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Improving Estimates of Opioid Prescriptions Filled in the Medicare Population Using Self Reports and Part D Claims Matching

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Abstract

Objectives: To generate accurate estimates of opioid prescription fills among Medicare beneficiaries using self-reported survey data and claims data, predict underreporting, and describe individual characteristics linked with opioid prescriptions.

Methods: We analyze data from the 2019 Medicare Current Beneficiary Survey (MCBS), a nationally representative survey of Medicare beneficiaries conducted by the Centers for Medicare & Medicaid Services (CMS), to estimate the proportion of beneficiaries aged 65 and over who filled opioid prescriptions in 2019. The MCBS uses claims matching to mitigate reporting error for beneficiaries with Part D coverage. In this study, we extend that methodology by adding regression modeling to predict which beneficiaries without Part D may have underreported opioid prescription fills in the survey.

Results: We find that 22.3 percent of beneficiaries with Part D coverage report at least one opioid prescription fill in the survey, and another 5.7 percent had opioids “discovered” during claims matching. Among beneficiaries without Part D, 18.3 percent reported at least one opioid in the survey, and we project that another 4.6 percent had opioid prescription fills that they did not report. Combining these figures together yields an overall estimate that 26.9 percent of all Medicare beneficiaries aged 65 and over (excluding those living in long-term care facilities) filled at least one opioid prescription in 2019.

Discussion: Claims matching paired with predictive modeling can improve survey-based estimates of opioid prescription fills. We discuss subgroups most likely to fill opioid prescriptions.

Introduction

Prescription opioid misuse is a public health crisis in the United States, and older Americans are at increased risk. Opioid use has increased among Medicare beneficiaries aged 65 and over, rising from 14.5 percent in 1996 to over 30.0 percent in 2014 (Haddad et al. 2019; Bromley et al. 2020). While prescription rates are declining, opioid use disorder and opioid-related deaths continue to increase for beneficiaries and older adults, respectively (Rudd et al. 2016; Scholl et al. 2019; Niles et al. 2020; Wilson et al. 2020). Beneficiaries face unique health challenges that may make them more susceptible to opioid use and misuse, including multiple comorbidities, chronic pain, sleep disorders, and mental and behavioral health issues (Wright et al. 2014; Dean 2017; Niles et al. 2020). Some conditions require complex drug therapy with multiple prescriptions for long periods of time, which can increase the risk for opioid harm (Dean 2017; Raman et al. 2019; Ramachandran et al. 2021).

To address this issue effectively, accurate and consistent measurement of opioid use among the Medicare population is needed; however, there are no established practices for generating such estimates. Different methodologies for measuring opioid use may yield inconsistent estimates and measurement gaps for some segments of the Medicare population. Estimates may be based on administrative data and/or survey data; all estimates cited earlier used some combination of administrative and survey data. In addition, some estimates are based on survey reports of medicines used by individuals while many rely on a proxy measure of prescriptions filled. In this study, we first assess the advantages and disadvantages of these methodologies. We then address several sources of error with an approach that improves estimates based on combined administrative and survey data for Medicare beneficiaries ages 65 and over, using opioid prescriptions fills as a proxy for use with predictive modeling. Table 1 summarizes five methodological approaches for estimating opioid use, including the approach used in the present study (displayed in last row).

Table 1. Comparison of methodologies for estimating opioid use

Sources of error (+ denotes advantage, – denotes disadvantage)

