Income-poor but Asset-rich: Effect of housing wealth on older adults' healthcare utilization

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Abstract

Do wealthier individuals use more healthcare services than those less affluent? We investigate this question by exploiting the booms and busts in the U.S. housing market – a natural experiment that generated considerable gains and losses for homeowners. We estimate the effect of wealth on older adults' healthcare utilization using the Instrumental Variables (IVs) approach with the region - year variations in house prices and households' loan-to-value (LTV) ratios to construct an instrument. As a robustness check for count-valued outcomes, we employ a new method of identification using heteroskedasticity (Lewbel, 2012). This method may be used to estimate a count model with endogenous regressors, where external instruments are not available. Using data from the 1996-2014 Health and Retirement Study (HRS), we find that an increase in wealth lowers the probability of hospital admissions, visits to doctors, prescription drug use, outpatient surgery and the use of special facilities or services. On the other hand, an increase in wealth leads to a higher probability of using dental services. At the intensive margin, the number of doctor visits decreases in response to positive wealth shock, but there is no significant effect on the number of nights in hospital. Overall, we find consistent evidence that wealthier individuals demand fewer health services but they have more out-of-pocket health expenditures compared to less wealthy individuals.

Keywords: housing wealth, healthcare utilization, HRS, identification

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1. Introduction

It is commonly known that wealthier people are healthier, happier and live longer (Schwandt, 2018; Mentzakis and Moro, 2009; Pool et al., 2018). However, little is known about the effect of economic resources on healthcare utilization. Money could afford more health services, but it may also improve health through providing a better lifestyle, thereby reducing the need to seek healthcare. Existing literature has recognized the important role of economic resources on the utilization of healthcare (Devaux, 2015). However, most studies to date have tended to focus on income rather than on wealth (Braveman et al., 2005). Failure to include wealth may seriously underestimate the role of economic resources on the use of medical care by the older population (Pollack et al., 2007). Our paper contributes to the existing literature by investigating the effects of wealth - an important economic resource, on older adults' healthcare utilization by exploiting the booms and busts in the U.S. housing market. Using the instrumental variable approach and a novel identification strategy proposed by Lewbel (2012), we find that older individuals use less healthcare, but, they spend more on their services in response to a windfall in wealth.

Previous studies have found that income loses its significance, whereas wealth becomes more important as a source of funding for older people (Boyle Torrey and Teauber, 1986; Feinstein, 1993; Alessie et al., 1997; Van Ourti, 2003). Housing equity is the most important asset for a large fraction of the older population (Doling and Elsinga, 2012; Venti and Wise, 1991). Furthermore, changes in wealth have a large impact on both welfare and consumption in old age (Case et al., 2005; Campbell and Cocco, 2007). Specifically, Doling and Horsewood (2011) found that housing equity could reduce the amount that people save and this could affect the use of healthcare services in old age. Given the importance of housing wealth in the household's financial decision, one would expect changes in wealth, especially a large unanticipated negative shock like the Great Recession to influence older individuals' utilization of healthcare.

Up until now, much of the research examining the link between wealth and healthcare has been descriptive in nature (Cooper et al., 2012; Rodrigues et al., 2018). The assumption that wealth is exogenous is likely to be violated due to various confounding factors. For example, demand for healthcare is associated with health behaviours (e.g. smoking, drinking), which are affected by education level, cognitive ability and health knowledge (Cutler and Lleras-Muney, 2010). These factors are also correlated with wealth. Further endogeneity also arises because individuals with poor health are less likely to participate in the labour force resulting in lower wealth accumulation, but, at the same time, they consume more healthcare.

To establish the causal relationship between wealth and the utilization of healthcare, many studies have proposed to use exogenous variation in economic resources such as oil price shocks, changes in public policy and housing prices as sources of identification. These studies find a significant effect of wealth on the demand for healthcare (Acemoglu et al., 2013; Moran and Simon, 2006; Goda et al., 2011; Tsai, 2015). However, such results do not provide a full picture because they use health expenditure, instead of healthcare utilization, as a proxy for the demand for healthcare. In many high-income countries like the United States, healthcare expenditure is driven by price, nor the need of the population. Indeed, a recent comparative study by Papanicolas et al. (2018) revealed that the U.S. population does not use healthcare more than other countries, but they are paying much more than other comparable OECD countries. Therefore, it is important to examine the effect of wealth on the demand for healthcare using healthcare utilization instead of using healthcare expenditure.

Cheng et al. (2018) were the first to establish the causal relationship between economic resources and healthcare utilization. They find that lottery winners with larger wins are more likely to choose private health services than public health services. However, their finding limits only to lottery winners which are difficult to generalize to general population. Overcoming these limitations, Costa-Font et al. (2019) propose the use of housing booms and busts to examine the effect of wealth on long-term care services. They find a significant increase in the use of paid home healthcare services and unpaid informal care, but no effect on nursing home care access. However, so far, there has been little discussion on the causal effect of wealth on other healthcare utilization such as hospitalization or doctor visits, on which this paper focuses.

