New York City Government Poverty Measure 2005–2015

An Annual Report from the Office of the Mayor

Appendix H: Medical Out-of-Pocket Expenditures

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NYC Opportunity

Appendix H

Medical Out-of-Pocket Expenditures

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-pays, 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., premiums and spending on medical care services) into the ACS.

This is the first year that we disaggregate the impacts of out-of-pocket expenses on premiums from medical spending. To do so, we impute premiums separately from medical spending.[1] Each component is imputed using predictive mean nearest neighbor algorithms. We also used this change in methodology as an opportunity to introduce improvement to our MOOP imputation. First, we used a two-part model to better deal with the skewed distribution of medical costs with a large proportion of zero values. This improved our assignment of zero costs – a large number of cases in the data. Next, a few important determinants of premiums and medical spending were used as match criteria to preserve joint distributions.

In the sections below, we provide more details on the MEPS, the source data from which we draw imputed values; our predictive mean matching methodology; and a brief evaluation of its performance.

Source of Data for Imputed Values: MEPS

MEPS data provide national estimates of health care utilization and spending, private and public health insurance coverage, and the availability, cost, and scope of private health insurance benefits for the U.S. population. MEPS file releases slightly lag the ACS, so for the 2015 NYCgov poverty measure we use the 2014 MEPS data adjusted by the medical care component of the Consumer Price Index for All Urban Consumers (CPI-U).[2]

1 There is a break in the series of our poverty data. This is because new methodology of MOOP imputation is applied to the year 2008 and onward. For prior years (2005–2007), we retain our old methodology as described in the MOOP appendix in prior issues of this report.

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

MEPS data have several advantages over other survey data. First, they capture coverage dynamics (e.g., multiple spells and plans, shifts from one plan to another) and the relationship between insurance and health care expenditure. Second, they measure MOOP with greater accuracy. Specifically, the MEPS collects health care expenses for all people for each medical event (hospital stays, office visits, prescription drugs, and other health care services and supplies) experienced in a given year, their health conditions, and the amount of 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 the household.

The MEPS contains two files that we use for our MOOP imputation. The Full Year (FY) file contains all the information pertaining to medical expenses except for health insurance premiums. Premiums for people that are privately insured are contained in the Person Round Plan Public Use (PRPL) file. For those on private insurance, we join the corresponding record from the FY file with the premium record from the PRPL file. For those on public insurance (i.e., Medicaid, Medicare Part B, or the State Children's Health Insurance Program [SCHIP]), we simulate program rules in order to logically impute missing premiums. For enrollees of Medicare Part C and Part D, missing premiums are derived from the Center for Medicare & Medicaid Services (CMS).[3]

Private insurance premiums are derived from the MEPS PRPL file, which contains records for people with private insurance. The MEPS PRPL file provides snapshot data on monthly out-of-pocket premiums paid for private coverage including hospital/physician, Medigap, dental, vision, and prescription medication coverage. In the 2014 MEPS PRPL file, for example, premium data are collected from all policyholders with private insurance coverage for Panel 19 as of Round 1 and Panel 18 as of Round 3. Yet the MEPS asks respondents to provide detailed information on the coverage that is effective throughout the calendar year. This evidently creates discrepancies in premium data. If an individual began their private insurance coverage in the middle of the year, a premium value would not be recorded in the PRPL file.

Unlike the MEPS, as our primary dataset the ACS collects information on health insurance plans that provide comprehensive health coverage. In addition, respondents are directed to report each of the types of comprehensive coverage they hold at the time they are surveyed.

In order to create a consistent and comparable insurance typology across the ACS and MEPS datasets that can be used for imputation, we refer only to the coverage reported at the beginning of the year for MEPS respondents. We also limit the premium records in MEPS PRPL files to those insurance plans providing

3 https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MCRAdvPartDEnrolData/index.html; https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovGenIn/index.html?redirect=/prescriptiondrugcovgenIn/

comprehensive health care, such as physician and hospital coverage. This excludes stand-alone insurance plans that provide dental, vision, or prescription coverage only. We summarize health insurance coverage for a nonelderly adult using five types of coverage, and create the following categorical summary variable of insurance coverage by their type and composition:

