B Additional Reduced Form Results

B.1 Robustness of Results to 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.

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

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

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

	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 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.

	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

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.

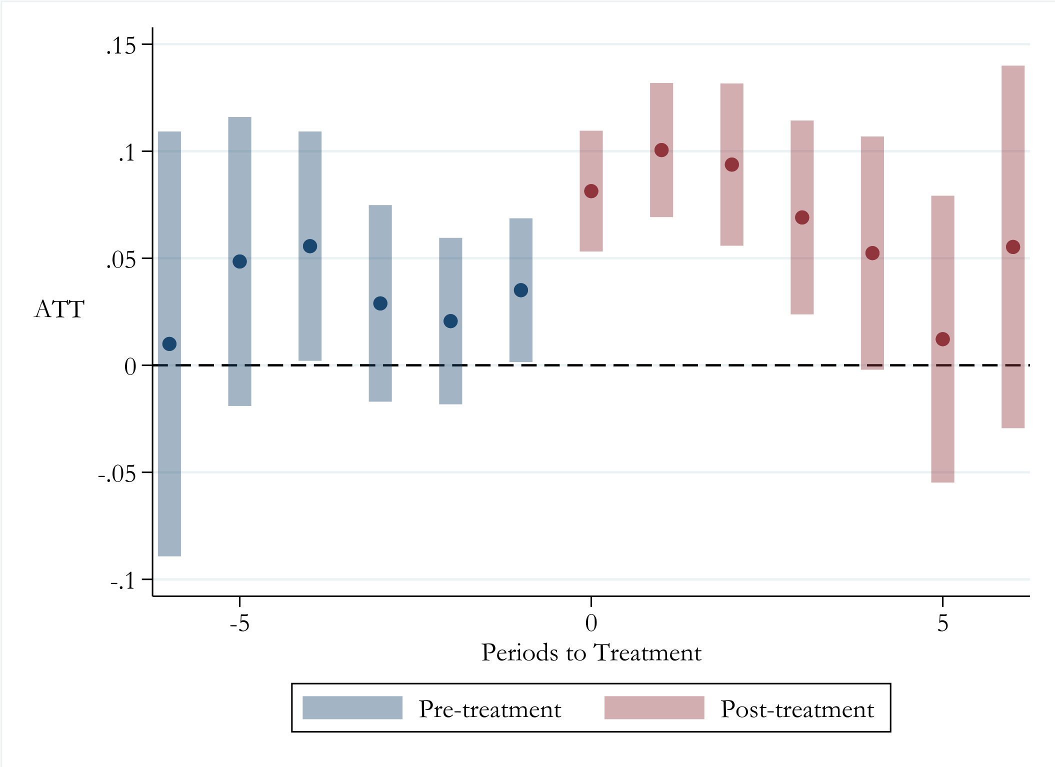


Figure B.1. Effect of Chronic Diagnosis on OOP Spending: Doubly-Robust Estimation of Sant'Anna and Zhao, 2020

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.