Given that informal care could influence the use of hospice care (Van Houtven and Norton, 2004), we hypothesize that doctor visits might also be affected by individuals' wealth. Furthermore, given the recent evidence on the negative effect of wealth on health after the Great Recession, one would expect the use of healthcare services to change in order to meet the needs of the population. Therefore, understanding the link between wealth and individuals' healthcare utilization is important to plan an effective response to the changes in population health needs during economic downturns.

Our paper contributes to the existing literature in two ways. Firstly, we provide evidence of causal wealth effect on healthcare utilization by exploiting exogenous variation in house prices during the U.S. 2007-2009 recession. To our knowledge to date, this is the first paper establishing such causal relationships in an institutional context where healthcare is privately provided. Even though most elderly' healthcare spending is covered by the Government through Medicare and Medicaid, many older American still have to fund their healthcare privately via private health insurance or out-of-pocket spending [1]. As homeowners could borrow up to 75-85% of their home value, housing wealth could play a critical role in funding healthcare in old age (Wei and Goodman, 2016). In 2015, a household could extract, on average, $145,242 from their primary home which could cover healthcare, approximately $ 10,739 per year and long-term-care services, approximately $88,000 per year (De Nardi et al., 2015).

Secondly, in this context, we apply a novel identification strategy for a

[1]Medicare and Medicaid are public insurance programs with Medicare covers all adults aged 65 and above whilst Medicaid targets only individuals from low-income families.

count model with endogenous regressors based on earlier work by Lewbel (2012). This method of identification relies on the presence of heteroskedasticity in the first-stage equation. Because identification is based on higher moments, estimates can be noisier and less reliable than the standard exclusion restriction estimators. However, this could be useful in applications where there are no traditional instruments or weak instruments. Another useful application of this strategy is a robustness check when traditional instruments available. Our findings show that on receipt of a windfall in wealth (both total wealth and housing wealth), healthcare utilization tend to decrease whilst out-of-pocket health expenditures increase. Our findings are consistent with previous finding showing that a negative wealth shock has a negative effect on health (Schwandt, 2018; Fichera and Gathergood, 2016).

The structure of the paper is as follows. The next section describes the dataset used in the analysis. The following section explains the empirical framework used for identification. The fourth section reports our estimation results and the paper ends with a discussion of the findings.

2. Data

We use the Health and Retirement Study (HRS) to investigate the effect of wealth on healthcare utilization. HRS is a nationally representative longitudinal study of US adults aged 50 and over. The HRS survey has been conducted biannually since 1992 and has followed individuals, who were born between 1931 to 1941, and their spouses. In 1993, a new cohort "AHEAD" including people born before 1924 was added to the data. Subsequent samples have periodically been added to maintain the sample of people above 50 years of age[2]. As the effects of wealth could affect any cohort, we include all cohorts in our analysis. The most recent cohort was interviewed in 2010, including people born between 1954 and 1959.

We use two different measures for household wealth. *Total wealth* is the net value of all wealth excluding any secondary residence. *Housing wealth* is the net value of the primary residence. These two variables were imputed for observations that have missing values by the RAND Center for the Study of Aging [3]. Given that housing price expansion started after Wave 2 (1994), we limit our data to Waves 3-12. As we are interested in the healthcare utilization of older adults, we focus on people who were at least 55 years old between 1996 and 2014 following Venti and Wise (1991). Moreover, as housing prices will more likely affect homeowners, we also restrict our sample to homeowners, i.e. who made up 78.8 percent of the original sample.

As our identification strategy relies on the regional variations in housing prices between 1996 and 2014, we use the regional House Price Index (HPI) to measure changes in regional housing prices. This is a broad measure for the movement of single-family house prices. It acts as a timely and accurate

[2]For more information regarding the HRS sample, please refer to https://hrs.isr.umich.edu.

[3]We have estimated the model using non-imputed observations and the results remain robust.

measure of house pricing trends at various geographic levels. It also provides tools to estimate changes in the rate of mortgage default, prepayments and housing affordability in specific areas. The HPI is collected from the Federal Housing Finance Agency (FHFA) and linked with individuals using their places of residence. The matching rate is very high in our sample, approximately 99.8 percent.

2.1. Dependent variables

We examine the effect of wealth on healthcare utilization, specifically on hospital care, doctor visits, outpatient care, prescription drugs, dental care and the use of special services such as counselors. The HRS survey also includes questions on the use of health services which allow us to measure the effect of wealth on the number of nights spent in the hospital and the number of doctor visits in the past two years[4]. We also estimate the effect of wealth on healthcare spending using the total out-of-pocket medical cost. Because that variable is heavily skewed toward the right, we use the log transformation of total medical cost in the analysis.