1. Employer Sponsored Insurance (ESI) only: Person is covered by an insurance policy sponsored by a current or former employer; this includes CHAMP and VA insurance
2. Non-ESI Private Only: Person is covered by a private non-group plan, including plans purchased through a state exchange
3. Public and Private Insurance: Person is covered by both public and private insurance
4. Public Only: Person is covered by public only (i.e., Medicaid, Medicare, or SCHIP)
5. Uninsured: Person is 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 coverage includes CHAMP, VA, and insurance sponsored by a current or former employer)
3. Medicare and Medicaid: Person is covered by both Medicaid and Medicare
4. Private or Medicaid: Person without Medicare who reports having private or public coverage other than Medicare
5. Uninsured: Person is uninsured for the entire calendar year

We use program rules to assign appropriate premiums for those on public insurance such as Medicaid, traditional Medicare Part B, and SCHIP. We assume all people identified in the MEPS as Medicare recipients have Medicare Part B. All Medicare recipients with incomes above 135 percent of the Federal Poverty Line (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.

All Medicare beneficiaries have the option of getting their Medicare coverage through Medicare Part C (known as the Medicare Advantage [MA] program) instead of through traditional Medicare coverage directly administered by the federal government. MA is a type of Medicare policy that allows private health insurance companies to provide Medicare Part A and Part B benefits. MA plans may include more services or benefits for additional premiums. According to our exploratory analysis of CMS data, in 2014 about 85 percent of the City's seniors with MA plans chose a plan that charges no premium beyond the standard Part B premiums collected by Medicare.

People also have the option to enroll in Medicare Part D, prescription drug coverage, which also requires a supplemental monthly premium. Many Medicare Advantage plans roll prescription drug coverage into their services. In addition, it is reported that a large majority of MA plan enrollees indeed have Part D coverage and MEPS respondents with MA plans often misreport their Part D coverage.[4] For those who reported Part C coverage in MEPS, we assign the average premiums of MA plans with prescription drug plans (MA-PDP).

We estimate population weighted average premiums paid by New York City seniors for MA plans using data from the CMS.[5] For those with Medicare Part C, we randomly assign a monthly premium of $46.97 until the proportion of enrollees paying the premiums is met; for example, in 2014, 15 percent of MA-PDP enrollees in the city paid some amount of supplemental premiums. We also estimate the geometric average of premiums for stand-alone prescription drug plans offered to NYC seniors using the PDP landscape data files. In 2014, the average premiums of stand-alone prescription drug plans offered to NYC seniors was $48.33 per month. We assign this average premium to those who reported Part D coverage in MEPS without Part C coverage.

To assign Child Health Plus premiums, we look at all children identified as public insurance recipients. We aggregate incomes for everyone in the same health insurance unit and compare that against the FPL. Families are required to pay a monthly per-child premium based on their income's percentage of the FPL. For all categories of participants there is also a family cap. For example, families with incomes between 160 percent and 222 percent of the FPL are required to pay a premium of $9 per child, per month. The premium is capped at the payment for three children ($27 per family, per month).[6]

New York State's Family Health Plus program, a Medicaid program, does not have a premium but does require co-payments based on different types of procedures. These co-payments are captured in the MEPS Full Year file.[7]

Once monthly premiums data are completed for health insurance coverage that is in effect at any time during Round 3/1, we calculate the number of months covered by each reported health insurance coverage. For each reported comprehensive insurance plan, we then annualize the monthly premiums by

4 Hill, Zuvekas and Zodet (2015). Validity of Reported Medicare Part D Enrollment in the Medical Expenditure Panel Survey. *Medical Care Research and Review.* 69(6): 737-750.

5 We combine the 2014 MA landscape source file and the monthly MA enrollment data by contract, plan, state, and county for March 2014, limiting the data to MA plans with drug benefits offered in NYC. 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.

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

7 The TOTSLF variable identifies total out-of-pocket expenditures by patient or patient's family (other than premiums).

multiplying them by the number of months. We then aggregate all premiums to the health insurance eligibility unit (HIEU) – the subfamily unit in which all family members would be eligible for coverage under one family plan. This is a necessity because unlike MEPS, ACS does not collect information on policyholder status and thus aggregation to a proper unit is required. Following the MEPS definition of HIEU, we use the following rules to identify who should be in the same health insurance unit (HIU) for the ACS families:

