Appendix H

Medical Out-of-Pocket Expenditures

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Following the National Academy of Sciences' (NAS) recommendation, the NYCgov measure of income is net of what families spend for their medical care. Medical out-of-pocket expenditures (MOOP) are the sum of co-payments, deductibles, and the cost of health services that are not covered by insurance, including health insurance premiums. Since the American Community Survey (ACS) does not report this information, it must be imputed from an outside data source. We use the Medical Expenditures Panel Survey (MEPS) to impute the two components of MOOP (i.e., private health insurance costs and spending on medical care services) into the ACS.

To distinguish the impacts of out-of-pocket expenses on premiums from other medical spending, premiums are separately imputed from medical spending. We use a predictive mean matching (PMM) method for both – a statistical matching technique that uses nearest neighbor algorithms – to identify and link similar units between the MEPS and ACS data. There are two distinct aspects of our application of PMM in MOOP imputations. First, distance in the PMM is constructed based on the conditional expected values estimated through a two-part model. The two-part models are chosen to account for the skewed distribution of medical costs with a large proportion of zero values. In addition, a few important determinants of premiums and medical spending were used as matching criteria. This is to further ensure that the important joint distributions are preserved for the subsequent data analysis.

This is the first edition of the report where we have implemented changes to the public premium imputation. In previous editions we simulated the public insurance program rules for MEPS respondents, then brought those values to the matched ACS respondents. We have now directly implemented this simulation in the ACS data file rather than in the MEPS data file. Note that the methodological change has been applied to the years 2013 through 2018 in this edition of the report, resulting in a break in the historic trend data of MOOP estimates for years prior to 2013. Future editions will more fully incorporate the change and provide seamless historic trends for the years 2008 through 2018.

In the sections below we provide more details on the MEPS: the source data from which we draw imputed values, the direct simulation of public insurance program rules for ACS respondents, our predictive mean matching methodology, and a brief evaluation of its performance.

Source Data: MEPS

MEPS data provide national estimates of health care utilization, expenditures, payment sources, and health insurance coverage for the U.S. civilian non-institutionalized population. The survey uses an overlapping panel design and introduces a new panel each year. For each panel, the data are collected through a series of five rounds of interviews covering a two-year span. The data from the overlapping panels are then used to produce annual estimates. Although it supports annual estimates, the information on premiums is limited to private health insurance coverage and collected only once per panel, at the beginning of the first round of each year's survey.

As source data for our MOOP imputation, the MEPS holds several key advantages over other surveys. First, it captures the changing dynamics of health insurance coverage status during the reference year (e.g., month-to-month change in coverage status and type, and durations without coverage) and the relationship between insurance and health care expenditures. Second, it measures MOOP with greater accuracy. Specifically, the MEPS collects health care expenses for all survey participants for each medical event (hospital stays, office visits, prescription drugs, and other health care services and supplies) experienced in a given year, the participants' health conditions, and the amount from each payment source (private, Medicare, Medicaid, and self or family). The MEPS then uses medical provider data to verify and replace, if needed, information about spending for health care events reported by a household.

Our sample of donor cases is constructed by linking the records of two interrelated 2017 MEPS data files: the Full Year (FY) and the Person Round Plan Public Use (PRPL) files. The former contains all the information pertaining to medical expenses. The latter provides monthly premiums paid out of pocket by the policyholder for each private plan held at the beginning of each data collection year. It also includes information on whether the reported plan was active for at least a day per month throughout 2017, enabling calculation of total premium payment for the duration of enrollment. Linking the PRPL file to the FY file requires careful consideration of the complex structure of the MEPS data. If an individual began their private insurance coverage in the middle of the year, the PRPL file does not capture the premium value. To bypass this limitation, we summarize each person's and family's coverage status and type, based on the coverage reported at the beginning of the year. The box below further describes health insurance typology.

HEALTH INSURANCE TYPOLOGY

We summarize health insurance coverage for nonelderly adults using five types of coverage, and create the following categorical summary variables of insurance coverage by type and composition:

1. Employer-Sponsored Insurance (ESI) Only: Individuals and family members covered by an insurance policy sponsored by a current or former employer; this includes Veterans Affairs (VA)-related insurance plans as well as insurance plans offered by the U.S. Department of Defense
2. Non-ESI Private Only: Individuals and family members covered by a private non-group plan, including plans purchased through a state exchange
3. Public and Private Insurance: Individuals and family members covered by both public and private insurance
4. Public Only: Individuals and family members covered by public only, i.e., Medicaid, Medicare, or State Children's Health Insurance Program (SCHIP)
5. Uninsured: Individuals and family members uninsured for the entire calendar year

The five categorical summary variables of insurance coverage for elderly adults include:

1. Medicare Only: Person is covered by Medicare only.
2. Medicare and Private Insurance: Person is covered by both Medicare and private coverage (private insurance includes health insurance offered through a current or former employer including health insurance coverage provided by the U.S. Department of Defense for military personnel and their dependents (TRICARE) and the Civilian Health and Medical Program of the Department of Veterans Affairs (CHAMPVA), as well as private health insurance plans offered by licensed brokers or agent).
3. Medicaid and Medicare: Person is covered by both Medicaid and Medicare.
4. Private or Medicaid: Person without Medicare reports having private or public coverage other than Medicare.
5. Uninsured: Person is uninsured for the entire calendar year.

