without a CGM

Notes: This figure presents the perceived match value, $E(\Theta_{ij})$, both without the technology (■) and with a CGM (▲) in utils (vertical axis) for each product (horizont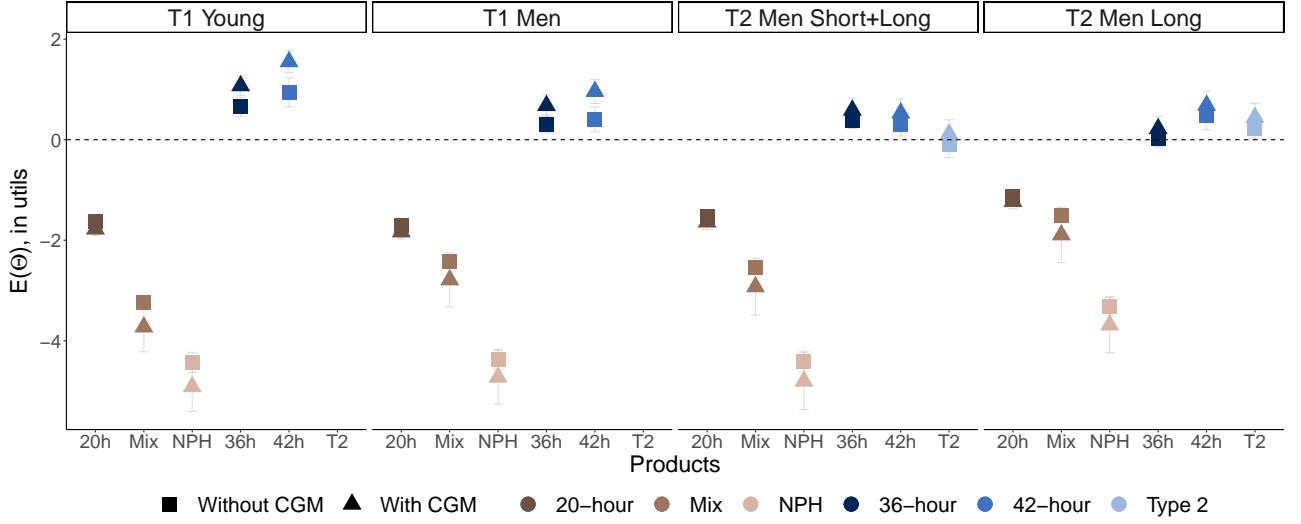al axis). The expectation assumes that $\mathbb{E}(\mu_{ij}) = \mu_{nj}$ for patient i in group n, resolving the initial uncertainty surrounding μ_{ij} for new drugs. The perceived match value without the technology corresponds to μ_{nj}. In contrast, the perceived match value with the technology is $\mu_{nj} + \nu_{nj}$, where ν_{nj} is the average across patients within a cluster. The 24-hour product (not shown) corresponds to the normalized good in each group. 'Mix' refers to insulin mixes, 'NPH' denotes human insulins, and 'Type 2' designates the combination of long-acting insulin and another molecule, meant exclusively for type 2 diabetes patients. New drugs are represented in blue, while old products are in brown. Only three clusters out of seven patient groups are displayed. The remaining clusters are presented in Figure 8.

Figure A16: Model fit: prescribed vs predicted product choice
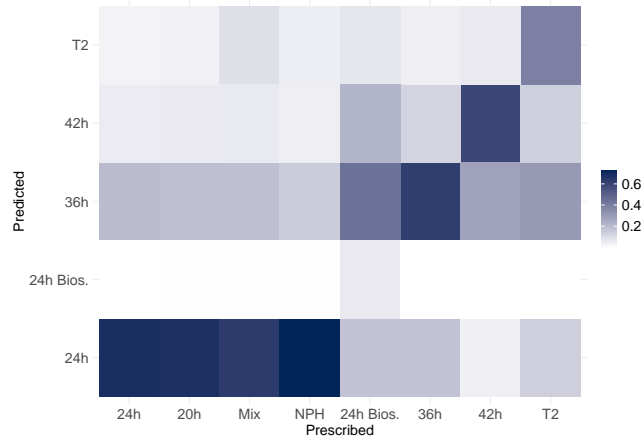
Notes: This figure compares the product prescribed in the actual data j^{obs} to $\hat{j} = \arg\max \hat{u}_{ikjv}$. The idiosyncratic shock is excluded from the prediction. Note that $\hat{j}$ never corresponds to the 20-hour, insulin mixes nor human insulin treatments.

