B Additional Reduced Form Results

B.1 Robustness of Results to Transformations

In the main text, I use the inverse hyperbolic sine transformation. Bellemare and Wichman (2020) show that for a model with continuous variables x and y and specification $\sinh^{-1}(y) = \beta x + \varepsilon$, the elasticity of y with respect to x is $(\beta x/y)\sqrt{y^2+1} \approx \beta x$ whenever $y \geq 2$. This may also refine estimates using the more common $\log(y+1)$ transformation. In this section, I show robustness of these results to other transformations.

Table B.2 demonstrates that results are robust to two standard transformations for skewed spending variables: the inverse hyperbolic sine transform, as reported in the main text, and the $\log(y+1)$ transformation.

B.2 Robustness of Results to Event Study Specification

Table B.1 shows the standard difference-in-differences coefficients for each of the main event study regressions performed in the main text.

I also explore robustness to the problem of negative weights and dynamic treatment effects common in two-way fixed-effects regressions. Implementing the Bacon decomposition of difference-in-differences estimation with variation in treatment timing (Goodman-Bacon et al., 2019) suggests that individuals who experience a chronic diagnosis in the home increase their out-of-pocket spending by 24.6%, more than double the estimates presented in the main text. Additionally, all weighted comparison groups are estimated to be positive in the primary specification. Furthermore, Table B.3 implements the robust alternative event study estimator described by de Chaisemartin and D'Haultfoeuille (2019) and Sant'Anna and Zhao (2020). Estimations are performed using the appropriate Stata packages (Rios-Avila and Naqvi, 2021; Chaisemartin et al., 2021). The overall ATTs estimated by the doubly-robust method for overall spending responses and prevention spending are 8% and 4%, respectively (Sant'Anna and Zhao, 2020). Figure B.1 illustrates the doubly-robust event study version of Figure 1 in the main text.

As mentioned in the text, the Bacon decomposition suggest that none of the weights used in the typical TWFE regressions are negative. This is illustrated in Figure B.2.

B.3 Discussion of Appropriate Control Groups

In reduced-form estimation, I include both not-yet-treated and never-treated households in the control group for each cohort. Doing so allows for separate identification of dynamic treatment effects from time fixed-effects, but may come at the cost of introducing violations in

Outcome Variable	Treated$_f \times$ Post$_t$	Adusted R^2	N
OOP, chronic, full sample	0.09***	0.51	1,538,162
	(0.012)		
OOP, chronic, zero-deductible plans	0.13***	0.55	390,335
	(0.020)		
OOP, acute, full sample	0.42***	0.50	1,374,481
	(0.031)		
OOP, acute, zero-deductible plans	0.39***	0.54	358,860
	(0.063)		
Billed spending, wellness visits, full sample	0.13***	0.43	1,538,162
	(0.013)		
Billed spending, wellness, zero-deductible plans	0.18***	0.40	390,335
	(0.027)		
Cardiovascular Prescriptions, Prob(fill scrip)	2.56	0.42	439,542
	(1.501)		
Cardiovascular Prescriptions, PDC	1.46	0.48	439,542
	(1.142)		
Billed Spending, Low Value Services	0.06***	0.20	1,538,162
	(0.011)		
Utilization, Low Value Services	0.03***	0.20	1,538,162
	(0.008)		

Notes: This table presents estimates for the standard difference-in-difference coefficients of the event study regressions reported in the paper. Standard errors are clustered at the household level. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$

Table B.1. Difference in Differences Coefficients, Main Regressions

	OOP spending, chronic			Billed spending, wellness		
	No Adjustment	CD	SZ	No Adjustment	CD	SZ
t	0.08***	0.06***	0.08***	0.12***	0.11***	0.08***
	(0.014)	(0.013)	(0.014)	(0.016)	(0.022)	(0.22)
$t+1$	0.10***	0.08***	0.10***	0.09***	0.07***	0.05**
	(0.016)	(0.016)	(0.016)	(0.017)	(0.018)	(0.22)
$t+2$	0.10***	0.06***	0.09***	0.10***	0.07***	0.03
	(0.018)	(0.018)	(0.019)	(0.021)	(0.021)	(0.026)
$t+3$	0.09***	0.04**	0.07**	0.11***	0.06***	0.02
	(0.018)	(0.021)	(0.023)	(0.022)	(0.021)	(0.026)
$t+4$	0.08***	0.02	0.05*	0.13***	0.07**	0.07*
	(0.025)	(0.025)	(0.028)	(0.025)	(0.021)	(0.36)
$t+5$	0.07***	-0.02	0.01	0.10***	0.02	0.06
	(0.030)	(0.031)	(0.034)	(0.030)	(0.034)	(0.44)
N	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161

Notes: This table compares regression results from the typical two-way fixed effects event study regression and the robust alternative estimators proposed by de Chaisemartin and D'Haultfoeuille (2019) and Sant'Anna and Zhao (2020). Note that pre-trends are not estimated using the command proposed by Chaisemartin et al. (2021), and are hence not reported). Standard errors clustered at the household level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.3. Model Comparison: Robust Estimation of Event Studies