We limit the use of premium records in the MEPS PRPL files to those insurance plans providing comprehensive health care coverage including both physician and hospital coverage. The exclusion of premiums paid for stand-alone dental, vision, or prescription coverage is necessary because they are not captured in the ACS. Total private premiums paid by the family are aggregated at the level of the health insurance unit (HIU) created in the ACS file – the subfamily unit in which all family members would be eligible for coverage under one family plan (see box on HIUs on the following page). This is necessary because unlike the MEPS, the ACS does not collect information on policyholder status. Thus, aggregation to a proper unit is required.

Finally, because MEPS data lag the ACS by one year, in order to bring them to 2018 values, all measures of MOOP are adjusted for inflation using the medical care component of the Consumer Price Index for All Urban Consumers (CPI-U).[1]

1 For further information about the MEPS, see the Agency for Healthcare Research and Quality website at: http://meps.ahrq.gov/mepsweb.

CONSTRUCTION OF HEALTH INSURANCE UNITS (HIUs)

Following the Medical Expenditures Panel Survey (MEPS) definition of HIU, we use the following rules to identify who should be in the same HIU for American Community Survey (ACS) families:

1. An adult, his or her spouse, and their unmarried biological, adopted, or stepchildren under age 19 must be in the same HIU.
2. Full-time college students ages 19 to 23 should also be placed in their parent's HIU; the result is a change in how we create NYCgov poverty units. Health insurance units take priority over tax unit assignment of young adults.
3. Married minors compose their own HIUs.
4. Unmarried children without parents present in the household are put in a nearest blood relatives' health insurance unit, including grandparents or great-grandparents.
5. Foster children form a separate health insurance unit from their foster parents.

Simulation of Premiums for Public Coverage

The MEPS does not collect information on premiums paid for public insurance coverage plans, including Medicaid, Medicare, and the State Children's Health Insurance Program (SCHIP). As a remedy, we simulate program rules in order to logically impute missing premiums for ACS respondents who are covered by public health insurance. The Family Health Plus Program, New York State's Medicaid program, does not require enrollees to contribute toward the premium. Thus, we assign zero premium costs to those who reported Medicaid coverage.

To assign Child Health Plus premiums, we first identify all children under the age of 19 who reported public insurance coverage. We aggregate incomes for everyone in the same health insurance unit and compare that against the Federal Poverty Line (FPL) to determine whether and what amount of premium a family with qualifying children is required to pay. Families with incomes less than 1.6 times the FPL are assigned zero premium. There is also a family cap for all categories of participants. For example, families with incomes between 160 percent and 222 percent of the FPL pay a premium of $9 per child, per month. The required monthly premium is capped at the payment for three children ($27 per family, per month).[2]

2 We use the health insurance unit as opposed to the family unit when capping the premium.

We assume that all ACS respondents who reported Medicare coverage have Medicare Part B. All Medicare recipients with incomes above 135 percent of the FPL are required to pay a monthly premium for Medicare Part B. If the Medicare participant is not married, we use only personal income when calculating their FPL percentage. For married participants we aggregate the income of both partners. For an elderly couple or single person whose income is above 135 percent of the FPL, we assign $130 per month and estimate total Part B premiums paid for the calendar year (see the box on Medicare, below).

MEDICARE

Medicare is a federally financed health insurance plan for elderly persons receiving Social Security disability payments and most persons with end-stage renal disease. Medicare has been in place since 1966 and comprises Part A and Part B. **Medicare Part A**, which provides hospital insurance, is automatically given to those eligible for Social Security. **Medicare Part B** provides medical insurance that pays for medical expenses and can be purchased for a monthly premium.

There are two options through which a Medicare beneficiary can get Medicare benefits:

- **Traditional Medicare:** Original Medicare is the coverage (Part A and Part B) managed by the federal government. Medicare directly pays a portion of the costs of any medical service it covers to any provider that accepts Medicare patients. Patients pay a percentage of the cost or, in some cases, a fixed amount for each covered service they receive.
- **Medicare Advantage (MA):** MA is a type of Medicare policy that allows private health insurance companies to provide Medicare Part A and Part B benefits. MA plans, often referred to as Medicare Part C, cover all Medicare services (both Part A and Part B) and may include more services or benefits for additional premiums. Each MA plan delivers Medicare benefits in a different way from the traditional Medicare. In other words, they can charge different out-of-pocket costs and also have different rules for how patients obtain services, including a requirement of a referral for a visit to a specialist and constraints on the use of out-of-network providers.