Figure A17: Counterfactual: market shares without vs with (dashed) CGMs over time
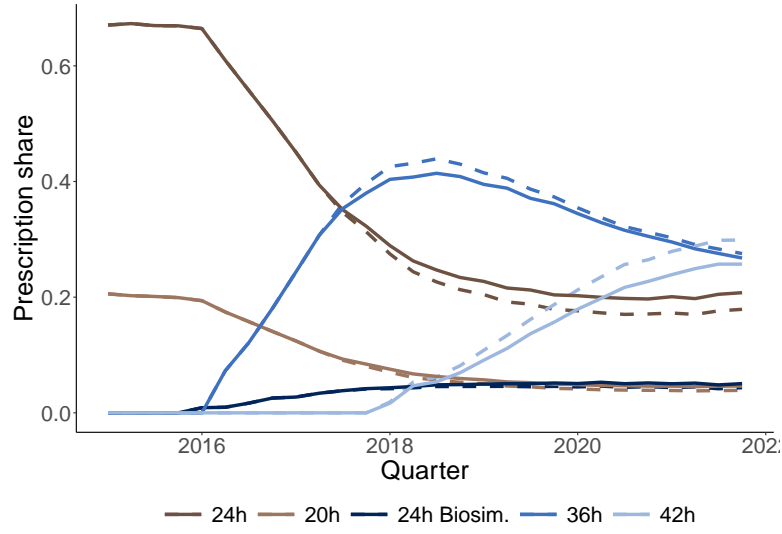
Notes: This figure plots the choice probabilities without CGMs (plain lines) and their counterparts as CGMs became available (dashed lines) over time. Insulin mixes (including the new Type II product) and human insulin shares are not represented.

Figure A18: Consumer surplus after sensor reallocation across physicians
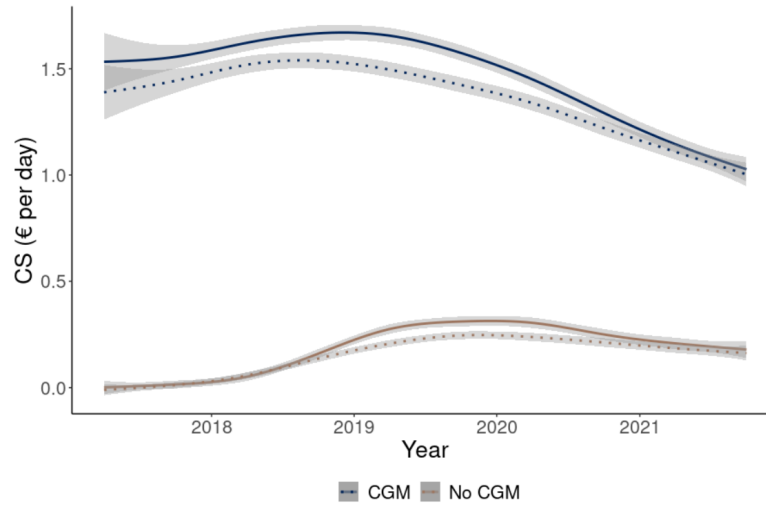
Notes: The figure presents the compensating variation (vertical axis), in euros per day, following a prescription happening in period t (horizontal axis). The average consumer welfare is presented for patients with CGM (blue curve) and without (brown curve). The plain line represents consumer welfare from the observed adoption pattern. The dotted lines represent welfare after reallocating sensors among patients, eliminating differences in sensor adoption at the physician level.