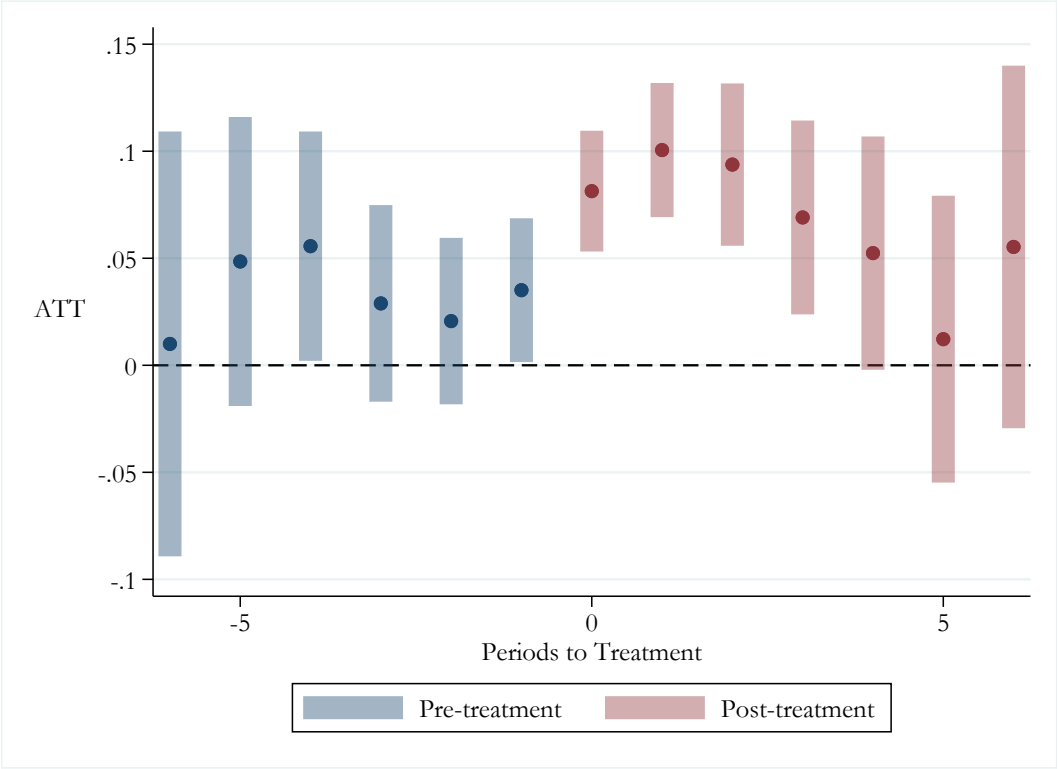


Figure B.1. Effect of Chronic Diagnosis on OOP Spending: Doubly-Robust Estimation of Sant'Anna and Zhao, 2020

Notes: This figure re-presents regression coefficients for the event study regression of Figure 1 in the main text, using the approach of Sant'Anna and Zhao, 2020. Rectangles show estimated average treatment effects and 95% confidence intervals for the effect of a new diagnosis on household OOP spending. Standard errors are clustered at the household level.

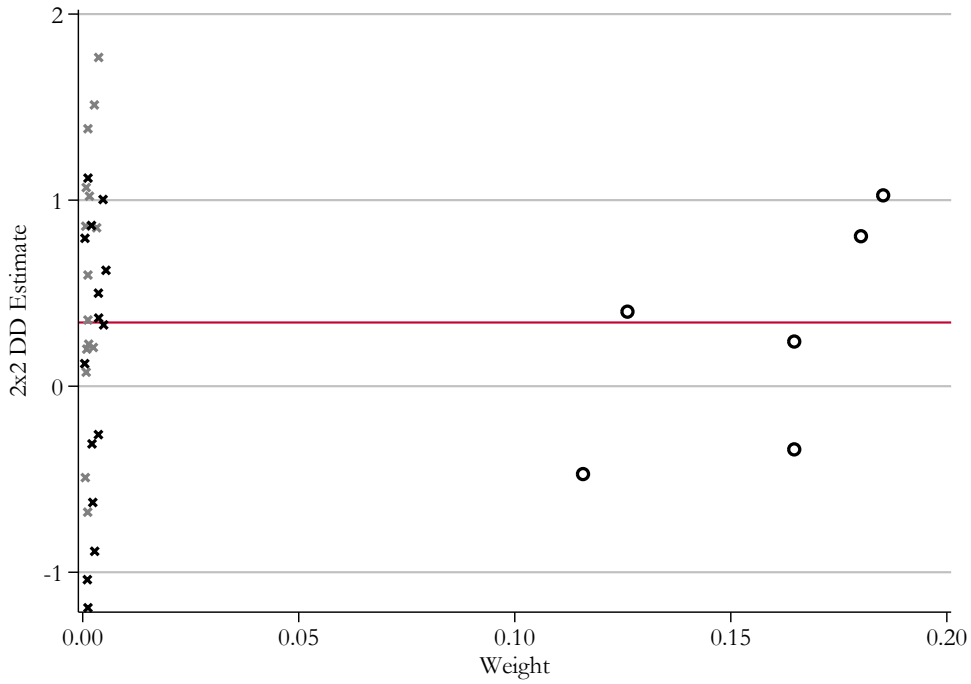


Figure B.2. Bacon Decomposition: Total OOP Following Chronic Diagnosis

Notes: This figure illustrates the estimated decomposition for how individual household-year cells contribute to the overall event study regression of Figure 1 in the main text, using the Bacon Decomposition. Each point represents a single 2x2 regression across a household-period, with its assigned weight shown on the x-axis and the estimated coefficient on the y-axis. All weights are nonnegative, and centered around the overall difference-in-differences coefficient, reported as the horizontal red line. Standard errors are clustered at the household level.