1. An adult, his or her spouse, and their unmarried biological, adopted, or step children under age 19 are inseparable; full time college students ages 19-23 should also be placed in their parent's HIU, regardless of whether they reside in the same dwelling unit with their parents[8]
2. Married minors compose their own HIUs
3. Unmarried children without parents present in the household are put in a nearest blood relatives' health insurance unit, including grandparents or great-grandparents
4. Foster children form a separate health insurance unit than their foster parents

Predictive-Mean Nearest Neighbor Matching Method Combined with Added Constraints

To impute out-of-pocket premiums and medical spending into ACS families, we employ a predictive-mean matching method (PMM) that matches the missing value to the observed value with the closest predicted mean. PMM typically combines a linear regression model and the nearest neighbor imputation approach to construct metrics for identifying and linking records from different sources that correspond to similar units. It uses a linear regression to estimate predictive means for both donors (complete units) and hosts (incomplete units). Then, a distance function based on the predictive means is used to select donors. Since this method imputes the non-observed variables in the recipient file with borrowed values from the donor file, it does a good job, in general, at reproducing the distribution of imputed values that are more like 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 at zero costs. Up until this year, we used a generalized additive model (GAM) to establish distance functions while finding the optimum transformation of MOOP, but it lacked stability in adequate classification of zero MOOP values.

To address this issue, we separately fit a two-part model for premium and medical spending. Two-part models, which are well known to provide flexibility in modeling mixed discrete-positive distributions,[9] utilize two separate equations

8 The result is a change in how we create NYCgov poverty units. Health insurance units take priority over tax unit assignment of young adults. See Appendix A for further discussion of this change.

9 Duan, Naihua, et al. "A Comparison of Alternative Models for the Demand for Medical Care." *Journal of Business & Economic Statistics*, Vol. 1, No. 2, 1983, pp. 115–126. Available at: www.jstor.org/stable/1391852.

to model the binomial and continuous components. The first stage is to estimate the probability that the household incurred non-zero medical 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 GAM approach.

We model the premium portion of MOOP at the health insurance unit level as a function of demographic and socioeconomic characteristics of health insurance unit and coverage type,[10] 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 incontestably accurate classification.[11] The overall rate of correct classification is estimated to be 82.1 percent, with 83 percent and 80.9 percent of true positive and negative groups classified correctly.

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 socio-economic characteristics of an individual including age, occupation, race/ethnicity, nativity, marital status, and education; whether a person has any functional difficulties; childbearing status; 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 that is 75.7 percent accurate with 84 percent of the true positive spending group correctly classified and 61.9 percent of the true zero medical spending group correctly classified.

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 ones are fit nonparametrically using smoothing spline functions.[12] The use of a natural log transformation is a common practice in the field of health economics for smoothing out skewed distributions and fitting the data better. However, this is done at the expense of prediction accuracy. Our exploratory analysis suggests that, by not using log transformations, the mean absolute prediction errors improve by about $1,100 from $2,625.80 to $1,551.70. The regression output is summarized in Table H.1.[13]

10 The reference person of a health insurance unit is usually a policyholder or designated person such 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 HIEUs.

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

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

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

Table H.1 (Part 1)

Regression Model of Medical Out-of-Pocket Spending, 2015

Dummy Variables	Premium**		Medical Spending**	
	Coefficient	t-Statistic	Coefficient	t-Statistic
(Intercept)	2105.60	8.52	819.15	8.22
Type and Composition of Health Insurance Coverage*				
Nonelderly-ESI only	(Reference Group)		-234.78	-5.56
Nonelderly-NonESI Private only	1295.64	10.14	-78.17	-1.46
Nonelderly-Private and Public	-694.60	-5.16	-133.78	-1.40
Nonelderly-Public Coverage only	-2742.11	-13.24	-325.10	-6.81
Elderly-Medicare only	-2323.05	-12.96	-378.77	-2.95
Elderly-Medicare and Private	-505.15	-3.13	-196.76	-1.52
Elderly-Medicare and Medicaid	-3008.77	-5.40	-1023.09	-6.70
Elderly-Private or Medicaid	-606.29	-1.49	-618.65	-2.68
Size of Health Insurance Unit (reference group: 1 person health insurance unit)				
2	757.97	6.80	-113.95	-2.61
3	1701.75	11.96	-261.33	-5.16
4	2020.82	12.66	-289.65	-5.29
5	1797.96	8.62	-189.66	-2.95
6	1507.88	4.50	-321.70	-3.52
7	1902.71	3.15	-585.57	-3.73
8	1181.55	1.07	-323.43	-1.45
9	4538.85	1.23	-	-
11	61.91	0.01	-	-
Race/Ethnicity (reference group: White)				
Non-Hispanic Black	-135.14	-1.33	-289.79	-7.95
Hispanic	-181.05	-1.61	-162.88	-4.43
Non-Hispanic Asian	-228.80	-1.50	-238.87	-4.32
Non-Hispanic Other Race	80.94	0.42	-132.21	-2.16
Occupation (reference group: Individuals with production and transportation occupations)[1]				
Management, Business, and Financial Operations, or Professional Occupations	-140.99	-1.17	-91.74	-2.19
Farming, Fishing, and Forestry, or Construction and Extraction Occupations	-364.21	-2.73	-79.53	-1.63
Military	-195.45	-0.18	-	-
Service Occupations	-356.91	-2.45	-134.48	-2.90
Sales Related or Office Support Occupations	-413.81	-3.21	-157.61	-3.59

