An Ounce of Prevention or a Pound of Cure?

The Value of Health Risk Information

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May 12, 2025

Abstract

I examine how individuals learn about health risks from household health shocks using US administrative data. When a family member is diagnosed with a chronic condition, relatives increase healthcare spending by 10%, a response that would require price declines as large as 50% to justify on demand alone. I quantify the mechanisms behind these effects, showing they are most consistent with individuals updating their beliefs about health risks. I evaluate the welfare and efficiency implications of this learning using a structural approach. I find that the majority of individuals overreact to diagnoses, overweighting their ex-post risks and offsetting potential welfare gains from informed decision-making.

Keywords: Health spillovers, consumer learning, behavioral health economics, discrete choice models, chronic illness

JEL codes: I12, I13, D83, D91, D12

*University of Toronto. alexander.hoagland@utoronto.ca. I am grateful to Kristen Blair, Corinne Andriola, Michael Darden, Randall Ellis, Keith Ericson, Itzik Fadlon, Sarah Gordon, Tal Gross, Jihye Jeon, Timothy Layton, Marc Rysman, and Paul Shafer for very helpful comments on this project. In addition, I am grateful to seminar participants from economics departments at Boston University, Brigham Young University, the Ohio State University, the University of Toronto, and Washington University in St. Louis. I am also grateful to seminar participants from the 10th Annual ASHEcon Conference, the 2021 iHEA Congress, the ASSA 2023 Annual Meeting, the Congressional Budget Office, and the Federal Trade Commission.

1 Introduction

Social networks provide important information for consumers making healthcare choices. Through connections with family, friends, and neighbors, individuals form expectations of their own health risks, learn about the value of specific medical practices, and identify pathways to receiving care. Family health experiences provide particularly influential sources of health information due to their proximity and relevance. Understanding how individual health experiences shape family health behaviors is essential for policies aiming to improve public health, including addressing high levels of healthcare spending or incentivizing the takeup of high-value health services.

One especially salient feature of a health shock is the information it communicates about risks for future shocks, particularly when risks are correlated within a household. Although health events may prompt individuals to update their beliefs about health risks, they can also drive changes in the expected prices of medical care (Anderson et al., 2024), household preferences for health consumption (Finkelstein et al., 2009), or knowledge about the availability of health services (Dwyer and Liu, 2013). Hence, decomposing and quantifying the mechanisms underlying these spillover effects is critical to understanding the efficiency and welfare implications of household responses to shocks.

More generally, identifying how beliefs about health risk evolve sheds light on the value of health information amid potential costs from imperfect information transmission. Theoretically, informative health events such as health shocks or preventive screening outcomes should improve individual risk beliefs, allowing for earlier detection of health conditions and improved health in the long run (Einav et al., 2020). Conceptually, however, there is a tension between the seriousness of a health event and appropriate belief updating: households responding to health shocks may either be slow to update their beliefs—incurring potentially large health and financial costs in the meantime—or may be overly responsive to uninformative events, placing large ex-post weights on low-probability health events even after conditioning on household genetic risk. These over-reactions may lead to over-consumption

of low-value care for the individual, potentially at the cost of crowding out other, more valuable health services. Assessing the welfare effects of new health information requires understanding whether, how quickly, and how precisely individuals respond to it.

In this paper, I examine these questions using new administrative data in the US, a novel setting in which to study household responses to health shocks. I use claims data for US households insured through their employers to examine how a new diagnosis of a chronic condition (for example, a cancer diagnosis for a parent or a child's diagnosis with type 1 diabetes) affects household health behaviors. I first provide clear reduced-form evidence that these health shocks generate spillover effects, and that the effects appear to be driven by responses to health *information* rather than other possible explanations. The observed spending increases are large, on the order of 10% for households; to put this into context, given a price elasticity of demand for medical care at -0.2, a 50% decline in prices would be required to rationalize these spending increases using price changes alone (Newhouse, 1993). These spillover effects include significant and persistent increases in both overall utilization and investments in disease-specific preventive care, novel evidence of responsiveness to new risk information.

Using administrative data in the United States allows me to study household health spillovers in a novel environment. This setting is particularly fruitful for studying spillover effects and learning about health risk, as households may also be subject to financial considerations and liquidity constraints (Gross et al., 2022). I test for these financial incentives, and show that spillover effects are unaffected by changes in the marginal price of future care, suggesting ex-post moral hazard responses do not drive the results.[1] The chronic diagnoses I study also induce larger changes in spending than similarly intensive, but uninformative, acute health events, which have been the focus of previous papers. Importantly, this suggests households respond to risk information in addition to any salience effects.

[1] As is common in the health economics literature, I use the phrase "moral hazard" to denote ex-post demand effects arising from changes in the price an individual faces for care (Einav et al., 2013).

In general, one would expect that new risk information should improve individual decision-making and, subsequently, welfare. Surprisingly, the welfare effects of chronic health shocks are ambiguous using only reduced-form evidence. I document that health shocks lead to increased take-up of "low-value" health services which do not typically benefit the marginal patient, even conditional on family medical histories (Colla et al., 2015). This increase is driven by low-value services that appear related to preventive care, including extraneous pre-operative screenings or imaging services; importantly, this suggests individuals may have trouble interpreting risk information signals from a chronic diagnosis or may not appropriately choose high-quality services conditional on their specific medical history. I also observe evidence that health shocks may directly affect household well-being via anxiety or salience effects; household members are roughly 3% more likely to use mental health prescriptions after a family diagnosis.

These findings motivate a structural approach to model how health shocks impact risk beliefs and, ultimately, welfare. I present a model where individuals learn about risks through preventive screening and household diagnoses. In the model, individual belief updating and changes in risk aversion—for example, through anxiety effects—affect household investments in health. I disentangle these mechanisms leveraging variation in spending across diagnosed individuals as an excluded instrument. This allows me to estimate the elasticity of health risk beliefs to health shocks using the observed demand data. To estimate the welfare effects of health risk information, I assess how households value risk information in the absence of anxiety and salience effects, and compare the model's predictions to counterfactual scenarios with more targeted risk signals. This mimics an experiment where only the health risk information is presented to households without the intensity of the actual health shock.

Counter to expected thought, information about future health risks is not welfare-improving for a majority of affected households. 68.2% of those presented with new risk information would be willing to pay to avoid the resulting change in their beliefs, with the average (median) utility loss amount to a \$790 (\$504) increase in the certainty equivalent annually. The

model's central finding is that new diagnoses in a household spur large changes in individual assessments of health risk, resulting in average posterior beliefs that are well above true diagnostic risk, even conditional on medical history. Bounding this updating can be welfare improving for 80% of households previously unwilling to pay for health risk information.

My analysis contributes to a well-established literature on the spillover effects of health shocks within a household. Family relationships provide important information for economic decisions, and economic shocks in a family affect the health of its members (Fontes et al., 2024). Acute family health shocks have similarly been shown to induce spillover demand changes (Fadlon and Nielsen, 2019; Hodor, 2021; Arteaga et al., 2025; Fadlon et al., 2025).[2] I contribute to this literature in three ways: First, I provide novel evidence for household spillovers in the US, where responses to health shocks are potentially very different than in other healthcare settings. Previous work has been limited to administrative data in publicly-funded health insurance systems or historical data despite the relevance of studying household health behaviors in the complex US healthcare system. Second, I provide clear reduced-form evidence disentangling learning about health risks from other relevant drivers of the observed effects. Finally, motivated by these results, I present a general framework to estimate the effect of a health shock on individual beliefs about health risk and the relative value of seeking care.

I also contribute to the literature on non-Bayesian learning in models of health behavior, combining two distinct threads of the learning literature (Bundorf et al., 2024). First, I emphasize the role of disproportionate weight individuals place on high-cost, low-probability events, which rationalize individual choices that would otherwise require unreasonably high levels of risk aversion to justify (Goldstein et al., 2023; Ortoleva, 2012; Spinnewijn, 2015).

[2] A rich literature has highlighted how individuals respond to their *own* diagnoses (Alalouf et al., 2024; Kim et al., 2019) and acute health events in their social network (Bouckaert et al., 2020; Yi et al., 2015). There is also a rich literature identifying how health shocks affect family members' employment and labor supply outcomes (Maestas et al., 2024; Fadlon and Nielsen, 2021; Arrieta and Li, 2023).

I combine these results with the literature studying the role of peer signals in learning, highlighting that individuals may over-emphasize high-risk peer signals relative to their own (Dasaratha et al., 2022; Bohren and Hauser, 2021). I incorporate these disparate findings into a novel structural approach modeling the evolution of beliefs about health risk. This work is related to other models of learning in healthcare settings (Darden, 2017; Crawford and Shum, 2005), but distinct in that by identifying the evolution of individuals' own health beliefs, I am able to comment on the efficiency of responses to household health shocks.

Finally, my work is relevant to a well-established literature exploring sub-optimal health decisions made by consumers (Abaluck and Compiani, 2020; Baicker et al., 2015; Handel and Kolstad, 2015). This includes discussions about whether improving health information would improve decision-making (Gruber et al., 2025; Finkelstein et al., 2022). I show that overcoming information frictions is not simply a matter of increased access to health information. Rather, individual responses to some information may not improve the care a patient receives but simply shift them from one type of poor decision-making to another while increasing health spending.

I present my empirical setting in Section 2. Following a discussion of major health events, I provide evidence of their spillover effects and the potential mechanisms driving them in Section 3. I then present the details of my model in Section 4 and its results in Section 6. Finally, I discuss the relevance of my findings and directions for future work in Section 7.

2 Empirical Setting & Data

Data on household health shocks and utilization come from the Merative (formerly IBM Truven) Marketscan *Commercial Claims and Encounters* Data from 2006 to 2018. These data contain detailed inpatient, outpatient, and pharmaceutical claims for households enrolled in an employer-sponsored insurance (ESI) plan provided through participating insurance carriers to several large U.S. firms.

Households are defined as all enrollees covered under a single insurance contract, including the primary employee and any covered dependents.[3] I limit the sample to only households with two or more members observed for two or more years and insured with one of eight large firms for whom plan benefit information is readily available. Households with any gaps in their enrollment or eligibility were dropped from the sample; those who simply change insurance plans, however, are included. My final sample consists of 353,403 households and 5,439,482 individual-year observations.[4]

Table 1 presents summary statistics for the full sample as well as for households in which an individual is affected by a chronic condition. In general, households are comprised of one to two adults and one to two children, with relatively generous insurance coverage. The average (median) household pays out-of-pocket for roughly 18% (16%) of their annual health consumption, and 21% of individuals in the sample do not face any cost-sharing during a year. Column 2 limits the sample to only household-years in which a chronic diagnosis occurred. Demographics are similar prior to the health event, but in the year of diagnosis, spending increases by an average (median) of 82% (66%). Affected households look very similar to the full sample in terms of insurance enrollment and plan generosity.

2.1 Major Health Events

Major health events, which communicate information about health risk to households, are identified by the Department of Health and Human Services' Hierarchical Condition Categories (HCC) diagnostic codes. HCCs are commonly used in risk adjustment models and

[3]Households may include dependent children living away from home, and may exclude family members such as spouses covered under their own ESI contract.

[4]Households need not be observed for the full 13 years to be included in the sample. The average household is observed for 7 years. Results are shown for an unbalanced panel but are robust to fully balancing the panel across 6 years. I also require the diagnosed individual to be observed for a full year after diagnosis, excluding less than 1% of households to avoid biasing my results due to fatal diagnoses.

identify a basic set of chronic illnesses that alter overall health utilization and spending. Many of these conditions—such as a parent's cancer diagnosis, a child's onset of type 1 diabetes, or the emergence of serious mental health conditions—are events that carry both emotional and informational weight for the entire household.

Table 2 illustrates the most common health shocks in my analysis as well as the median age of onset. These include common conditions affecting family members across a number of disease categories, including cancers, chronic cardiovascular conditions, autoimmune conditions (e.g., type 1 diabetes), and mental health conditions.[5] As reported in Table 1, the average (median) household in my sample spends $532 ($212) OOP on the health shock in the year of diagnosis, and then $489 ($190) each year that follows on recurring care costs.

Across this set of conditions, there is considerable variation in the age of diagnosis as well as relative severity. Particularly, roughly 1/3 of the new diagnoses in my sample occur for children under the age of 18. Appendix Figure A1 showcases this variation—some conditions such as type 1 diabetes and asthma affect mainly children and younger adults, while other conditions such as cancers are more frequently diagnosed for older adults. I use the full set of chronic conditions to assess overall responses to new health information across the household, as well as to explore intra-household variation in responses in Section 3.

2.2 Additional Variable Definitions

The rich variation of the data allows me to evaluate how new chronic diagnoses affect many utilization and quality measures. I define three additional outcome variables which will be useful in identifying the mechanisms by which new health information changes household behavior: preventive health services, acute health events, and the use of low-value health

[5] I limit my classification of health events to non-pregnancy HCCs that occur with high frequency; see Appendix Tables A1, A2, and A3 for details. To ensure that I identify new diagnoses, I require that relevant diagnosis codes appear during or after an individual's second observed year.

services. Appendices A.2 and A.3 contain a full set of all diagnostic information, procedure codes, and therapeutic classes used in the construction of each of these variables.

Preventive health services. First, I define a set of health services typically considered to be preventive in nature, consistent with previous work and federal guidelines (Hoagland and Shafer, 2021; USPTF, 2022). Preventive screenings and wellness visits constitute an important point of entry for the identification of other health concerns and are generally considered to be an important form of high-value care (Tong et al., 2021).

Acute health events. Second, I define a set of *acute* health events, to capture health shocks of similar severity to new chronic diagnoses, but which are transient in nature and do not communicate intra-household health risk information. I identify acute health events as new HCCs within households for conditions which typically do not persist past a year, including hospitalizations for severe viral infections or other non-chronic conditions. Appendix Section A.2 compares acute and chronic events by pre-event spending, event cost, and hospitalization incidence, finding the two groups to be generally comparable.

Low-value health services. Finally, I define categories of medical utilization which are frequently labeled as "low-value" by medical professionals and health officials (Chua et al., 2016; Colla et al., 2015).[6] Low-value services include both those whose cost typically outweighs the benefits to an average patient (e.g., some surgeries, such as arthroscopy) and services which are chronically over utilized in ways that dramatically lower their return (e.g., some imaging services, such as MRI for migraines). I define instances of low-value consumption based on an individual's diagnosis and procedure codes as well as their diagnostic history, based on previous work (Colla et al., 2015). I subdivide these services into five categories: pediatric services, including imaging services and the early use of medications such as antibiotics; adult prescription drugs, such as the use of opiates to treat migraines;

[6]Services are based on recommendations from the Choosing Wisely initiative (Bhatia et al., 2015). Appendix Section A.3 lists these services and their categorizations.

unnecessary imaging services for adults; extraneous screening services for adults, including cardiac testing before low-risk surgeries; and adult surgical procedures.

While some health services may be valuable for individuals at elevated risk, here I define low-value care using established clinical guidelines that explicitly account for variation in risk profiles. The services classified as low-value in this study—for example, routine imaging for uncomplicated headaches or pre-operative testing for low-risk surgeries—delineate services providing minimal or no benefit even for at-risk populations (Colla et al., 2015; Chua et al., 2016). Hence, the value of these services is not sensitive to the elevated (but still modest) risk conferred by most family histories (Kirkham et al., 2015). I excluded services where clinical evidence supports differential benefit based on a known family history of disease (e.g., genetic testing following breast cancer diagnoses).

3 Spillover Effects of Household Health Events

To estimate the causal impact of health shocks on health choices, I use a local projections difference in differences (LP-DID) estimator (Dube et al., 2025). This estimator performs a "stacked" regression of treated units combined with their clean controls to estimate treatment effects without bias from naive staggered adoption designs with heterogeneous treatment effects (Roth et al., 2023). The regression uses local projections methods to restrict the estimation sample so that previously-treated observations (which may be experiencing time-varying or heterogeneous treatment effects post-adoption) are not included in the control group, eliminating bias.[7] Formally, for a household f and $h = 4$ years pre- and post-

[7]The LP-DID regression performs similarly to other approaches in this context, including weighted stacked DID regressions (Wing et al., 2024; Cengiz et al., 2019) and imputation estimators (Sun and Abraham, 2020; Callaway and Sant'Anna, 2021). As I do not include any additional covariates, this approach is identical to a stacked regression (Cengiz et al., 2019).

treatment, I estimate the equation

$$y_{f,t+h} - y_{f,t-1} = \beta_h^{\text{LP-DID}} \Delta D_{ft} + \alpha_f + \tau_t + \varepsilon_{ft}^h, \tag{1}$$

where the sample is restricted to newly treated households ($\Delta D_{ft} = 1$) or clean controls ($\Delta D_{f,t+h} = 0$) and effects are estimated relative to $t-1$. To assess spillover responses, my main outcomes Y_{ft} aggregate utilization across a household *excluding* those who experience the major health event. I measure these outcomes both in counts (e.g., number of visits) and log-transformed spending (both total and OOP).[8] Throughout, reported coefficients can be interpreted as approximate percentage changes in the outcome variable, relative to the year before the shock, $t-1$. Standard errors are clustered at the household level.

This empirical strategy rests on the standard parallel-trends identifying assumption: absent the realization of the health shock, the outcomes of the treatment and control households would evolve in parallel. This assumption can be tested by assessing treatment and control group outcomes in pre-event periods. Average effects over several periods are calculated as discussed in Dube et al. (2025). This procedure recovers a variance-reweighted ATT using clean controls and positive weights, producing a single post-effect coefficient akin to a traditional pooled difference-in-differences estimator.

Figure 1 presents the dynamic causal effects of a health shock on household utilization for all non-diagnosed individuals. The first panel illustrates that non-diagnosed household members increase their annual OOP spending by about 10% relative to the year before the event. For the median (average) household, this corresponds to an increase of about \$50 (\$115) annually, beginning in the year of the shock and persisting for at least four years.[9]

[8] In Appendix Figure B1, I show that my results are a conflation of effects along both extensive and intensive margins. Results are also robust to using alternative transformations of the dependent variable. Effects were estimated using the LPDID package in Stata (Busch and Girardi, 2023).

[9] In Figure 1, I show effects for six years around the time of diagnosis in order to illustrate the full life cycle of the treatment effect before returning to baseline. Subsequent figures limit this to four years.

This constitutes a sizable increase in health spending. For reference, given the range of estimates for the price elasticity of demand for healthcare services from -0.2 (Newhouse, 1993) to -1.5 (Kowalski, 2016), this magnitude of change in health spending would require between a 7% and 50% decline in prices to be induced as a pure demand effect. Recent work has argued that demand for preventive care is even less price sensitive than demand for other medical services, suggesting that this might be a conservative range (Haviland et al., 2011). As another way to benchmark these estimated effects, note that the estimated spending increases are the average equivalent of the OOP cost of an additional physician's office visit per person per year for the median affected household (two for the average household), or roughly 12% (28%) of an inpatient visit's OOP costs.[10]

While health events may generate spillovers in household spending for many reasons, households responding to the information contained in a diagnosis may be more likely to seek out preventive screenings. The second panel of Figure 1 estimates the effect of chronic diagnoses on the total utilization of preventive services (Section 2.2). Here, too, I find that new diagnoses in a household are associated with strong responses. Affected, non-diagnosed household members increase their overall use of wellness visits by about 3% relative to a median of 4 visits annually. These effects persist for longer than overall spending increases, with statistically significant increases observed even five years after the shock.[11]

One might be concerned that anticipation of a diagnosis—through, for example, deteriorating health—may introduce unobserved pre-trends into the analysis, even for adjacent household members. For comparison, I present results in Appendix Figure B3 illustrating how diagnoses affect the focal individuals, which allows me to directly observe anticipation

[10]These results are qualitatively similar whether or not I include other household children in the main specification, as shown in Appendix Figure B.2.

[11]Panel B measures preventive care in visits rather than spending to account for the fact that the Affordable Care Act (ACA)'s cost-sharing exclusion disrupted the costs for preventive services for those with ESI (Shafer et al., 2021).

effects. The figure shows no anticipation effects in a pre-trend, and suggests that diagnosed individuals increase their spending only in the year of diagnosis.