	OOP, chronic diagnosis		OOP, acute diagnosis		Wellness spending		Low-value spending	
	$sinh^{-1}(y)$	$log(y+1)$	$sinh^{-1}(y)$	$log(y+1)$	$sinh^{-1}(y)$	$log(y+1)$	$sinh^{-1}(y)$	$log(y+1)$
$t-5$	-0.02	-0.02	-0.11	-0.10	-0.09**	-0.08**	-0.06*	-0.05*
	(0.028)	(0.026)	(0.070)	(0.064)	(0.031)	(0.028)	(0.033)	(0.03)
$t-4$	0.02	0.01	-0.11	-0.10	-0.03	-0.03	-0.04	-0.03
	(0.024)	(0.022)	(0.059)	(0.055)	(0.026)	(0.024)	(0.028)	(0.024)
$t-3$	0.00	0.00	-0.02	-0.02	-0.02	-0.02	-0.03	-0.02
	(0.020)	(0.018)	(0.052)	(0.048)	(0.022)	(0.020)	(0.023)	(0.021)
$t-2$	-0.00	-0.00	-0.07	-0.06	-0.03	-0.03	-0.01	-0.01
	(0.017)	(0.015)	(0.045)	(0.042)	(0.019)	(0.017)	(0.020)	(0.018)
$t-1$	–	–	–	–	–	–	–	–
t	0.08***	0.07***	-0.01	-0.01	0.12***	0.11***	0.05*	0.04*
	(0.014)	(0.013)	(0.041)	(0.037)	(0.016)	(0.015)	(0.018)	(0.016)
$t+1$	0.10***	0.10***	0.10*	0.09*	0.09***	0.08***	0.05**	0.04**
	(0.016)	(0.014)	(0.047)	(0.043)	(0.017)	(0.016)	(0.019)	(0.017)
$t+2$	0.10***	0.09***	0.06	0.07	0.10***	0.10***	0.05*	0.04*
	(0.018)	(0.017)	(0.055)	(0.050)	(0.020)	(0.018)	(0.021)	(0.019)
$t+3$	0.09***	0.08***	0.10	0.09	0.11***	0.10***	0.04	0.04
	(0.018)	(0.019)	(0.062)	(0.057)	(0.022)	(0.020)	(0.024)	(0.021)
$t+4$	0.08***	0.08***	0.14	0.13	0.13***	0.12***	0.09**	0.08**
	(0.025)	(0.022)	(0.074)	(0.068)	(0.025)	(0.023)	(0.028)	(0.024)
$t+5$	0.07***	0.06*	0.12	0.12	0.10***	0.09***	0.12***	0.11***
	(0.030)	(0.028)	(0.088)	(0.081)	(0.030)	(0.027)	(0.033)	(0.029)
R^2	0.51	0.52	0.50	0.51	0.43	0.44	0.20	0.20
N	1,538,161	1,538,161	1,374,359	1,374,359	1,538,161	1,538,161	1,538,161	1,538,161

Notes: This table presents estimates for the main event study regression results reported in the paper. The first column of each pair of results are the results shown graphically in the text, while the second column uses the log transformation. Standard errors are clustered at the household level. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$

Table B.2. Robustness: Inverse Hyperbolic Sine & Log Transformations

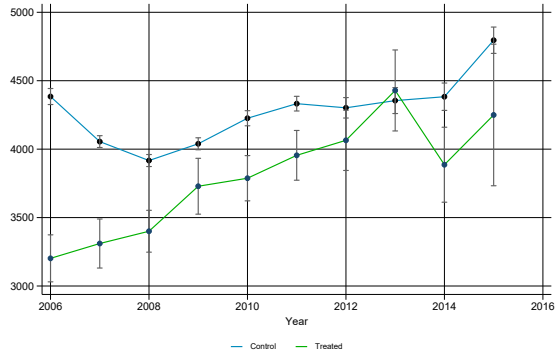
the parallel trends assumption: namely, it may be the case that in the absence of major health events, treated households and never-treated households may have had differing spending and utilization trajectories.

This is less likely to be true in my setting than in other contexts, for a number of reasons. First, the diagnoses included here span a large range of chronic conditions, including those that do not ultimately affect lifetime health or spending for diagnosed individuals (e.g., asthma or major depressive disorder). As spending and quality of life are unlikely to be meaningfully affected by these diagnoses, it is unlikely that in the absence of a diagnosis, these groups would have differed on some other measure affecting health utilization. Second—and perhaps more important—these diagnoses are largely heritable and unaffected by health behaviors such as diet, exercise, or engaging in other risky behaviors such as smoking. Given this, there is unlikely to be selection of less healthy households (whose health may have deteriorated for other, unobserved, reasons in the absence of diagnosis) into the treatment versus control groups.

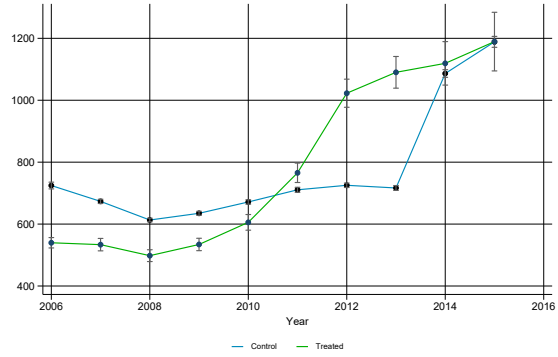
Finally, I show that (a) treatment and control groups are balanced (Figure B.2) and (b) my results are robust to considering only not-yet-treated households in the control group (Figure B.2). Note that in both panel (a) and panel (b) of Figure B.2, effects have a shorter duration than suggested when including never-treated units in the comparison group. This is likely due to the fact that year fixed-effects are not separately identified in this setting, making long-term comparisons difficult.

Figure B.2. Spending Trends of Treatment and Control Households, Pre-Diagnosis

(a) Total Spending/Person (Leave One Out)



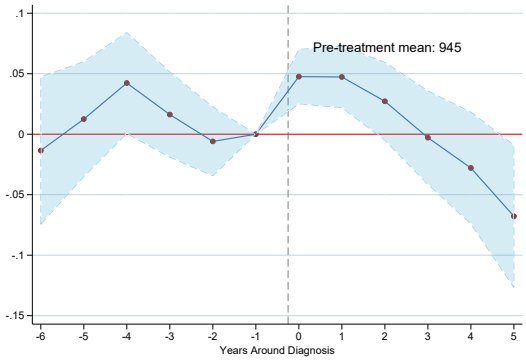
(b) OOP/Person (Leave One Out)



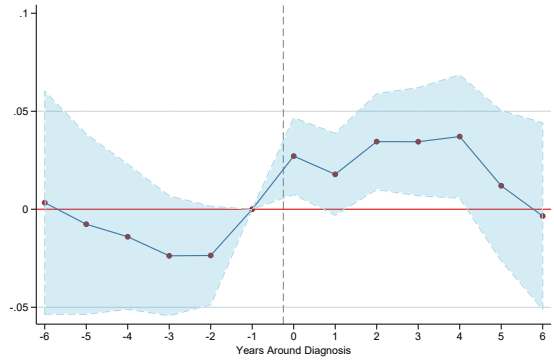
Note: Add notes here.