Figure A19: Changes in profits due to incomplete learning
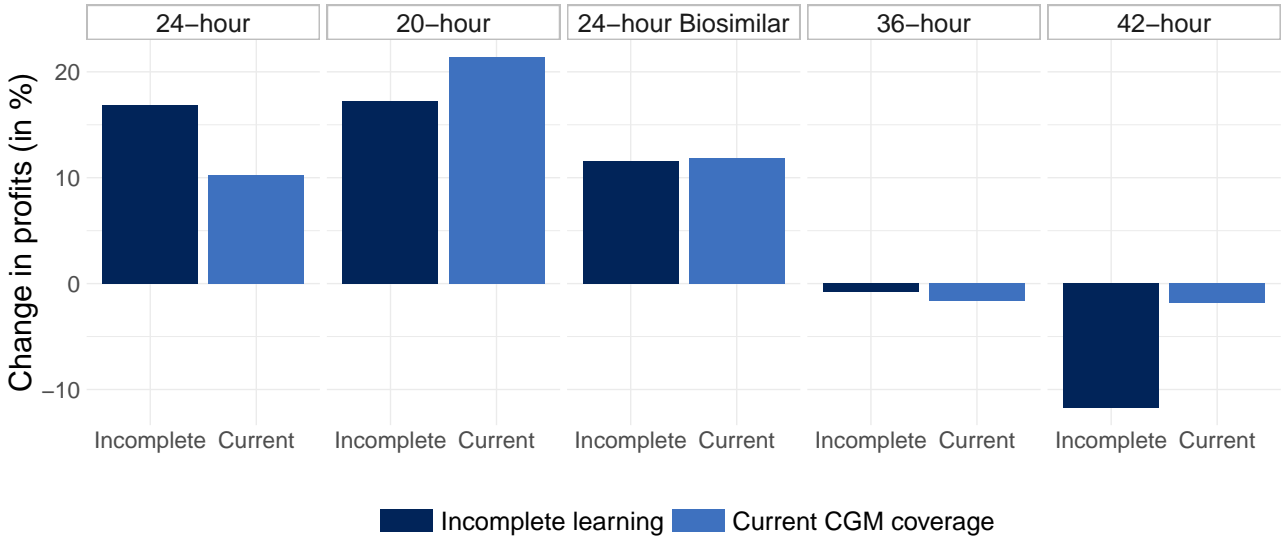
Notes: Change in profits for 2021 compared with the 'frictionless' case where the choice is made under complete learning for each patient. Each bar corresponds to the profits from product j in 2021 in a given scenario. 'Incomplete learning' corresponds to the scenario in which glucose sensors are not available. 'Current CGM coverage' corresponds to the scenario in which glucose sensors insurance coverage is available and some patients adopt, reflecting the current situation. The profits in the 'frictionless' case are normalized to 100 for each product, and each scenario is compared to this baseline. Bars above (below) zero suggest higher (lower) profits than if the choice was made under complete learning for all patients. For each product, the first bar corresponds to changes in profits in the absence of CGMs, and the second bar corresponds to the changes in profits under the current coverage and adoption decisions.