Medicare Prescription Drug Coverage (PDP): Medicare offers beneficiaries prescription drug coverage (known as Part D) but does not administer the PDP benefits. Instead, the delivery of this optional drug coverage is completely privatized. Medicare contracts with private companies that are authorized to sell Medicare PDP. There are two main sources of Part D coverage:

- **Stand-alone PDP plans:** These are offered by private companies approved to sell prescription drug coverage only.
- **MA-PDP:** MA often rolls prescription drug coverage into their services and offers hospital, medical, and prescription drug coverage under a single policy.

The ACS does not collect information on whether an individual with Medicare has Part C and/or Part D coverage and how much the premiums cost. To remedy this lack of information, we randomly assign Medicare Part C and Part D coverage status to identified Medicare beneficiaries in the ACS, matching the share of Medicare beneficiaries enrolled in Part C and Part D at the county level using the Centers for Medicare and Medicaid Services' (CMS) Part C and Part D Market penetration data. In 2018, the share of Medicare beneficiaries in Medicare Advantage plans varies across boroughs, from 37 percent in Manhattan to 57 percent in the Bronx.[3] Likewise, Medicare Part D penetration varies significantly across the five boroughs. For example, 40 percent of Medicare beneficiaries in Manhattan were enrolled in Medicare Part D drug plans whereas only 27 percent of beneficiaries living in the Bronx were enrolled.

In addition, Part C and Part D premiums are also derived from the CMS data.[4] In calculating a population-weighted average premium for Part C, we limit the CMS enrollee and premium data to Medicare Advantage Plans that offer prescription benefits.[5] Not all Part C enrollees, however, are required to pay additional premiums. According to our analysis of the CMS data, about 46 percent of MA-PDP (Medicare Advantage Prescription Drug Plan) enrollees in the city paid some amount of supplemental premiums.[6] Our analysis also reveals that on average, New York City's elderly with MA-PDP pay substantially lower premiums than the national average. The weighted average monthly premiums for MA-PDP are estimated to be $45.40 for New York City enrollees and about $67.37 for the nation. For these reasons, we randomly assign the average monthly premium of $45.40 found for NYC enrollees in the CMS data until the control target – 46 percent of Medicare Beneficiaries in ACS who are assigned Medicare Part C coverage – is met.

For Medicare beneficiaries who are randomly selected to have Part D coverage without Part C, we estimate the geometric mean of premiums for stand-alone prescription drug plans offered to New York City seniors using the CMS data.[7] In 2018, the average premium of stand-alone prescription drug plans offered to NYC seniors was $43.64 per month. We assign this average premium to those who were assigned Part D coverage in the ACS.

3 July 2018 monthly MA penetration data are available at: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MCRAdvPartDEnrolData/MA-State-County-Penetration-Items/MA-State-County-Penetration-2018-07

4 https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MCRAdvPartDEnrolData/index

5 A large majority of Medicare Advantage plan enrollees actually have drug coverage. See Hill, Zuvekas, and Zodet, "Validity of Reported Medicare Part D Enrollment in the Medical Expenditure Panel Survey." 2015. *Medical Care Research and Review*, 69(6): 737–750.

6 We combine the 2018 MA landscape source file and the monthly MA enrollment data by contract, plan, state, and county for March 2018, limiting the data to MA plans with drug benefits offered in New York City. From the city-relevant contract and enrollment data, we then estimate the proportion of the city's MA enrollees with "zero-premium plans." We exclude programs of all-inclusive care for the elderly (PACE), Special PACE, Special Needs Plans, Part B Only Plans, and Employer-sponsored MA plans. Using non-zero premium plans and their enrollment data, we then estimate population weighted average premiums of MA plans offered to NYC Medicare beneficiaries.

7 The PDP landscape source file contains premium data for state, contract, and plan, whereas the PDP enrollment data are provided for state, county, and contract numbers. Since these two data sets are provided at a different level, population weighted average premiums cannot be estimated. For this reason, we use the geometric mean that accounts for the volatile growth in premiums in the PDP market, as well as variation across insurance plans.

Predictive Mean Nearest Neighbor Matching Method with Added Constraints

To impute out-of-pocket premiums and medical spending into ACS families, we employ a PMM method that identifies respondents with similar characteristics between the ACS and MEPS. It involves a regression of MOOP values on a vector of predictors in the sample of MEPS families that will donate their MOOP values. Predicted values are then computed for both MEPS donors and ACS recipient families. Finally, the donor with the closest predicted value to a particular ACS recipient is chosen and that donor's observed value is transferred to the recipient. This method imputes the non-observed variables in the recipient file with borrowed values from the donor file. It does an acceptable job, in general, of reproducing the distribution of imputed values found in the donor file. Yet application of PMM is still challenging in the context of MOOP. This is because MOOP data typically feature a skewed positive distribution with a large mass of costs at zero.

To address the issue, we separately fit a two-part model for premium and medical spending. Two-part models are well known to provide flexibility in modeling mixed discrete-positive distributions by utilizing two separate equations to model the binomial and continuous components.[8] The first stage is to estimate the probability that a household incurred non-zero costs. Since this is a binomial component, we use a probit model. The second stage involves estimating dollar amounts of medical spending for households with positive probabilities of incurring non-zero medical costs using a generalized additive model (GAM) approach.