Figure B.2. Effect of Chronic Diagnoses on Non-Diagnosed Household Members' Spending: Not Yet Treated Households Only as Controls

(a) $\sinh^{-1}$(Total OOP Spending)



(b) # Wellness Visits

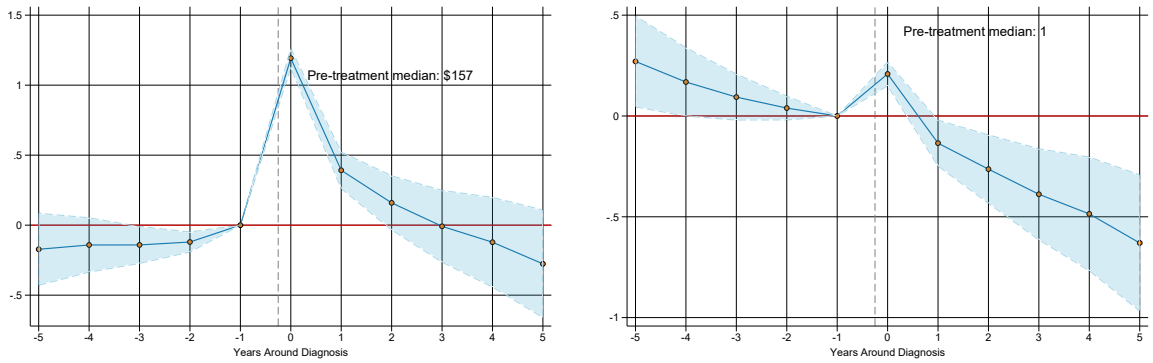


Notes: These figures show estimated coefficients and 95% confidence intervals for the effect of a new chronic diagnosis on medical spending. Control group is limited only to not-yet-treated households in regressions. In both panels, the sample includes spending for all household members without major health events. In panel (a), the dependent variable is the inverse hyperbolic sine of total OOP spending; panel (b) estimates the effect on total spending (insurer spending + OOP spending) on wellness visits only. Coefficients are presented relative to the year prior to diagnosis. Spending is measured in 2020 USD. Standard errors are clustered at the household level.

B.4 Household Response to Major Medical Events

Figure B.2. Effect of Chronic Diagnoses on OWN Healthcare Utilization

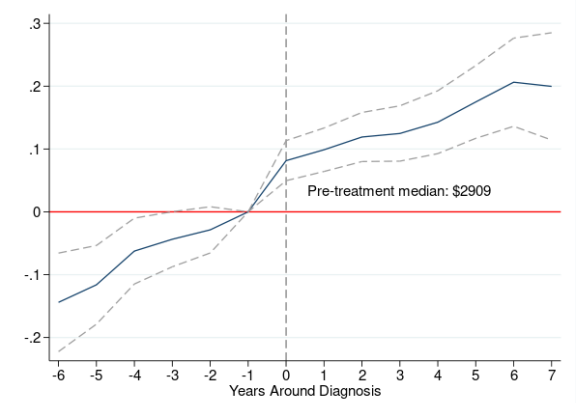
(a) $\sinh^{-1}$(Total OOP Spending) (b) # of Preventive Visits



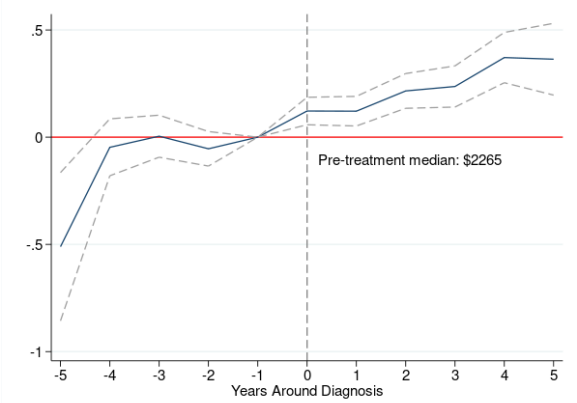
Notes: Figures show regression coefficients from "stacked" TWFE regressions, with 95% confidence intervals. Regressions estimate the effect of a new chronic diagnosis on the medical utilization of the diagnosed individual. In panel (a), the dependent variable is the inverse hyperbolic sine of total OOP spending; panel (b) estimates the effect on the number of household preventive services per year using Poisson regression. Coefficients are presented relative to the year prior to diagnosis. Spending is measured in 2020 USD. Standard errors are clustered at the household level.

Figure B.3. Estimated Effect of a Chronic Diagnosis on Billed Non-Diagnosed Spending

(a) Full sample



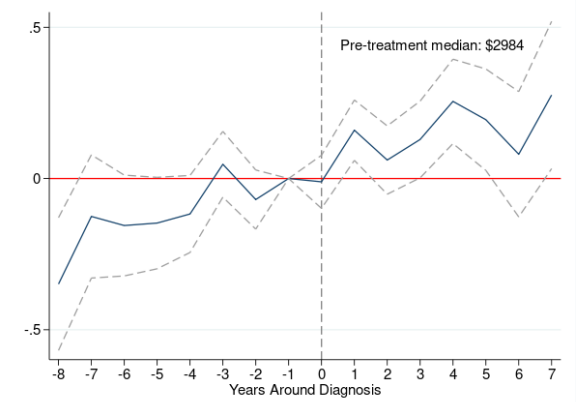
(b) Households facing zero deductible



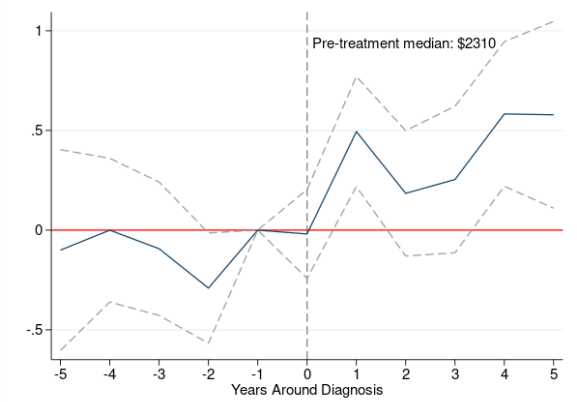
Note: Dependent variable is the inverse hyperbolic sine of total billed spending for all non-diagnosed individuals in a household. Coefficients are presented relative to the year prior to diagnosis. Spending is measured in 2020 USD. Standard errors are clustered at the household level.