3.1 Changes as Responses to New Health Risk Information

These results suggest that a new chronic diagnosis induces a meaningful, persistent change in household demand for healthcare. Next, I turn to exploring the mechanisms behind these effects: I first show that effects are indicative of individuals reassessing their health risks given new health information, and consider alternative explanations in Section 3.3.

If a chronic diagnosis in a home conveys information about health risks, we would expect affected household members to internalize that the risk of a specific diagnosis or condition. For example, household members witnessing a new diabetes diagnosis learn something about their risk for diabetes, rather than for other conditions like asthma. In contrast, if a diagnosis changes behavior merely through changes in demand (price effects) or marginal utility (salience or anxiety effects), responses may be more general. This provides useful identifying variation to test the hypothesis that households are responding to risk information by examining whether responses are concentrated among disease-specific spending.

Appendix Figure B4 shows trends in the raw data for diabetes screenings. Households respond to a diabetes diagnosis by investing in roughly 33% more diabetes screenings, while those affected by another chronic shock do not change their use of these screenings. Appendix Figure B5 shows these results within the LP-DID regression framework, illustrating how diabetes and non-diabetes diagnoses affect use of diabetes screenings, as well as how cancer and non-cancer diagnoses affect use of cancer screenings. I consistently observe that households respond by seeking out disease-specific preventive information, while those affected by another condition (e.g., a non-diabetes or non-cancer diagnosis) do not. If anything, those affected by other conditions reduce their use of diabetes and cancer screenings as they substitute towards other types of care.

This additional variation in responses across diagnosis lends itself to a triple differences modification of Equation 1.[12] This approach separates the disease-specific effect of risk information from more general diagnosis effects. Formally, I estimate the effect of a new chronic diagnosis on a household f's decision to screen for a condition in group g as a function of whether their health event also belonged to that group. In the notation of the LP-DID specification used in Equation 1, this is:

$$Pr(\text{Screening})_{f,t+h,g} - Pr(\text{Screening})_{f,t-1,g} = \beta_h^{\text{LP-DD}} \Delta D_{ft} + \beta_h^{\text{LP-DDD}} (\Delta D_{ft} \times G_f) + \alpha_f + \tau_t + \varepsilon_{ft}^h, \tag{2}$$

where G_f indicates that household f experienced a diagnosis in a particular group, g. Here, $\beta_h^{\text{LP-DDD}}$ identifies the effect of a diagnosis of interest on the screening of interest, with the three-way interaction capturing whether the health shock was of a type relevant to the screening (e.g., a diabetes diagnosis when the outcome variable is a diabetes screening). For example, when the outcome of interest is diabetes screenings, the first difference $\beta_h^{\text{LP-DD}}$ identifies how any chronic diagnosis changes diabetes screenings, while $\beta_h^{\text{LP-DDD}}$ identifies the specific effect of a diabetes diagnosis compared to any other chronic diagnosis in a household. The formalization of these comparisons in a pooled triple-differences framework allows me to succinctly report multiple effects while maximizing statistical power.

I estimate several versions of Equation 2 for different diagnoses-screening pairs. These include the impact of new diabetes and cancer diagnoses on their respective screenings and the effect of diabetes diagnoses on cholesterol screenings. Table 3 presents the results in two panels. First, I highlight that new chronic diagnoses alter specific preventive behaviors in cases where they transmit important information about health risk. Specific diagnoses such

[12] This is akin to a triple-differences approach in that there are essentially two treatment groups and a control group, providing separate margins of treatment based on the type of index event. Below I present this as a triple-differences specification with a three-way interaction, but this is numerically equivalent to a stratified difference-in-differences using a fully saturated specification, given the fixed effects.

as cancer and diabetes increase the likelihood that a non-diagnosed household member will seek out specific screenings by 13.2% and 21.1%, respectively. Diabetes diagnoses are also associated with an increase in cholesterol screenings of 7.2%.

Table 3 also reports results for two placebo regressions. These regressions show the effect of (a) new diabetes diagnoses on obesity screenings and (b) new mental health diagnoses on depression screenings. These results are informative of how diagnoses shape behavior when the risk information is more opaque or when there are not clear preventive actions to respond to that risk. For example, while obesity is an important risk factor for chronic conditions such as diabetes, it is typically externally verifiable prior to a physician's diagnosis, limiting the value of obesity screenings even for at-risk household members. Similarly, household members at risk of mental health conditions may under-utilize depression screenings after another family member is diagnosed with a mental health condition given the absence of clear preventive behaviors to avoid adverse mental health events. I find no evidence that health shocks affect these screenings; taken together, these results highlight that households exhibit targeted responses to health risk information when that information is communicated and when targeted responses are possible.[13]

3.2 Quality of Induced Spending Changes

Given these results, a natural question is whether new information improves overall quality of care. While new diagnoses could feasibly lead to substitution of healthcare towards high-value preventive services, affected individuals may increase overall consumption, with limited regard for a service's underlying risk-mitigating value. I examine how diagnoses affect household consumption of low-value care.

[13]Appendix Table B1 further highlights within-family variation in responses based on individual relationships and risk. For example, children and siblings respond to health shocks with strong genetic risk components—such as cancer—while spouses are more responsive to health shocks with a stronger lifestyle component—such as type 2 diabetes.

Table 4 presents the pooled post-event effect of a new chronic diagnosis in each of five categories on both the extensive margin (the probability of any use) and intensive margin (spending).[14] New chronic diagnoses are estimated to increase total low-value spending by about 4.8%; however, this is not statistically significant and masks significant heterogeneity across services. Disentangling this provides useful intuition for what information households react to. Households may seek out different types of care if they are responding to new risk information—by demanding low-value screenings such as preoperative screenings—or responding to marginal price changes following a diagnosis—by demanding elective surgeries.

New chronic diagnoses increase the likelihood that households will utilize pediatric low-value care (21.2%), imaging (6.1%), and low-value screening services (9.1%), but decrease the likelihood of using low-value surgical services (21.0%). Similarly on the intensive margin, households spend more on pediatric care (7.2%), imaging (3.4%), and screenings (6.1%), while decreasing demand for elective surgeries by 6.5%. I find no effect on the misuse of prescription drugs among adults. Taken with the previous results, these findings suggest affected households increase utilization of a broad set of preventive and "psuedo-preventive" services, with less distinction between the average return on those services.[15]

[14] In panel (a), I rescale coefficients relative to the pre-treatment mean of utilization, so that reported estimates can be interpreted as percentage changes. I also use billed spending, rather than OOP spending, to avoid capturing changes to cost-sharing rates for these services due to policy changes such as the ACA, which may have impacted services such as imaging and cardiac stress tests (Hoagland and Shafer, 2021).

[15] Appendix Figure B6 shows the dynamic effects for each of these services on the extensive margin. Note that the interpretation of effects on elective surgery use are complicated by a statistically significant pre-trend. However, other effects—including the increases in use of low-value care—do not suffer from these pre-trends. Note also that these increases are the result of joint decision-making between patients and providers (Hoagland et al., 2023).

3.3 Alternative Explanations for Spending Changes

My results suggest household health shocks provide important health risk information that changes behavior. However, individuals may be responding to other features inherent in a health shock; I explore these possible mechanisms in this section.

Moral Hazard Effects. A natural response to Figure 1 is to conclude that the spending increase is driven by induced demand responses among non-diagnosed individuals. Chronic diagnoses such as diabetes imply consistent, predictable costs on a household—such as through insulin prescriptions and endocrinologist visits. These additional costs, which are largely fixed for the individual, effectively reduce cost-sharing for the rest of the household, lowering future spot prices of (non-chronic) health care (Eichner, 1998; Kowalski, 2016).[16]

Two features of the data suggest that price responses alone cannot explain my results. As noted above, the marginal price changes would have to be relatively sizable to justify the large increases in spending reported in Figure 1. Second, the costs of a chronic diagnosis are typically larger in the year of diagnosis than in future years, especially when a diagnosis requires hospitalization. This would lead observed spillover effects to be much larger closer to the diagnostic event and muted in following years, which is at odds with Figure 1.

I can test for moral hazard effects directly by examining responses among households enrolled in plans with zero family deductibles. For these households, health events for one household member do not change the marginal prices of care for other household members; hence, were moral hazard driving the responses, I would not expect to observe any spillover effects on consumption for this group. Figure 2 presents these results; even among this sample, I continue to find strong spillover effects. There are no statistically significant differences in total spending increases between this group and the full sample. What's more, the number of additional preventive care visits is roughly 1.5–2 times larger for those without deductibles, suggesting that when households do not need to contribute to a deductible, they

[16] Appendix Figure B7 provides descriptive evidence highlighting that following a chronic diagnosis, the probability of a household meeting their deductible increases.

may consume additional preventive care as their beliefs about health risks increase. These differences suggest that if anything, price effects in the full sample limit household responses to major health events (Anderson et al., 2024).

Salience and Anxiety Effects. In addition to price effects, health events may affect household preferences for medical care. This could happen if, for example, a health shock such as a serious hospitalization led households to become more risk averse to serious medical events, affecting the marginal utility of health care. As a result of this increased anxiety, households might make additional preventive investments to provide real health benefits associated with reducing worry.[17] These salience and anxiety effects, importantly, are distinct from responses to the true risk information contained in a specific condition.

In Appendix B, I test for these effects in two ways. First, I assess how households respond to acute health shocks—for example, a hospitalization for a viral infection—rather than a chronic one. Acute events do not provide health risk information but may still generate salience effects. Second, I assess whether health shocks led to worsened household well-being, using takeup of mental health medications after the shock as a proxy for household mental health. Unlike in Figure 1, household spending and preventive care investments do not respond to acute hospitalizations, except for a transitory spending increase in the year of diagnosis (Appendix Figure B8). I do observe that affected individuals increase their spending on antidepressant prescriptions by roughly 2.5–3.5% following a diagnosis in their home (Appendix Figure B9). These findings suggest that there may be small salience or anxiety effects driving some of the observed responses, but that these changes in risk preferences alone are likely insufficient to explain overall changes in behavior.[18]

[17] This result would be akin to the converse of results found in Oster et al. (2013), for example.

[18] To put this into context, this increase is approximately a 0.24% increase in total spending. Appendix Figure B10 shows that the estimated effects in Figure 1 are virtually unchanged if I exclude any spending broadly related to mental health from the analysis (roughly 8% of all spending). I also consider the possibility that health events such as diagnoses may give families institutional knowledge about the healthcare system. I test this by examining a unique case where a diagnosis provides information about risk but not institutions:

4 Empirical Model of Belief Formation

Based on the results above, individuals may respond to health shocks in their household by updating their beliefs about their health risks, but in potentially harmful ways. These responses may be the result of belief updating or, potentially, changes to risk preferences due to anxiety or salience effects. To disentangle these channels and understand the welfare effects of new health risk information, I estimate a model of belief formation for households learning about health risks. In the model, one individual's health shock propagates health information across a household, leading each member to update their belief about subsequent health risks. The goal of the model is to identify implied health expectations based on observed health utilization choices—separate from other potential mechanisms—and measure changes in welfare associated with potentially under-informed beliefs, net of anxiety or salience effects.

Relative to the reduced-form evidence, the central contributions of the model are three-fold. First, the model isolates the effect of health risk information on shaping behavior, separate from the anxiety effects observed in Section 3. Second, the model identifies both the level of perceived health risks and how those beliefs are implied to change following health shocks, given the observed choice data. Finally, the model allows for welfare calculations, and considering counterfactual simulations for how different responses to health shocks (primarily in belief updating) would affect estimated consumer choices and welfare.

Formally, consider a household comprised of individuals $i \in \mathcal{I}_f$. In year t, each person faces a negative health shock with probability p_{it}, so that their expected utility is given by

$$EU_{it} = p_{it}U(W_{it} - d_{it}) + (1 - p_{it})U(W_{it}), \tag{3}$$

adherence to statins. Specifically, I show that household members respond to a health event by increasing overall adherence to statins regardless of the fact that they already have institutional knowledge about how to obtain them. The results are presented in Appendix Figure B11.

where d_{it} represents the within-period costs associated with a health shock and W_{it} represents individual wealth, net of all health spending that does not depend on the chronic health shock.[19] I suppose that individual utility indices $U(W)$ are increasing in wealth and concave to indicate risk aversion. As a simple parameterization, consider a simple utility index with constant relative risk aversion (CRRA) governed by the parameter γ_{it}:

$$EU_{it} = p_{it}\frac{(W_{it} - d_{it})^{1-\gamma_{it}}}{1-\gamma_{it}} + (1-p_{it})\frac{W_{it}^{1-\gamma_{it}}}{1-\gamma_{it}}, \tag{4}$$

4.1 Spending Decisions and Health Investments

Households choose investments in health care to learn about their health risks and, potentially, mitigate the expected costs of negative health shocks. Households may have misinformed beliefs about health risks, given by

$$\tilde{p}_{it} = \overline{p}_{it} + \delta_{it} \tag{5}$$

where δ_{it} represents an individual-specific shift in perceived health risks away from a baseline predicted risk, $\overline{p}_{it}$. This measure is a proxy for true (latent) health risks, and is similar to the information a medical professional might have access to and convey in a preventive setting. I construct $\overline{p}_{it}$ using logistic regressions predicting each individual's probability of a new chronic diagnosis in a year as a function of observable demographics, past household health events, and family medical history such as pre-existing conditions.[20]

[19] One can suppose that individuals choose other health spending to match some non-chronic health shock, following previous literature (Cardon and Hendel, 2001; Einav et al., 2013). By explicitly separating out chronic cost health risks as d_{it}, I focus on the relevant choice while leveraging empirical data on diagnoses in my sample to construct expected shocks.

[20] Specifically, for an individual i and diagnosis d, the underlying risk is the predicted probability from the logistic regression $\mathbb{1}\{d = 1\} = \vec{\delta}(agesex_i) + \gamma_1 \text{Past Acute Event}_i + \gamma_2 \text{Past Chronic Event}_{-i} + \gamma_3 \text{Past Acute Event}_{-i} + \vec{\delta}(familyhistory_i) + \varepsilon$ for a vector of age-sex bins and dummies for pre-existing

Suppose that individuals make a continuous choice s_{it} of how much preventive care to consume, measured using OOP spending.[21] Investments in preventive care play two important functions. First, they directly offset the expected costs of a health shock d_{it} in each period, for example by making it more likely that a chronic condition is discovered in a primary care setting rather than via a costly hospitalization. Second, preventive care provides information to correct biased beliefs about risk. Individuals choose s_{it} to maximize the overall expected utility in each period,

$$EU_{it} = (p_{it} + \theta(s_{it})\delta_{it})\frac{(W_{it} - d_{it} - (1-b)s_{it})^{1-\gamma_{it}}}{1-\gamma_{it}} + (1 - (p_{it} + \theta(s_{it})\delta_{it}))\frac{(W_{it} - s_{it})^{1-\gamma_{it}}}{1-\gamma_{it}}, \quad (6)$$

where $\theta(s_{it})$ denotes the corrective effects of s_{it} on beliefs and $b(s_{it})$ denotes its direct effects on diagnostic costs. These two functions, importantly, separate the informational and physical health returns to preventive care investments. I assume $\theta(s) = 1/(\theta \cdot s)$ and $b(s_{it}) = b \cdot s_{it}$.

Solving the expected-utility maximization problem is straightforward, with s_{it} chosen according to the first order condition

$$-\frac{\delta}{\theta s^2}\left[\frac{(W-d-(1-b)s)^{1-\gamma} - (W-s)^{1-\gamma}}{1-\gamma}\right] = \left(p + \frac{\delta}{\theta s}\right)(1-b)(W-d-(1-b)s)^{-\gamma} + \left[1 - \left(p + \frac{\delta}{\theta s}\right)\right](W-s)^{-\gamma}, \quad (7)$$

where I suppress the subscripts moving forward. That is, preventive investments balance the utility-weighted marginal benefit of improved information ($\theta'(s)\delta$) and the expected return to preventive care in the bad state of the world with the marginal cost of additional care ($U_W(W-s)$). The equilibrium values of s_{it}, taking functional forms as given, depend on individual beliefs p_{it}, errors in beliefs δ_{it}, risk aversion γ_{it}, the potential costs of a diagnosis d_{it}, and benefits of prevention b.

conditions in a family's medical history. Individual risk probabilities are then pooled across diagnoses with $\overline{p_i}$ set as the maximum probability of a diagnosis.

[21] This is to be consistent with Figure 1; results are qualitatively robust to using billed spending.

4.2 The Role of Health Shocks

When a chronic health shock affects an individual, that shock propagates through a household and provides each member with new information about health risks $\tilde{p}_{it}$ as well as generating potential salience effects affecting risk aversion γ_{it}.[22] Identifying the welfare effects of these shocks depends on separately identifying changes in these effects.

Given the quasi-randomness of these diagnoses, I model spillover effects as discrete shifts to Equation 6. That is, let τ_δ indicate a shift in beliefs due to updated risk information from a health shock, and τ_γ be the corresponding shift in the risk aversion parameter to capture salience effects. This changes the first-order condition of the model to be:

$$-\frac{(\delta+\tau_\delta)}{\theta s^2}\left[\frac{(W-d-(1-b)s)^{1-(\gamma+\tau_\gamma)}-(W-s)^{1-(\gamma+\tau_\gamma)}}{1-(\gamma+\tau_\gamma)}\right]= \tag{8}$$
$$\left(p+\frac{(\delta+\tau_\delta)}{\theta s}\right)(1-b)(W-d-(1-b)s)^{-(\gamma+\tau_\gamma)}+\left[1-\left(p+\frac{(\delta+\tau_\delta)}{\theta s}\right)\right](W-s)^{-(\gamma+\tau_\gamma)},$$

The parameter τ_δ is the change in beliefs needed to rationalize the LP-DID results in Figure 1 after adjusting for anxiety effects (τ_γ). That is, by including these coefficients as moments in estimation and using information about changes to household marginal OOP costs following health shocks (which are known), one can back out an implied value for τ_δ.

Theoretically, separate identification of changes in probability weights and risk aversion is not straightforward. However, in this context, τ_γ can be separately identified from τ_δ using the changes in how *diagnosed individuals* respond to their index events as an excluded instruments. For these individuals, we can assume that $\tau_\delta = 0$, as for them $p_{it} = 1$ effectively post-diagnosis.[23] Hence, any observed changes in their use of preventive care can be

[22] Note that the model can easily be generalized to include additional mechanisms such as moral hazard. I use the results from Section 3 to guide the model formulation and mechanisms considered.

[23] Increases in preventive care for individuals with chronic conditions may also include additional care to maintain one's chronic condition. I exclude these visits from true preventive visits using CPT modifier codes in the claims data (Hoagland et al., 2024, 2025). However, note that here any measurement error would serve

attributed entirely to changes in risk aversion. I therefore assume that risk aversion parameters are constant within a household and use LP-DID results for increases in preventive spending among diagnosed individuals in the years following their diagnosis to identify τ_γ. This allows me to identify anxiety effects overall, and then use residual changes in spending and preventive investments to back out shifted beliefs (τ_δ).

Identification of both baseline beliefs and the shift implied by a health shock is important for identifying welfare effects. However, estimated equilibrium beliefs on their own are not informative about the correctness or precision of belief updating following a major health event. To define a notion of "over" or "under" reaction, I compare implied beliefs to two important quantities: an individual's own predicted risk for health shocks given demographic information ($\overline{p}_i$), and additional estimates from the epidemiological literature quantifying the genetic risk of diagnoses given family histories.