Table 1 presents summary statistics for healthcare utilization. A quarter of respondents had an overnight stay in hospital whereas 94 percent of the respondents visited doctors during the previous two years. The majority of individuals used prescription drugs (81%) and dental care services (67%). Only 21 percent of the respondents reported having any outpatient surgery. Interestingly, very few people reported using any special services such as

[4]Note that doctor visits include general practitioners and specialists.

counselors or at rehabilitation centres (9%). The average log medical cost is 7.24.

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Table 1: Summary statistics - Dependent variables

	Obs[a]	Mean	Std.Dev.
Hospital care			
Any overnight stay in hospital	114,079	0.25	0.44
Number of nights in hospital	113,606	2.09	9.58
Doctor visits			
Any doctor visit	113,790	0.94	0.24
Number of doctor visits	110,276	9.69	17.68
Prescription drugs			
Used prescription drugs	114,279	0.81	0.39
Outpatient care			
Any outpatient surgery	114,066	0.21	0.41
Dental care			
Any dentist visits	114,085	0.67	0.47
Special services			
Special services used	113,850	0.09	0.29
Health expenditure			
Log(Out-of-pocket medical cost)	104,270	7.24	1.39

[a] Sample sizes are different due to missing values in outcome variables.

Source: HRS 1996 - 2014.

Table 2: **Summary statistics - Key explanatory variables**

	Obs[a]	Mean	Std.Dev.
Wealth			
Log(Total wealth)	103,089	12.49	1.27
Log(Housing wealth)	113,881	11.54	1.01
Demographics			
Age	114,419	69.46	9.33
Male	114,419	0.45	0.50
Black/African American	114,419	0.10	0.31
Other race	114,419	0.04	0.19
Married	114,419	0.70	0.46
Years of schooling (top coded 17)	114,295	12.62	3.14
Currently employed	114,419	0.24	0.43
Household characteristics			
Number of people in household	114,419	2.12	1.00
Log(household income)	113,864	10.61	0.98
Health and Disability			
At least 2 or more ADL/iADL limitations	114,321	0.09	0.29
BMI	113,025	27.19	5.26
Mental health (CESD score)	106,171	1.25	1.78
Have any health insurance	113,457	0.96	0.19
Regional characteristics			
Regional unemployment rate	114,213	5.84	1.67

[a] Sample sizes are different due to missing values in variables.

Source: HRS 1996 - 2014.

2.2. Key explanatory variables

A typical individual in our sample was a white married 70-year-old woman who had a high school education (Table 2). On average, at least two individuals were living in the same household. Only 24 percent of the respondents worked while 96 percent of them had health insurance (either public or private). This pattern is not surprising given the sample's age and gender composition. Very few respondents had two or more Activities of Daily Living (ADL)/Instrumental Activities of Daily Living (iADL) limitations (9%). The average BMI for respondents in the sample is 27.19. CESD score is a clinically validated mental health scale with a higher score implying worse mental health (Radloff, 1977).