Figure B.4. Estimated Effect of an Acute Health Event on Billed Non-Diagnosed Spending

(a) Full sample



(b) Households facing zero deductible



Note: Dependent variable is the inverse hyperbolic sine of total billed spending for all non-diagnosed individuals in a household. Coefficients are presented relative to the year prior to diagnosis. Spending is measured in 2020 USD. Standard errors are clustered at the household level.

In this section, I include additional results from a suite of two-way fixed effects models estimating the causal effect of major medical events on health behaviors. Figures B.3 and B.4 illustrate the estimated effect on billed spending for both chronic and acute medical events.

I also explore the effect of acute health events on household out-of-pocket spending, similar to Figure 1 in the text. In general, acute events do not generate the same household response that chronic diagnoses do.

To explore the role that these conditional price changes have on the observed spending responses, I first examine the potentially heterogeneous effects of major medical events by families' typical pre-diagnosis deductible contributions. Figure B.5 illustrates various difference-in-difference estimates for the effect of a major medical event on billed spending, estimated on the sample of families who contributed up to a certain fraction of their deductible on average prior to diagnosis. For this approach, I examine billed spending instead of OOP spending because OOP spending will mechanically rise more for those who tend to have a larger portion of their deductible to pay off, as the deductible is typically the largest contributor to OOP expenses.

The figure shows much larger utilization effects among families that typically spent less than a quarter of their deductible OOP. In fact, families that spent 10% or less of their deductible on average prior to diagnosis are estimated to increase their utilization by about 50%. These large effects decay as more of the sample is included, and I find that even families spending 50% of their deductible may not increase their health utilization following major medical events. Taken together, these results suggest that the families who experience the largest price reductions in care are not the families increasing their utilization the most, suggesting that demand responses are not the major driver of health behavior changes.

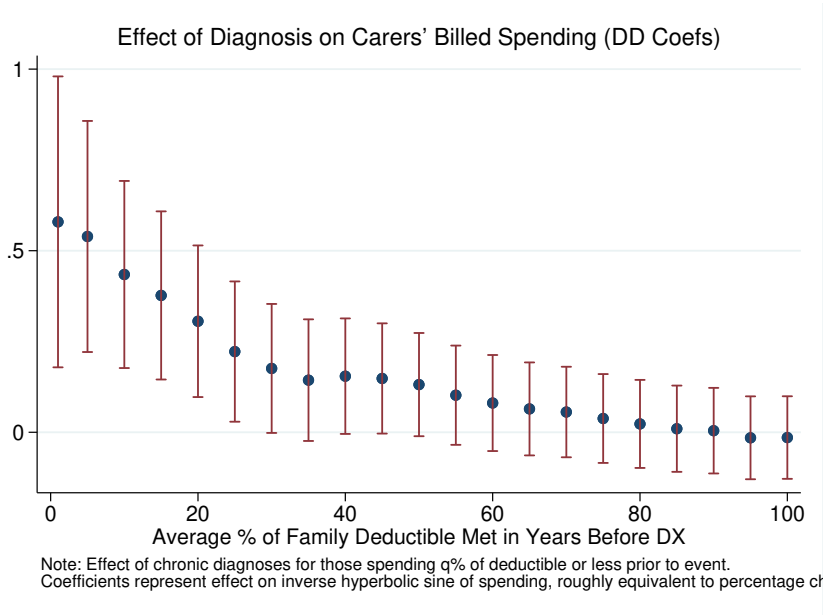


Figure B.5. Spending Responses Differ Based on Pre-Diagnosis Spending

Finally, I find a strong extensive margin response among household members who experience major medical events in their families. Table B.4 shows that individuals are more likely to spend any positive amount (billed and OOP) on medical care, use any outpatient visits or preventive care, or fill any prescriptions. This effect is strongest in the year of the

diagnosis and decays slightly over time, but remains significant for five years following the health event.

Table B.4. Estimated Extensive Margin Health Effects of Family Diagnosis

	Year of Event ($t = 0$)	Following Years ($t > 0$, averaged)
Any Billed Spending	1.54***	0.60***
	(0.08)	(0.13)
Any OOP Spending	2.62***	1.41***
	(0.11)	(0.18)
Any Outpatient Visits	2.20***	0.65***
	(0.09)	(0.15)
Any Preventive Care	3.23***	0.90***
	(0.15)	(0.22)
Any Prescription Fills	4.74***	2.45***
	(0.41)	(0.53)

Notes: Table shows estimated difference-in-difference regression coefficients for the effect of a new chronic diagnosis (N=1,538,161). Outcome variables are dummy variables indicating the likelihood of each outcome, scaled from 1 to 100. Standard errors clustered at the household level are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

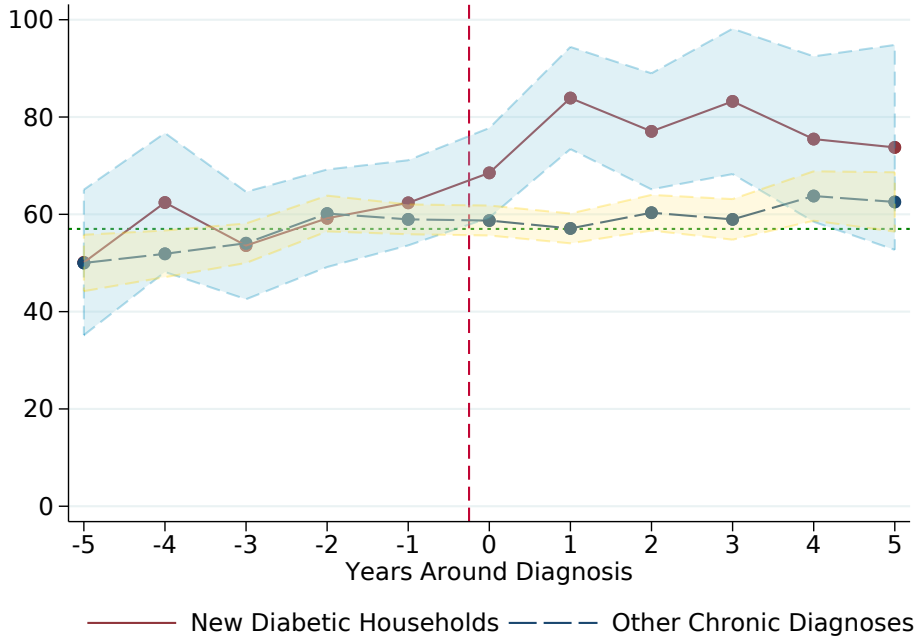
B.5 Disease-Specific Screenings: Additional Results

Figure B.6 illustrates, in the raw data, the central takeaway from Section 3.2 in the paper: that households respond to a new diagnosis by selecting into services related to that diagnosis. The figure shows that households with a newly diagnosed diabetic takeup more diabetes screenings than households affected by a non-diabetes chronic diagnosis.