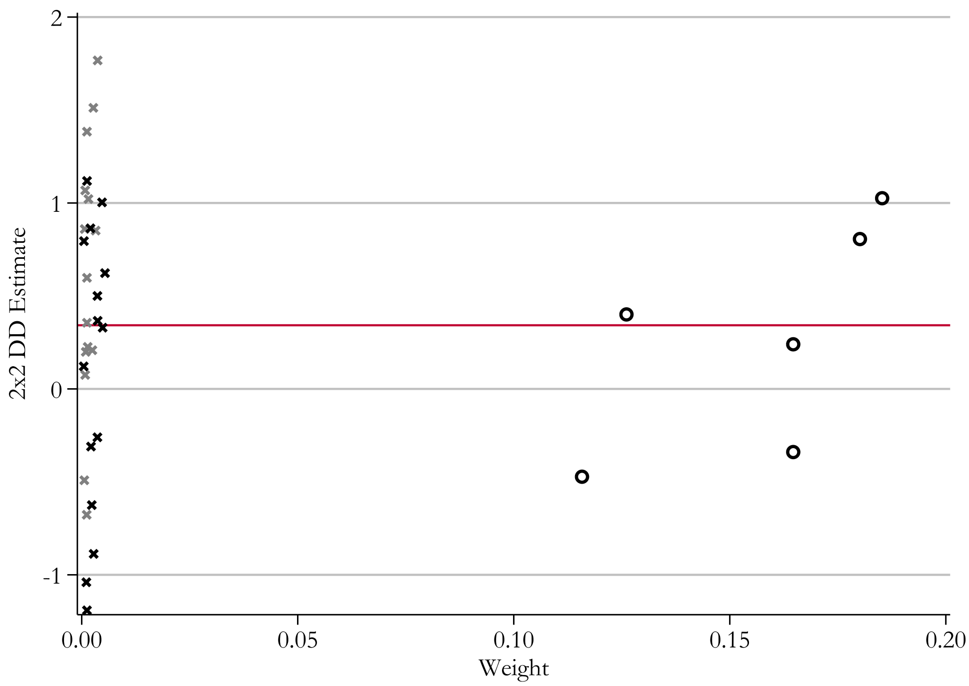


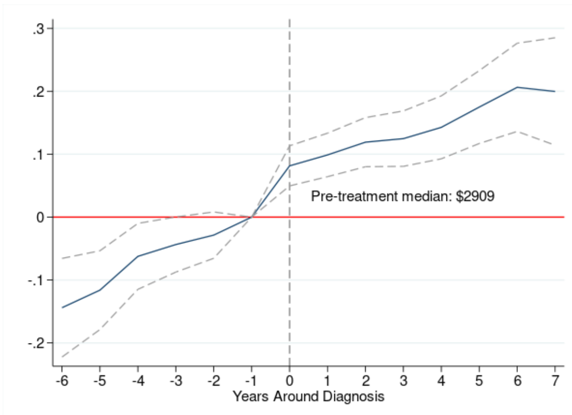
Figure B.2. Bacon Decomposition: Total OOP Following Chronic Diagnosis

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.

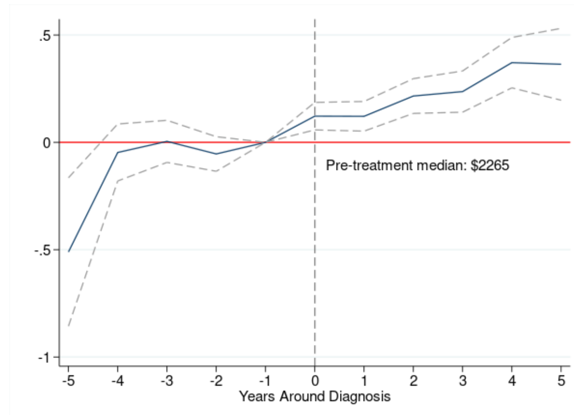
B.3 Household Response to Major Medical Events

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

(a) Full sample



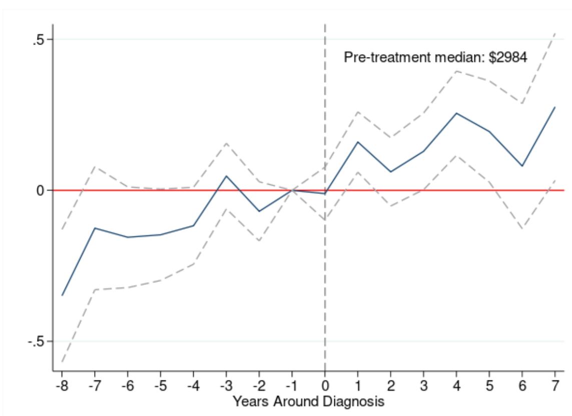
(b) Households facing zero deductible



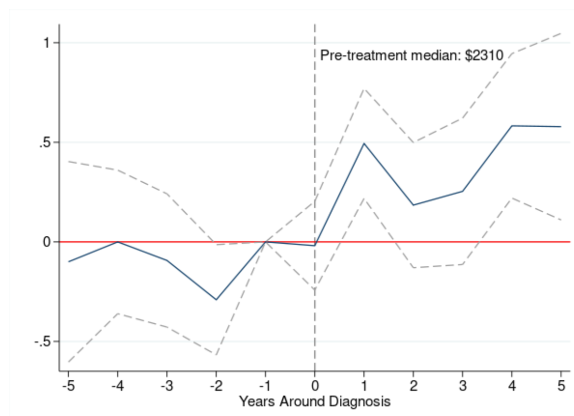
Note: Dependent variable is the inverse hyperbolic sine of total billed spending for all non-diagnosed individuals in a household. Coefficients are presented relative to the year prior to diagnosis. Spending is measured in 2020 USD. Standard errors are clustered at the household level.

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.