(Table continues on next page.)

Table H.1 (Part 2 – continued from previous page)

Regression Model of Medical Out-of-Pocket Spending, 2015

Dummy Variables	Premium**		Medical Spending**	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Education (reference group: Less than high school)				
High School or Some College	4.31	0.03	202.27	4.90
Bachelor's Degree or Higher	33.63	0.24	361.00	7.49
Married	652.89	6.01	39.81	0.96
Female	-69.11	-1.07	64.20	2.84
Nativity (reference group: Foreign born living in the U.S. less than 15 years)				
U.S. Born	299.70	1.65	49.13	0.81
Foreign Born Living in the U.S. 15 Years or More	141.82	0.75	53.18	0.81
Other Characteristics				
Work Full-Time	139.13	1.51	-60.46	-1.78
Pregnant	-	-	193.72	2.69
Middle Age	-	-	-156.38	-1.70
Family Income below 200% of the Federal Poverty Line	-373.80	-2.90	16.78	0.35
Child	1174.06	1.45	489.95	4.89
Functional Difficulty	15.03	0.20	510.93	16.39
	EDF	**F-Statistic**	**EDF**	**F-Statistic**
Total Income Aggregated at the Health Insurance Unit	8.29	9.11	8.14	9.79
Age	4.45	26.67	8.41	15.37
Premium Contributions	-	-	8.46	6.63

Source: 2014 Medical Expenditure Panel Survey inflated to 2015 prices using the CPI Medical Index.
* Uninsured individuals 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.
** Premium was generated at the HIU level and medical spending was generated at the person level.
1 Reference group also includes nonworking individuals and children.

ACS and MEPS cases are matched based on their predicted values of premiums and medical spending, conditional on it 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.[14] 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 a single MEPS case cannot donate more than ten times.

As mentioned above, we implement PMM with the added constraints of both host and donor cases being in the same imputation cells to draw imputed values from a

14 Morris et al. Tuning multiple imputation by predictive mean matching and local residual draws. *BMC Medical Research Methodology*. 2014. 14:75.

more comparable donor in MEPS. 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.[15] For example, NYCgov poverty data is often used at relatively aggregate levels classified by broad categories (e.g., poverty by age group or marginal impact of MOOP on elderly). Thus, it is important to include such attributes as matching criteria.

Table H.2 shows the distribution of MOOP values in the MEPS, and the PMM values in the ACS for 2015. The matched MOOP values for medical spending and premiums in the ACS are very similar to those in the MEPS. The percent of HIUs estimated to have zero premium expenditures differs by just 1.3 percentage points between the ACS and the MEPS. The percent of estimated zeros for per-person medical expenditures differs by 2.4 percentage points. This similarity holds when aggregated to the Poverty Unit level, with proportions of households with zero MOOP expenditures at 9.1 and 8.4 percent in the ACS and MEPS respectively (a difference of just 0.7 percentage points). Our new matching methodology – the two-part model – did a particularly good job at replicating the proportion of zero expenditure. It also uses a two-round matching process: ACS cases that are predicted to have positive spending but do not get matched in the first round of MEPS donation undergo a second round of matching to assign them a MOOP expenditure value. The result, which we see in Table H.2, is a closely approximated MOOP distribution between the MEPS and the ACS.