5 Estimation & Identification

Estimation of the model requires isolating three categories of parameter values: baseline household beliefs and risk aversion (δ, γ); the value of preventive care (θ, b); and the shift parameters induced by health events affecting household beliefs and risk aversion $(\tau_\delta, \tau_\gamma)$.[24]

I estimate the model via GMM, using moments from the decision-making problem and implied spending patterns. Parameter identification requires three steps. First, prior to health shocks, I identify baseline household parameters (δ and γ) given variation across individuals and diseases in diagnosis costs d and underlying risk $\overline{p}$. These parameters enter an individual's FOC in slightly different ways. For example, two individuals with the same demographics and equivalent values for δ will have different levels of responsiveness to changes

to overweight anxiety effects as a potential mechanism, ultimately attenuating the shifts in risk beliefs that I am attempting to identify. Appendix Figure C1 illustrates the observed responses for diagnosed individuals.

[24] Following Section 3, I exclude moral hazard effects from the model and estimate it only on those enrolled in plans without a family deductible.

in d based on their risk aversion, γ; on the other hand, variation in true individual risk $\overline{p}$, conditional on γ, identifies δ. Importantly, this means that some features of the spending distribution—for example, those affecting the extensive margin decision of consuming care—are affected by only one parameter (in this case, δ) and not the other (γ). Finally, I leverage the panel structure of the data and the assumption that γ is constant within households.

I next identify the benefits from preventive care (b, θ). First, b is directly estimated using the relationship between increases in preventive care utilization and the relative savings in diagnosis costs for subsequent diagnoses within a household.[25] Second, θ is identified using pre-diagnosis variation in the observed choice of s, conditional on δ.

Finally, I identify the shifts in individual parameters induced by health events. Here, identification uses the same intuition as above, relying on moments that separately identify δ from γ and, importantly, considering how realized decisions vary before and after the health event. Formally, in addition to the variation across time in these moments, I also include a direct estimation of τ_γ based on differences in preventive care investments made by *diagnosed* individuals, as discussed above; given that risk aversion is a household-level parameter, the responses of the diagnosed individual identify changes in anxiety or salience for all affected household members. After accounting for this shift, I include moments for simulated LP-DID coefficients in my sample and compare them to the observed estimates following Equation 1. These moments, taken with time variation in the others, identify τ_δ.

Overall, I include moments in four categories: (1) the individual's FOC and implied risk premium; (2) differences in the center of the predicted and observed spending distributions, including the average, median, and RMSPE; (3) differences in the spread of these distributions, including the fraction of individuals choosing 0 spending in a year and the standard deviation of spending choices; and (4) LP-DID regression coefficients following Equation 1 for

[25] Of the 62,528 households with a health shock, roughly 18,652 (29.8%) experience more than one chronic event within the sample period.

health spending and preventive visits via indirect inference. I include 16 moment conditions in total, presented in Appendix Table C1.

Equilibrium decision-making in this model is influenced by other auxiliary parameters including the baseline wealth W and loss associated with the health shock d. I calibrate W and d using (1) the median per-person after-tax income of individuals enrolled in ESI plans ($29,644) and (2) the empirical distributions of chronic health shocks at the HCC level. In estimation, I allows s to be both all OOP spending and only preventive care spending to match the intuition of the non-structural components of the paper. Separate estimation for both levels of s also allows the model to be informative of low-value spending or utilization of care downstream of preventive care; overall, the key results are qualitatively unchanged.

6 Structural Results

Table 5 presents the equilibrium model parameters estimated by GMM. Baseline risk beliefs are highly skewed: prior to a health shock, average (median) individual beliefs about health risks are 23.4% (1.0%). Considering a relative in-sample diagnosis rate of about 2.7%, roughly 39% of individuals under-estimate their true health risk by over 50%, while 54.2% *over*-estimate their risk by 50%. This variation is particularly important, given that households exhibit relatively high levels of risk aversion with substantial noise in the distribution.

Preventive care is therefore an important vehicle for individual learning: investments in health spending are estimated to reduce diagnostic costs by roughly 13 cents per dollar invested, while also substantially correcting beliefs about risk. The equilibrium value of θ, 0.093, is interpreted relative to baseline values of δ. Specifically, for each additional $100 of spending, the gap between $\tilde{p}$ and $\overline{p}$ is reduced by 17%.[26]

Panel (c) of Table 5 presents the key model finding, also visualized in Figure 3: how health shocks affect beliefs. In general, estimation suggests that there are negligible changes in risk

[26] Overall, the estimated model matches the implied spending distribution and regression coefficients well. Appendix Figure C2 presents descriptive figures summarizing the overall model fit.

aversion following a health event—if anything, households may slightly *reduce* the weight they place on adverse events.[27] However, beliefs are highly elastic to new risk information: following a health shock, the average (median) individual belief spikes to 34.4% (15.3%) and remains elevated for the five years after diagnosis. These changes are large relative to the unconditional probability of a chronic event (roughly 2.7%, shown in green).

On their own, these estimated beliefs are uninformative about the value of household reactions, as large changes in beliefs could be warranted by the conditional risk distributions individuals face given a family member's diagnosis. I therefore place these changes in context by comparing them to expected *ex-post* conditional probabilities of a diagnosis, based on external clinical estimation. Figure 3 shows this estimated range in orange for a sibling's conditional risk of developing type 1 diabetes given another sibling's diagnosis (Harjutsalo et al., 2005). This is an example where there is large conditional risk-sharing, so the signal is particularly informative. However, estimated changes in beliefs well exceed this standard measure of conditional health risk even 4 years after the event year.

6.1 The Welfare Effects of Health Shocks

Based on the estimated structural parameters and Equation 6, I can construct a measure of each individual's expected utility gain from new health risk information. My measure of welfare compares equilibrium expected utility across various states of the world, allowing households to respond to information by changing their spending decisions and holding anxiety and salience effects fixed. That is, I vary only the extent to which health shocks affect beliefs and measure implied differences in expected utility, both as a percentage change in utility and in the resulting change in risk premia and certainty equivalents.[28]

[27] Anxiety effects alone cannot plausibly rationalize the increases seen in Figure 1. At the mean parameter values, if $\tau_\delta = 0$ then γ would have to increase more than 50-fold to generate even a 5% spending increase.

[28] Letting $\tau_\gamma > 0$ has little practical effect on these calculations given the small scale estimated for anxiety effects. Throughout, I present results only for affected household members in the year of diagnosis.

This exercise reveals three important results. First, correct information—even for households with incorrectly low beliefs—is generally welfare-improving. This is intuitive: even though raising p_{it} to a "true" level of predicted risk $\overline{p}_{it}$ mechanically introduces uncertainty lowering expected utility (Equation 6), households optimally adjust their spending to minimize diagnostic risk. I first compare household outcomes when a health shock changes p to this predicted risk level rather than the full "over-updating" implied by τ_δ (Figure 3). I find modest gains for correct information in this scenario, with household expected utility increasing by 0.15%. Put another way, household certainty equivalents would increase by $36 when given correct information about their risks.

Second, and despite the overall value of information, equilibrium belief updating is not welfare improving for the majority of affected households. I next compare household outcomes given their implied belief updating, relative to the counterfactual of a health shock that only affects τ_γ and not beliefs. I find 68.2% of affected individuals in my sample would be willing to pay to *avoid* new information, and only 20% prefer the updating implied by the health shock. Utility differences here are more sizable, with declines of 8.1% (0.6%) in average (median) utility. Ultimately, responses to health shocks cost households an additional $790 ($504) per year.[29]

Finally, I find these welfare losses stem from two principal channels. First, as beliefs about health risks rise after a health shock, households re-optimize their spending decisions, leading to increases in predicted spending of 25% at the median and 17% at the mean (in line with Figure 1 and Table 4). However, even after re-optimizing to accommodate updated beliefs, households still experience utility losses given the overly large weight placed on severe adverse events. I investigate this further in the next section by showing how welfare changes when new information is placed into better context.

[29] Appendix Figure C3 shows the full distribution of utility losses across the affected individuals in the sample in both percentage changes in utility as well as changes to the certainty equivalent/risk premia.

6.2 The Role of Belief Updating in Welfare Penalties

I perform simple counterfactual scenarios imposing arbitrary upper bounds belief updating. This exercise intuitively illustrates how much of the utility loss from a health shock can be mitigated when patients respond more appropriately to signals of conditional risk.

Figure 4 presents the results for those who incurred welfare penalties from new health risk information. I impose an upper limit on post-diagnosis beliefs and allow it to vary between 0 and 1; at each point, I estimate the fraction of individuals with a strictly positive WTP for information. This fraction increases dramatically even under loose restrictions prohibiting large swings in beliefs. When the cap is not binding, 20% of individuals have a positive WTP for information; however, even restricting beliefs to be 10% or fewer—a relatively generous bound as noted above—expand this share to be over 65%. Of those unwilling to pay for health information without a cap, roughly 80% value information with a cap at 3% or lower.

Taken together, the model estimates and counterfactual simulations suggest that health shocks generate welfare losses primarily through two channels: (1) households over-updating their beliefs about health risks; and (2) households increasing spending in ways that ultimately reduce utility. My results suggest that the majority of welfare losses arise from the first mechanism, where belief updating is disproportionate relative to true risk. This has important policy implications, as it suggests that improving how individuals interpret risk information may be more effective than simply increasing access to information. Interventions that help individuals contextualize family health events through targeted counseling, clearer risk communication in primary care, or digital health tools could help households respond appropriately to diagnostic information. For example, genomics-based risk calculators or clinical decision support systems embedded into EHR systems may help direct physicians and patients to appropriate, calibrated responses based on family histories.

6.3 Additional Policy Simulations

The structural model estimated here allows me to consider broader policy simulations evaluating alternative approaches to improve the value of risk information. Health-related spillovers—especially within families—can be leveraged as policy tools to improve screening and public health, and have therefore attracted recent research (Acosta et al., 2021). However, welfare implications of differing approaches are not obvious, particularly given limited understanding of individual reactions to information.

The model I estimate can provide insight into the policy value of tools such as genomics-based risk calculators or polygenic risk scores for calibrating responses to health information. Appendix Figure C4 shows the results of a simple simulation predicting the value of revealing targeted health information based on patient demographics and estimated belief responses. In panel (a), I first highlight that households with the lowest true risk incur the greatest utility losses from health shocks. This makes sense, as these households are the most likely to internalize health risks well above their true predicted risk and, ultimately, overspend. Importantly, however, these households also benefit the least from the revelation of true health risk information, as proxied by $\overline{p}_{it}$. In panel (b), I show that except for very low-risk individuals (for whom learning $p \approx 0$ would dramatically increase utility) the value of true information increases with risk. That is, targeted revelation of risk information can benefit high-risk individuals while, in theory, avoiding the negative welfare effects of over-reaction for low-risk households. This suggests value in policies leveraging medical histories and machine learning, for example, to construct more targeted approaches to screenings and the transmission of new risk information.

Overall, the model suggests that interventions seeking to improve information *interpretation*, rather than simply information *access*, may be more valuable and effective. Health literacy programs that either improve the precision of risk signals or more clearly underscore the value of specific health services for a risk condition may improve patient welfare while reducing overall health spending. This may include improving the return on primary care

investments as a way to correct inappropriate health beliefs or to limit the use of pseudo-preventive low-value services.

The model results could be extended in meaningful ways to improve its use for policy evaluation. First, future work could incorporate additional discretion over individual chronic care costs. This is particularly interesting in non-ESI populations, including uninsured or Medicaid-enrolled individuals for whom chronic diagnoses may impose large financial burdens or liquidity constraints (Gross et al., 2022). Future work might also integrate this model with other costs incurred through living with a chronic condition, including earnings penalties and job lock (Biasi et al., 2025; Eriksen et al., 2021; Garthwaite et al., 2014).

7 Conclusion

This paper estimates how information about health risks drives the level and quality of utilization choices. Health shocks such as new diagnoses transmit information about risk to other household members, who subsequently change their use of both high- and low-return services. However, while access to new health information changes behavior in meaningful ways, it does not necessarily leave individuals better off.

I use a structural approach to quantify the welfare effects of new health information. I find that for nearly one-half of affected individuals, information gains are swamped by overly large shifts in estimated *ex-post* risks. Bounding how much individuals increase their risk beliefs post-diagnosis makes information welfare-improving for over 80% of individuals.

Increasing understanding of how consumers interpret new information is at least as vital as improving their access. Family health experiences are powerful forces in shaping individual behaviors and decisions; however, witnessing these experiences may induce over-corrections in future consumption decisions. Individuals and families living with the risk of chronic illness may be better off as they are taught to seek out high-value medical care and temper high expectations of negative outcomes.

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Table 1. Household Summary Statistics

	Full Sample	Households Affected by Chronic Events
Panel A: Household Demographics		
Family size	2.84 (0.001)	3.11 (0.004)
Employee age	45.01 (0.007)	43.61 (0.039)
Enrollee age	30.87 (0.008)	29.37 (0.041)
% female employees	41.57 (0.037)	41.04 (0.190)
% female enrollees	50.17 (0.021)	50.11 (0.109)
Risk score, year $t-1$	0.95 (0.001)	1.01 (0.008)
Panel B: Household Medical Utilization		
Total medical spending	\$2,504 [\$680] (4.51)	\$4,546 [\$1,130] (73.13)
OOP medical spending	\$443 [\$110] (0.53)	\$614 [\$175] (4.39)
% enrollees w/ 0 spending	15.39 (0.015)	10.35 (0.067)
% enrollees w/ 0 OOP	21.04 (0.017)	14.68 (0.077)
Household deductible	\$415 (0.619)	\$419 (3.094)
% w/ 0 deductible	28.04 (0.032)	32.47 (0.180)
Panel C: Individual Major Medical Events		
Total cost, Diagnosis	—	\$4,164 [\$1,319] (156.81)
OOP, Diagnosis	—	\$532 [\$212] (27.36)
OOP, Recurring	—	\$489 [\$190] (24.78)
$N_{\text{households}}$	353,403	62,528
$N_{\text{individuals}}$	1,087,353	194,844

Notes: Enrollees are employees plus their covered dependents. Spending values are reported in 2020 USD. Standard errors are reported in parentheses and sample medians are in brackets. Panel B includes unconditional spending averages for the entire household (summing across all household members) while Panel C includes conditional spending averages for affected individuals only. Column 2 limits the sample to only household-years in which a chronic diagnosis occurred. In this column, risk score is calculated only in the year prior to the major medical event.

Health Shock Category	**Conditions/Diagnostic Groups**	**Median Age**
Cancers	Breast cancer, prostate cancer, thyroid cancer	52
Cardiovascular Conditions	Congestive heart failure, heart arrhythmias	50
Autoimmune Conditions	Diabetes, multiple sclerosis, rheumatoid arthritis	50
Mental Health Conditions	Major depressive, bipolar, and personality disorders	38
Others	Asthma, inflammatory bowel disease, seizures	20

Table 2. Sample Chronic Condition Health Shocks

Notes: Table summarizes the most common chronic conditions used as health shocks throughout the paper. For a complete list and relevant diagnostic and procedure codes, see Appendix A.1.

Table 3. Effect of Chronic Diagnoses on Take-Up of Disease-Specific Preventive Care

Own Screening (Dependent Variable)	Household Diagnosis	Pre-Diagnosis Average	Effect of Any Diagnosis ($\beta^{\text{LP-DD}}$)	Effect of Specified Diagnosis ($\beta^{\text{LP-DDD}}$)
Panel A: Main Effects				
Cancer	Cancer	20.72	0.299*	2.253***
			(0.1226)	(0.5328)
Diabetes	Diabetes	6.18	-0.401***	0.953***
			(0.0940)	(0.2828)
Cholesterol	Diabetes	16.97	-0.177	0.884*
			(0.1370)	(0.3993)
Panel B: Placebo Regressions				
Obesity[1]	Diabetes	1.01	0.021	0.009
			(0.0372)	(0.1135)
Depression	Depression	0.34	-0.052	-0.022
			(0.0396)	(0.0816)

Notes: Table presents 5 LP-DDD regressions estimating the effect of a chronic condition on spillover household investments in disease-specific preventive care (Equation 2). Outcome variables are binary indicators for a screening (column 1); the specific diagnosis d is listed in column 2. DD coefficients ($\beta^{\text{LP-DD}}$) indicate the effect of *any* chronic diagnosis on screenings, while DDD coefficients ($\beta^{\text{LP-DDD}}$) indicate the (additive) effect of *specific* diagnoses. [1]Outcome is measured using diagnostic codes. Here, I report average effects over the full post-period, as discussed in Section 3 and Dube et al. (2025). This procedure recovers a variance-reweighted ATT using clean controls and positive weights, producing a single post-effect coefficient akin to a traditional pooled difference-in-differences estimator. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Table 4. Estimated Effects of Chronic Illness on Low-Value Care Utilization

Population	All	Pediatric	Adult Services			
Service Category	—	All Services	Prescriptions	Imaging	Screening	Surgery
Panel A: Pr(Any Use)						
LP-DID Pooled Effect	0.030	0.212***	-0.426	0.061*	0.091**	-0.210***
	(0.0221)	(0.0562)	(0.2346)	(0.0270)	(0.0302)	(0.0534)
Panel B: Log(Total Billed Spending)						
LP-DID Pooled Effect	0.048	0.072***	-0.004	0.034***	0.061**	-0.065***
	(0.0331)	(0.0170)	(0.0034)	(0.0096)	(0.0246)	(0.0180)

Notes: Table shows pooled LP-DID treatment effects for the effect of a new chronic diagnosis. Outcome variables are the likelihood of any spending in each category as well as the log of billed spending in each category (Section 2.2). In panel (a), coefficients are scaled relative to the pre-treatment mean, so that coefficients can be interpreted as percentage changes. Standard errors clustered at the household level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

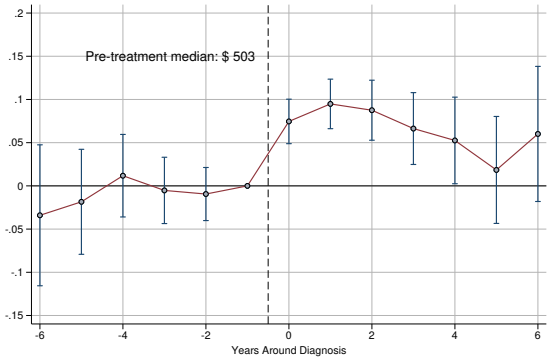
Table 5. Estimated Structural Parameters

		Estimate	95% Confidence Interval
Panel A: Baseline Model Parameters			
Baseline risk beliefs ($\tilde{p}_{\text{Pre}}$)			
$\mu_{\tilde{p}_{\text{Pre}}}$	Mean	0.234	[0.229, 0.239]
$\text{med}(\tilde{p}_{\text{Pre}})$	Median	0.010	[0.004, 0.016]
$\sigma_{\tilde{p}_{\text{Pre}}}$	Standard Deviation	0.353	[0.303, 0.403]
Baseline risk aversion (γ)			
μ_γ	Mean	3.029	[2.783, 2.793]
$\text{med}(\gamma)$	Median	2.790	[2.752,2.823]
σ_γ	Standard Deviation	1.290	[1.255, 1.325]
Panel B: Parameters Governing Preventive Care Investments			
b	Average Health Shock Savings	0.130	[0.124, 0.136]
θ	Average Belief Correction	0.093	[0.090, 0.095]
Panel C: Effects of Health Shocks			
Shift Parameters			
τ_δ	Effect on Beliefs	0.748	[0.734, 0.761]
τ_γ	Effect on Risk Aversion	-0.003	[-0.004, -0.002]
Post-Event risk beliefs ($\tilde{p}_{\text{Post}}$)			
$\mu_{\tilde{p}_{\text{Post}}}$	Mean	0.344	[0.339, 0.349]
$\text{med}(\tilde{p}_{\text{Post}})$	Median	0.153	[0.147, 0.159]
$\sigma_{\tilde{p}_{\text{Post}}}$	Standard Deviation	0.367	[0.317, 0.417]
Post-Event risk aversion (γ)			
μ_γ	Mean	3.024	[2.783, 2.793]
$\text{med}(\gamma)$	Median	2.780	[2.742, 2.818]
σ_γ	Standard Deviation	1.300	[1.265, 1.335]

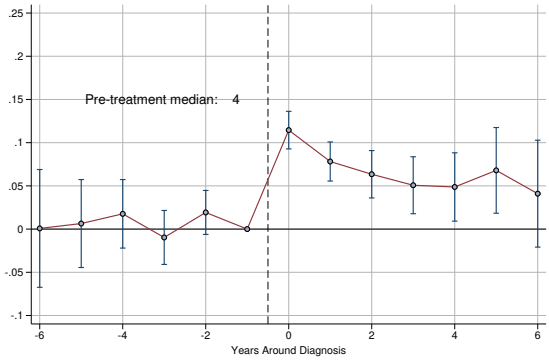
Notes: Table presents estimated equilibrium parameters of the model estimated via GMM on a sample of $N = 281,964$ enrollees in $98,976$ households without family deductibles. Standard errors are calculated using the GMM optimal weighting matrix. 95% confidence intervals for predicted means and medians are calculated via bootstrapping. Here, the household choice variable is total OOP dollars; results are similar when considering only choices of preventive care.