We model costs for private premiums at the health insurance unit level as a function of demographic and socioeconomic characteristics of health insurance unit and coverage type,[9] including age, marital status, sex, race/ethnicity, occupation, poverty status, education, size of health insurance unit, and presence of people with functional difficulty in the family. Our binary prediction model for positive premium costs rendered satisfactory classification accuracy.[10] The overall accuracy of our classification model is 82.62 percent, with 96.60 percent and 83.19 percent, respectively, for recall and precision performance measures.

We built a model for out-of-pocket expenses on medical care services as a function of the sum of premiums paid by all members of a health insurance unit: demographic and socioeconomic characteristics of an individual including age, occupation, race/ethnicity, nativity, marital status, and education; whether a person has any functional difficulties; and types of health insurance coverage. A more accurate prediction model would include variables containing detailed clinical conditions and events, as well as attributes of health insurance coverage – but that information is not available in the ACS. Omitting these important predictors resulted in a classification

8 Naihua Duan, et al. "A Comparison of Alternative Models for the Demand for Medical Care." 1983. *Journal of Business & Economic Statistics*, 1(2): 115–126. Available at: http://www.jstor.org/stable/1391852

9 The reference person of a health insurance unit is usually a policyholder or person designated as the head of household or family if no adult policyholder is present in the unit. When there are multiple policyholders in the unit, we rank them in order of full-time job, total personal income, nearest blood relationship to the householder, and age. We flag the one with the highest rank as a designated reference person of the HIU.

10 The binomial regression output can be provided by the authors upon request.

that is 76.70 percent accurate, with 86.30 percent of the true positive spending correctly classified and 79.57 percent of classified positive costs actually being positive (data not shown).

We fit the continuous component using nonparametric techniques via a GAM model. This allows different functional forms for each independent variable. Binary variables used in the regression are included as dummy variables, while continuous variables are nonparametrically fit using smoothing spline functions.[11] The regression output is summarized in Table H.1.[12]

ACS and MEPS cases are matched based on their predicted values of premiums and medical spending, conditional on both being positive. When cases are matched, the actual premium and medical spending values from the MEPS case are donated. A major drawback of the PMM method is that a donor can easily donate multiple times, which may lead to inefficiency.[13] A remedy to this issue would be to permit a single donation per donor. However, there are slightly less than half as many donor cases in the MEPS as cases in the ACS. For this reason, we use penalty weights to ensure that a single MEPS case cannot donate more than ten times.

As mentioned above, to draw imputed values from a more comparable donor in the MEPS, we implement a PMM with the added constraints of both host and donor cases being in the same imputation cells. For premium imputation, for example, we constructed allocation cells based on health insurance coverage type, presence of child in health insurance unit, and income quartiles. For medical spending, it is extremely important to preserve the relationship between health status, attributes of health insurance coverage, ages, and income. We thus use coverage type by age; any difficulty in hearing, vision, cognitive, ambulatory, or self-care; and two income subgroups – below or above 200 percent of the FPL. These matching criteria are used to better preserve the joint distribution of MOOP and important demographic characteristics, which is essential to classification accuracy of the poor. Otherwise, subsequent data analyses could suffer from match biases.[14] For example, NYCgov poverty data is often used at relatively aggregate levels classified by broad categories, i.e., poverty by age group or marginal impact of MOOP on the elderly. Thus, it is important to include such attributes as matching criteria.

Figure H.1 illustrates how closely our method replicates the distribution of MOOP in the ACS. Panel A in Figure 1 plots a distribution of imputed private premiums in the ACS overlaid with that of the MEPS data. Panel B shows the distributions of medical spending per person between the ACS and MEPS. Panel C compares the distribution of families' aggregate MOOP values across the two databases. In each panel, the dashed lines represent the median values in each data set. As is evident in Panel A, the imputed ACS data replicate the distribution of private premiums reported in the

11 Smoothing splines are a particular type of nonparametric smoothing technique. For an overview of smoothing spline functions and GAM, see: Luke John Keele, *Semiparametric Regression for the Social Sciences*. 2008. West Sussex, England: John Wiley and Sons, Ltd.

12 Nonparametric variables do not have reported coefficients, but rather have smoothed bivariate plots. These plots are available from the authors upon request.

13 Morris et al. "Tuning Multiple Imputation by Predictive Mean Matching and Local Residual Draws." 2014. *BMC Medical Research Methodology*, 14:75.

14 Bollinger and Hirsch. "Match Bias from Earnings Imputation in the Current Population Survey: The Case of Imperfect Matching." 2006. *Journal of Labor Economics*, 24:3.