The main paper presents triple difference regressions that verify that households affected by new diagnoses increase the takeup of relevant screenings, for example for cancer and diabetes. To verify these results, I also conducted two "placebo" regressions for cases where health events communicate no useful *risk* information, and hence are expected to change disease-specific screenings little. These include the effect of new diabetes diagnoses on obesity diagnoses (a diagnosis which, while an important risk factor for some types of diabetes, is externally verifiable prior to a household diagnosis), and the effect of a new household mental health condition on screenings for depression. In the second case, while mental health diagnoses may provide meaningful risk information to households, such information may incidentally *reduce* the value of preventive depression screening relative to immediately

Figure B.6. Rate of Diabetes Screenings Around Time of Diagnoses

(a) Diabetes Screenings (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.

seeking treatment. A lack of observed response in these placebo cases underscores the specific role of risk information in changing behavior.

Table B.4 presents the estimation results from these six regressions in two panels. The first panel, discussed at length in the paper, highlights that new chronic diagnoses alter specific preventive behaviors in cases where they transmit important information about health risk. The second panel reports results for placebo regressions including obesity diagnoses and depression screenings. Here, I find no strong evidence that health events alter screenings. This is consistent with the notion that individuals respond by altering their use of preventive care only when the major health event communicates health risk information that necessitates preventive care utilization. Other dimensions of a health event (e.g., new information

Table B.4. 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 (β_{DD})	Effect of Specified Diagnosis (β_{DDD})
Panel A: Main Effects				
Hypertension[1]	Any Chronic[2]	2.01	-0.27**	0.39***
		(0.007)	(0.102)	(0.110)
Cancer	Cancer	20.72	-0.01	2.74***
		(0.021)	(0.113)	(0.509)
Diabetes	Diabetes	6.21	-0.46***	1.31***
		(0.012)	(0.086)	(0.279)
Cholesterol	Diabetes	17.01	-0.22	1.23***
		(0.019)	(0.126)	(0.389)
Panel B: Placebo Regressions				
Obesity[1]	Diabetes	1.04	0.02	0.10
		(0.005)	(0.035)	(0.110)
Depression	Depression	0.36	-0.01	-0.08
		(0.003)	(0.037)	(0.077)

Notes: Table presents six triple-difference regressions for how diagnoses affect household investments in disease-specific preventive care. Outcome variables are binary indicators for the screening in the first column; treatment variables are a binary indicator for the diagnosis in the second column. Difference-in-differences coefficients (β_{DD}) indicate the effect of *any* chronic diagnosis on screenings, while triple differences coefficients (β_{DDD}) indicate the (additive) effect of *specific* diagnoses. Standard errors clustered at the household level shown in parentheses. [1]Due to unavailability of procedure codes, these outcomes are measured using diagnostic codes. [2]Here, the reference group is all acute major health events. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$

about the value of preventive care generally) do not appear to drive utilization decisions for preventive care. Taken together, the observed ways in which major health events affect the use of preventive care are all consistent with a model where households interpret new diagnoses as signals of their own health risk, altering their behaviors accordingly.

B.6 Intra-Familial Relationships

For example, while a diabetes diagnosis is most likely to affect adult household members with similar lifestyles to the original diagnosed individual,[1] a mental health diagnosis may have a stronger genetic component. Hence, households where an adult was diagnosed with diabetes may choose to screen other adults, such as spouses, while households where someone received a mental health diagnosis may choose to screen children or siblings of the affected individual.

Screening *Diagnosis*	Hypertension *Any Chronic*	Diabetes *Diabetes*	Cholesterol *Diabetes*	High BMI *Diabetes*	Cancer *Cancer*	Depression *MDD/Bipolar*
$\text{Post}_t \times \text{Diagnosis}_f$	0.39***	-0.85***	-2.20***	-0.38**	2.55***	0.30**
	(0.03)	(0.21)	(0.29)	(0.12)	(0.43)	(0.10)
$\text{Post}_t \times \text{Diagnosis}_f \times \text{Parent}_j$	-0.34**	3.49*	3.73	1.73*	-1.90	-0.93***
	(0.11)	(1.71)	(2.26)	(0.70)	(2.49)	(0.13)
$\text{Post}_t \times \text{Diagnosis}_f \times \text{Spouse}_j$	-0.74***	2.54***	5.15***	1.03***	-3.33***	-0.62***
	(0.13)	(0.45)	(0.60)	(0.20)	(0.81)	(0.11)
$\text{Post}_t \times \text{Diagnosis}_f \times \text{Sibling}_j$	0.09	0.76	2.89	0.16	1.56	0.68*
	(0.04)	(1.09)	(1.86)	(0.69)	(1.55)	(0.32)
Observations	4,039,602	3,680,725	3,680,725	3,680,725	3,671,064	3,724,608
Adjusted R^2	0.024	0.217	0.388	-0.025	0.473	0.117

Standard errors in parentheses

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

Notes: 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 top row. The specific chronic illness used as the Diagnosis_f dummy is shown in the second row. Standard errors are clustered at the household level.

Table B.5. DDD Estimates: Disease-Specific Spending

To assess these potentially heterogeneous effects, I utilize a simple difference-in-differences framework. In Table B.5, I present estimation results for the same six diagnosis/outcome pairs shown in Table 3. The dependent variable—either a screening or a new diagnosis—is shown in the top row, with the treatment variable—the chronic illness affecting the household—below 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.