Figure 1. Effect of Chronic Diagnoses on Other Household Members' Utilization

(a) log(Total OOP Spending+1)



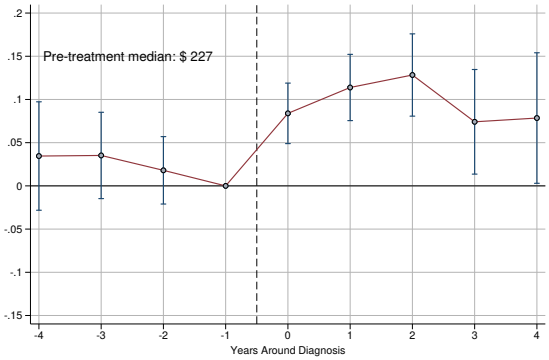
(b) # of Preventive Visits



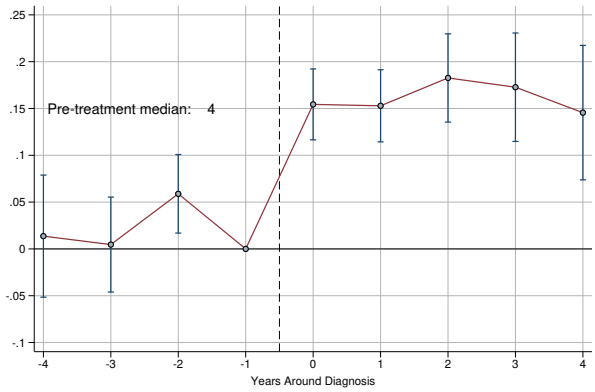
Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on medical utilization of other (non-diagnosed) household members, measured as (a) the logarithm of total OOP spending +1, and (b) number of household preventive services per year. Standard errors are clustered at the household level.

Figure 2. Effect of Chronic Diagnoses on Utilization: Households Facing Zero Deductible

(a) log(Total OOP Spending+1)

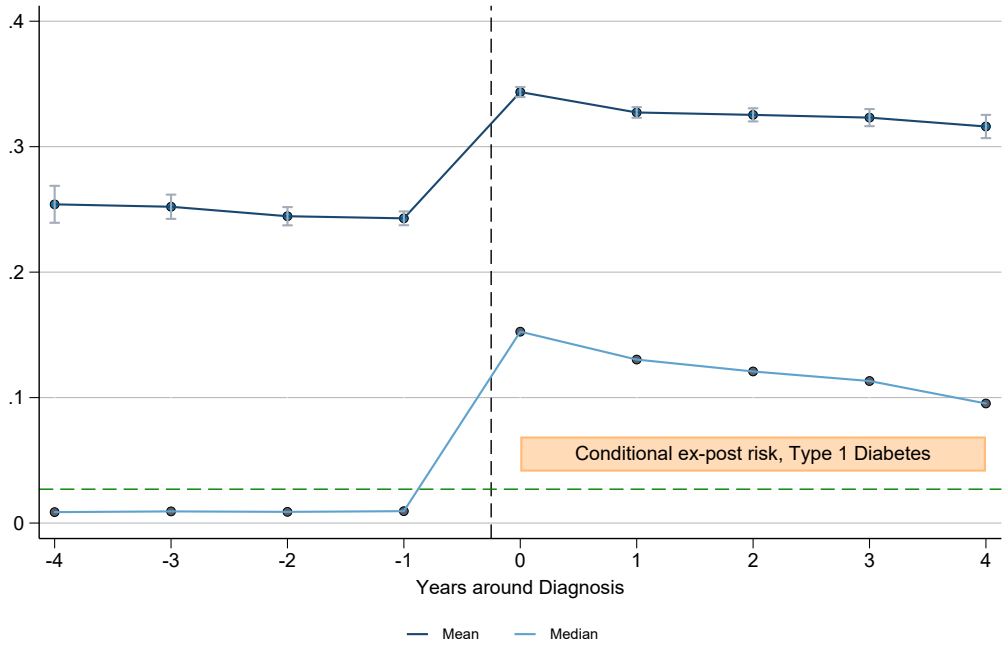


(b) # of Preventive Visits



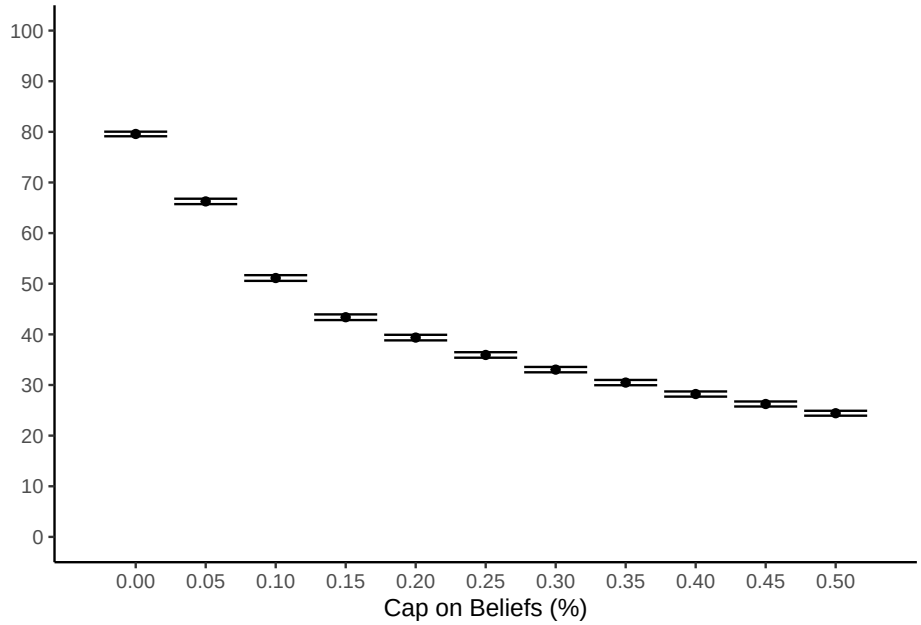
Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. The sample is restricted to households enrolled in ESI plans with zero deductible at the time of the event. Regressions estimate the effect of a new chronic diagnosis on medical utilization of other (non-diagnosed) household members, measured as (a) the logarithm of total OOP spending +1, and (b) number of household preventive services per year. Standard errors are clustered at the household level.

Figure 3. Model Predictions: Beliefs Around a New Diagnosis



Notes: Figure shows recentered time series indicating average and median individual risk beliefs for the same population (individuals affected by a new chronic diagnosis in their home), averaged over draws from individual posterior distributions. The green horizontal line in Panel (b) illustrates the average in-sample rate of diagnosis (∼2.7%); the orange range indicates the estimated *ex-post* risk of a diagnosis of type 1 diabetes following a sibling's diagnosis ([4.1%,6.9%]) (Harjutsalo et al., 2005).

Figure 4. Bounding τ_δ Increases the % of Individuals Valuing Health Risk Information



Notes: Figure shows results from a counterfactual simulation bounding the extent to which beliefs update following a chronic diagnosis. Each point represents the result of a different simulation where beliefs are capped at the indicated value. The $y-$axis shows the fraction of individuals affected by a chronic diagnosis who are predicted to have a higher expected utility in the year of the chronic health shock when they incorporate the information than when they do not, subject to the cap. Sample is restricted to those whose value of health risk information was negative without the cap on beliefs and evaluated in the year of diagnosis.

A Data Preparation

A.1 Identifying Major Health Events

I assign major health events using a set of chronic and acute HCCs (Section 2). Table A1 identifies each major health event as well as its corresponding status (acute/chronic) and accompanying diagnosis codes. Prior to October 2015, Marketscan claims data relied on ICD-9-CM diagnosis codes, transitioning to ICD-10-CM diagnosis codes thereafter.