MEPS, perfectly matching the median values. Panel B also shows a near perfect replication of highly skewed medical spending distribution with a long tail. Panel C compares the distribution of aggregate MOOP values across the two data sets by poverty unit.[15]

Table H.2 reports mean and percentile values of premiums, medical spending, and total MOOP reported and/or aggregated at three different levels. Note that unlike Figure H.1, Table H.2 reports aggregate premiums, including simulated costs of public health coverage premiums. One noticeable difference that emerged in this table is New York City's smaller share of zero expenditures compared to the nation. Specifically, the percent of HIUs estimated to have zero premium expenditures differs by 6 percentage points between the ACS and the MEPS (36.8 percent in the ACS compared to 42.8 percent in the MEPS). The percent of estimated zeros for per-person medical expenditures differs by 4.2 percentage points. This is not a surprising result given that New York City's uninsured rate has been significantly lower than national rates.[16] It should be noted, however, that the observed discrepancy disappears when the costs of premiums as well as medical spending are aggregated to the Poverty Unit level, when costs of all family members are taken in to account. The proportions of households with zero MOOP expenditures are 8.0 percent and 8.3 percent in the MEPS and the ACS, respectively.

Note that MEPS data provide national estimates of health care spending not specific to New York City families. It is not clear at this time whether imputations derived from the nationally representative data overestimate MOOP for New York City families (perhaps due to New York City's relatively generous Medicaid and Child Health Plus programs), or whether imputations underestimate medical costs (perhaps because well-insured low-income families use more medical care and, therefore, incur more related out-of-pocket medical costs). We are exploring other sources that may provide insights into differences between spending patterns of families in New York City and the nation as a whole, with an eye to improving our imputation in future reports.

Table H.3 reports the impact of MOOP on the poverty rate for the years 2013 to 2018. MOOP has a substantial impact on the poverty rate, increasing poverty in the city by between 2.8 and 3.2 percentage points in this time period. The impact of MOOP dropped dramatically starting in 2008 (not shown). This is likely the result of the better statistical match relative to the prior time period, with more fine-grained matching criteria and better distance functions.

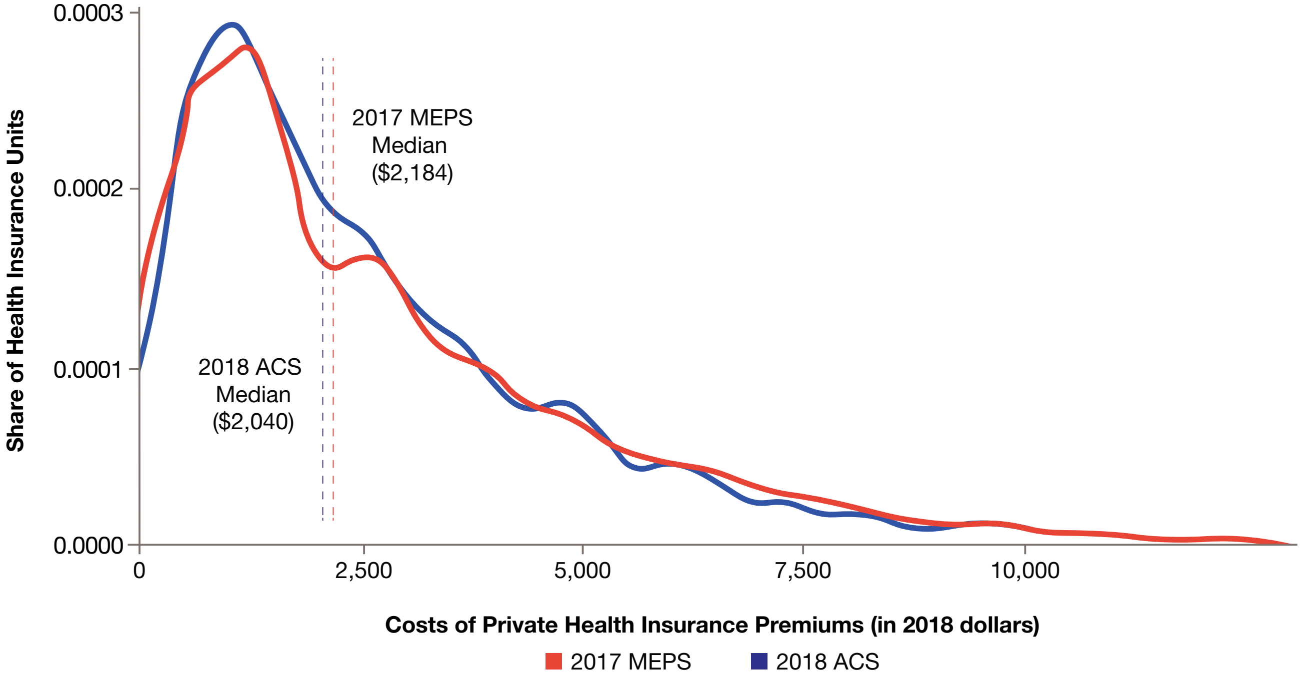
Table H.3 also reports the impact of MOOP on poverty among the elderly, the group most affected by medical spending. The MOOP adjustment raises elderly poverty by a much larger amount, ranging from 3.5 percentage points to 4.5 percentage points. The impact of MOOP on the elderly led to a considerable change in the way we understand their poverty. For every year shown, the elderly have had a higher overall poverty rate than the city as a whole.