Throughout, I find consistent evidence that households respond by not only selecting

[1]The vast majority of diabetes diagnoses in my sample are for Type 2 Diabetes Mellitus, which generally affects adults and risk of which is increased or decreased based on specific lifestyle choices, such as diet and exercise. The same is not as true for Type 1 DM diagnoses.

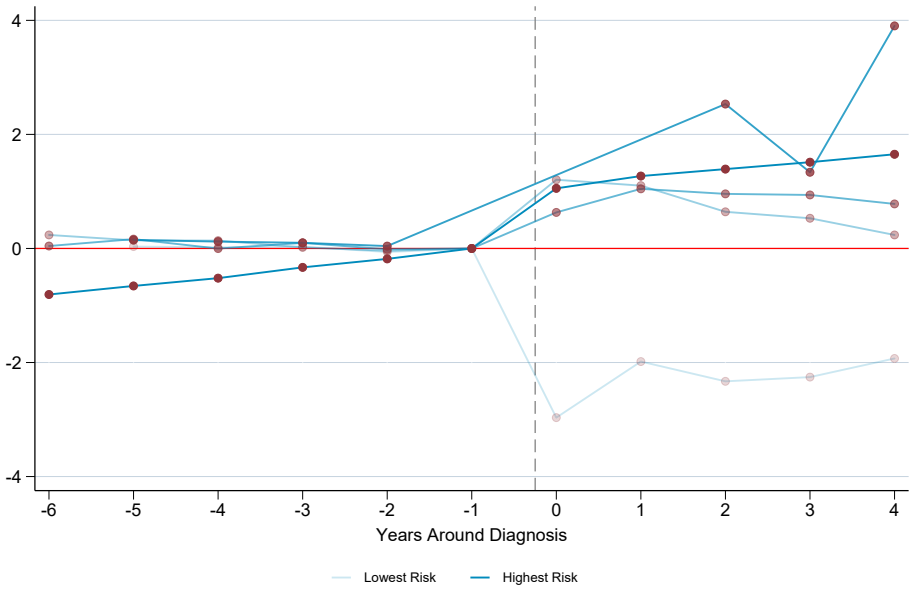
screenings associated with the health events they experienced, but also selecting which individuals to screen based on their associated risk. New hypertension diagnoses following a chronic event are concentrated among children rather than parents and spouses, suggesting that households are identifying previously ignored risks among the previously lower-risk members of their household. Additionally, households affected with diabetes 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.

As an alternative test to salience, I explore how each individual reacts differently to a diagnosis in their home stratified by their pre-event diagnostic risk. This uses the risk proxy described in Section 5 of the main paper.

B.6.1 Stratifying by Pre-Event Diagnostic Risk

In addition to the tests reported in the main paper, I test further for differences between salience effects and responses to new risk information. Specifically, I use within-household variation in pre-event diagnostic risk for households affected by chronic conditions, using the risk proxy described in Section 5 of the paper.

Figure B.6. Spillover Responses to Chronic Diagnosis, by Pre-Event Diagnostic Risk



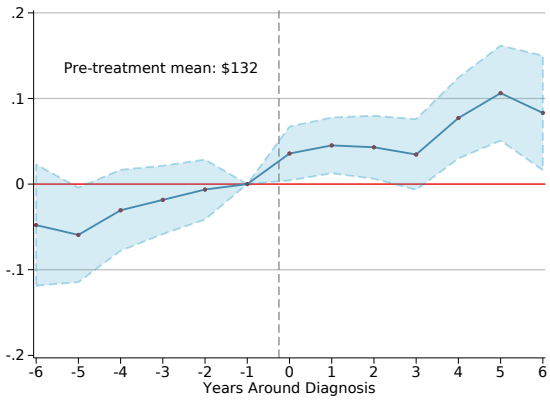
Notes: Figure show estimated coefficients for the effect of a new chronic diagnosis on medical spending, for household members stratified by pre-diagnosis risk (see Section 5 for a precise definition). The dependent variable is the inverse hyperbolic sine of total OOP spending, measured in 2020 USD. Standard errors are clustered at the household level.

Figure B.6 presents the results. I find that household members with greater risk respond more to health events, while the least risky household members actually decrease their spending following a diagnosis in the home. This is conducive with the hypothesis that households respond more to the risk information contained in a diagnosis rather than the overall salience of an event (which would impact all household members equally); households may even shift resources within the home to prioritize the most at-risk households following a diagnosis.

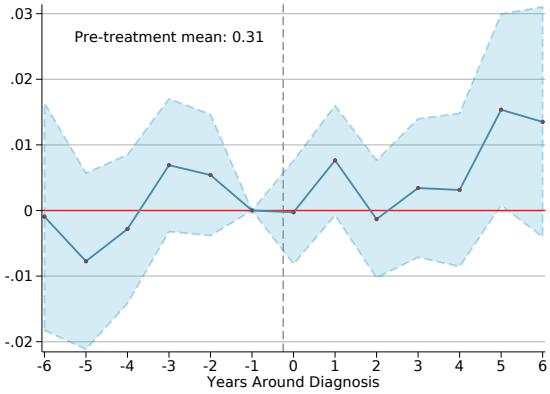
B.7 Low Value Care

Figure B.6. Chronic Diagnoses Increase Utilization of Low-Value Care

(a) Billed Low-Value Spending



(b) Low-Value Utilization (Rate/Person)



Notes: This figure shows estimated coefficients and 95% confidence intervals for the effect of major health events on the use of low-value services (see Appendix A for definitions). In the first panel, the outcome is the inverse hyperbolic sine of billed spending. In the second panel, the outcome is the number of low-value services used per household member. Spending is measured in 2020 USD. Standard errors are clustered at the household level.