Measure (Data source)	Coverage	Measurement	Systematic
Prescription fills (Pharmacy data)[1]	– Excludes prescriptions obtained from public health systems, VA[2], or mail order	– May include medicines not actually used – May exclude misuse of medicines prescribed to others	+ Not subject to recall and social desirability bias
Prescription fills (Claims data)[3]	– Excludes those without drug coverage – May miss medicines paid for out of pocket or supplemental insurance	– May include medicines not actually used – May exclude misuse of medicines prescribed to others	+ Not subject to recall and social desirability bias
Medicines used (Survey data)[4]	+ Includes medicines from all sources	– Limited to medicines used + Includes medicines used but prescribed to others	– Subject to recall and social desirability bias
Prescription fills (Matched survey **and claims data**)[5]	+ Includes medicines from all sources	– May include medicines not actually used – May exclude misuse of medicines prescribed to others	+ Mitigates recall and social desirability bias for those with drug coverage – Does not mitigate recall and social desirability bias for those without drug coverage
Prescription fills (Matched **survey and claims data with predictive modeling**)[6]	+ Includes medicines from all sources	– May include medicines not actually used – May exclude misuse of medicines prescribed to others	+ Mitigates recall and social desirability bias for those with drug coverage + Mitigates underreporting among those without drug coverage

1 CDC 2019b
2 Veteran's Administration
3 Kuo et al. 2016; Axeen 2018; Han et al. 2018; Jeffery et al. 2018; Raman et al. 2019; Morden et al. 2021; Ramachandran et al. 2021
4 CDC 2019a; Substance Abuse and Mental Health Services Administration, 2019
5 Haddad et al. 2019; Bromley et al. 2020
6 Present study

Administrative sources rely on the proxy measure of prescription fills rather than actual medicine use. A key advantage is that they are not subject to the recall bias associated with self-reported survey data (Steinman et al. 2015). For example, the Centers for Disease Control and Prevention (CDC) uses IQVIA™ Xponent® and the Total Patient Tracker® (TPT)[7] to track opioid prescriptions filled from retail pharmacies. While critical to assessing opioid prescribing patterns and understanding availability of prescription opioids, these estimates do not capture issues associated with medicine adherence or polysubstance use. They may also yield lower estimates since they do not account for prescriptions filled through public health systems, the Veterans Health Administration (VHA), or mail order (CDC 2019b). Further, administrative sources typically do not capture demographic or health information, which are vital to understanding opioid prescribing patterns and designing effective policy interventions.

Another administrative source is Medicare Part D prescription drug claims. Claims data can be used to identify opioid prescriptions filled among beneficiaries with Part D coverage by relying on additional coding schemas or external administrative data to categorize drug classes and opioid prescription dosages and schedules (Kuo et al. 2016; Axeen 2018; Han et al. 2018; Jeffery et al. 2018; Raman et al. 2019; Morden et al. 2021; Ramachandran et al. 2021). This approach allows researchers to estimate national prescription drug fills among older beneficiaries with Part D (Kuo et al. 2016). However, such approaches may result in lower estimates since only 70 percent of beneficiaries are enrolled in Medicare Part D plans (CMS 2020). Medicare beneficiaries' prescriptions paid for out-of-pocket, covered by private insurance, or obtained through illicit means are excluded (Kuo et al. 2016; Axeen 2018; Jeffery et al. 2018; Raman et al. 2019). It is also not possible to assess whether beneficiaries use prescribed medicines as intended with claims data alone (Kuo et al. 2016; Axeen 2018; Han et al. 2018; Raman et al. 2019; Ramachandran et al. 2021).

Opioid use and prescription fills can also be self-reported in surveys, although survey responses are subject to recall and social desirability bias (Wright et al. 2014; Davis et al. 2017; Haddad et al. 2019). Variations in question wording may also affect comparability. The National Health Interview Survey (NHIS) and the National Survey of Drug Use and Health (NSDUH) use similar designs to measure opioid use in the general population by asking about medicines used (rather than prescriptions filled). However, the NHIS and NSDUH demonstrate how different questionnaire designs on opioid-related topics can lead to misreporting.

[7] IQVIA specializes in health information technology and clinical research. IQVIA's Xponent dataset includes national estimates of the number of opioid prescriptions filled at retail pharmacies. Their TPT dataset includes national estimates of the number of unique Americans who had at least one opioid prescription filled during a given year from retail pharmacies. Both datasets offer 92 percent coverage of opioid prescriptions (CDC 2019b).