15 Poverty units represent the extended family unit in the ACS household. See Appendix A for details.

16 In 2018, the share of New Yorkers lacking health insurance was 7.2 percent whereas the national uninsured rate was 8.7 percent, a gap of 1.5 percentage points.

Figure H.1
Distribution of Medical Out-of-Pocket Expenditure (MOOP) in MEPS and ACS

Panel A. Distribution of Out-of-Pocket Payments for Private Health Insurance Premiums



Source: America Community Survey Public Use Micro Sample as augmented by NYC Opportunity and 2017 Medical Expenditure Panel Survey(MEPS) inflated to 2017 prices using the CPI medical Index.
Note: Cases with zero expeneses are excluded.

Panel B. Distribution of Out-of-Pocket Payments for Medical Expenses

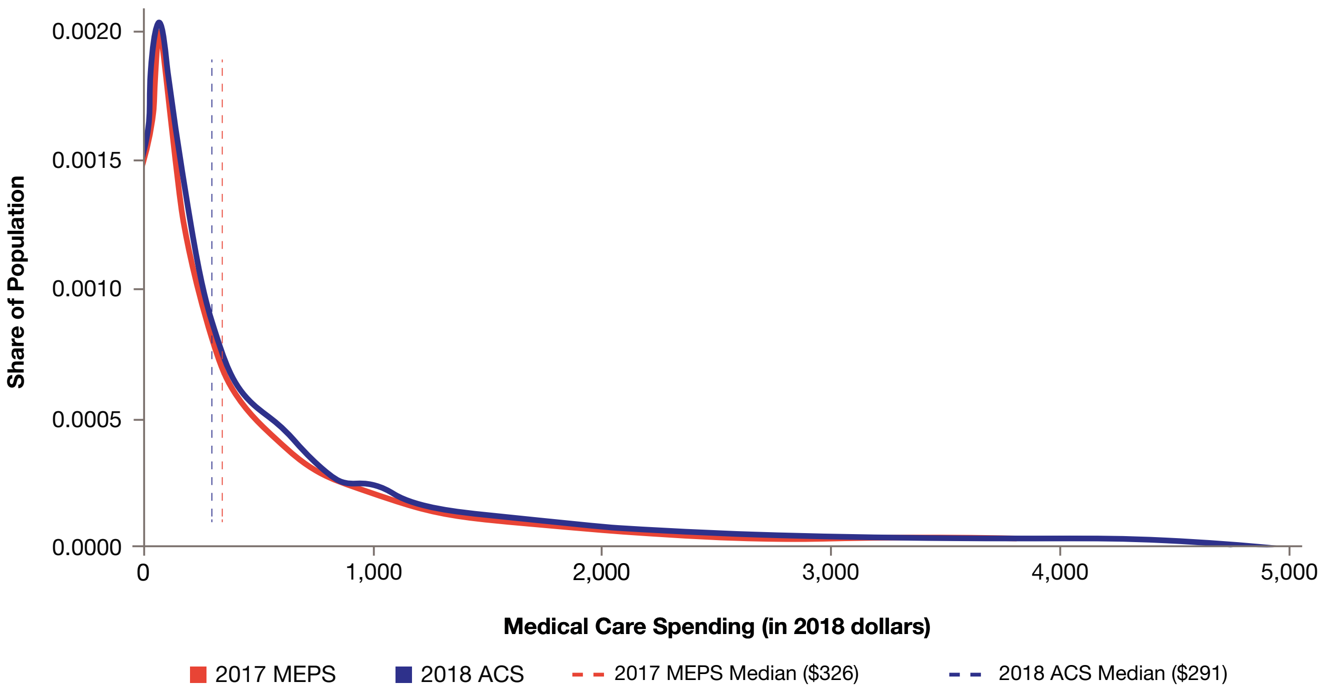


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Figure H.1 *(continued)*

Distribution of Medical Out-of-Pocket Expenditure (MOOP) in MEPS and ACS

Panel C. Total MOOP

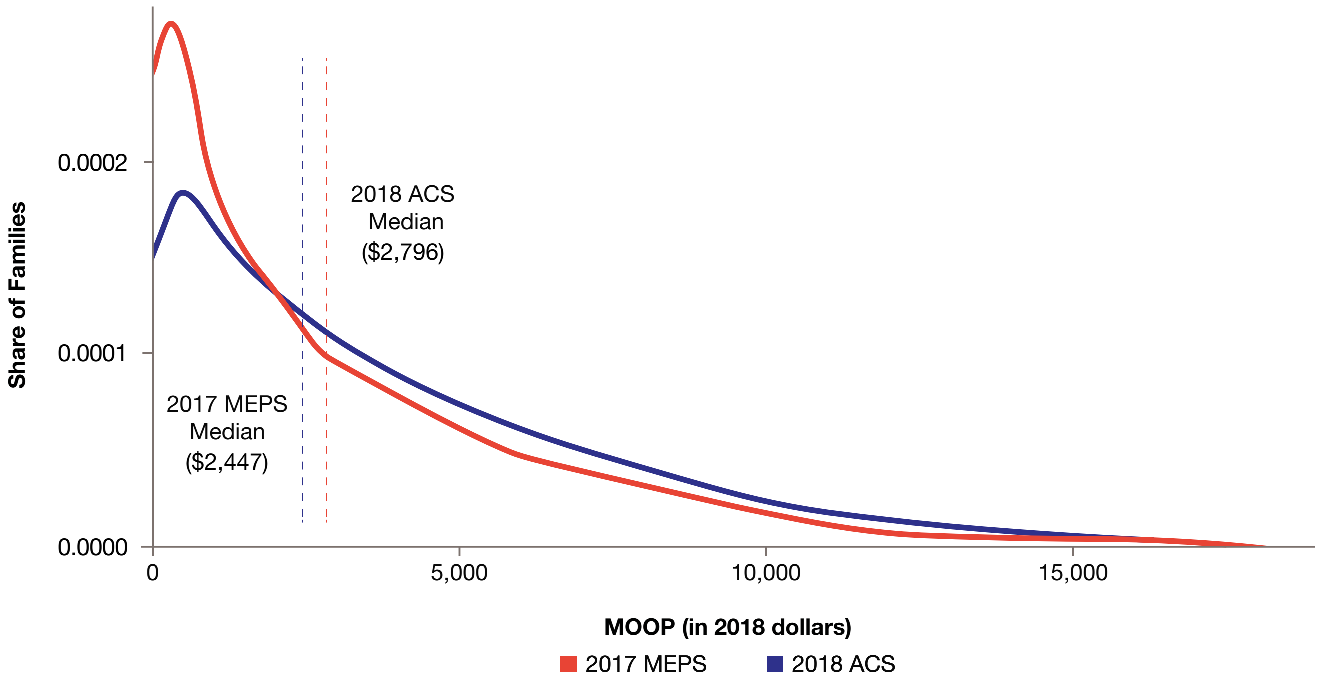

Table H.1
Regression Model to Predict Medical Out-of-Pocket Spending, 2018

	Private Premium		Medical Spending	
	Coefficient	t-Statistic	Coefficient	t-Statistic
(Intercept)	2694.106	9.923	1262.698	12.163
Type and Composition of Health Insurance Coverage*				
Nonelderly ESI only	(Reference Group)		-264.883	-4.258
Nonelderly – Non-ESI Private Only	963.776	6.728	-32.39	-0.507
Nonelderly – Private and Public	-910.68	-5.683	-254.233	-2.302
Nonelderly – Public Only	—	—	-361.606	-6.104
Nonelderly – Uninsured	—	—	(Reference Group)	
Elderly – Medicare Only	—	—	-623.809	-5.414
Elderly – Medicare and Private	-1206.288	-6.669	-446.515	-3.828
Elderly – Medicare and Medicaid	—	—	-1298.935	-8.724
Elderly – Private or Medicaid	-848.159	-1.92	-944.435	-3.767
Uninsured	—	—	(Reference Group)	
Size of Health Insurance Unit (Reference Group: 1 person health insurance unit)				
2	757.011	5.563	-154.029	-3.09
3	1743.963	10.528	-219.964	-3.801