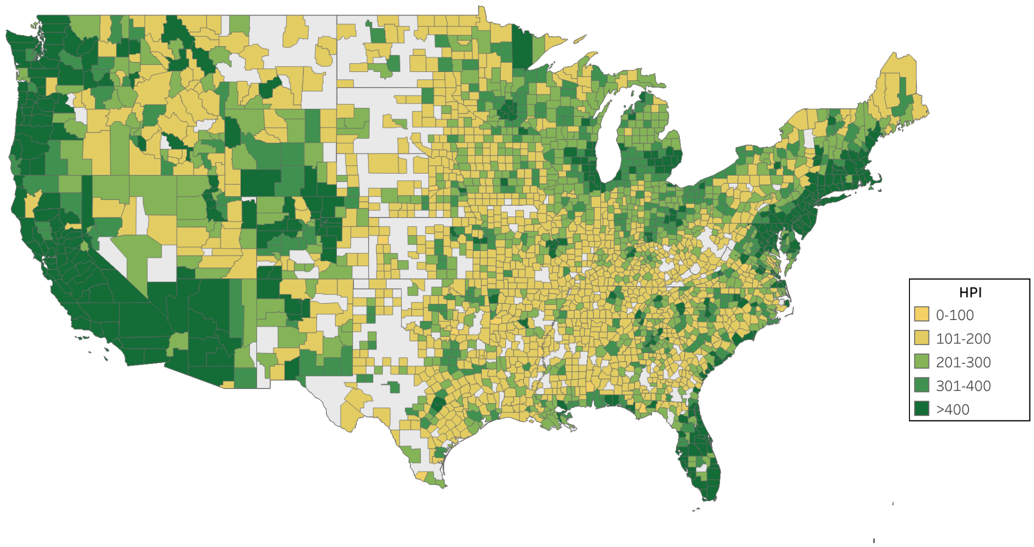
3. Identification strategies

3.1. External Instrumental Variables

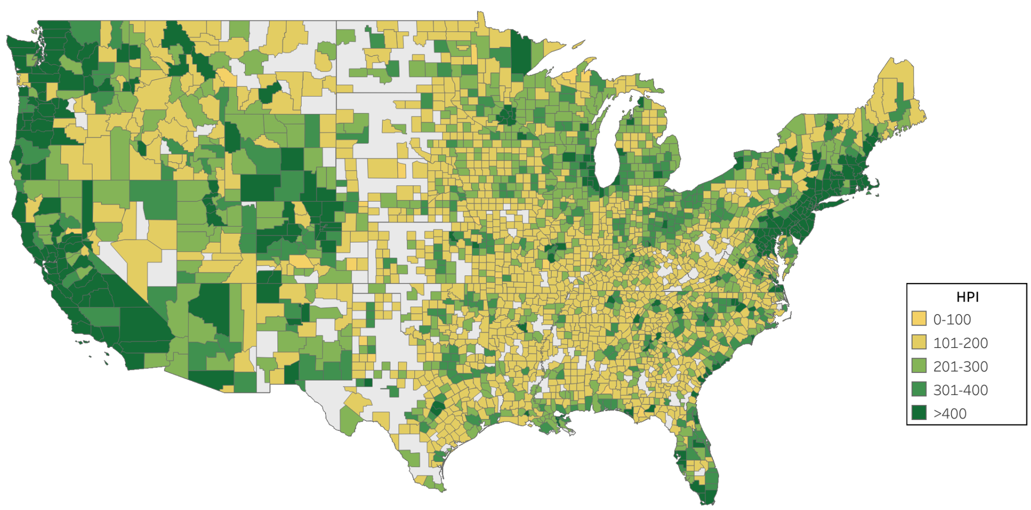
Before the COVID-19, the Great Recession in 2007-2009 is considered the worst economic downturn in the US since the Great Depression. During the two years at the heightened of the recession, an average American household lost approximately $50,000 in wealth due to changes in the housing market and stock market (Pfeffer et al., 2013). Such a large wealth shock may affect homeowners' healthcare utilization both directly and indirectly. Previous studies have found that a negative wealth shock can worsen health (Fichera and Gathergood, 2016) which may result in a higher demand for healthcare. On the other hand, homeowners, especially ones with mortgages had to change their consumption behaviour to make up for the loss in wealth resulting in lower healthcare spending.

Despite the common trend in housing prices during 2007-2009, the effect from the Great Recession varied across the regional market. After the Great Recession in 2007 - 2009, there were substantial variations in the housing prices across the United States (Figure 1). We exploit this exogenous regional variation in housing prices between 1996 and 2014 and use as instruments for investigating the effect of wealth on healthcare utilization. Our strategy follows an approach similar to that proposed by (Costa-Font et al., 2019). They show that there is a strong correlation between the change in housing prices and homeowners' assets between 1996 and 2010. On the other hand, their study finds no evidence that housing prices affect the wealth and healthcare utilization of renters. Our paper differs from Costa-Font et al. (2019)'s study in two main ways. Firstly, we focus more on primary care and hospitalization as the study outcomes. Secondly, our instrument does not utilize only the regional variation in housing price but also the individual variation in the Loan-to-Value ratio which enables larger between variation in the instrumental variable, improving the identification results.

Previous studies also show that the effect of housing prices on home equity relies on homeowners' leverage. The greater the leverage, that is the mortgage debt, the larger the effect of depreciation on housing prices (Garriga et al., 2017). To capture this heterogeneous effect of housing prices across individuals, we interact the HPI with households' loan-to-value (LTV) ratios to generate out instrument allowing the instrument to vary at the individual-



(a) House Price Index before 2007



(b) House Price Index after 2009

Figure 1: Heterogeneity in housing prices before and after the Great Recession

year level. The LTV ratio is expressed as the ratio of the primary residence mortgage loan to the home value. The LTV ratio has been used to measure financial fragility for older adults (Lusardi et al., 2018) and is widely used in practice by lenders and financial institutions to assess lending risk before approving a mortgage. Amongst the homeowners, 69.5 percent of them own their house outright (i.e. LTV ratio = 0). Excluding these individuals, on average, the LTV ratio is 40.8 percent. Overall, our instrument captures not only the variation in regional housing prices but also the variation from individuals' timing on home buying/re-mortgaging.

One potential concern is that the housing price or LTV ratio may correlate with other macroeconomic conditions such as the unemployment rate. The unemployment rate might affect wealth and other factors that could influence demand for healthcare such as the capacity to pay for health services. To mitigate this problem, we include the regional unemployment rate which was collected from the Bureau of Labour Statistics from 1996 to 2014.