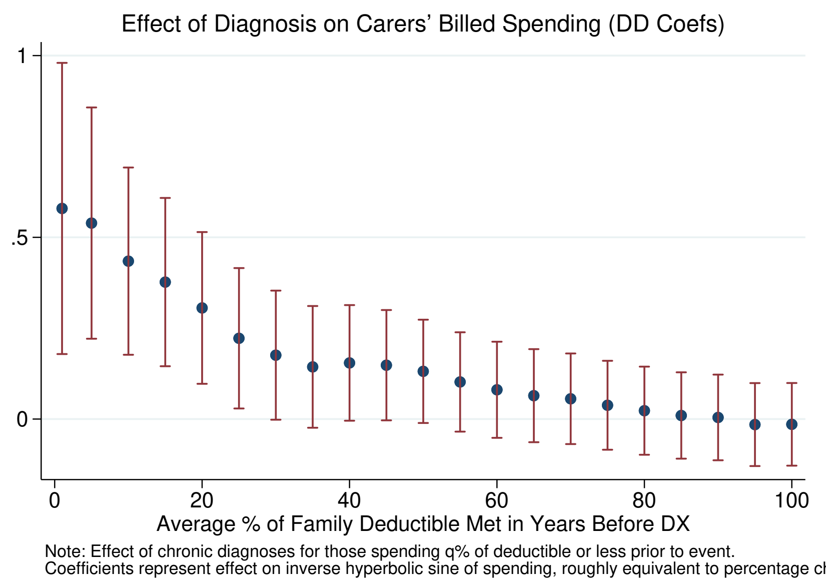


Figure B.5. Spending Responses Differ Based on Pre-Diagnosis Spending

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.4 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.

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

[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.

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.

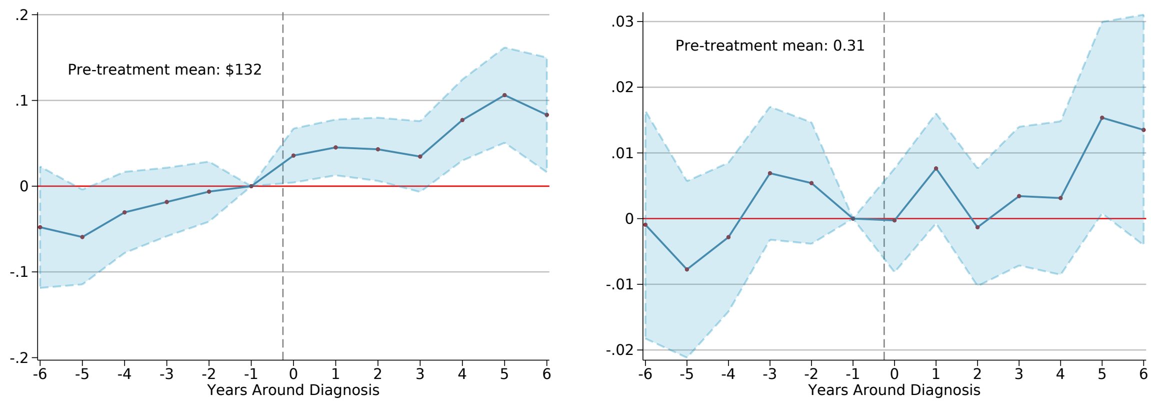
Table B.5. DDD Estimates: Disease-Specific Spending

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 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.

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.

B.5 Low Value Care

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.6 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)).

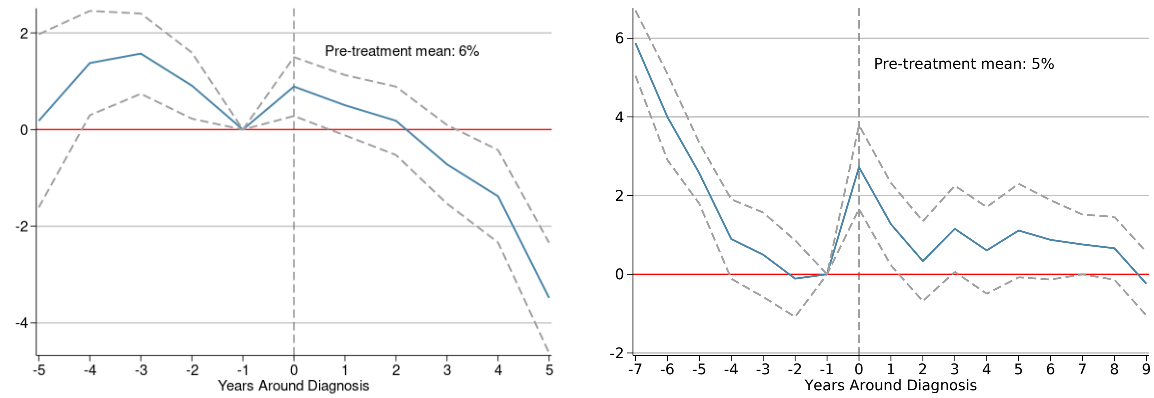
Service Category	All Pediatric		Adult Drugs		Adult Imaging		Adult Screening		Adult Surgery	
Outcome Variable	Spending	Rate	Spending	Rate	Spending	Rate	Spending	Rate	Spending	Rate
DiD										
$\text{Post}_t \times \text{Diagnosis}_f$	0.05***	0.02***	-0.00	-0.00	0.03***	0.01***	0.10***	0.03***	-0.10***	-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

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.