A better measure of the match quality is seen in the conditional distributions. By looking at the matched values conditional on matching criteria, we can see whether the medical spending patterns are reproduced in the ACS. Panel A in Table H.3 reports the mean and median medical spending in the MEPS and ACS, per person, by type of insurance coverage and age. The mean and median values are relatively close to the MEPS data for nonelderly adults. However, notable differences are found for seniors with Medicare coverage and private or Medicaid.

Panel B displays the mean and median premium estimates in the MEPS and the ACS by insurance and elderly status for all families. Like the medical spending values in Panel A, the mean and median premium estimates are very similar for all families across the ACS and the MEPS. The only notable exception is families with elderly present but only covered by private or Medicaid.

15 Bollinger and Hirsch. Match Bias from Earnings Imputation in the Current Population Survey: The Case of Imperfect Matching. *Journal of Labor Economics*. 2006. Vol. 24, No. 3.

Table H.2

Comparison of MOOP Distributions, MEPS and ACS, 2015

	Premiums Per Health Insurance Unit	Medical Spending Per Person	Premiums	Medical Spending	Total MOOP
Panel A. 2014 MEPS (in 2015 dollars)					
Mean	$1,597	$589	$1,866	$1,027	$2,893
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	$9
25	$0	$0	$0	$81	$276
50	$431	$130	$821	$411	$1,684
75	$2,402	$592	$2,683	$1,177	$4,239
90	$4,742	$1,539	$5,182	$2,596	$7,344
95	$6,412	$2,602	$6,958	$4,026	$9,366
99	$11,331	$6,125	$12,263	$8,755	$16,352
N	17,353	32,456	14,086	14,086	14,086
Percent of Zero	45.5%	27.3%			8.4%
Panel B. 2015 ACS					
Mean	$1,412	$485	$1,980	$1,114	$3,094
Aggregate (in millions)	$7,190	$4,060	$7,020	$3,950	$1,100
Percentile					
1	$0	$0	$0	$0	$0
5	$0	$0	$0	$0	$0
10	$0	$0	$0	$3	$4
25	$0	$1	$0	$87	$254
50	$369	$107	$1,077	$441	$1,869
75	$2,053	$480	$2,989	$1,354	$4,606
90	$4,187	$1,242	$5,312	$2,959	$7,733
95	$5,871	$2,159	$7,147	$4,274	$10,108
99	$10,247	$4,896	$12,008	$8,996	$17,205
N	41,215	69,103	29,565	29,565	29,565
Percent of Zero	46.8%	24.9%			9.1%

Sources: American Community Survey Public Use Micro Sample as augmented by NYC Opportunity and 2014 Medical Expenditure Panel Survey (MEPS) inflated to 2015 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.

Note that MEPS data provide national estimates of health care spending not specific to New York City families. New York City has a much more diversified population in terms of race and ethnicity. Our exploratory analysis (not reported here) also revealed that the city's families have higher income than MEPS 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'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

Table H.3

Comparison of MEPS and ACS MOOP Values by Age and Insurance Status, 2015

Panel A: Out-of-Pocket Medical Spending Per Person										
	Nonelderly Individual					Elderly Individual				
	ESI Only	Non-ESI Private Only	Private and Public	Public Only	Uninsured	Medicare Only	Medicare and Private	Medicare and Medicaid	Uninsured	Private or Medicaid
MEPS										
Mean	$593	$651	$672	$191	$378	$1,171	$1,513	$314	$348	$969
Median	$195	$173	$106	$0	$12	$571	$817	$109	$94	$705
ACS										
Mean	$639	$586	$395	$105	$287	$871	$1,130	$229	$352	$813
Median	$246	$216	$50	$0	$0	$363	$605	$80	$164	$486
Panel B: Out-of-Pocket Premiums Per Health Insurance Unit										
	With No Elderly Present in Unit					With Elderly Present in Unit				
	ESI Only	Non-ESI Private Only	Private and Public	Public Only	Uninsured	Medicare Only	Medicare and Private	Medicare and Medicaid	Uninsured	Private or Medicaid
MEPS										
Mean	$2,511	$2,052	$2,122	$48	$0	$787	$3,224	$57	$0	$2,635
Median	$1,724	$198	$1,221	$0	$0	$646	$2,683	$0	$0	$2,057
ACS										
Mean	$2,255	$1,632	$2,071	$5	$0	$732	$3,299	$3	$0	$2,464
Median	$1,564	$411	$1,232	$0	$0	$588	$2,660	$0	$0	$1,642

Sources: American Community Survey Public Use Micro Sample as augmented by NYC Opportunity and 2014 Medical Expenditure panel Survey (MEPS) inflated to 2015 prices using the CPI Medical Index.
Note: Premium was generated at HIU level and medical spending was generated at the person level.

in New York City and the nation as a whole with an eye to improving our imputation in future reports.