Given that variations in housing prices and LTV ratio are exogenous after controlling for individuals' demographics, birthplace, health and disability, regional unemployment rate, year and region fixed effect, we can estimate the effect of wealth on healthcare utilization using the following equations:

$$Y_{idt} = f(\gamma W_{idt} + \beta_1 X_{idt} + \phi_d + \psi_t + \epsilon_{1idt}) \tag{1}$$

$$W_{idt} = \delta Z_{idt} + \beta_2 X_{idt} + \phi_d + \psi_t + \epsilon_{2idt} \tag{2}$$

where Y_{idt} is healthcare utilization of individual i living in region d at time t; W_{idt} is individual i's wealth and housing wealth at time t; X_{idt} are individuals' age, gender, race, level of education, health status, ADL/iADL, employment and income status, insurance coverage, and region d's unemployment rate; ϕ_d is region fixed effect; ψ_t is year fixed effect; $\epsilon_{1idt}, \epsilon_{2idt}$ are error terms. Function f is either the probit function (e.g. any doctor visits, etc.) or Poisson function (e.g. numbers of doctor visits, etc.)

Estimation of γ will be biased due to the non-zero correlation between ϵ_{1it} and ϵ_{2it}. We use the instrument Z_{idt} which is the interaction of housing prices in region d at time t and individual i's LTV ratio at time t for identification of γ. We pool the observations across waves and estimate the pooled IV model using maximum likelihood estimation (IV-Probit) and two-steps Generalized Method of Moment (GMM) estimation (IV-Poisson). We cluster the standard errors at the individual level to account for serial correlation within an individual across time.

3.2. Internal Instrumental Variables

In the case of endogeneity, it is well understood that the standard inferential methods are invalid and the IV method can be used to overcome this problem. The IV method requires the availability of instruments that are correlated with the endogenous variables but are not correlated with the error term. Once valid instruments are available, the regression parameters can be consistently estimated using GMM or maximum likelihood (Greene, 2003). However, the quality of IV estimators strongly depends on the instruments used. If the instruments are weak or invalid, or both, IV estimators may be inconsistent and might have larger mean squared error than estimators which assume exogeneity. Several methods have been proposed to deal with weak instruments (Bound et al., 1995; Stock et al., 2002; Hahn and Hausman, 2002). However, most are based on the assumption of the availability of exogenous instruments. In practice, it can be difficult to come up with valid "observed" instruments, thus this has motivated researchers to study new methods of identification, using higher moments such as variance or covariance.

The idea of using heteroskedasticity in estimation can be dated back to Wright (1928). Recent articles that use higher moments as a source of identification include articles by Dagenais and Dagenais (1997); Lewbel (1997); Cragg (1997); Erickson and Whited (2002). In this paper, we will follow the method proposed by Lewbel (2012) and apply it to the case of count data for the first time. The identification comes from regressors being uncorrelated with the product of heteroskedastic errors. A similar approach by Klein and Vella (2010) also imposed restrictions on the variance and covariance of errors. Moreover, it requires a specific form of heteroskedasticity that imposes strong restrictions on third and higher moments of errors to depend on regressors.

We let Y_{it} be the count variable measuring healthcare utilization (e.g. number of doctor visits), following Windmeijer and Santos Silva (1997), we assume that function f has an exponential form, so we can write Equation (1) and (2) as

$$Y_{idt} = exp(\gamma W_{it} + \beta_1 X_{idt} + \phi_d + \psi_t + \epsilon_{1it}) \quad (3)$$

$$W_{it} = \beta_2 X_{idt} + \phi_d + \psi_t + \epsilon_{2it} \quad (4)$$

This system of equations would be weakly identified as there are no instruments Z_{idt} (see equations). Lewbel (2012) shows that γ can be estimated consistently using instruments $(Z - \bar{Z}\hat{\epsilon_{2it}})$ under the assumptions that $cov(Z, \epsilon_{1it}\epsilon_{2it}) = 0$ and $cov(Z, \epsilon_{2it}^2) \neq 0$. The vector Z is a set of exogenous regressors, which could be some or entire vectors of X; and $\bar{Z}$ is the sample mean of Z. The residual $\hat{\epsilon}_{2it}$ is then estimated from the reduced form of Equation (4). The assumption that Z is uncorrelated with $\epsilon_{1it}\epsilon_{2it}$ means that the instruments $(Z - \bar{Z})\hat{\epsilon}_{2it}$ are valid, with the strength of the instruments being proportional to the degree of heteroskedasticity of ϵ_{2it} and Z. The former assumption can be satisfied if Z is strictly exogenous in both equations. The latter assumption can be easily tested using the Breusch and Pagan (1979) test for Equation (4). Estimation of endogenous regressors can be obtained using the two-stage least square estimator (TSLS) with the generated instruments.

Following the methods suggested by Lewbel (2012), we impose the restrictions sets: $cov(Z, \epsilon_{1it}\epsilon_{2it}) = 0$ and $cov(Z, \epsilon_{2it}^2) \neq 0$. Because our outcomes are count valued, we use the two-step Generalized Method of Moments (GMM) estimator for count data proposed by Windmeijer and Santos Silva (1997). Our method can be combined with external instruments to improve efficiency when the instruments are weak. The estimation of the Generated Instrumental Variable (GIV) model is carried out as follows[5]:

- *Step 1:* Estimate Equation (4) by OLS and predict residual $\hat{\epsilon}_{2it}$.
- *Step 2:* Generate the set of instruments by multiplying $(Z - \bar{Z})$ with predicted residual $\hat{\epsilon}_{2it}$ where Z includes some or all exogenous regressors X_{it}, and $\bar{Z}$ is the sample mean of Z.
- *Step 3:* Estimate IV-Poisson model using the set of generated instruments.