Figure A20: Consumer welfare losses due to incomplete learning without glucose sensors
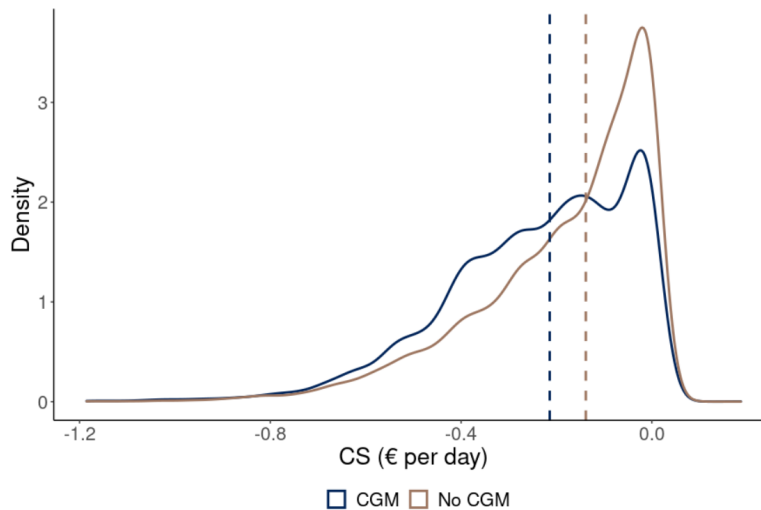
Notes: The figure plots the distribution of compensating variations between the frictionless case and relying exclusively on partial information across patients. Distributions are plotted separately for patients who adopted the technology in the observed coverage scheme (blue curve) and those who did not (brown curve). The top and bottom 2.5% are not represented here for clarity. The vertical dashed line corresponds to the median loss for each patient population.

Table A1: Summary statistics, patient level

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

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

Table A3: Drivers of adoption

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

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

Table A4: Accurate prediction, per year and patient group

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

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

Table A5: Market shares with vs without CGM in 2021

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

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

Table A6: Toward product design: product features

| | Supply | | Priors | | | | μ_{nj} | | | |
	mc_j	Duration	μ_{0j}	$(V_j^0)^{1/2}$	μ_{1j}	μ_{2j}	μ_{3j}	μ_{4j}	μ_{5j}	μ_{6j}	μ_{7j}
42-hour (Obs)	mc_{42}	1.75	-3.49	2.65	0.94	0.5	0.40	0.26	0.31	0.77	0.47
72-hour	$1.15 \times mc_{42}$	3	-3.57	2.70	$0.5\mu_{n,42}$			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 April 2024. The marginal cost is assumed to be 15% higher than the 42h version.

Table A7: Patient selection

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

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.

Table A8: 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.2. 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%.

Table A9: 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 A10: Information set and non-user switching behavior

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

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.

Table A11: Steady state market shares in 2021, complete vs partial information

			Product		
Complete			New	New	New
Information	24-hour	20-hour	24-h biosimilar	36-hour	42-hour
Yes	0.095	0.020	0.076	0.271	0.383
No	0.122	0.028	0.095	0.264	0.332
Users	0.106	0.024	0.085	0.267	0.363

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

B Data construction

B.1 Sample selection

I rely on exhaustive micro-level data for France from the *Système National des Données de Santé (SNDS)*. The data 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.[48] 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.[49] Note that the prescriber ID corresponds to the hospital ID for physicians working at the hospital. On the patient side, I focus on patients who were already familiar with insulin injections and glucose measurement before April 2016. I impose the following restrictions among patients: (i) The first long-acting insulin prescription was recorded before April 1st, 2016, and the last prescription was written after January 1st, 2016; (ii) The time between the first and last prescription 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 1st, 2016;[50] (v) The patient was an adult, 74 or younger, in 2015. On the physician side, I consider (i) The diabetes specialists working in or out of the hospital; (ii) The prescribers with a first prescription to *any patient* before January 2016; (iii) The practitioners who wrote at least 24 prescriptions and switched a treatment at least once for *any patients in my sample* between 2016 and 2021. Table A7 compares the characteristics of patients in the final sample to those in the initial dataset. Focusing on the set of incumbent insulin patients, Table A2 provides summary statistics about the physicians involved in their therapy.

Most of the descriptive analysis relies on this sample. Note that (i) The first 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

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

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

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

diabetes specialists working outside the hospital.

B.2   Risk of mismeasurement in CGM adoption

This section documents the risk of mismeasurement in digital device adoption when relying on claims data. It considers sequentially the risk for patients eligible for coverage and those not eligible for CGM coverage.