Table A1: Diagnosis Codes for Sample HCCs

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
Acute Liver Failure	No	0063, 0700, 07020, 07021, 07041, 07042, 07043, 07049, 0706, 07071, 570, 5711, 5720, 5721, 5734, 7744	A064, B150, B160, B162, B1711, B190, B1911, B1921, K7010, K7011, K7200, K750, K751, K762, K763, P591, P5920, P5929
Acute Myocardial Infarction	No	41001, 41011, 41021, 41031, 41041, 41051, 41061, 41071, 41081, 41091, 4295, 4296	I2101, I2102, I2109, I2111, I2119, I2121, I2129, I213, I214, I220, I221, I222, I228, I229, I234, I235, I511, I512
Adrenal/Pituitary Disorders	Yes	0363, 2510, 25200, 25201, 25202, 25208, 2521, 2528, 2529, 2530, 2531, 2532, 2533, 2534, 2535, 2536, 2537, 2538, 2539, 2540, 2541, 2548, 2549, 2550, 25510, 25511, 25512, 25513, 25514, 2552, 2553, 25541, 25542, 2555, 2556, 2558, 2559, 25801, 25802, 25803, 2581, 2588, 2589, 5881, 58881	A391, E035, E15, E200, E208, E209, E210, E211, E212, E213, E214, E215, E220, E221, E222, E228, E229, E230, E231, E232, E233, E236, E237, E240, E241, E242, E243, E244, E248, E249, E250, E258, E259, E2601, E2602, E2609, E261, E2681, E2689, E269, E270, E271, E272, E273, E2740, E2749, E275, E278, E279, E310, E311, E3120, E3121, E3122, E3123, E318, E319, E320, E321, E328, E329, E344, E892, E893, E896, N251, N2581
Asthma	Yes	49300, 49301, 49302, 49310, 49311, 49312, 49381, 49382, 49390, 49391, 49392	J4520, J4521, J4522, J4530, J4531, J4532, J4540, J4541, J4542, J4550, J4551, J4552, J45901, J45902, J45909, J45990, J45991, J45998
Brain Infections	No	00321, 0065, 01300, 01301, 01302, 01303, 01304, 01305, 01306, 01310, 01311, 01312, 01313, 01314, 01315, 01316, 01320, 01321, 01322, 01323, 01324, 01325, 01326, 01330, 01331, 01332, 01333, 01334, 01335, 01336, 01340, 01341, 01342, 01343, 01344, 01345, 01346, 01350, 01351, 01352, 01353, 01354, 01355, 01356, 01360, 01361, 01362, 01363, 01364, 01365, 01366, 01380, 01381, 01382, 01383, 01384, 01385, 01386, 01390, 01391, 01392, 01393, 01394, 01395, 01396, 0360, 0361, 037, 04500, 04501, 04502, 04503, 04510, 04511, 04512, 04513, 04520, 04521, 04522, 04523, 04590, 04591, 04592, 04593, 0498, 0499, 0520, 0543, 0550, 05601, 05821, 05829, 0620, 0621, 0622, 0623, 0624, 0625, 0628, 0629, 0630, 0631, 0632, 0638, 0639, 064, 0662, 06640, 06641, 06642, 06649, 071, 0722, 09040, 09041, 09042, 09049, 09181, 0940, 0941, 0942, 0943, 09481, 09482, 09483, 09484, 09485, 09486, 09489, 0949, 09882, 10081, 11283, 1142, 11501, 11511, 11591, 3200, 3201, 3202, 3203, 3207, 32081, 32082, 32089, 3209, 3211, 3213, 3214, 3218, 32301, 3231, 3232, 32341, 32351, 32361, 32362, 32381, 3239, 3240, 3241, 3249, 325	A0101, A0221, A066, A170, A171, A1781, A1782, A1783, A1789, A179, A203, A2781, A3211, A3212, A34, A35, A390, A3981, A4281, A4282, A5040, A5041, A5042, A5043, A5044, A5045, A5049, A5141, A5210, A5211, A5212, A5213, A5214, A5215, A5216, A5217, A5219, A522, A523, A5481, A5482, A6921, A800, A801, A802, A8030, A8039, A804, A809, A820, A821, A829, A830, A831, A832, A833, A834, A835, A836, A838, A839, A840, A841, A848, A849, A850, A851, A852, A858, A86, A888, A89, A922, A9230, A9231, A9232, A9239, B004, B0111, B020, B050, B0601, B1001, B1009, B262, B375, B384, B4081, B4281, B431, B5741, B5742, B6011, G000, G001, G002, G003, G008, G009, G01, G02, G0400, G0401, G0402, G042, G0430, G0431, G0432, G0439, G0481, G0490, G053, G060, G061, G062, G07, G08
Breast and Prostate Cancer	Yes	1740, 1741, 1742, 1743, 1744, 1745, 1746, 1748, 1749, 1750, 1759, 179, 1800, 1801, 1808, 1809, 1820, 1821, 1828, 1840, 1841,	C4A0, C4A10, C4A11, C4A12, C4A20, C4A21, C4A22, C4A30, C4A31, C4A39, C4A4, C4A51, C4A52, C4A59, C4A60,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
		1842, 1843, 1844, 1848, 1849, 185, 1880, 1881, 1882, 1883, 1884, 1885, 1886, 1887, 1888, 1889, 1892, 1893, 1894, 1898, 1899, 1900, 1901, 1902, 1903, 1904, 1905, 1906, 1907, 1908, 1909, 1950, 1951, 1952, 1953, 1954, 1955, 1958, 1992, 20100, 20101, 20102, 20103, 20104, 20105, 20106, 20107, 20108, 20110, 20111, 20112, 20113, 20114, 20115, 20116, 20117, 20118, 20120, 20121, 20122, 20123, 20124, 20125, 20126, 20127, 20128, 20140, 20141, 20142, 20143, 20144, 20145, 20146, 20147, 20148, 20150, 20151, 20152, 20153, 20154, 20155, 20156, 20157, 20158, 20160, 20161, 20162, 20163, 20164, 20165, 20166, 20167, 20168, 20170, 20171, 20172, 20173, 20174, 20175, 20176, 20177, 20178, 20190, 20191, 20192, 20193, 20194, 20195, 20196, 20197, 20198, 20900, 20901, 20902, 20903, 20910, 20911, 20912, 20913, 20914, 20915, 20916, 20917, 20920, 20921, 20922, 20923, 20924, 20925, 20926, 20927, 20929, 20930, 20931, 20932, 20933, 20934, 20935, 20936, 2250, 2251, 2252, 2253, 2254, 2258, 2259, 2273, 2274, 22802, 2370, 2371, 2373, 2375, 2376, 2379, 2396, 7595, 7596	C4A61, C4A62, C4A70, C4A71, C4A72, C4A8, C4A9, C50011, C50012, C50019, C50021, C50022, C50029, C50111, C50112, C50119, C50121, C50122, C50129, C50211, C50212, C50219, C50221, C50222, C50229, C50311, C50312, C50319, C50321, C50322, C50329, C50411, C50412, C50419, C50421, C50422, C50429, C50511, C50512, C50519, C50521, C50522, C50529, C50611, C50612, C50619, C50621, C50622, C50629, C50811, C50812, C50819, C50821, C50822, C50829, C50911, C50912, C50919, C50921, C50922, C50929, C510, C511, C512, C518, C519, C52, C530, C531, C538, C539, C540, C541, C542, C543, C548, C549, C55, C577, C578, C579, C61, C661, C662, C669, C670, C671, C672, C673, C674, C675, C676, C677, C678, C679, C680, C681, C688, C689, C6900, C6901, C6902, C6910, C6911, C6912, C6920, C6921, C6922, C6930, C6931, C6932, C6940, C6941, C6942, C6950, C6951, C6952, C6960, C6961, C6962, C6980, C6981, C6982, C6990, C6991, C6992, C760, C761, C762, C763, C7640, C7641, C7642, C7650, C7651, C7652, C768, C7A00, C7A010, C7A011, C7A012, C7A019, C7A020, C7A021, C7A022, C7A023, C7A024, C7A025, C7A026, C7A029, C7A090, C7A091, C7A092, C7A093, C7A094, C7A095, C7A096, C7A098, C7A1, C7A8, C802, C8100, C8101, C8102, C8103, C8104, C8105, C8106, C8107, C8108, C8109, C8110, C8111, C8112, C8113, C8114, C8115, C8116, C8117, C8118, C8119, C8120, C8121, C8122, C8123, C8124, C8125, C8126, C8127, C8128, C8129, C8130, C8131, C8132, C8133, C8134, C8135, C8136, C8137, C8138, C8139, C8140, C8141, C8142, C8143, C8144, C8145, C8146, C8147, C8148, C8149, C8170, C8171, C8172, C8173, C8174, C8175, C8176, C8177, C8178, C8179, C8190, C8191, C8192, C8193, C8194, C8195, C8196, C8197, C8198, C8199, D1802, D320, D321, D329, D330, D331, D332, D333, D334, D337, D339, D352, D353, D354, D420, D421, D429, D430, D431, D432, D433, D434, D438, D439, D443, D444, D445, D446, D447, D496, Q851, Q858, Q859
Cardio-Respiratory Failure	No	42741, 42742, 4275, 514, 5184, 51881, 51882, 51883, 51884, 769, 7703, 7704, 7705, 7707, 77084, 77985, 78550, 78551, 7980, 7981, 7982, 7989, 9584	I462, I468, I469, I4901, I4902, J182, J80, J810, J811, J9600, J9601, J9602, J9610, J9611, J9612, J9620, J9621, J9622, J9690, J9691, J9692, P220, P260, P261, P268, P269, P270, P271, P278, P279, P280, P2810,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			P2811, P2819, P285, P2981, R570, R579, T794XXA
Central Nervous System Infections, Except Viral Meningitis	No	00321, 0065, 01300, 01301, 01302, 01303, 01304, 01305, 01306, 01310, 01311, 01312, 01313, 01314, 01315, 01316, 01320, 01321, 01322, 01323, 01324, 01325, 01326, 01330, 01331, 01332, 01333, 01334, 01335, 01336, 01340, 01341, 01342, 01343, 01344, 01345, 01346, 01350, 01351, 01352, 01353, 01354, 01355, 01356, 01360, 01361, 01362, 01363, 01364, 01365, 01366, 01380, 01381, 01382, 01383, 01384, 01385, 01386, 01390, 01391, 01392, 01393, 01394, 01395, 01396, 0360, 0361, 037, 04500, 04501, 04502, 04503, 04510, 04511, 04512, 04513, 04520, 04521, 04522, 04523, 04590, 04591, 04592, 04593, 0498, 0499, 0520, 0543, 0550, 05601, 05821, 05829, 0620, 0621, 0622, 0623, 0624, 0625, 0628, 0629, 0630, 0631, 0632, 0638, 0639, 064, 0662, 06640, 06641, 06642, 06649, 071, 0722, 09040, 09041, 09042, 09049, 09181, 0940, 0941, 0942, 0943, 09481, 09482, 09483, 09484, 09485, 09486, 09489, 0949, 09882, 10081, 11283, 1142, 11501, 11511, 11591, 3200, 3201, 3202, 3203, 3207, 32081, 32082, 32089, 3209, 3211, 3213, 3214, 3218, 32301, 3231, 3232, 32341, 32351, 32361, 32362, 32381, 3239, 3240, 3241, 3249, 325	A0101, A0221, A066, A170, A171, A1781, A1782, A1783, A1789, A179, A203, A2781, A3211, A3212, A34, A35, A390, A3981, A4281, A4282, A5040, A5041, A5042, A5043, A5044, A5045, A5049, A5141, A5210, A5211, A5212, A5213, A5214, A5215, A5216, A5217, A5219, A522, A523, A5481, A5482, A6921, A800, A801, A802, A8030, A8039, A804, A809, A820, A821, A829, A830, A831, A832, A833, A834, A835, A836, A838, A839, A840, A841, A848, A849, A850, A851, A852, A858, A86, A888, A89, A922, A9230, A9231, A9232, A9239, B004, B0111, B020, B050, B0601, B1001, B1009, B262, B375, B384, B4081, B4281, B431, B5741, B5742, B6011, G000, G001, G002, G003, G008, G009, G01, G02, G0400, G0401, G0402, G042, G0430, G0431, G0432, G0439, G0481, G0490, G053, G060, G061, G062, G07, G08
Cerebral Aneurysm and Arteriovenous Malformation	No	4373, 74781	A5205, I671, Q282, Q283
Chronic Hepatitis	Yes	07022, 07023, 07032, 07033, 07044, 07054, 57140, 57141, 57142, 57149	B180, B181, B182, B188, B189, K730, K731, K732, K738, K739, K754
Chronic Skin Ulcer	Yes	4540, 4542, 45911, 45913, 45931, 45933, 68601, 70710, 70711, 70712, 70713, 70714, 70715, 70719, 7078, 7079	I83001, I83002, I83003, I83004, I83005, I83008, I83009, I83011, I83012, I83013, I83014, I83015, I83018, I83019, I83021, I83022, I83023, I83024, I83025, I83028, I83029, I83201, I83202, I83203, I83204, I83205, I83208, I83209, I83211, I83212, I83213, I83214, I83215, I83218, I83219, I83221, I83222, I83223, I83224, I83225, I83228, I83229, I87011, I87012, I87013, I87019, I87031, I87032, I87033, I87039, I87311, I87312, I87313, I87319, I87331, I87332, I87333, I87339, L88, L97101, L97102, L97103, L97104, L97109, L97111, L97112, L97113, L97114, L97119, L97121, L97122, L97123, L97124, L97129, L97201, L97202, L97203, L97204, L97209, L97211, L97212, L97213, L97214, L97219, L97221, L97222, L97223, L97224, L97229, L97301, L97302, L97303, L97304, L97309, L97311,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			L97312, L97313, L97314, L97319, L97321, L97322, L97323, L97324, L97329, L97401, L97402, L97403, L97404, L97409, L97411, L97412, L97413, L97414, L97419, L97421, L97422, L97423, L97424, L97429, L97501, L97502, L97503, L97504, L97509, L97511, L97512, L97513, L97514, L97519, L97521, L97522, L97523, L97524, L97529, L97801, L97802, L97803, L97804, L97809, L97811, L97812, L97813, L97814, L97819, L97821, L97822, L97823, L97824, L97829, L97901, L97902, L97903, L97904, L97909, L97911, L97912, L97913, L97914, L97919, L97921, L97922, L97923, L97924, L97929, L98411, L98412, L98413, L98414, L98419, L98421, L98422, L98423, L98424, L98429, L98491, L98492, L98493, L98494, L98499, I70231, I70232, I70233, I70234, I70235, I70238, I70239, I70241, I70242, I70243, I70244, I70245, I70248, I70249, I7025, I70331, I70332, I70333, I70334, I70335, I70338, I70339, I70341, I70342, I70343, I70344, I70345, I70348, I70349, I7035, I70431, I70432, I70433, I70434, I70435, I70438, I70439, I70441, I70442, I70443, I70444, I70445, I70448, I70449, I7045, I70531, I70532, I70533, I70534, I70535, I70538, I70539, I70541, I70542, I70543, I70544, I70545, I70548, I70549, I7055, I70631, I70632, I70633, I70634, I70635, I70638, I70639, I70641, I70642, I70643, I70644, I70645, I70648, I70649, I7065, I70731, I70732, I70733, I70734, I70735, I70738, I70739, I70741, I70742, I70743, I70744, I70745, I70748, I70749, I7075
Congestive Heart Failure	Yes	39891, 40201, 40211, 40291, 40401, 40403, 40411, 40413, 40491, 40493, 4150, 4160, 4161, 4168, 4169, 4170, 4171, 4178, 4179, 4250, 42511, 42518, 4252, 4253, 4254, 4255, 4257, 4258, 4259, 4280, 4281, 42820, 42821, 42822, 42823, 42830, 42831, 42832, 42833, 42840, 42841, 42842, 42843, 4289, 4290, 4291	A3681, B3324, I0981, I110, I130, I132, I2601, I2602, I2609, I270, I271, I272, I2781, I2789, I279, I280, I281, I288, I289, I420, I421, I422, I423, I424, I425, I426, I427, I428, I429, I43, I501, I5020, I5021, I5022, I5023, I5030, I5031, I5032, I5033, I5040, I5041, I5042, I5043, I509, I514, I515
Diabetes w/ Complications	Yes	24940, 24941, 24950, 24951, 24960, 24961, 24970, 24971, 24980, 24981, 24990, 24991, 25040, 25041, 25042, 25043, 25050, 25051, 25052, 25053, 25060, 25061, 25062, 25063, 25070, 25071, 25072, 25073, 25080, 25081, 25082, 25083, 25090, 25091, 25092, 25093, 3572, 36201, 36202, 36203, 36204, 36205, 36206, 36207, 36641	E0821, E0822, E0829, E08311, E08319, E08321, E08329, E08331, E08339, E08341, E08349, E08351, E08359, E0836, E0839, E0840, E0841, E0842, E0843, E0844, E0849, E0851, E0852, E0859, E08610, E08618, E08620, E08621, E08622, E08628, E08630, E08638, E08649, E0865, E0869, E088, E0921, E0922, E0929, E09311, E09319, E09321, E09329, E09331, E09339, E09341, E09349, E09351, E09359, E0936, E0939, E0940, E0941, E0942, E0943, E0944, E0949,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			E0951, E0952, E0959, E09610, E09618, E09620, E09621, E09622, E09628, E09630, E09638, E09649, E0965, E0969, E098, E1021, E1022, E1029, E10311, E10319, E10321, E10329, E10331, E10339, E10341, E10349, E10351, E10359, E1036, E1039, E1040, E1041, E1042, E1043, E1044, E1049, E1051, E1052, E1059, E10610, E10618, E10620, E10621, E10622, E10628, E10630, E10638, E10649, E1065, E1069, E108, E1121, E1122, E1129, E11311, E11319, E11321, E11329, E11331, E11339, E11341, E11349, E11351, E11359, E1136, E1139, E1140, E1141, E1142, E1143, E1144, E1149, E1151, E1152, E1159, E11610, E11618, E11620, E11621, E11622, E11628, E11630, E11638, E11649, E1165, E1169, E118, E1321, E1322, E1329, E13311, E13319, E13321, E13329, E13331, E13339, E13341, E13349, E13351, E13359, E1336, E1339, E1340, E1341, E1342, E1343, E1344, E1349, E1351, E1352, E1359, E13610, E13618, E13620, E13621, E13622, E13628, E13630, E13638, E13649, E1365, E1369, E138
Diabetes w/o Complications	Yes	24900, 24901, 25000, 25001, 25002, 25003, V5867	E089, E099, E109, E119, E139, Z794
Fibrosis of Lung	Yes	135, 4950, 4951, 4952, 4953, 4954, 4955, 4956, 4957, 4958, 4959, 500, 501, 502, 503, 504, 505, 5060, 5061, 5062, 5063, 5064, 5069, 5080, 5081, 515, 5160, 5161, 5162, 51630, 51631, 51632, 51633, 51634, 51635, 51636, 51637, 5164, 5165, 51661, 51662, 51663, 51664, 51669, 5168, 5169, 5171, 5172, 5178, 5183, 5186	B4481, D860, D862, J60, J61, J620, J628, J630, J631, J632, J633, J634, J635, J636, J64, J65, J660, J661, J662, J668, J670, J671, J672, J673, J674, J675, J676, J677, J678, J679, J680, J681, J682, J683, J684, J688, J689, J700, J701, J82, J8401, J8402, J8403, J8409, J8410, J84111, J84112, J84113, J84114, J84115, J84116, J84117, J8417, J842, J8481, J8482, J8483, J84841, J84842, J84843, J84848, J8489, J849, J99, M3213, M3301, M3311, M3321, M3391, M3481, M3502
Heart Arrhythmias	Yes	4260, 4270, 4271, 4272, 42731, 42732, 42781	I442, I470, I471, I472, I479, I480, I481, I482, I483, I484, I4891, I4892, I492, I495
Inflammatory Bowel Disease	Yes	5550, 5551, 5552, 5559, 5560, 5561, 5562, 5563, 5564, 5565, 5566, 5568, 5569	K5000, K50011, K50013, K50014, K50018, K50019, K5010, K50111, K50113, K50114, K50118, K50119, K5080, K50811, K50813, K50814, K50818, K50819, K5090, K50911, K50913, K50914, K50918, K50919, K5100, K51011, K51013, K51014, K51018, K51019, K5120, K51211, K51213, K51214, K51218, K51219, K5130, K51311, K51313, K51314, K51318, K51319, K5140, K51411, K51413, K51414, K51418, K51419, K5150, K51511, K51513, K51514, K51518, K51519, K5180, K51811, K51813, K51814, K51818, K51819, K5190, K51911, K51913, K51914, K51918,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			K51919, K50012, K50112, K50812, K50912, K51012, K51212, K51312, K51412, K51512, K51812, K51912
Intestinal Obstruction	No	5370, 5373, 53781, 5600, 5601, 5602, 56030, 56031, 56032, 56039, 56081, 56089, 5609, 7505, 7511, 7512, 7513, 7514	K311, K313, K315, K50012, K50112, K50812, K50912, K51012, K51212, K51312, K51412, K51512, K51812, K51912, K560, K561, K562, K563, K5641, K5649, K565, K5660, K5669, K567, Q400, Q410, Q411, Q412, Q418, Q419, Q420, Q421, Q422, Q423, Q428, Q429, Q431, Q432, Q433
Intracranial Hemorrhage	No	09487, 430, 431, 4320, 4321, 4329, 7670, 77210, 77211, 77212, 77213, 77214, 7722	I6000, I6001, I6002, I6010, I6011, I6012, I6020, I6021, I6022, I6030, I6031, I6032, I604, I6050, I6051, I6052, I606, I607, I608, I609, I610, I611, I612, I613, I614, I615, I616, I618, I619, I6200, I6201, I6202, I6203, I621, I629, P100, P101, P102, P103, P104, P108, P109, P110, P111, P112, P520, P521, P5221, P5222, P523, P524, P525, P526, P528, P529
Ischemic or Unspecified Stroke	No	43301, 43311, 43321, 43331, 43381, 43391, 43401, 43411, 43491	I6300, I63011, I63012, I63019, I6302, I63031, I63032, I63039, I6309, I6310, I63111, I63112, I63119, I6312, I63131, I63132, I63139, I6319, I6320, I63211, I63212, I63219, I6322, I63231, I63232, I63239, I6329, I6330, I63311, I63312, I63319, I63321, I63322, I63329, I63331, I63332, I63339, I63341, I63342, I63349, I6339, I6340, I63411, I63412, I63419, I63421, I63422, I63429, I63431, I63432, I63439, I63441, I63442, I63449, I6349, I6350, I63511, I63512, I63519, I63521, I63522, I63529, I63531, I63532, I63539, I63541, I63542, I63549, I6359, I636, I638, I639
Lupus	Yes	0993, 4465, 7100, 7102, 7105, 7108, 7109, 71110, 71111, 71112, 71113, 71114, 71115, 71116, 71117, 71118, 71119, 7144, 71489, 7149, 725	M0230, M02311, M02312, M02319, M02321, M02322, M02329, M02331, M02332, M02339, M02341, M02342, M02349, M02351, M02352, M02359, M02361, M02362, M02369, M02371, M02372, M02379, M0238, M0239, M064, M1200, M12011, M12012, M12019, M12021, M12022, M12029, M12031, M12032, M12039, M12041, M12042, M12049, M12051, M12052, M12059, M12061, M12062, M12069, M12071, M12072, M12079, M1208, M1209, M315, M316, M320, M3210, M3211, M3212, M3213, M3214, M3215, M3219, M328, M329, M3500, M3501, M3502, M3503, M3504, M3509, M351, M353, M355, M358, M359, M368
Major Depressive and Bipolar Disorders	Yes	29600, 29601, 29602, 29603, 29604, 29605, 29606, 29610, 29611, 29612, 29613, 29614, 29615, 29616, 29620, 29621, 29622, 29623, 29624, 29625, 29626, 29630, 29631, 29632, 29633, 29634, 29635, 29636, 29640, 29641, 29642, 29643, 29644, 29645, 29646, 29650, 29651, 29652, 29653, 29654, 29655, 29656,	F3010, F3011, F3012, F3013, F302, F303, F304, F308, F309, F310, F3110, F3111, F3112, F3113, F312, F3130, F3131, F3132, F314, F315, F3160, F3161, F3162, F3163, F3164, F3170, F3171, F3172, F3173, F3174, F3175, F3176, F3177, F3178, F3181, F3189, F319, F322, F323, F332, F333, T1491,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
		29660, 29661, 29662, 29663, 29664, 29665, 29666, 2967, 29680, 29681, 29682, 29689, 29690, 29699, E9500, E9501, E9502, E9503, E9504, E9505, E9506, E9507, E9508, E9509, E9510, E9511, E9518, E9520, E9521, E9528, E9529, E9530, E9531, E9538, E9539, E954, E9550, E9551, E9552, E9553, E9554, E9555, E9556, E9557, E9559, E956, E9570, E9571, E9572, E9579, E9580, E9581, E9582, E9583, E9584, E9585, E9586, E9587, E9588, E9589, E959	T360X2A, T360X2S, T361X2A, T361X2S, T362X2A, T362X2S, T363X2A, T363X2S, T364X2A, T364X2S, T365X2A, T365X2S, T366X2A, T366X2S, T367X2A, T367X2S, T368X2A, T368X2S, T3692XA, T3692XS, T370X2A, T370X2S, T371X2A, T371X2S, T372X2A, T372X2S, T373X2A, T373X2S, T374X2A, T374X2S, T375X2A, T375X2S, T378X2A, T378X2S, T3792XA, T3792XS, T380X2A, T380X2S, T381X2A, T381X2S, T382X2A, T382X2S, T383X2A, T383X2S, T384X2A, T384X2S, T385X2A, T385X2S, T386X2A, T386X2S, T387X2A, T387X2S, T38802A, T38802S, T38812A, T38812S, T38892A, T38892S, T38902A, T38902S, T38992A, T38992S, T39012A, T39012S, T39092A, T39092S, T391X2A, T391X2S, T392X2A, T392X2S, T39312A, T39312S, T39392A, T39392S, T394X2A, T394X2S, T398X2A, T398X2S, T3992XA, T3992XS, T400X2A, T400X2S, T401X2A, T401X2S, T402X2A, T402X2S, T403X2A, T403X2S, T404X2A, T404X2S, T405X2A, T405X2S, T40602A, T40602S, T40692A, T40692S, T407X2A, T407X2S, T408X2A, T408X2S, T40902A, T40902S, T40992A, T40992S, T410X2A, T410X2S, T411X2A, T411X2S, T41202A, T41202S, T41292A, T41292S, T413X2A, T413X2S, T4142XA, T4142XS, T415X2A, T415X2S, T420X2A, T420X2S, T421X2A, T421X2S, T422X2A, T422X2S, T423X2A, T423X2S, T424X2A, T424X2S, T425X2A, T425X2S, T426X2A, T426X2S, T4272XA, T4272XS, T428X2A, T428X2S, T43012A, T43012S, T43022A, T43022S, T431X2A, T431X2S, T43202A, T43202S, T43212A, T43212S, T43222A, T43222S, T43292A, T43292S, T433X2A, T433X2S, T434X2A, T434X2S, T43502A, T43502S, T43592A, T43592S, T43602A, T43602S, T43612A, T43612S, T43622A, T43622S, T43632A, T43632S, T43692A, T43692S, T438X2A, T438X2S, T4392XA, T4392XS, T440X2A, T440X2S, T441X2A, T441X2S, T442X2A, T442X2S, T443X2A, T443X2S, T444X2A, T444X2S, T445X2A, T445X2S, T446X2A, T446X2S, T447X2A, T447X2S, T448X2A, T448X2S, T44902A, T44902S, T44992A, T44992S, T450X2A, T450X2S, T451X2A, T451X2S, T452X2A, T452X2S, T453X2A, T453X2S, T454X2A, T454X2S, T45512A, T45512S, T45522A, T45522S, T45602A, T45602S, T45612A, T45612S, T45622A, T45622S, T45692A, T45692S,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			T457X2A, T457X2S, T458X2A, T458X2S, T4592XA, T4592XS, T460X2A, T460X2S, T461X2A, T461X2S, T462X2A, T462X2S, T463X2A, T463X2S, T464X2A, T464X2S, T465X2A, T465X2S, T466X2A, T466X2S, T467X2A, T467X2S, T468X2A, T468X2S, T46902A, T46902S, T46992A, T46992S, T470X2A, T470X2S, T471X2A, T471X2S, T472X2A, T472X2S, T473X2A, T473X2S, T474X2A, T474X2S, T475X2A, T475X2S, T476X2A, T476X2S, T477X2A, T477X2S, T478X2A, T478X2S, T4792XA, T4792XS, T480X2A, T480X2S, T481X2A, T481X2S, T48202A, T48202S, T48292A, T48292S, T483X2A, T483X2S, T484X2A, T484X2S, T485X2A, T485X2S, T486X2A, T486X2S, T48902A, T48902S, T48992A, T48992S, T490X2A, T490X2S, T491X2A, T491X2S, T492X2A, T492X2S, T493X2A, T493X2S, T494X2A, T494X2S, T495X2A, T495X2S, T496X2A, T496X2S, T497X2A, T497X2S, T498X2A, T498X2S, T4992XA, T4992XS, T500X2A, T500X2S, T501X2A, T501X2S, T502X2A, T502X2S, T503X2A, T503X2S, T504X2A, T504X2S, T505X2A, T505X2S, T506X2A, T506X2S, T507X2A, T507X2S, T508X2A, T508X2S, T50902A, T50902S, T50992A, T50992S, T50A12A, T50A12S, T50A22A, T50A22S, T50A92A, T50A92S, T50B12A, T50B12S, T50B92A, T50B92S, T50Z12A, T50Z12S, T50Z92A, T50Z92S, T510X2A, T510X2S, T511X2A, T511X2S, T512X2A, T512X2S, T513X2A, T513X2S, T518X2A, T518X2S, T5192XA, T5192XS, T520X2A, T520X2S, T521X2A, T521X2S, T522X2A, T522X2S, T523X2A, T523X2S, T524X2A, T524X2S, T528X2A, T528X2S, T5292XA, T5292XS, T530X2A, T530X2S, T531X2A, T531X2S, T532X2A, T532X2S, T533X2A, T533X2S, T534X2A, T534X2S, T535X2A, T535X2S, T536X2A, T536X2S, T537X2A, T537X2S, T5392XA, T5392XS, T540X2A, T540X2S, T541X2A, T541X2S, T542X2A, T542X2S, T543X2A, T543X2S, T5492XA, T5492XS, T550X2A, T550X2S, T551X2A, T551X2S, T560X2A, T560X2S, T561X2A, T561X2S, T562X2A, T562X2S, T563X2A, T563X2S, T564X2A, T564X2S, T565X2A, T565X2S, T566X2A, T566X2S, T567X2A, T567X2S, T56812A, T56812S, T56892A, T56892S, T5692XA, T5692XS, T570X2A, T570X2S, T571X2A, T571X2S, T572X2A, T572X2S, T573X2A, T573X2S, T578X2A, T578X2S, T5792XA, T5792XS,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			T5802XA, T5802XS, T5812XA, T5812XS, T582X2A, T582X2S, T588X2A, T588X2S, T5892XA, T5892XS, T590X2A, T590X2S, T591X2A, T591X2S, T592X2A, T592X2S, T593X2A, T593X2S, T594X2A, T594X2S, T595X2A, T595X2S, T596X2A, T596X2S
Multiple Sclerosis	Yes	340, 3410, 3411	G35, G360, G370, G375
Personality Disorder	Yes	30012, 30013, 30014, 30015, 3006, 3010, 30110, 30111, 30112, 30113, 30120, 30121, 30122, 3013, 3014, 30150, 30151, 30159, 3016, 3017, 30181, 30182, 30183, 30184, 30189, 3019	F21, F440, F441, F4481, F481, F600, F601, F602, F603, F604, F605, F606, F607, F6081, F6089, F609
Pulmonary Embolism and Deep Vein Thrombosis	No	41511, 41512, 41513, 41519, 4162, 45111, 45119, 45181, 45183, 4530, 4532, 4533, 45340, 45341, 45342, 45350, 45351, 45352, 45372, 45374, 45375, 45376, 45377, 45382, 45384, 45385, 45386, 45387	I2690, I2692, I2699, I2782, I8010, I8011, I8012, I8013, I80201, I80202, I80203, I80209, I80211, I80212, I80213, I80219, I80221, I80222, I80223, I80229, I80231, I80232, I80233, I80239, I80291, I80292, I80293, I80299, I820, I82210, I82211, I82220, I82221, I82290, I82291, I823, I82401, I82402, I82403, I82409, I82411, I82412, I82413, I82419, I82421, I82422, I82423, I82429, I82431, I82432, I82433, I82439, I82441, I82442, I82443, I82449, I82491, I82492, I82493, I82499, I824Y1, I824Y2, I824Y3, I824Y9, I824Z1, I824Z2, I824Z3, I824Z9, I82501, I82502, I82503, I82509, I82511, I82512, I82513, I82519, I82521, I82522, I82523, I82529, I82531, I82532, I82533, I82539, I82541, I82542, I82543, I82549, I82591, I82592, I82593, I82599, I825Y1, I825Y2, I825Y3, I825Y9, I825Z1, I825Z2, I825Z3, I825Z9, I82621, I82622, I82623, I82629, I82721, I82722, I82723, I82729, I82A11, I82A12, I82A13, I82A19, I82A21, I82A22, I82A23, I82A29, I82B11, I82B12, I82B13, I82B19, I82B21, I82B22, I82B23, I82B29, I82C11, I82C12, I82C13, I82C19, I82C21, I82C22, I82C23, I82C29
Rheumatoid Arthritis	Yes	1361, 4460, 4461, 44620, 44621, 44629, 4463, 4464, 4466, 4467, 6960, 7101, 7103, 7104, 71120, 71121, 71122, 71123, 71124, 71125, 71126, 71127, 71128, 71129, 7140, 7141, 7142, 71430, 71431, 71432, 71433, 71481, 7200	L4050, L4051, L4052, L4053, L4054, L4059, M0500, M05011, M05012, M05019, M05021, M05022, M05029, M05031, M05032, M05039, M05041, M05042, M05049, M05051, M05052, M05059, M05061, M05062, M05069, M05071, M05072, M05079, M0509, M0510, M05111, M05112, M05119, M05121, M05122, M05129, M05131, M05132, M05139, M05141, M05142, M05149, M05151, M05152, M05159, M05161, M05162, M05169, M05171, M05172, M05179, M0519, M0520, M05211, M05212, M05219, M05221, M05222, M05229, M05231, M05232,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			M05239, M05241, M05242, M05249, M05251, M05252, M05259, M05261, M05262, M05269, M05271, M05272, M05279, M0529, M0530, M05311, M05312, M05319, M05321, M05322, M05329, M05331, M05332, M05339, M05341, M05342, M05349, M05351, M05352, M05359, M05361, M05362, M05369, M05371, M05372, M05379, M0539, M0540, M05411, M05412, M05419, M05421, M05422, M05429, M05431, M05432, M05439, M05441, M05442, M05449, M05451, M05452, M05459, M05461, M05462, M05469, M05471, M05472, M05479, M0549, M0550, M05511, M05512, M05519, M05521, M05522, M05529, M05531, M05532, M05539, M05541, M05542, M05549, M05551, M05552, M05559, M05561, M05562, M05569, M05571, M05572, M05579, M0559, M0560, M05611, M05612, M05619, M05621, M05622, M05629, M05631, M05632, M05639, M05641, M05642, M05649, M05651, M05652, M05659, M05661, M05662, M05669, M05671, M05672, M05679, M0569, M0570, M05711, M05712, M05719, M05721, M05722, M05729, M05731, M05732, M05739, M05741, M05742, M05749, M05751, M05752, M05759, M05761, M05762, M05769, M05771, M05772, M05779, M0579, M0580, M05811, M05812, M05819, M05821, M05822, M05829, M05831, M05832, M05839, M05841, M05842, M05849, M05851, M05852, M05859, M05861, M05862, M05869, M05871, M05872, M05879, M0589, M059, M0600, M06011, M06012, M06019, M06021, M06022, M06029, M06031, M06032, M06039, M06041, M06042, M06049, M06051, M06052, M06059, M06061, M06062, M06069, M06071, M06072, M06079, M0608, M0609, M061, M0620, M06211, M06212, M06219, M06221, M06222, M06229, M06231, M06232, M06239, M06241, M06242, M06249, M06251, M06252, M06259, M06261, M06262, M06269, M06271, M06272, M06279, M0628, M0629, M0630, M06311, M06312, M06319, M06321, M06322, M06329, M06331, M06332, M06339, M06341, M06342, M06349, M06351, M06352, M06359, M06361, M06362, M06369, M06371, M06372, M06379, M0638, M0639, M0680, M06811,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			M06812, M06819, M06821, M06822, M06829, M06831, M06832, M06839, M06841, M06842, M06849, M06851, M06852, M06859, M06861, M06862, M06869, M06871, M06872, M06879, M0688, M0689, M069, M0800, M08011, M08012, M08019, M08021, M08022, M08029, M08031, M08032, M08039, M08041, M08042, M08049, M08051, M08052, M08059, M08061, M08062, M08069, M08071, M08072, M08079, M0808, M0809, M081, M0820, M08211, M08212, M08219, M08221, M08222, M08229, M08231, M08232, M08239, M08241, M08242, M08249, M08251, M08252, M08259, M08261, M08262, M08269, M08271, M08272, M08279, M0828, M0829, M083, M0840, M08411, M08412, M08419, M08421, M08422, M08429, M08431, M08432, M08439, M08441, M08442, M08449, M08451, M08452, M08459, M08461, M08462, M08469, M08471, M08472, M08479, M0848, M0880, M08811, M08812, M08819, M08821, M08822, M08829, M08831, M08832, M08839, M08841, M08842, M08849, M08851, M08852, M08859, M08861, M08862, M08869, M08871, M08872, M08879, M0888, M0889, M0890, M08911, M08912, M08919, M08921, M08922, M08929, M08931, M08932, M08939, M08941, M08942, M08949, M08951, M08952, M08959, M08961, M08962, M08969, M08971, M08972, M08979, M0898, M0899, M300, M301, M302, M303, M308, M310, M311, M312, M3130, M3131, M314, M317, M3300, M3301, M3302, M3309, M3310, M3311, M3312, M3319, M3320, M3321, M3322, M3329, M3390, M3391, M3392, M3399, M340, M341, M342, M3481, M3482, M3483, M3489, M349, M352, M360, M450, M451, M452, M453, M454, M455, M456, M457, M458, M459, M488X1, M488X2, M488X3, M488X4, M488X5, M488X6, M488X7, M488X8, M488X9
Seizures	Yes	1361, 4460, 4461, 44620, 44621, 44629, 4463, 4464, 4466, 4467, 6960, 7101, 7103, 7104, 71120, 71121, 71122, 71123, 71124, 71125, 71126, 71127, 71128, 71129, 7140, 7141, 7142, 71430, 71431, 71432, 71433, 71481, 7200	G40001, G40009, G40011, G40019, G40101, G40109, G40111, G40119, G40201, G40209, G40211, G40219, G40301, G40309, G40311, G40319, G40401, G40409, G40411, G40419, G40501, G40509, G40801, G40802, G40803, G40804, G40811, G40812, G40813, G40814, G40821, G40822, G40823, G40824, G4089, G40901, G40909, G40911, G40919, G40A01,