Both the NHIS[8] and NSDUH[9] ask respondents about use of prescription pain relievers in the past year, although only NHIS explicitly uses the term "opioids" in the question text (CDC 2019a; Substance Abuse and Mental Health Services Administration 2019). Both surveys instruct respondents to exclude common over-the-counter pain relievers like aspirin. This focus on pain relief may unintentionally lead to underreporting of opioids prescribed for other purposes, like mental health treatment. The NHIS instructs respondents using specific drug names while the NSDUH includes names and pictures of opioids. These examples may help prompt recall, but opioids are a large class of medicines, making it difficult to provide a comprehensive list. Some respondents may be more familiar with "street names" for opioids rather than brand or generic names (Palamar 2019).

In the NHIS and NSDUH, underreporting can occur if respondents do not realize that their medicines are opioids. Visual aids on the NSDUH have been associated with selected overreporting, including scenarios where respondents mistook pictures of certain opioids for over-the-counter medicines. One such medicine is Tylenol 3, which contains codeine and should be classified as an opioid but has been mistaken for regular Tylenol in visual aids on the NSDUH (Bilgen and Miller 2019; Miller 2019) and underreported in other studies (Palamar 2019).

Research suggests that single item measures of this type also result in lower estimates of opioid use than measures based on a multi-item series or with specific framing of medication use (e.g., "narcotics" vs. "pain relievers") (Biondo and Chilcoat 2014). Surveys often avoid the word "opioid" to mitigate misunderstandings about which drugs are opioids and reduce social desirability bias in reporting (Willson et al. 2019). There is some evidence that embedding prescription misuse in broader lifestyle questions may improve the reliability of self-reports by allowing interviewers to build rapport with respondents before asking sensitive questions (McBride 2010). Techniques aimed at normalizing behavior (e.g., asking about aspects of drug use respondents enjoy) can make it more socially acceptable to provide accurate information but can also lead to overreporting (Latkin et al. 2017).

This paper contributes to research on best practices by offering an improvement on the existing methodology that combines survey data and administrative claims, shown in the last row of Table 1. Other approaches that have combined survey and administrative data are able to mitigate some sources of error through the inclusion of claims data, but this only improves data for individuals with Part D coverage – individuals without Part D are not present in claims data. In the present study, we aim to improve data for individuals without Part D coverage by predicting underreporting of opioid prescription fills and thus improving estimation. We do this by assessing underreporting among those with Part D coverage and then applying that knowledge to beneficiaries without Part D. This approach does require making some assumptions about similarities between these two subsets of the Medicare

[8] The 2019 NHIS question (variable OPD12M_A) asked: "These next questions are about the use of prescription pain relievers called opioids. When answering these questions, please do not include over-the-counter pain relievers such as aspirin, Tylenol, Advil, or Aleve. During the past 12 months, have you taken any opioid pain relievers prescribed by a doctor, dentist, or other health professional? Examples include hydrocodone, Vicodin, Norco, Lortab, oxycodone, OxyContin, Percocet, and Percodan. If you are not sure, please tell me the name of the drug and I can look it up."

[9] The 2019 NSDUH question (variables PR01-PR03) asked: "Please look at the names and pictures of the pain relievers shown below. Please note that some forms of these pain relievers may look different from the pictures, but you should include any form that you have used. In the past 12 months, which, if any, of these pain relievers have you used?"

population. Based on prior analyses (Defever, et al. 2023), we know that beneficiaries with Part D coverage generally fill more prescriptions than those without coverage, which is expected because (1) individuals who need more prescription drugs may acquire drug coverage at a higher rate than those who need fewer drugs and (2) those who already have Part D coverage may be more likely to fill prescriptions than those without coverage because they face lower out-of-pocket drug costs. Our approach involves predicting underreporting of opioids among those with Part D coverage, generating predicted probabilities based on beneficiary characteristics, and applying these predicted probabilities to those without Part D coverage. Our approach accounts for differences in socio-demographic and health-related factors between these two groups. It should be noted that there may be other systematic differences between groups related to reporting behaviors (e.g., susceptibility to social desirability bias) that may impact these predictions, so results should be interpreted with caution.