4	2002.312	10.891	-344.39	-5.557
5	2526.503	9.557	-370.67	-4.789
6	2394.364	5.91	-344.848	-3.295
7	827.548	0.968	-63.515	-0.29
8	1688.279	0.971	-296.088	-0.989
Race/Ethnicity (Reference Group: White)				
Non-Hispanic Black	-183.632	-1.521	-297.008	-7.032
Hispanic	-269.426	-2.139	-179.271	-4.397
Non-Hispanic Asian	-618.413	-3.406	-329.831	-5.259
Non-Hispanic Other Race	103.216	0.433	-131.186	-1.821

Continued on the following page

Table H.1 *(continued)*

Regression Model to Predict Medical Out-of-Pocket Spending, 2018

Occupation (Reference Group: Individuals with production and transportation occupations)				
Management, Business and Financial Operations, or Professional Occupations	-7.502	-0.046	-7.12	-0.147
Farming, Fishing and Forestry, or Construction and Extraction Occupations	-320.166	-1.807	-41.007	-0.705
Military	426.805	0.326	—	—
Service Occupations	-584.981	-3.049	-81.744	-1.496
Sales Related or Office Support Occupations	-66.485	-0.389	-41.149	-0.782
Education (Reference Group: Less than high school)				
High School or Some College	64.762	0.693	29.35	0.793
Bachelor's Degree or Higher	48.657	0.479	264.589	6.309
Married	847.438	6.455	-10.731	-0.226
Female	-110.904	-1.43	111.623	4.315
Nativity (Reference Group: Foreign born living in the U.S. less than 15 years)				
U.S. Born	-357.674	-1.681	-35.223	-0.501
Foreign Born living in the U.S. 15 years or more	-157.692	-0.713	-118.575	-1.551
Other Characteristics				
Work Full-Time	234.977	2.021	-141.416	-3.55
Middle Age	—	—	-115.158	-1.56
Family Income below 200% of the Federal Poverty Line (Poor, Near Poor)	-231.277	-1.317	4.148	0.078
Child	-1004.589	-0.389	294.949	3.185
Functional Difficulty	33.947	0.329	426.793	11.529
Non-Parametric Variables	**EDF**	**F-Statistic**	**EDF**	**F-Statistic**
Total Income Aggregated at the Health Insurance Unit	7.044	8.186	5.028	7.25
Age	2.668	31.575	3.863	23.434
Premium Contributions	—	—	7.959	3.235