Diagnostic Category	Chronic?	Diagnosis Codes (ICD-9-CM)	Diagnosis Codes (ICD-10-CM)
			G40A09, G40A11, G40A19, G40B01, G40B09, G40B11, G40B19, P90, R5600, R5601, R561, R569
Sepsis and Shock	No	0031, 0202, 0223, 0362, 0380, 03810, 03811, 03812, 03819, 0382, 0383, 03840, 03841, 03842, 03843, 03844, 03849, 0388, 0389, 04082, 0545, 77181, 78552, 78559, 99590, 99591, 99592, 99593, 99594	A021, A207, A227, A267, A327, A392, A393, A394, A400, A401, A403, A408, A409, A4101, A4102, A411, A412, A413, A414, A4150, A4151, A4152, A4153, A4159, A4181, A4189, A419, A427, A483, A5486, B007, B377, P360, P3610, P3619, P362, P3630, P3639, P364, P365, P368, P369, R571, R578, R6510, R6511, R6520, R6521
Thyroid Cancer	Yes	1720, 1721, 1722, 1723, 1724, 1725, 1726, 1727, 1728, 1729, 1860, 1869, 1871, 1872, 1873, 1874, 1875, 1876, 1877, 1878, 1879, 193, 1941, 1945, 1946, 1948, 1949, 1991, 23770, 23771, 23772, 23773, 23779, 2592	C430, C4310, C4311, C4312, C4320, C4321, C4322, C4330, C4331, C4339, C434, C4351, C4352, C4359, C4360, C4361, C4362, C4370, C4371, C4372, C438, C439, C600, C601, C602, C608, C609, C6200, C6201, C6202, C6210, C6211, C6212, C6290, C6291, C6292, C6300, C6301, C6302, C6310, C6311, C6312, C632, C637, C638, C639, C73, C750, C754, C755, C758, C759, C801, D030, D0310, D0311, D0312, D0320, D0321, D0322, D0330, D0339, D034, D0351, D0352, D0359, D0360, D0361, D0362, D0370, D0371, D0372, D038, D039, E340, Q8500, Q8501, Q8502, Q8503, Q8509
Unstable Angina	No	41000, 41002, 41010, 41012, 41020, 41022, 41030, 41032, 41040, 41042, 41050, 41052, 41060, 41062, 41070, 41072, 41080, 41082, 41090, 41092, 4110, 4111, 41181, 41189	I200, I230, I231, I232, I233, I236, I237, I238, I240, I241, I248, I249, I25110, I25700, I25710, I25720, I25730, I25750, I25760, I25790
Viral Meningitis	No	0470, 0471, 0478, 0479, 048, 0490, 0491, 0530, 05472, 0721, 3212, 3220, 3221, 3222, 3229	A870, A871, A872, A878, A879, A880, B003, B010, B021, B051, B0602, B261, B2702, B2712, B2782, B2792, D8681, G030, G031, G032, G038, G039

Table Notes: The set of ICD-9-CM and ICD-10-CM diagnosis codes corresponding to each diagnostic category come from the United States Department of Health and Human Services (HHS) Hierarchical Classification of Conditions (HCC) model for the year 2020.

When assigning HCCs, I exclude diagnoses associated with the following place of service and procedure codes, due to their high potential for false positive diagnoses, as is done in the HHS-HCC risk adjustment model:

Place of Service Codes		
	12	Private residence home
	31	Skilled nursing facility
	32	Nursing home
	33	Custodial care
	34	Hospice
	41	Ambulance – land
	42	Ambulance – other
	65	Renal dialysis
	81	Independent lab
	99	Unknown
Procedure Codes		
	36415-36416	Drawing blood
	70000-76999	X-ray and ultrasound
	78000-78999	Imaging
	80000-87999	Lab tests
	88000-88099	Autopsy
	88104-88299	Cytopathology
	88300-88399	Surgical Pathology
	88720-88741	In Vivo
	92551-92569	Hearing tests
	93000-93350	ECG and ultrasound
	99000-99001	Specimen handling
	A0021-A0999	Ambulance
	A4206-A999	Medical and surgical supplies
	B4304-B999	Enteral Supplies
	G0001	Drawing blood
	E0100-E9999	Durable medical equipment
	K0001-K9999	Wheelchairs and accessories
	L0100-L4599	Orthotics
	L5000-L9900	Prosthetics
	P2028-P9999	Pathology and Lab
	R0070-R0076	Radiology

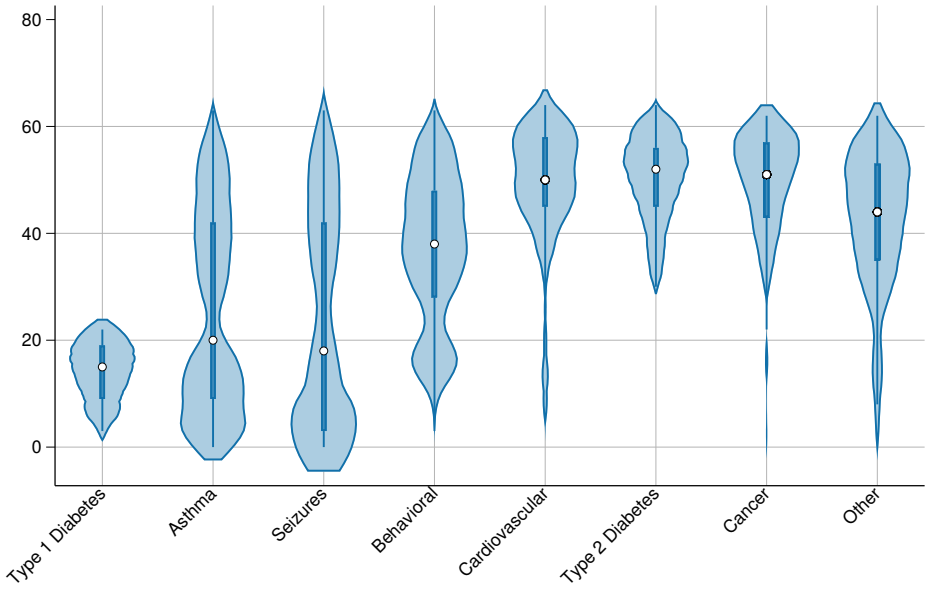
Table A.2. Excluded places and procedures for major health events

Table A.3 identifies additional demographic information, as well as illustrating the balance in my sample across households with and without a chronic condition in the family. The table also shows the frequency of the various chronic conditions utilized in my sample. Households with chronic conditions are not markedly different in terms of age or sex composition or family size, but do incur significantly higher medical costs in a year. They are not, however, more likely to switch insurance plans from year to year. There is wide variation in the onset of chronic illnesses; the three most common illnesses are asthma, major depressive disorder, and diabetes.

	Full Sample	Households with chronic conditions
Demographics & Utilization		
Enrollee age	30.87 (0.008)	29.61 (0.046)
% female enrollees	50.17 (0.000)	50.46 (0.001)
Mean [median] total spending	$2,504 [$680]	$3,378 [$958]
	(4.51)	(23.75)
Mean [median] OOP spending	$443 [$110]	$532 [$151]
	(0.53)	(3.15)
Incidence of chronic illness (per 1,000 individuals)		
Adrenal & pituitary disorders	0.22	7.35
Asthma	2.93	96.08
Breast/prostate cancer	0.35	11.58
Chronic hepatitis	0.10	3.23
Chronic skin condition	0.23	7.46
Congestive heart failure	0.14	4.52
Diabetes with complications	0.39	12.72
Diabetes without complications	1.18	38.57
Fibrosis of lung	0.46	15.10
Heart arrhythmias	0.00	0.00
Inflammatory bowel disease	0.14	4.65
Lupus	0.16	5.20
Major depressive/biploar disorder	1.62	52.76
Multiple sclerosis	1.10	36.17
Personality disorder	0.09	2.81
Rheumatoid arthritis	0.17	5.70
Seizures	0.30	9.82
Thyroid cancer	0.14	4.69
N_{families}	353,403	52,747
$N_{\text{individuals}}$	1,087,353	165,694

Table A.3. Relative Incidence of Chronic Conditions

Figure A1. Median Age of Diagnosis, by Disease Category



Notes: Figure depicts a violin plot showing the age distribution at the time of diagnosis across the chronic conditions included in my analytical sample.

A.2 Balance Between Acute and Chronic Health Events

As discussed in Section 2.2, Table A.1 also contains indicators for acute health events. Table A3 summarizes the differences between chronic and acute shocks: acute health events tend to be slightly more expensive and require longer and more frequent hospitalization (albeit with a much higher degree of variance given variation across patients, providers, and regions). These acute health events are used as a proxy for major health events that transmit no information about health risk across households, but rather merely affect household marginal utility for seeking care in the future (e.g., with the goal of avoiding future hospitalizations). Hence, given the discussion in the paper, the fact that acute health events appear to be slightly more costly and serious suggests that salience effects in the absence of all health risk information do not sufficiently drive changes in household spending and preventive care investments.

	Chronic Diagnoses	Acute Diagnoses
Diagnostic Cost (Total)	\$15,157.86	\$19,524.75
	(\$31,144.20)	(\$26,017.18)
Diagnostic Cost (OOP)	\$694.23	\$1,088.59
	(\$1,153.49)	(\$1,345.13)
% Hospitalized	4.57%	38.51%
	(20.89)	(48.66)
Conditional Average LOS	4.64	7.62
	(6.21)	(8.66)
Yearly Spending, $t-1$ (Total)	\$3,899.31	\$5,442.77
	(\$11,826.62)	(\$13,771.54)
Yearly Spending, t (Total)	\$8,733.58	\$43,459.49
	(\$56,804.61)	(\$172,342.18)
Yearly Spending, $t+1$ (Total)	\$5,507.51	\$7,907.61
	(\$13,970.13)	(\$18,627.87)
Yearly Spending, $t-1$ (OOP)	\$624.58	\$846.60
	(\$1,965.44)	(\$1,395.10)
Yearly Spending, t (OOP)	\$1,067.83	\$2,595.42
	(\$3,098.01)	(\$8,213.94)
Yearly Spending, $t+1$ (OOP)	\$823.13	\$1,158.98
	(\$1,710.75)	(\$2,381.75)
Observations	68,765	10,100

Notes: Table shows average differences between individuals affected by chronic and acute health events. Diagnostic codes used for construction are shown in Table A.1. All currencies normalized to 2020 USD.

Table A3. Balance between acute and chronic health events

A.3 Identifying Low-Value Services

Low value services are identified at the procedure level using CPT codes for medical procedures and therapeutic classes for prescription medications. I aggregate these services into five broad categories, as illustrated in the following table.