Table H.4 reports the impact of MOOP on the poverty rate for the years 2005 to 2015. MOOP has a substantial impact on the poverty rate, increasing poverty throughout the city by between 2.6 and 3.6 percentage points in this time period. The impact of MOOP on the poverty rate is larger in 2005–2007 than in 2008–2012. This is likely the result of the better statistical match in the latter time period, with more fine-grained matching criteria and a better metrics of distance function.

Table H.4 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 3.8 percentage points to 7.5 percentage points. The impact of MOOP on the elderly led to a considerable change in the way we understand their poverty. The elderly have had a higher overall poverty rate than the city as a whole for every year from 2005 through 2015, with the exception of 2011 (where the elderly poverty rate was 20.3 percent compared to the citywide rate of 20.7 percent).

Table H.4

Impact of Out-of-Pocket Premium Payment and Medical Spending on Poverty Rates, 2005–2015

(Numbers are Percent of the Population)

	2005*	2006*	2007*	2008	2009	2010	2011	2012	2013	2014	2015**
A. All Persons											
Total NYC Opportunity Income	20.3	20.0	19.8	19.0	19.4	20.6	20.8	20.7	20.7	20.6	19.9
Net of Total MOOP	16.9	16.4	16.1	15.9	16.1	17.8	18.1	18.1	18.0	18.0	17.1
Net of Medical Spending	N/A	N/A	N/A	17.3	17.8	19.3	19.4	19.4	19.3	19.3	18.7
Net of Premium Contributions	N/A	N/A	N/A	17.4	17.4	19.0	19.4	19.3	19.3	19.0	18.0
Marginal Effects of MOOP	3.5	3.6	3.6	3.1	3.3	2.8	2.6	2.6	2.7	2.6	2.8
Marginal Effect of Medical Spending	N/A	N/A	N/A	1.7	1.6	1.3	1.3	1.3	1.4	1.2	1.2
Marginal Effect of Premium Contributions	N/A	N/A	N/A	1.7	1.9	1.6	1.4	1.4	1.4	1.6	1.9
B. Elderly											
Total NYC Opportunity Income	24.7	23.5	22.9	22.9	23.1	21.4	21.9	20.3	21.5	20.8	21.6
Net of Total MOOP	17.2	16.7	16.5	17.0	17.3	16.2	17.2	16.4	16.9	16.5	17.1
Net of Medical Spending	N/A	N/A	N/A	19.5	20.3	19.0	19.4	18.5	19.3	18.6	19.5
Net of Premium Contributions	N/A	N/A	N/A	20.0	19.4	18.9	19.3	18.2	18.8	18.4	18.8
Marginal Effects of MOOP	7.5	6.8	6.4	5.9	5.8	5.2	4.7	3.8	4.5	4.2	4.5
Marginal Effect of Medical Spending	N/A	N/A	N/A	3.4	2.8	2.5	2.4	1.8	2.2	2.2	2.1
Marginal Effect of Premium Contributions	N/A	N/A	N/A	2.9	3.6	2.5	2.6	2.0	2.7	2.4	2.8

Source: American Community Survey Public Use Micro Sample as augmented by NYC Opportunity and 2014 Medical Expenditure Survey (MEPS) inflated to 2015 prices using the CPI Medical Index.

*For the years 2005-2007, we do not disaggregate the premium portion from other medical spending. This is because type of health insurance coverage has a pivotal role in our improved methodology but is not available in the ACS for those years. Thus, we use a method that we utilized for previous years' poverty reports. This creates a major break in our data series. For detailed description of prior year's MOOP methodology see our reports published prior to this year, for example, http://www1.nyc.gov/assets/opportunity/pdf/15_poverty_measure_report.pdf.

**Medical care out-of-pocket spending in 2015 is preliminary, given that 2015 MEPS data has not been made available to the public. We will revisit and update the estimates of MOOP for 2015 in future reports. Thus, we advise caution in using the estimates for 2015.