For individuals eligible for the technology, purchases of sensors directly from the device manufacturer are not reimbursed by the health insurance scheme. Coverage is fully provided in the case of a prescription. These patients have no incentive to buy the technology outside the scope of my data. The coverage decision comes 2.5 years after the device was available in the EU, such that the adoption date imputed from the claims data is subject to left censoring. This concern is mitigated by the low sales volumes for the most popular technology before insurance coverage (40k sensors in 2015 according to the HTA evaluation) and by the timing of adoption in the population according to claims data. The share of patients with a first sensor reimbursement in the first three months following the coverage decision remains limited (Figure A6a). I describe in the paragraph below how I recover the effective adoption date for patients adopting before the coverage decision. Individuals dropping out of using digital devices is an important issue when studying the impact of wearable technologies (Patel et al. (2015)). Technological features of the current device allow this challenge to be overcome. CGM relies on disposable sensors that must be replaced every 14 days. Patients not renewing their prescriptions are assumed to drop out from continuous monitoring. In practice, such cases are rare due to the comfort that the device provides to the patient (Figure A6).

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

to the 'censored' population to infer their true date of adoption. In particular, I estimate the following model, linking the number of test strips reimbursed to patient i in quarter q and CGM use in the 'uncensored' population:

$$CGM_{iq} = \alpha_0 strips_{iq} + \gamma \mathbf{1}(strips_{i,t+1})\mathbf{1}(strips_{i,t+2})strips_{i,2015} + \beta X_i + \varepsilon_{iq} \qquad (28)$$

where $strips_{iq}$ measures the average number of strips reimbursed per day per quarter, and X_i includes diabetes type, gender and age. I use the estimates out-of-sample to predict the quarter of adoption in the 'censored' population, relying on Youden's index to classify observations based on their predicted probability. Table A8 reports the risks of Type I and Type II errors in the 'uncensored' sample, which are respectively 17.6% and 24.6%. I consider that a patient in the 'censored' sample adopted the technology at t if the model predicts adoption for three quarters in a row. Figure A9 plots the cumulative distributions of observed and predicted adoption quarters for early users. The CGM adoption quarter differs for approximately 18% of the patients.

Among patients treated with long-acting insulin, patients ineligible for coverage represent 32% of individuals (Table A1). In this case, measurement error in device adoption is possible if they buy the technology out-of-pocket. However, Guerci et al. (2023) suggest that patients outside of the eligibility criteria had access to the technology as no prior authorization was required. Moreover, the alternative glucose measurement system relies on disposable strips such that the number of strips reimbursed represents a good proxy for glucose testing intensity. If individuals were to adopt the technology outside the insurance system, strip reimbursement for these patients would decrease as measurement systems are substitutes for each other. I study the evolution of strip reimbursements for CGM users and nonusers over time in Figure A8. Figure A8a plots the average daily number of strips reimbursed before and after CGM adoption. Strip consumption decreases by 2.5 strips on average after adopting the technology.[51] The average for nonusers stays relatively constant despite fluctuations across quarters. This suggests that the consumption of nonuser glucose testing strips remains unaffected by the introduction of CGM. These descriptive facts do not rule out completely the adoption of the technology outside of the insurance scheme but suggest that it is uncommon.

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

C Further descriptive evidence

C.1 Substitution toward insulin pump

Patients can use an insulin pump instead of short-acting and long-acting insulin to stabilize their glucose levels. These patients rely exclusively on short-acting insulin and only are prescribed long-acting insulin in case of a pump breakdown. The long-acting insulins prescribed to pump users are excluded from the prescriptions that physicians are learning from. Significant improvements in the pump technology have occurred over the past decade. While patients using a pump are largely using glucose sensors (Table A7), the pump system is not in the physician's choice set in the main specification. This choice is motivated by two facts. First, the coverage for insulin pumps remains restricted in France. Second, while patients in my sample are increasingly relying on a pump system, there is no change in the pattern of pump adoption after the coverage of CGM (Figure A7), and the total number of patients remains limited (70k).[52]

C.2 Detailing as an alternative source of learning

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

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[52]There exists a discrepancy with the share of pump users displayed in Table A1, primarily because the table excludes patients relying on a pump system for the entire period and focuses on patients with long-acting insulin prescriptions, and hence does not represent the share of pump users in the overall patient population.