4. Results

4.1. First-stage estimation

Table 3 presents the first stage estimation of the external IV model. We examine the validity of the instrument in predicting total wealth and housing wealth. It is apparent from this table that the instrument "*HPI* x *LTV ratio*" is significantly correlated with both housing wealth and total wealth. One standard deviation increase in this instrument is associated with a decline of 0.2 percent in housing wealth and by 0.16 percent in total wealth.

In order to ensure that exclusion restrictions hold, we include a full set of controls including demographics, health and disability, household characteristics, regional unemployment rate, year FE, region FE, birthplace. After including control variables, the coefficients are larger in magnitude compared to models without control variables but they stillremain strongly significant.

[5]Estimation codes are user-written which will be provided upon request.

Table 3: Effect of house price on Housing wealth and Total wealth

	Without controls		With controls	
Variables	***Housing wealth***	***Total wealth***	***Housing wealth***	***Total wealth***
HPI x LTV ratio	-0.0022***	-0.0016***	-0.0036***	-0.0030***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Constant	11.6531***	12.5005***	7.9206***	5.3764***
	(0.0070)	(0.0093)	(0.2284)	(0.2733)
Observations	113,675	114,056	102,951	103,308
F-test[a]	1,728.47	534.49	6,739.24	3,073.38
R-squared	0.0479	0.0167	0.4026	0.4703

Note: Standard errors are clustered at the individual level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Controls include demographics, health and disability, household characteristics, regional unemployment rate, year FE, region FE, birthplace. [a] Null hypothesis of F-test is the coefficient on HPI x LTV ratio equals to 0.

All the F-test statistics are greater than 10 even when we control for demographics, birthplace, household characteristics, health and disability, regional unemployment rate, year and region fixed effects. This confirms that our instrument is, indeed, strongly correlated with the endogenous regressors: total wealth and housing wealth.

4.2. Effect of wealth on healthcare utilization

4.2.1. Hospitalization and doctor visits

Table 4 shows the estimation of the wealth effect on the probability of hospital admission and doctor visits using the Pooled Probit and IV-Probit models. We include a full set of control variables including demographics, birthplace, health and disability, household characteristics, region and year fixed effects and regional unemployment rate. The standard errors are clustered at the individual level.

What stands out from this table is the significant effect of wealth on the probability of hospital admission and visits to doctors across different models. In the pooled model, when we ignore endogeneity, wealth is negatively correlated with the probability of hospital admission while it is positively associated with the probability of doctor visits. Once we account for endogeneity, the wealth effects become smaller which suggests that the pooled Probit models may be biased upward. Indeed, wealth may be positively correlated with some confounding factors such as preferences, dietary and lifestyles that may determine healthcare utilization. We find that a 10 percent increase in wealth (total wealth and housing wealth) can reduce the probability of hospital admission by 0.61 to 0.74 percentage points, and can reduce the probability of doctors visits by 0.79 to 0.9 percentage points, holding other factors constant.

We next estimate the effect of wealth on the intensity of hospital admission and doctor visits (intensive margin). Table 5 presents the estimation of

Table 4: Effect of wealth on hospitalization and doctor visits

Model	Pooled Probit	Pooled Probit	IV Probit	IV Probit
	Any overnight stays in hospital			
Log(Total wealth)	-0.011***		-0.074***	
	(0.002)		(0.018)	
Log(Housing wealth)		-0.006***		-0.061***
		(0.002)		(0.015)
Log likelihood	-54,619.54	-54,408.76	-190,815.84	-174,445.67
Observations	103,268	102,825	103,182	102,825
	Any doctor visits			
Log(Total wealth)	0.005***		-0.090***	
	(0.001)		(0.029)	
Log(Housing wealth)		0.004***		-0.079***
		(0.001)		(0.024)
Log likelihood	-21,083.30	-157,021.52	-20,986.01	-140,673.95
Observations	103,039	102,955	102,955	102,599

Note: IV models are estimated using only one external instrument. Sample size is different due to missing values across outcomes and covariates. Coefficients are reported as AME. Standard errors are clustered at the individual level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include demographics, health and disability, household characteristics, regional unemployment rate, year FE, region FE, birthplace.

the wealth effect on the number of nights in the hospital and the number of doctor visits using four different models: the Pooled Poisson, the IV-Poisson model with external instruments (EIV), the IV-Poisson model with generated instruments (GIV), and the IV-Poisson with both external and generated instruments. Generated instruments are created using the method described in Section 3.2. To ensure that the generated instruments are valid (i.e. the covariance between instruments and products of the error terms equal 0), we chose age, gender, race and years of schooling to generate the instruments as they are predetermined in Equations (3) and (4).