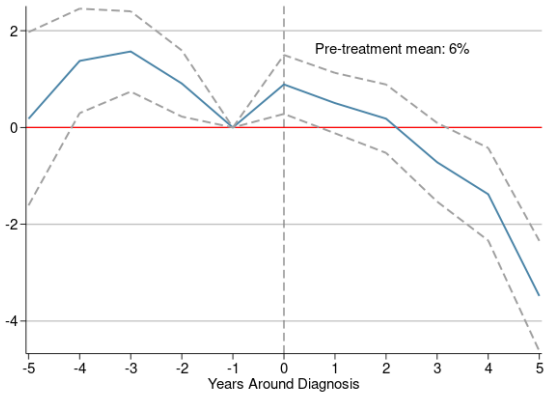
Figure B.6 presents estimates for the effect of new chronic diagnoses on the overall utilization of low-value services, including both total spending and overall utilization rates. Major health events are associated with a small increase in overall low-value spending of about 5 percent. In contrast, the average rate of service use among non-diagnosed household members does not change meaningfully following a diagnosis. Table B.6 depicts the event study regressions discussed in the text.

B.8 Plan Choices

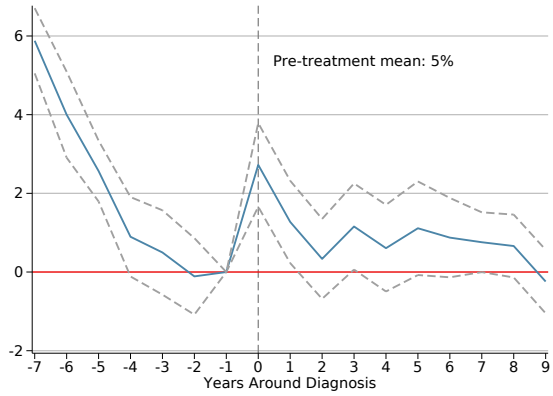
Finally, using the portion of my sample with identifiable plan choice information, I estimate the effect of chronic health events on household decisions to switch plans. Figure B.7 illustrates that affected households are less likely to switch insurance plans following their major health events relative to the general population. I observe both that plan switches do not become more likely overall (Panel (a)), and that even among active choosers, plan switches do not become higher-quality (proxied by the use of zero-deductible plans; see Panel (b)).

Figure B.7. Effect of Chronic Diagnoses on Health Plan Switching

(a) Pr(Any Health Plan Switch)



(b) Pr(Switch to 0-Deductible—Any Switch)



Note: These figures assess the impact of major health events on plan switches. The outcome variables are a binary indicator for whether the household switched plans in the first panel, and whether they switched plans to a plan with zero-deductible in the second panel. The second panel restricts the sample to those who ever made an active plan choice. Standard errors are clustered at the household level.

Service Category	All Pediatric		Adult Drugs		Adult Imaging		Adult Screening		Adult Surgery	
Outcome Variable	Spending	Rate	Spending	Rate	Spending	Rate	Spending	Rate	Spending	Rate
DiD										
$\text{Post}_t \times$ Diagnosis$_f$	0.05***	0.02***	-0.00	-0.00	0.03***	0.01***	0.10***	0.03***	-0.10***	-0.04***
	(0.017)	(0.003)	(0.000)	(0.000)	(0.013)	(0.002)	(0.014)	(0.005)	(0.012)	(0.002)
Adjusted R^2	0.192	0.228	0.143	0.259	0.123	0.141	0.163	0.151	0.230	0.255
Event Study										
$t-4$	-0.04**	-0.02*	0.01	0.00*	0.01	-0.00	-0.10***	-0.05***	0.09***	0.03***
	(0.014)	(0.008)	(0.003)	(0.002)	(0.016)	(0.005)	(0.021)	(0.011)	(0.012)	(0.004)
$t-3$	-0.02	-0.01	0.00	0.00	-0.01	-0.01	-0.03	-0.09	0.04***	0.02***
	(0.012)	(0.007)	(0.002)	(0.001)	(0.013)	(0.004)	(0.019)	(0.010)	(0.010)	(0.003)
$t-2$	-0.01	-0.01*	0.00	0.00	0.01	0.00	-0.02	0.00	0.01	0.01**
	(0.010)	(0.005)	(0.002)	(0.001)	(0.016)	(0.004)	(0.016)	(0.010)	(0.009)	(0.002)
$t-1$	–	–	–	–	–	–	–	–	–	–
t	0.02**	0.008	0.00	0.00	0.01	0.01	0.03*	0.008	-0.03***	-0.01***
	(0.009)	(0.004)	(0.002)	(0.001)	(0.010)	(0.003)	(0.015)	(0.008)	(0.008)	(0.002)
$t+1$	0.03***	0.01***	0.00	0.00	0.03***	0.01***	0.07***	0.04***	-0.07***	-0.02***
	(0.009)	(0.005)	(0.002)	(0.001)	(0.011)	(0.003)	(0.015)	(0.008)	(0.009)	(0.003)
$t+2$	0.04***	0.02***	-0.00	0.00	0.02*	0.01**	0.06***	0.02	-0.08***	-0.03***
	(0.010)	(0.005)	(0.002)	(0.00)	(0.012)	(0.003)	(0.016)	(0.009)	(0.011)	(0.003)
$t+3$	0.05***	0.02***	-0.00	-0.00	0.03**	0.02***	0.07***	0.03**	-0.11***	-0.05***
	(0.011)	(0.006)	(0.002)	(0.001)	(0.013)	(0.004)	(0.018)	(0.011)	(0.013)	(0.005)
$t+4$	0.04***	0.02***	0.00	0.00	0.06***	0.02***	0.10***	0.03*	-0.10***	-0.05***
	(0.013)	(0.007)	(0.003)	(0.002)	(0.016)	(0.005)	(0.021)	(0.012)	(0.016)	(0.005)
Adjusted R^2	0.192	0.228	0.143	0.259	0.123	0.141	0.163	0.151	0.230	0.255
N	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161	1,538,161

Notes: Table shows estimated difference-in-difference and event study regression coefficients for the effect of a new chronic diagnosis. Two outcome variables are reported for each category: the inverse hyperbolic sine of billed spending and the number of low-value services used per household member. See Appendix A for service definitions. Spending is measured in 2020 USD. Standard errors clustered at the household level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.6. Estimated Effects of Chronic Illness on Low-Value Care Utilization, by Category