C.3 Switching cost estimation

To rule out that switching costs differ across glucose measurement systems, I rely on a reduced-form model comparing prescription shares for new and existing patients. While the demand for incumbents is subject to both switching costs and learning upon product entry, new patients' demand is only affected by learning as this group has no prior experience with any long-acting insulin. As these groups may have different insulin needs, I compare the relative choice between two bioequivalent products. In particular, I consider separately the demand for the 24-hour product from physicians of medical specialty, m, for patients in group, $I \in \{N, E^A, E^{\bar{A}}\}$, among new patients, N, existing patients adopting, E^A, and not adopting CGM, $E^{\bar{A}}$. Denoting s_{jq}^{mI} the prescription share of Lantus (L) and its biosimilar (B) indexed by $j \in \{L, B\}$ and at time q, I estimate switching costs relying on the following model

$$log(s_{Bq}^{mI}) - log(s_{Lq}^{mI}) = \Delta\delta_q^m + \alpha\Delta p_q^m + c_1 \mathbf{1}(I \in \{E^{\bar{A}}, E^A\}) + (c_2 + c_3 CGMv_q^m)\mathbf{1}(I = E^A) + \Delta\xi_q \tag{29}$$

$log(s_{Bq}^{mI}) - log(s_{Lq}^{mI})$ proxies the difference in mean utility between the biosimilar, B, and the branded version, Lantus, L. $\Delta\delta_q^m$ is a time trend that accounts for information frictions. Δp_q^m is the difference in prices.[53] $CGMv_q^m$ is the share of prescriptions to patients wearing a CGM. c_1, c_2, and c_3 arise only in the biosimilar demand for incumbent patients and proxy for switching costs. The model is estimated by OLS, and the results are displayed in Table A9. $\hat{c}_1 < 0$ suggesting positive switching costs, yet no heterogeneity across glucose measurement systems as $\hat{c}_2$ and $\hat{c}_3$ are not significant. From these estimates, the willingness to pay to remain on the treatment patients are familiar with lies around ~ 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. For each physician k and quarter t, I count the number of switches to the 42-hour product for patients without a CGM. Physicians' information set, denoted F_{kq}, is approximated using the number of appointments up to $t-1$ where the patient 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 t,

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

Y_{kq}, is documented using a Poisson model:

$$E(Y_{kq}|X) = \exp\left(\alpha + \lambda_1 \mathbf{1}(F_{kq} > 0) + f(F_{kq}) + \gamma X_k + \delta_q\right) \tag{30}$$

f is a quadratic function of F_{kq}. $\mathbf{1}(F_{kq} > 0)$ captures the extensive margin. The model is estimated from physician-quarter combinations with more than 11 visits. Table A10 presents the results. Going from 10 experience feedbacks to 20 increases the occurrence of switches to the 42-hour product by 16.2%. Digital technology feedback seems to dampen the spillovers. Specifications B and C consider the correlation between the information set and switching for eligible nonusers and non-eligible patients separately. Eligible patients are more similar to CGM users in terms of observable and unobservable characteristics than non-eligible patients. For eligible individuals, receiving feedback from CGM versus the traditional measurement system has no significant impact on the magnitude of the spillover effect. For non-eligible individuals, the spillover effect is significantly weaker if the feedback is received from a patient using a CGM. If physicians extrapolate based on patients' similarities, this effect may be driven by patient heterogeneity (Alsan et al. (2024)).