Category	Service	CPT Codes / Therapeutic Classes	Additional restrictions (age/sex restrictions, diagnosis or procedure codes)
All Pediatric	Vitamin D Screening	82306,82652	Age < 18
All Pediatric	Cervical Cancer Screening	87620,87621,87622, 87623, 87624, 87625, 88141, 88142, 88143, 88147, 88148, 88150, 88152, 88153, 88154, 88155, 88164, 88165,88166, 88167, 88174, 88175, G0123, G0124, G0141, G0143, G0144, G0145, G0147, G0148, P3000, P3001, Q0091	Age < 18, age >= 14, female
All Pediatric	Head imaging for headache	70450,70460,70470,70551,70552,70553	Age < 18, Diagnosis codes: 3390, 3391, 3460, 3461, 3462, 3464, 3465, 3467, 3468, 3469, 7840, 3393, G440, G441, G442, G444, G430, G431, G435, G437, G438, G439, 30781,33983, 33984, 33985, R51, R510, R519, G4483, G4484, G4485
All Pediatric	Antibiotics for upper respiratory infections	Antibiotics (multiple classes)	Diagnosis codes: 460,465, J00, J06, H65, H60, H61, H62, 3810, 3814
All Pediatric	Antibiotics for bronchiolitis	Antibiotics (multiple classes)	Diagnosis codes: 46611,46619, J210, J218
All Pediatric	Cough or cold medicine	Antitussives, Expectorants, Mucolytics, Cough/Cold Combinations	Age < 6
Adult Drugs	Opioids to treat migraines	Opiate Agonists, Opiate Part Agonists, Opiate Antagonists	Diagnosis codes: 346**, G43**
Adult Imaging	Head imaging for headache	70450,70460,70470,70551,70552,70553	Diagnosis codes: 3390, 3391, 3460, 3461, 3462, 3464, 3465, 3467, 3468, 3469, 7840, 3393, G440, G441, G442, G444, G430, G431, G435, G437, G438, G439, 30781,33983, 33984, 33985, R51, R510, R519, G4483, G4484, G4485
Adult Imaging	Imaging for lower-back pain	72010, 72020,72052, 72100, 72110, 72114,72120, 72200, 72202, 72220, 72131, 72132, 72133, 72141, 72142, 72146, 72147, 72148,72149, 72156, 72157, 72158	Diagnosis codes: 7213, 7226, 7242, 7243, 7244,7245, 7246,7385, 7393,7394, 8460, 8461, 8462, 8463, 8468, 8469, 8472, M432, M512, M513, M518, M533, M545, M541, M543, M998, 72190, 72210, 72252, 72293, 72402,72470, 72471, 72479, M47817, M532X7, M9903, M9904, S338XXA, S336XXA, S339XXA, S335XXA, M47819, M4647, M4806, M532X8

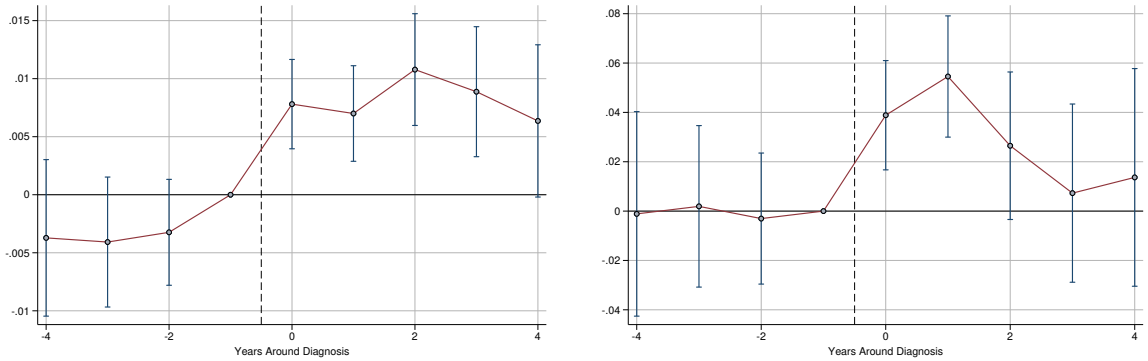
Category	Service	CPT Codes / Therapeutic Classes	Additional restrictions (age/sex restrictions, diagnosis or procedure codes)
Adult Imaging	Screening for carotid artery disease	36222, 36223, 36224, 70498, 70547, 70548,70549, 93880, 93882, 3100F	Diagnosis codes: 430, 431, 434,436,781, I63, I66, R25, R26, R27, R29, R47, G45, H34, R55, R20, 4350, 4351, 4353, 4358, 359,3623, 7802, 7820, I609, I619, 43301, 43311, 43321, 43331,43381, 43391, 99702, V1254, 36284, 78451, 78452, 78459, I6789, I67848, I97811, I97821, Z8673, H3582
Adult Imaging	Cardiac imaging	0144T, 0145T, 0146T, 0147T, 0148T, 0149T, 0150T, 75552, 75553, 75554, 75555, 75556, 75557, 75558, 75559, 75561, 75562, 75565, 75571, 75572, 75573, 75574, 78451, 78452, 78453, 78454, 78460, 78461, 78464, 78465, 78478, 78480, 78459, 78481, 78483, 78491, 78492, 78494, 78496, 78499	
Adult Screening	Vitamin D Screening	82306,82652	
Adult Screening	Cardiac testing for low-risk patients	93015, 93016, 93017, 93018, 93350, 93351,78451, 78452, 78453, 78454, 78460, 78461,78464, 78465, 78472, 78473, 78481, 78483,78491, 78492, 93303, 93304, 93306, 93307, 93308, 93312,93315, 93318, 3120F, 93000, 93005, 93010, G0366, G0367, G0368, G0403, G0404, G0405	
Adult Screening	Pre-operative testing before low-risk surgery	71010, 71015, 71020, 71021, 71022, 71023, 71030, 71034, 71035, 93303, 93304, 93306, 93307, 93308, 93312, 93315, 93318, 94010, 78451, 78452, 78453, 78454, 78460, 78461, 78464, 78465, 78472, 78473, 78481, 78483, 78491, 78492, 93015, 93016, 93017, 93018, 93350, 93351	Procedure codes for surgery: 19120, 19125, 47562, 47563, 49560, 58558
Adult Surgery	Arthroscopic surgery for knee osteoarthritis	29877, 29879, G0289	Diagnosis codes: 8360, 8361, 8362, 7170, S832, 71741, M23202, M23205

Table Notes: Pediatric low-value services are defined based on Chua et al. (2016). Adult low-value services are based on definitions given in Bhatia et al. (2015), Chandra et al. (2021), and Colla et al. (2014).

B Additional Reduced Form Results & Robustness

Figure B1. Estimated Spillover Effects on Total Spending, by Margin

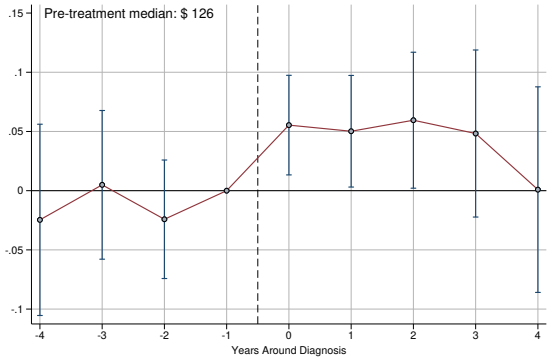
(a) Pr(Spending > 0) (b) log(Spending|Spending> 0)



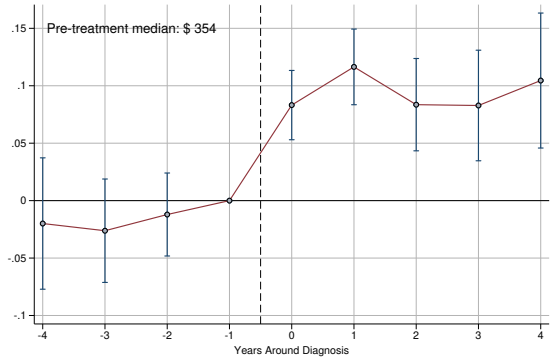
Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on medical utilization of other (non-diagnosed) household members, measured as (a) the probability of any healthcare spending and (b) the logarithm of total OOP spending conditional on spending being greater than 0. Standard errors are clustered at the household level.

Figure B2. Spillover Effects of Chronic Diagnoses on OOP Spending by Age

(a) Children

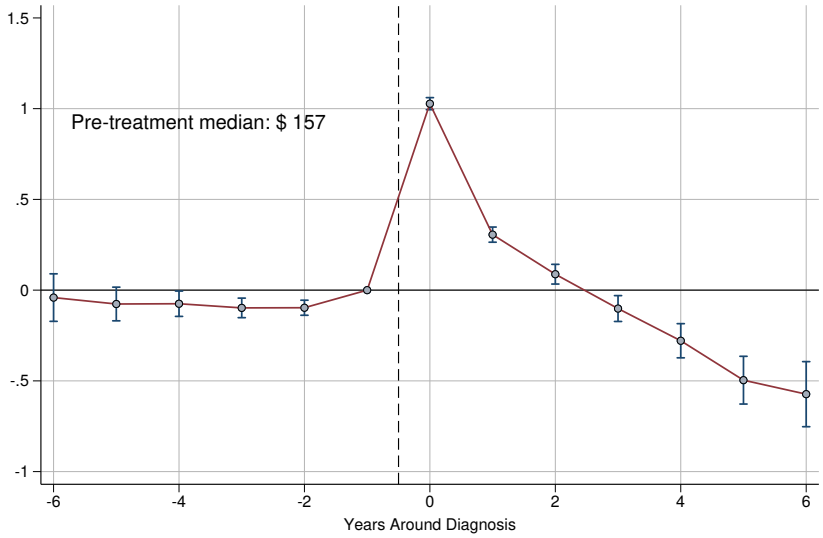


(b) Adults



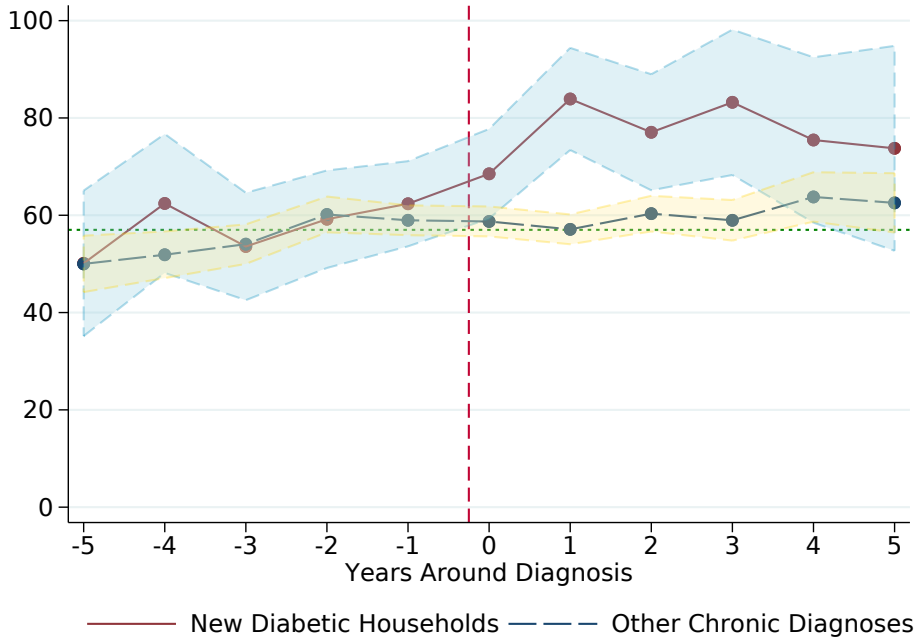
Notes: Figures show LP-DID regression coefficients and 95% confidence intervals for estimation of Equation (1). Outcome variable is the log of OOP spending, estimated separately on (a) children aged 0–17 and (b) adults aged 18+. Compare with Figure 1a in the main text.

Figure B3. Effect of Chronic Diagnoses on Diagnosed Individual's Healthcare Utilization



Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regression estimates the effect of a new chronic diagnosis on medical utilization of *diagnosed* household members, measured as the logarithm of total OOP spending +1. Compare with Figure 1a in the main text.

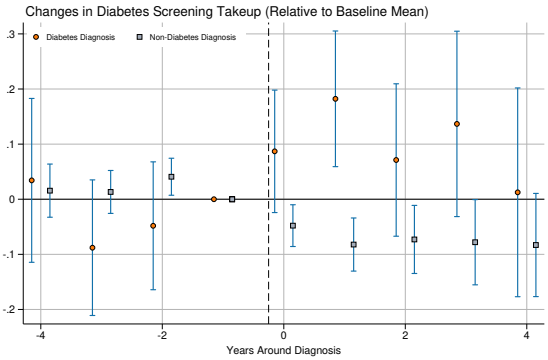
Figure B4. Rate of Diabetes Screenings Around Time of Diagnoses (Rate/1,000 Adults)



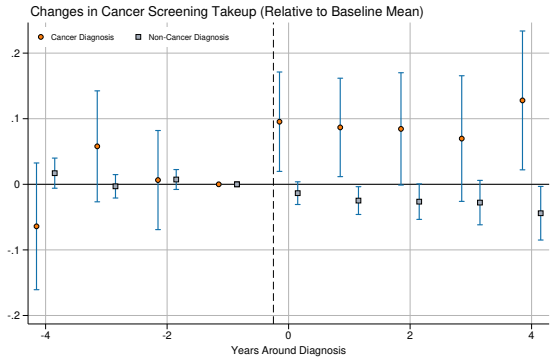
Notes: Figure plots re-centered time series that depict the associations between household diagnoses and the takeup of diabetes screenings for adults within a household. Utilization rates of diabetes screenings for non-diagnosed household members 18 years of age and older, measured in rates per 1,000 adults, are shown, including averages and 95% confidence intervals. The top (solid maroon) line indicates average rates for households who experience a diabetes diagnosis, and the bottom (dashed navy) line indicates rates for those affected by other chronic diagnoses. The horizontal, dotted green line indicates the average utilization rate for all other households in the sample who do not experience a diagnosis, about 59 screenings per 1,000 adults. Individuals whose family members are diagnosed with conditions other than diabetes do not appear to significantly alter their screening behaviors from unaffected households (whose average is depicted in the horizontal, dotted green line). On the other hand, household members of those diagnosed with diabetes increase screenings in the first three years following the diagnosis, being about 36% more likely to be screened for diabetes than unaffected individuals.

Figure B5. Spillover Effects of Chronic Diagnoses on Preventive Screenings

(a) Diabetes Screenings



(b) Cancer Screenings



Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on screening utilization of other (non-diagnosed) household members, measured as (a) diabetes screenings and (b) cancer screenings. Within each panel, results are stratified by whether or not the index event was (a) a diabetes diagnosis and (b) a cancer diagnosis. Standard errors are clustered at the household level.

Diagnosis	*Type 2 Diabetes*			*Cancer*	*MDD/Bipolar*
Screening	Diabetes	Cholesterol	High BMI	Cancer	Depression
$\text{Post}_t \times \text{Diagnosis}_f$	-0.85***	-2.20***	-0.38**	2.55***	0.30**
	(0.21)	(0.29)	(0.12)	(0.43)	(0.10)
$\text{Post}_t \times \text{Diagnosis}_f \times \text{Parent}_j$	3.49*	3.73	1.73*	-1.90	-0.93***
	(1.71)	(2.26)	(0.70)	(2.49)	(0.13)
$\text{Post}_t \times \text{Diagnosis}_f \times \text{Spouse}_j$	2.54***	5.15***	1.03***	-3.33***	-0.62***
	(0.45)	(0.60)	(0.20)	(0.81)	(0.11)
$\text{Post}_t \times \text{Diagnosis}_f \times \text{Sibling}_j$	0.76	2.89	0.16	1.56	0.68*
	(1.09)	(1.86)	(0.69)	(1.55)	(0.32)
Observations	3,680,725	3,680,725	3,680,725	3,671,064	3,724,608
Adjusted R^2	0.217	0.388	-0.025	0.473	0.117

Standard errors in parentheses

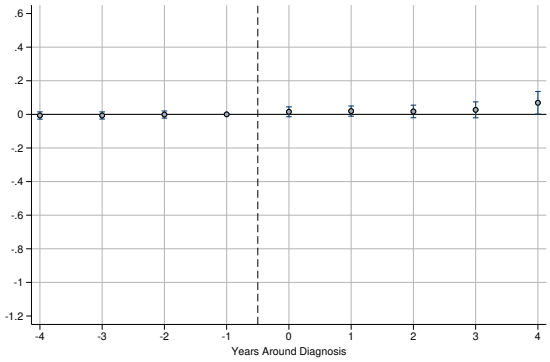
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table tests the extent to which spillover effects differ based on household relationships and diagnosis. Table shows results of a difference-in-differences estimation strategy highlighting the potentially differential effects of chronic illnesses on preventive care utilization by household relationships. The primary outcome variable in each column is a screening or new diagnosis, shown in the second row. The specific chronic illness used as the Diagnosis_f dummy is shown in the first row in italics. I explore the potentially heterogeneous responses for four family relationships: parents, spouses, siblings, and children of the affected individual, with children as the reference group. Standard errors are clustered at the household level. The coefficients suggest that households respond by not only selecting screenings associated with the health events they experienced, but also selecting which individuals to screen based on their associated risk. Households affected with type 2 diabetes diagnoses focus screenings on spouses more than on children, consistent with the lifestyle factors that affect diabetes risk. In contrast, households affected with chronic illnesses that communicate a greater level of genetic risk—cancer and mental health conditions—choose instead to screen children and siblings (in the case of mental health conditions) more than parents or spouses.

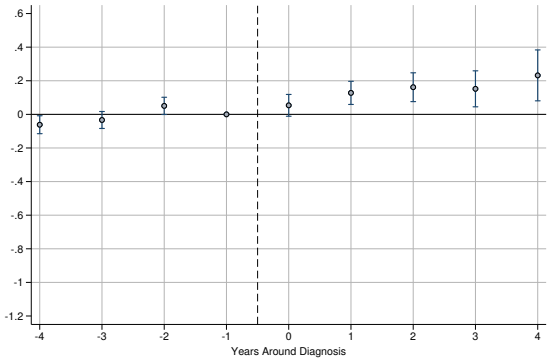
Table B1. Heterogeneous Spillover Effects by Household Relationships and Diagnosis

Figure B6. Dynamic Effects of Chronic Diagnoses on Household Low-Value Care Utilization

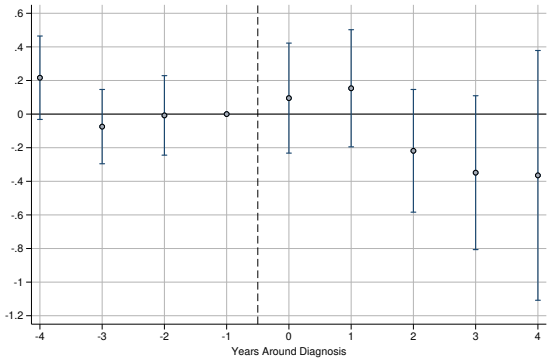
(a) Any Low-Value Care Use



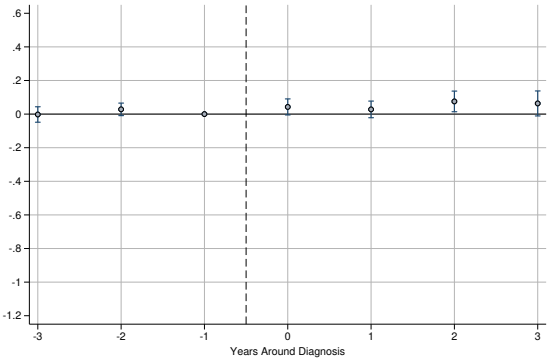
(b) Pediatric Low-Value Care



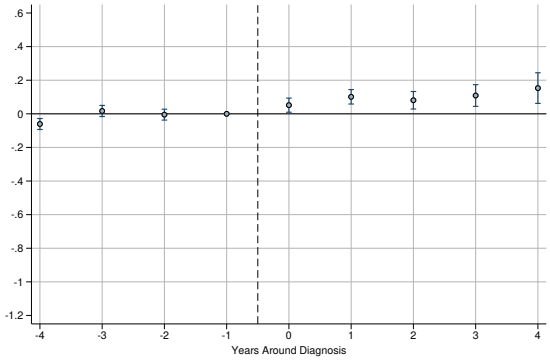
(c) Prescriptions



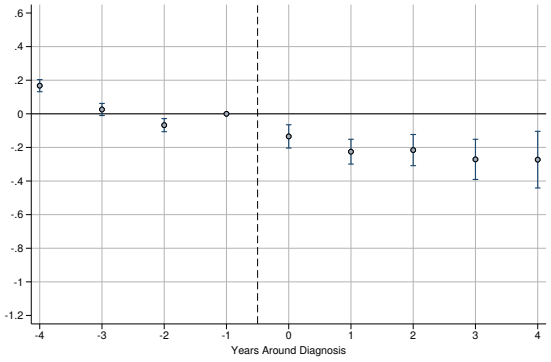
(d) Imaging



(e) Screening



(f) Surgery

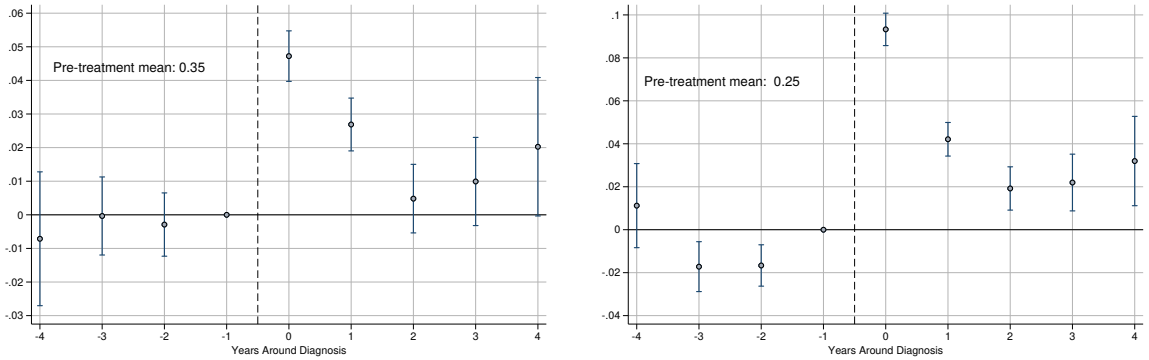


Notes: Figures show LP-DID regression coefficients and 95% confidence intervals for estimation of Equation (1). Outcome variable is a binary indicator for any use of the given low-value care category at the household-year level (Section 2.2 in the main text). Coefficients are scaled relative to the pre-treatment mean, so that coefficients can be interpreted as percentage changes. Standard errors clustered at the household level. Compare with Table 4 in the main text, which shows pooled effects.