As the identification requires the presence of heteroskedasticity to ensure that the generated instruments are strong, we conduct the Breusch-Pagan test for heteroskedasticity in Equation (3). As the p-value is 0.000, we can reject the null hypothesis that conditional variance is constant. We also conduct the over-identification test for these generated instruments there is a suggestive evidence of the generated instruments' validity. The test for overidentifying restrictions in the model using both generated and external instruments also fails to reject the null hypothesis which is that generated and external instruments are simultaneously uncorrelated with the error terms.

Although the effect of wealth is comparable between the probability of hospital admission and doctor visits, we find mixed evidence regarding the wealth effect on the intensity of these two services. From the table, we can see that numbers of doctor visits decline significantly as wealth increases. A one percent change in wealth reduces numbers of doctor visits by 0.841 to

Table 5: **Effect of wealth on intensity of hospital care and doctor care**

Model	***Pooled Poisson***	***Pooled Poisson***	***EIV Poisson***	***EIV Poisson***	***GIV Poisson***	***GIV Poisson***	***Both IVs***	***Both IVs***
	Numbers of nights stayed in hospital							
Log(Total wealth)	-0.137***		-0.100		-0.382		-0.140	
	(0.028)		(0.089)		(0.281)		(0.097)	
Log(Housing wealth)		-0.084***		-0.058		-0.559		-0.132
		(0.031)		(0.075)		(0.353)		(0.081)
Overidentification test	NA	NA	NA	NA	0.231	0.847	0.159	0.554
Cragg-Donald F-stat	NA	NA	1E+04	2E+04	152.689	180.846	1,549.276	3,046.634
Kleibergen-Paap F-stat	NA	NA	3,071.067	6,749.198	16.334	17.07	477.86	973.619
Observations	102,909	102,467	102,823	102,467	102,909	102,467	102,823	102,467
	Numbers of doctor visits							
Log(Total wealth)	-0.036		-1.033***		-1.039*		-1.109***	
	(0.069)		(0.222)		(0.596)		(0.217)	
Log(Housing wealth)		-0.020		-0.841***		-1.253*		-0.889***
		(0.077)		(0.184)		(0.688)		(0.169)
Overidentification test	NA	NA	NA	NA	0.348	0.175	0.298	0.260
Cragg-Donald F-stat	NA	NA	9,994.345	2E+04	185.131	277.278	1,549.276	2,969.548
Kleibergen-Paap F-stat	NA	NA	3,011.073	6,659.532	19.926	36.113	477.86	964.844
Observations	100,089	99,671	100,012	99,671	100,089	99,671	100,012	99,671

Note: Coefficients are reported as AME. Sample size is different due to missing values across outcomes and covariates. Standard errors are clustered at the individual level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Controls include demographics, health and disability, household characteristics, regional unemployment rate, year FE, region FE, birthplace.

1.033 visits (ceteris paribus). Interestingly, we find no evidence of the wealth effect on the number of nights in the hospital. However, this is not surprising given the age distribution in our sample. The majority of individuals in our dataset are above 65 and are eligible for Medicare. Medicare recipients are eligible for full coverage only if they stay in the hospital for no more than a maximum of 60 days. Given that 99.9 percent of respondents stayed less than 120 nights in the last two years, we expect that they might be fully covered by Medicare and thus, wealth changes may not significantly affect the length of stay in hospital.

Comparing the GIV and EIV models, it is clear that these two models exhibit very similar patterns. Estimation using the GIV model also shows a negative correlation between wealth and the number of doctor visits while no significant effect is found on the number of nights in hospital. However, the GIV estimation results in much higher coefficients and standard errors compared with traditional IV estimation. After we combine the generated instruments with an external instrument, the GIV estimates become more comparable to the EIV estimation. This finding is consistent with the simulation result by Lewbel (2012). Overall, our method of identification is very satisfactory, given the assumptions on the presence of heteroskedasticity and on the covariance restriction are satisfied. In the case of no available external instruments, identification via heteroskedasticity could be a good starting point. It is also worth noting that this method can be used to improve the efficiency of estimation when instruments are weak.

4.2.2. Other medical care

We also examine the effect of wealth on other healthcare services including prescription drugs, outpatient care, dental care, special services and out-of-pocket expenditure in Table 6. Prescription drugs, outpatient care, dental care and special services are modeled using the Probit function. For total out-of-pocket health expenditure, we use pooled OLS as the base model and we use the IV-FE model to account for potential endogeneity.

These results are consistent with our expectations and with previous findings on the effect of wealth on health. Demand for health services, except dental care lowers as wealth increases. The positive effect of wealth on the demand for dental care services may occur because dental services are considered as luxury goods. Indeed, as public programs covering oral health are limited in scope or are non-existent for adults (US Department of Health and Human Services, 2016), individuals can be expected to pay full cost for dental services.