D   Multi-product bargaining

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

$$\pi_{ft}(\mathbf{p}_t) = \sum_{\forall j \in \mathcal{J}_f} (p_{jt} - c_{jt}) q_{jt}(\mathbf{p}_t) \tag{31}$$

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

$$\Delta_{ft} CS(\mathbf{p}_t) = \sum_{\forall i,k} \frac{1}{\lambda} \ln\left(\sum_{\forall j \in \mathcal{J}} \exp(u_{ikjt}(p_{jt}, d_j, a_{it}|\mathcal{I}_{kt})) \right) - \sum_{\forall i,k} \frac{1}{\lambda} \ln\left(\sum_{\forall j' \notin \mathcal{J}_f} \exp(u_{ikj't}(p_{j't}, d_{j'}, a_{it}|\mathcal{I}_{kt})) \right) \tag{32}$$

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

$$\max_{\mathbf{p}_{ft}} [\pi_{ft}(\mathbf{p}_t)]^{b_{ft}} [\Delta_{ft} CS(\mathbf{p}_t)]^{1-b_{ft}} \tag{33}$$

Let's consider the case where the firm bargain over two products, indexed by j and j'. The

FOC with respect to the price of product j, p_{jt}, is given by:

$$b_{ft}\frac{\partial \pi_{ft}(\mathbf{p}_t)/\partial p_{jt}}{\pi_{ft}(\mathbf{p}_t)} + (1-b_{ft})\frac{\partial \Delta_{ft}CS(\mathbf{p}_t)/\partial p_{jt}}{\Delta_{ft}CS(\mathbf{p}_t)} = 0 \tag{34}$$

where

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

and

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

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

$$\frac{\partial \pi_{ft}(\mathbf{p}_t)}{\partial p_{jjt}} + \beta_{ft}h_{jt}\pi_{ft}(\mathbf{p}_t) = 0$$

$$q_{jt}(\mathbf{p}_t) + \left(p_{jt}-c_{jt}\right)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + \left(p_{j't}-c_{j't}\right)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft}h_{jt}\left((p_{jt}-c_{jt})q_{jt}(\mathbf{p}_t) + (p_{j't}-c_{j't})q_{j't}(\mathbf{p}_t)\right) = 0$$

$$\left(p_{jt}-c_{jt}\right)\left(\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft}h_{jt}q_{jt}(\mathbf{p}_t)\right) + (p_{j't}-c_{j't})\left(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft}h_{jt}q_{j't}(\mathbf{p}_t)\right) + q_{jt}(\mathbf{p}_t) = 0 \tag{35}$$

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

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

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

Plugging Equation 36 into Equation 35,

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

$$-q_{jt}(\mathbf{p}_t) + q_{j't}(\mathbf{p}_t)\left(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft}h_{j't}q_{j't}(\mathbf{p}_t)\right)^{-1}\left(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft}h_{jt}q_{j't}(\mathbf{p}_t)\right) \tag{37}$$

such that

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

$$-q_{jt}(\mathbf{p}_t)\left(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} + \beta_{ft}h_{j't}q_{j't}(\mathbf{p}_t)\right) + q_{j't}(\mathbf{p}_t)\left(\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}} + \beta_{ft}h_{jt}q_{j't}(\mathbf{p}_t)\right) \tag{38}$$

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

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

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

the first order condition becomes,

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

such that

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

$$c_{jt} = p_{jt} + \left[\beta_{ft}h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)} + \left(\beta_{ft}h_{j't} + \frac{\partial q_{j't}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)}\right)\frac{\left(q_{j't}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} - q_{jt}(\mathbf{p}_t)\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}}\right)}{\left(q_{jt}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{j't}} - q_{j't}(\mathbf{p}_t)\frac{\partial q_{j't}(\mathbf{p}_t)}{\partial p_{jt}}\right)}\right]^{-1} \tag{41}$$