Figure B7. Effects of Chronic Diagnoses on Meeting Household and Individual Deductibles

(a) Pr(Meet Family Deductible)

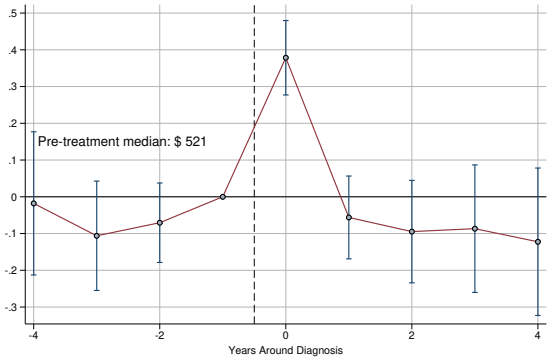
(b) Pr(Meet Individual Deductible, Diagnosed Individual)



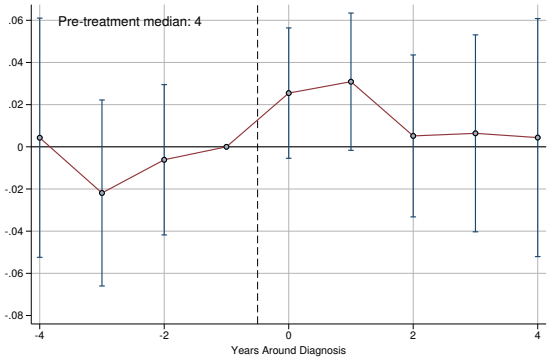
Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on the probability that a diagnosed household will meet their deductible in a given year (panel a) or that a diagnosed individual will meet their deductible (panel b). Standard errors are clustered at the household level.

Figure B8. Effect of Acute Health Events on Other Household Members' Utilization

(a) log(Total OOP Spending+1)



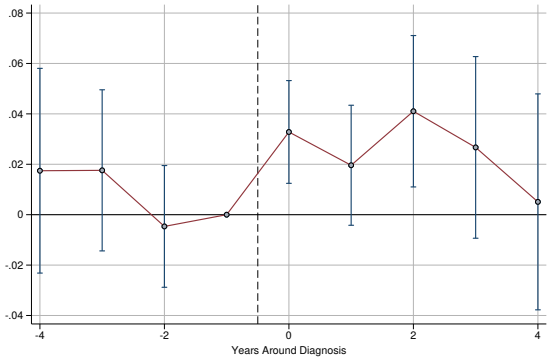
(b) # of Preventive Visits



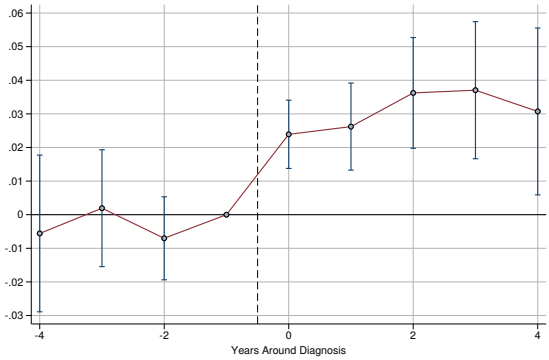
Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regressions estimate the effect of an acute hospitalization (Section **??**) on medical utilization of other (non-diagnosed) household members, measured as (a) the logarithm of total OOP spending +1, and (b) number of household preventive services per year.

Figure B9. Spillover Effects of Chronic Diagnoses on Utilization of Antidepressants

(a) Pr(Any Antidepressant Use)

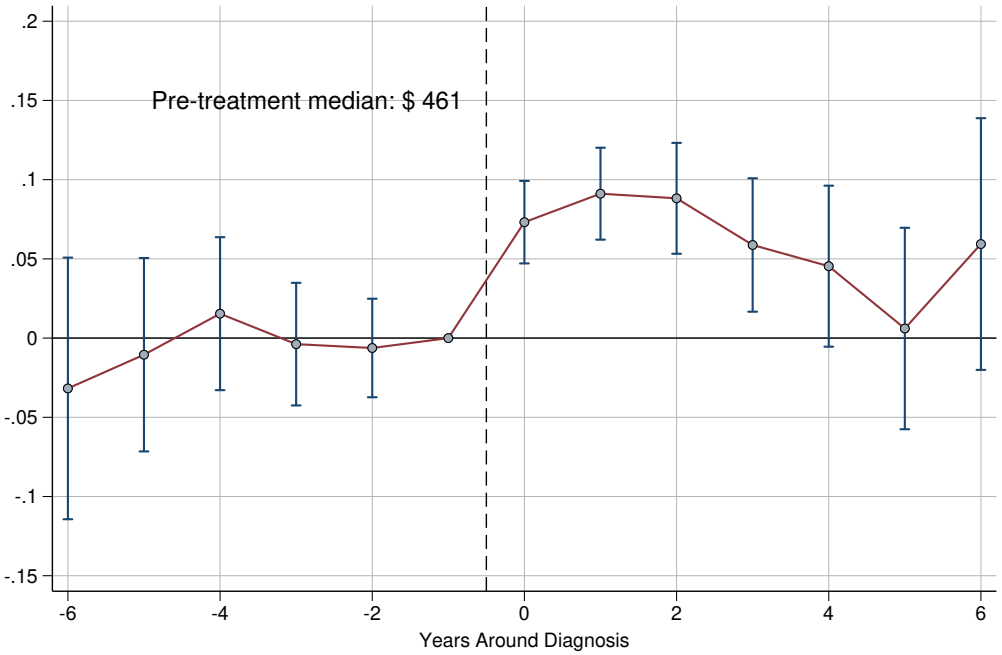


(b) Log(OOP Spending + 1)



Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on medical utilization of other (non-diagnosed) household members, measured as (a) the likelihood of filling any antidepressant prescription in a given year and (b) the log of OOP spending on antidepressant medication + 1. Standard errors are clustered at the household level.

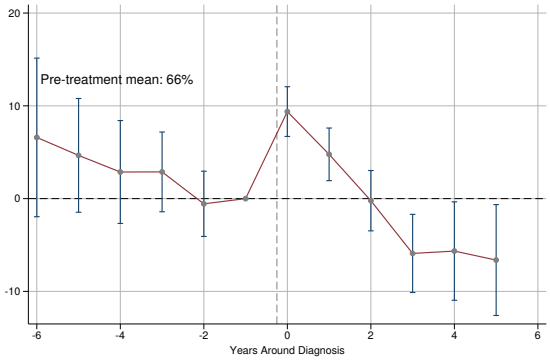
Figure B10. Robustness of Figure 1 to Excluding Mental Health-Related Health Spending



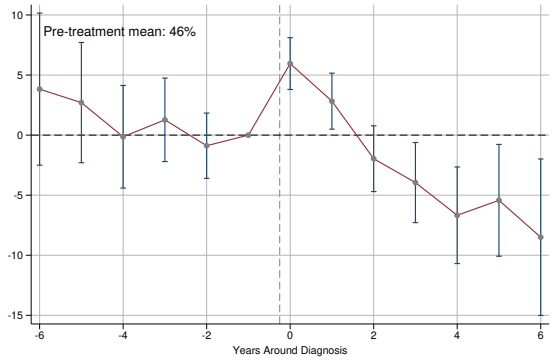
Notes: Figures show LP-DID regression coefficients and 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on medical utilization of other (non-diagnosed) household members. The outcome is measured as the logarithm of total OOP spending for non mental-health related care, +1. Spending is dropped for all claims with any mental health diagnosis present as well as for all prescriptions in therapeutic classes used to treat mental health conditions; as such, this is a potentially aggressive approach at reducing spending and removes roughly 8% of spending. Standard errors are clustered at the household level. Compare with Figure 1, panel (a).

Figure B11. Effect of Chronic Diagnoses On Adherence to Existing Preventive Medications

(a) Pr(Refill Old Prescription)



(b) Proportion of Days Covered



Notes: Figures show regression coefficients and 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on adherence to preventive medications, measured as (a) a binary indicator for whether the prescription was refilled during the year, and (b) the proportion of days in a year covered by the medication. Standard errors are clustered at the household level; covariates include a measure of the number of years an individual has been in the sample. The sample includes individuals with preventive prescriptions for at least two years pre-diagnosis. Diagnoses in a household spur a resurgence in multiple measures of adherence, with affected individuals around ten percentage points more likely to fill a prescription immediately after a household health event. This illustrates that individuals respond to updated risk beliefs communicated by a diagnosis, not simply new information about the logistics of obtaining care.

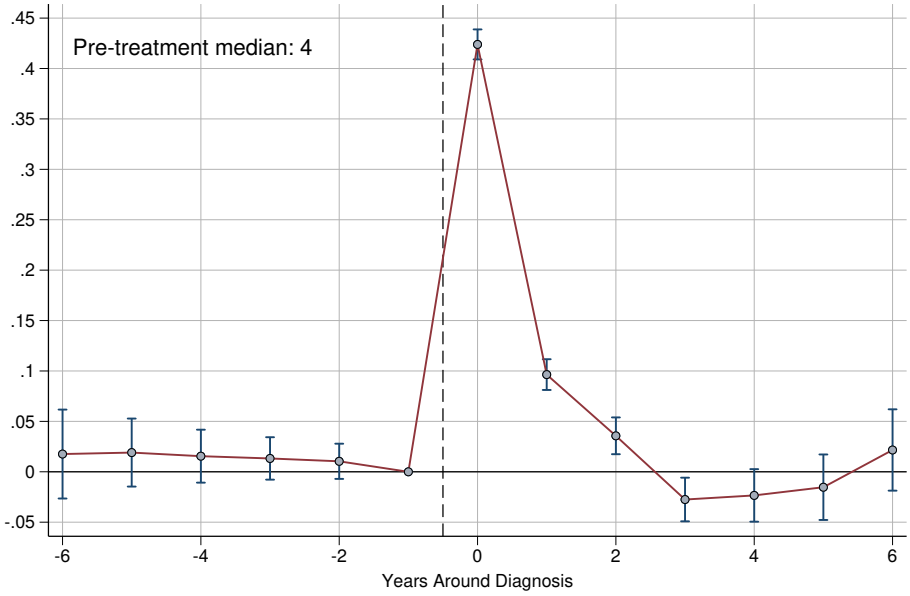
C Model Fit & Robustness

Table 1. Summary of Moment Conditions in GMM Estimation

#	**Moment Description**
Panel A: Utility-maximizing behavior	
1	Equilibrium first-order condition (deviations from 0)
2	Implied risk premium given CARA utility (difference between expected consumption and CARA certainty equivalent)
3	Additional moment penalizing FOCs with value larger than 100 utils (for training model)
Panel B: Predicted Spending, Central Tendency	
4	Differences in average predicted and observed spending
5	Differences in median predicted and observed spending
6	RMSPE in spending (full distribution)
Panel C: Predicted Spending, Spread	
7	Standard deviation of predicted and observed spending distribution
8	Share of individuals with zero spending (predicted - observed)
9	Additional moment penalizing fraction of individuals with predicted beliefs outside the unit interval (for training model)
10–11	Interaction terms between implied distribution of δ and predicted spending
12–13	Interaction terms between implied distribution of γ and predicted spending
Panel D: Dynamic Treatment Effects	
14–16	LP-DID regression coefficients for health spending (Equation 1; 3 periods)

Notes: Table presents the 16 moment conditions used in estimating the model presented in Section 4 of the main paper. See Section 5 for details on estimation and replication package for implementation in R.

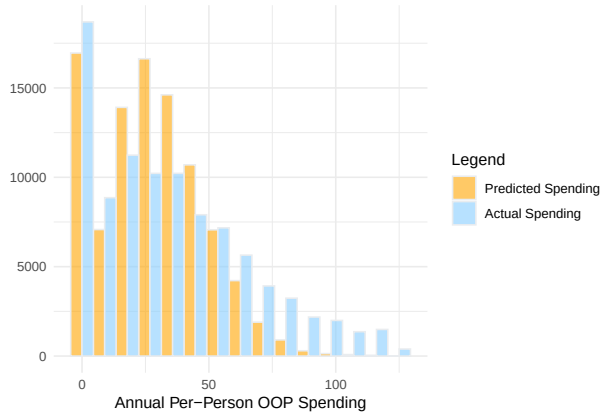
Figure 1. Effect of Chronic Diagnoses on Diagnosed Household Members' Preventive Utilization



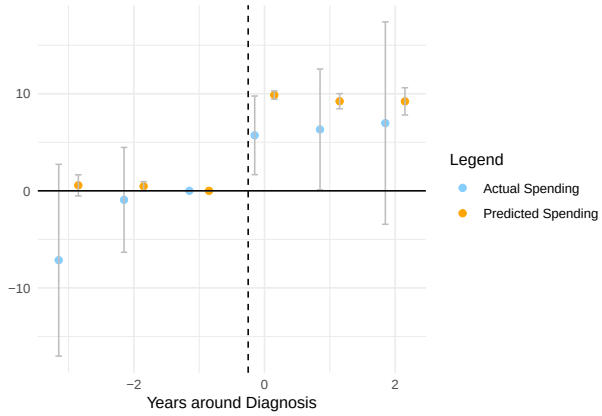
Notes: Figure shows estimated coefficients and 95% confidence intervals for the effect of a new chronic diagnosis on preventive care utilization for the diagnosed individual. Compare with Figure 1b. This effect is used to identify τ_γ in Section 5 of the paper. Standard errors are clustered at the household level.

Figure 2. Model Predictions: Non-Diagnosed Spending and Beliefs Around a New Diagnosis

(a) Spending Distributions



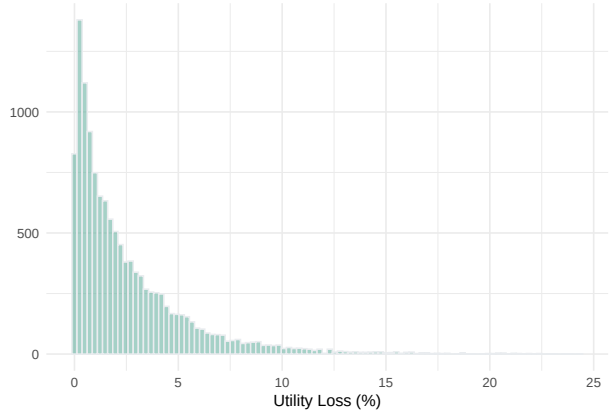
(b) Effect of Health Event on OOP (Levels)



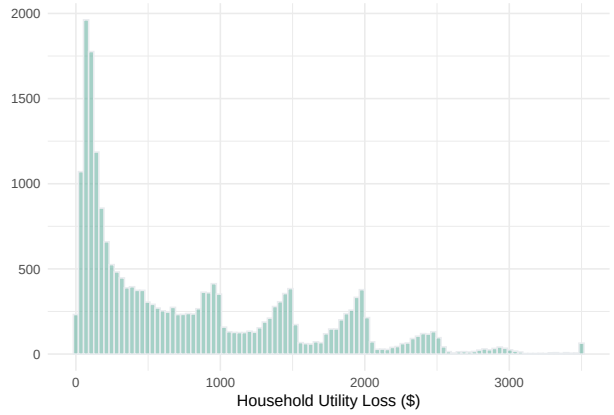
Notes: Figures show recentered time series for model predictions of spending both overall and around the time of health shocks. The first panel illustrates the predicted and observed distribution of per-person OOP spending annually. The second panel illustrates level changes in OOP spending, measured in 2020 USD. Note that both of these are unmatched moments, as discussed in the main text.

Figure 3. Estimated Changes in Household Welfare Following New Health Information

(a) Percent Change in Utility



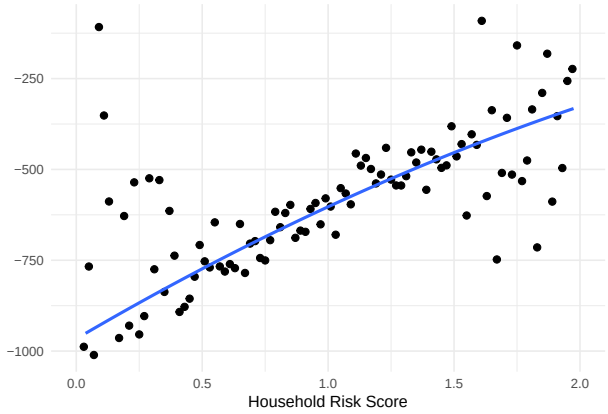
(b) Changes in Household Certainty Equivalent ($)



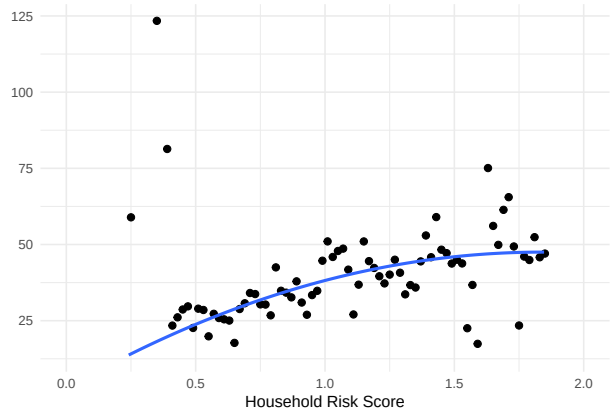
Notes: Figures show estimated changes in household willingness to pay associated with major health events, measured in percent reduction in (a) average non-diagnosed household member utility and (b) total dollar reductions in the household-level certainty equivalent. In both panels, salience effects (changes to γ) are imposed to be 0, allowing for estimation only of household health events. Distribution is shown for the 68.2% of individuals with welfare losses from the information. Welfare effects are calculated in the year of the diagnosis relative to a benchmark in which no information is transmitted. Graphs are truncated at 25% in panel (a) and $3500 in panel (b) to better visualize main distributions.

Figure 4. Variation in Household Risk and WTP for (True) Health Information

(a) Change in Household CE, Equilibrium



(b) Change in Household CE, True Information



Notes: Figures show binscatters depicting the variation in household WTP for health risk information based on underlying risk for health shocks. Risk is measured as predicted probability of a health shock, $\overline{p}_{it}$; results are robust to using a general risk score instead. Risk scores are normalized to have an average of 1, so that individuals with a score over 1 are considered more at-risk for health shocks than average, and those with a score below 1 are less at-risk. In panel (a), the outcome is expected change in household CE for new health risk information given implied belief updating estimated in the model in Section 5. In panel (b), this outcome is modified so that a health shock gives correct information about health risk. Binscatters are constructed using 100 bins and a quadratic fit line.