Even though wealthier individuals demand fewer healthcare services, they have more out-of-pocket health expenditures. This pattern is consistent with the previous finding by De Nardi et al. (2015) suggesting that the poor use more health services but most of the cost is covered by the Government. Another potential explanation for these findings is the quality of care. Homeowners may switch to cheaper or lower quality care services to recover the loss from the unanticipated wealth shock. Our findings are robust across gender, age groups and veteran status. Surprisingly, there is no evidence on the effect of wealth on healthcare utilization of uninsured individuals; and this suggests that wealth may influence healthcare utilization through insurance coverage. Wealth effects on individuals with private insurance are smaller than individuals with public insurance in services that are not largely covered in welfare programs such as prescription drugs, dental services and special services. We also find some evidence of wealth effect on health, mostly in mental health,

Table 6: Effect of wealth on other medical care

Model	Log(Total wealth)		Log(Housing wealth)	
	Base	***IV***	***Base***	***IV***
	Regular use of prescription drugs[a]			
Any prescribed drugs	-0.004*	-0.070***	-0.005**	-0.055***
	(0.002)	(0.025)	(0.002)	(0.021)
Log-likelihood	-45,319.36	-181,589.32	-45,042.76	-165,222.78
Observations	103,372	103,286	102,929	102,929
	Outpatient care[a]			
Any outpatient surgery	0.003**	-0.037**	0.003**	-0.029**
	(0.002)	(0.018)	(0.002)	(0.015)
Log-likelihood	-52,611.89	-188,775.26	-52,426.81	-172,364.65
Observations	103,252	103,166	102,809	102,809
	Dental care[a]			
Any dentist visits	0.070***	0.110***	0.061***	0.090***
	(0.002)	(0.023)	(0.002)	(0.018)
Log-likelihood	-53,817.83	-190,058.06	-54,078.02	-174,163.70
Observations	103,320	103,234	102,877	102,877
	Special services[a]			
Used special services	0.001	-0.077***	0.002	-0.068***
	(0.001)	(0.021)	(0.001)	(0.018)
Log-likelihood	-29,331.07	-165516.47	-29,206.66	-149,224.43
Observations	103,233	103,147	102,790	102,790
	Out-of-pocket health expenditure[b]			
Log(Medical cost)	0.095***	0.074**	0.075***	0.051**
	(0.006)	(0.020)	(0.007)	(0.020)
R-squared	0.0761	0.0757	0.0740	0.0760
Observations	94,894	90,165	94,521	89,870

Note: Coefficients are reported as AME. Sample size is different due to missing values across outcomes and covariates. Standard errors are clustered at individual level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Controls include demographics, health and disability, household characteristics, regional unemployment rate, year FE, region FE, birthplace.

[a] Base model: pooled Probit, IV model: IV-Probit.

[b] Base model: pooled OLS, IV model: IV-FE.

obesity and disability which could explain the rising demand in healthcare during the recession.

5. Discussion and Conclusion

In this paper, we exploit the quasi-experimental variation in the housing wealth caused by unanticipated changes in housing prices after the Great Recession. Using this identification strategy, we investigate the effect of wealth on healthcare utilization, specifically hospital care and doctor visits. We also examine the wealth effect on other common medical services such as dental care, outpatient care, prescription drugs and special services. The analysis employs the traditional Instrumental Variables strategy and a novel identification method using heteroskedasticity-generated instruments on count data. We find consistent evidence that a wealth shock does influence individuals' demand for healthcare services. Overall, demand for all healthcare services, except dental care decreases as wealth increases. The wealth effect is the largest for doctor visits and dental care.

We also examine the wealth effect on the intensity of hospital care and doctor visits. Our results show that a positive wealth shock reduces the number of doctor visits, but we find no evidence of the wealth effect on the number of nights in the hospital. These findings suggest that an economic downturn like that in the Great Recession, when housing asset values declined by 16 percent on average during 2007-2010, would increase the number of doctor visits by at least 8 visits. This is equivalent to almost twice the size of the effect of having at least two ADLs limitations. However, out-of-pocket expenditures increase as wealth increases.

In summary, we find strong evidence supporting the causal effect of wealth on healthcare utilization using both the traditional IV model and the Generated IV model. Estimation of the Generated IV model is somewhat similar to the traditional method but exhibits much larger estimates. This new method of identification can be used to estimate a count model with endogenous regressors, when there are no external instruments available or to improve the efficiency of estimation when instruments are weak. There is also suggestive evidence that wealth may influence healthcare utilization through insurance coverage and the effects are robust across different types of insurance. However, we observe a larger effect on individuals with public insurance compared to individuals with private insurance, especially for the services that are not covered by public insurance programs. In terms of policy implication, our study confirms the effect of wealth on utilization of healthcare services and provides critical information for the future planning of healthcare supply in response to future economic downturns, especially the upcoming recession induced by the COVID-19 pandemic.

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