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

$$c_{jt} = p_{jt} + \left[\beta_{ft}h_{jt} + \frac{\partial q_{jt}(\mathbf{p}_t)/\partial p_{jt}}{q_{jt}(\mathbf{p}_t)}\right]^{-1} \tag{42}$$

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

$$\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{jt}} = \sum_{\forall i,k}\sum_{\forall v \in t} -\alpha s_{ikjv}(\mathbf{p}_t)(1 - s_{ikjv}(\mathbf{p}_t)) \tag{43}$$

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

$$\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{j't}} = \sum_{\forall i,k} \sum_{\forall v \in t} \alpha s_{ikjv}(\mathbf{p}_t) s_{ikj'v}(\mathbf{p}_t) \qquad (44)$$

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

E Counterfactual scenarios

E.1 Sensor reallocation

The counterfactual in Section 6.2 suggests that information spillovers from CGM users to nonusers are limited. The consumer surplus generated by the technology mostly accrues to patients using the device. As Table A3 suggests that adoption is heterogeneous across physicians, the lack of spillovers could be limited by little variation in CGM adoption within the set of patients followed by a given physician. Considering the extreme case where all patients within a cluster at a particular practice are either adopting or non-adopting, nonusers cannot benefit from the information generated by CGM users. To analyze whether this phenomenon drives the lack of spillovers, I compute the equilibrium shares and the consumer surplus generated by glucose sensors under an alternative allocation of CGM, which eliminates differences across physicians. To that end, first, 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, $\hat{p}_i$. Two patients with similar characteristics have the same probability of adopting the device. I randomly select patients to adopt the technology, fixing the number of users to the number observed in the data and using the predicted probability of adoption, $\hat{p}_i$, as weights. Adoption dates are allocated randomly. I compute consumer welfare under this alternative allocation and present the results (relative to the allocation observed in the data) in Figure A18.

E.2 Losses from partial information without glucose sensors

By generating continuous glucose data, the digital device emphasizes the inefficiencies arising from incomplete learning in prescription drug choice. Observing the choices for patients under complete learning helps quantify the costs of relying solely on partial information, in terms of market shares, foregone profits and consumer welfare. In this section, I use the estimates for ν_{ij} to measure the losses from incomplete learning. I assess how much of this information gap is bridged by providing broad access to CGMs.

I begin by considering the complete information scenario in which every patient uses a CGM as the 'frictionless' solution. In this case, physicians have access to each patient's true clinical match values, Θ_{ij}. I then compare this market outcome to two scenarios in which (i) the technology was never available and (ii) CGM coverage is available, but some patients do not adopt the device, reflecting the current situation. Comparing the frictionless case to the first scenario, in which choices rely exclusively on partial information, emphasizes the losses from incomplete learning in terms of industry profits and consumer welfare. To abstract away from the uncertainty about new drugs' performance upon market entry, I focus on the steady-state choice probabilities that prevail once this friction is resolved. The steady-state choice probabilities are obtained by assuming physicians receive a precise signal from patients about the performance of new drugs ($\sigma_0 = 0.001$ and $\sigma_1 = 0$) and by restricting my attention to the last year of the data, which is over 36 months after the last product entered the market.[54] The new equilibrium prices are computed for each drug under each scenario. Table A11 shows each product's steady-state shares, and Figure A19 presents the profits. A comparison of the first two rows highlights the products that win (older drugs) and those that lose (new products) due to incomplete learning. When these losses are measured in terms of consumer welfare, partial information accounts for €-0.36 per day on average across prescriptions — 8 times less than the daily cost of continuous glucose monitoring. Providing broad CGM coverage for patients closes 54.8% of this gap, slightly above the adoption rate, since patients using CGMs experience greater losses from partial information (Figure A20).

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[54]Given the initial prior variance and the signal precision presented in Table 3, the uncertainty level becomes negligible after a physician receives the first feedback.