*Individuals who reported no private health insurance (i.e., the uninsured or individuals with public coverage only) are not included in the sample for premium prediction. However, they are in the sample for medical spending prediction and serve as the reference group.
Source: 2017 Medical Expenditure Panel Survey, inflated to 2018 prices using the CPI Medical Index.
Note: Premiums was aggregated to the HIU level and medical spending generated at the person level.

Table H.2
Comparison of MOOP Distributions, MEPS, and ACS, 2018

	Premiums Per Health Insurance Unit	Medical Spending Per Person	Premiums	Medical Spending	Total MOOP
			Per Poverty Unit		
Panel A. 2017 MEPS (in 2018 dollars)					
Mean	$1,798	$649	$2,138	$1,379	$3,517
Aggregate (in millions)	N.A.	N.A.	N.A.	N.A.	N.A.
Percentile					
1	$0	$0	$0	$0	$0
5	$0	$0	$0	$0	$0
10	$0	$0	$0	$0	$15
25	$0	$0	$0	$95	$395
50	$556	$136	$1,056	$529	$2,090
75	$2,668	$614	$3,128	$1,587	$5,087
90	$5,303	$1,688	$5,947	$3,600	$8,661
95	$7,309	$2,880	$7,783	$5,505	$11,537
99	$12,848	$7,243	$13,585	$11,415	$19,594
N	16,499	30,140	13,339	13,339	13,339
Percent with Zero Cost	42.8	27.7	—	—	8%
Panel B. 2018 ACS					
Mean	$1,767	$610	$2,424	$1,382	$3,806
Aggregate (in millions)	$8,780	$5,010	$8,680	$4,950	$13,600
Percentile					
1	$0	$0	$0	$0	$0
5	$0	$0	$0	$0	$0
10	$0	$0	$0	$4	$15
25	$0	$5	$0	$122	$594
50	$672	$148	$1,300	$590	$2,398
75	$2,500	$600	$3,599	$1,652	$5,468
90	$4,800	$1,579	$6,149	$3,628	$9,199
95	$6,600	$2,705	$8,391	$5,637	$12,291
99	$12,732	$6,450	$15,028	$10,650	$20,583
N	40,983	68,273	29,726	29,726	29,726
Percent with Zero Cost	36.8	23.5	—	—	8.3

Sources: American Community Survey Public Use Micro Sample as augmented by NYC Opportunity, and 2017 Medical Expenditure Panel Survey (MEPS) inflated to 2018 prices using the CPI Medical Index.
Note: N.A. – Not applicable due to the fact that the MEPS provides data at the U.S. level as opposed to the New York City level.

Table H.3
Impact of Out-of-Pocket Premium Payment and Medical Spending on Poverty Rates, 2013–2018

(Numbers are Percent of the Population)

	2013	2014	2015	2016	2017	2018*
Panel A. All Persons						
Total NYC Opportunity Income	20.5	20.2	19.6	19.0	19.3	19.1
Net of Total MOOP	17.3	17.2	16.7	16.2	16.1	16.1
Net of Medical Spending	19.1	18.9	18.4	17.8	17.7	17.6
Net of Premium Contributions	18.4	18.2	17.8	17.3	17.3	17.2
Marginal Effects of MOOP	3.2	3.0	2.9	2.8	3.1	3.0
Marginal Effect of Medical Spending	1.4	1.3	1.3	1.3	1.5	1.4
Marginal Effect of Premium Contributions	2.1	2.0	1.8	1.8	1.9	1.9
Panel B. Elderly						
Total NYC Opportunity Income	21.6	20.6	20.4	20.9	20.7	21.8
Net of Total MOOP	17.4	16.1	16.9	17.1	16.5	17.6
Net of Medical Spending	19.9	18.4	18.8	19.1	18.5	19.8
Net of Premium Contributions	19.0	18.0	18.4	18.4	18.4	19.3
Marginal Effects of MOOP	4.2	4.5	3.5	3.9	4.2	4.2
Marginal Effect of Medical Spending	1.7	2.2	1.5	1.8	2.2	2.0
Marginal Effect of Premium Contributions	2.6	2.6	2.0	2.5	2.2	2.4

Source: American Community Survey (ACS) Public Use Micro Sample as augmented by NYC Opportunity and 2017 Medical Expenditure Survey (MEPS) inflated to 2018 prices using the CPI Medical Index.
*Medical out-of-pocket spending in 2018 is based on 2017 data. 2018 MEPS data was not available at the time this report was written. We will revisit and update MOOP estimates for 2018 when data is available. Thus, we advise caution in using the estimates for 2018.