Our approach has three advantages that may fill some gaps in existing methodologies. First, it includes self-reported data collected via the enumeration of all prescription medicines rather than identifying opioids as a separate drug class. Determination of opioid prescriptions filled is possible during post-processing by matching medicine names to an administrative list of opioids. This may alleviate reporting error, misidentification of drugs, and social desirability bias. Second, we match self-reports of prescription fills from the survey data with prescription fills found in Medicare Part D claims. We use the matched data to estimate the magnitude of underreporting among survey self-reports. Third, we use a modeling approach to understand beneficiary characteristics that may be associated with underreporting and apply this knowledge for beneficiaries without Part D coverage. We then estimate additional opioid prescription fills that are missing from self-reported survey data for beneficiaries without Part D.

We hypothesize that our methodological enhancements will result in higher estimates than existing benchmarks, given our focus on reducing underreporting. We anticipate that the results of this analysis will be helpful to other researchers interested in improving estimates, even if they are unable to use this complex methodology, by offering insights into the magnitude of differences observed with these enhancements.

Methods

Analytic Universe and Data Sources

We use data from the Medicare Current Beneficiary Survey (MCBS), a longitudinal survey of a nationally representative sample of the Medicare population conducted by the Centers for Medicare & Medicaid Services (CMS).[10] The MCBS includes Medicare beneficiaries who are 65 and over as well as

[10] A full description of the MCBS methodology, including details about the population under study, sample selection, data collection methods, sample sizes, response rates, weighting, and data processing is available in the MCBS 2019 Methodology Report (CMS 2021e).

beneficiaries who are younger than 65 and qualify for Medicare based on certain disabling conditions. The MCBS has separate surveys for beneficiaries who live in residential community settings and those who live in long-term care facilities.[11] However, the present study is limited only to beneficiaries aged 65 and over who live in residential settings (i.e., not long-term care settings) who were continuously enrolled in Medicare in 2019.

MCBS data are collected for the same beneficiary continuously up to three times a year over four years. The survey asks beneficiaries or designated proxy respondents[12] to enumerate all prescribed medicines filled since their prior interview, regardless of whether the beneficiary took the medicine (CMS, 2021a).[13] MCBS prescription medicine data collection relies on respondent recall and documentation such as prescription bottle labels and pharmacy receipts. Interviewers enter medicine information using the Prescription Medicine Lookup (PMLU), a specially developed tool powered by the First Databank (FDB) MedKnowledge™ database of prescribed medicines (Defever, et al. 2023). Interviewers search for medicines by name, and the tool presents corresponding options for medicine dosages and forms.

In MCBS data post-processing, prescription medicine data are annualized by combining reports from each data collection round included in a particular “data year.” The present study focuses on 2019, which includes five data collection rounds from Fall 2018 through Winter 2020. The annualized survey-reported prescription drug fill data are enhanced by matching to Part D claims for beneficiaries with Part D coverage (Haddad et al. 2019). CMS performs this hierarchical, sequential, and iterative match process using medicine name, dosage, form, quantity, and cost (Eppig and Chulis 1997). Claims matching helps mitigate error from recall bias and social desirability bias. In cases where respondents fail to report medicines, but claims exist, claims information is incorporated into the final MCBS data to improve data quality (Defever, et al. 2023). During the claims matching step, CMS also removes medicines obtained outside of the year of interest, which is necessary because prescription fill dates are not collected in the survey, and survey reference periods can span calendar years.

Our analyses use final prescription medicine data from the 2019 MCBS Cost Supplement Limited Data Set (LDS) (CMS 2021b).[14] The Cost Supplement is a set of nine files containing information about medical events and associated costs for beneficiaries who were continuously enrolled in Medicare during 2019. We use the prescription medicine segment data, which include survey-reported medicines with matches in the claims data as well as medicines that were only present in one of the two sources: survey reports or claims. In the 2019 data year, 35 percent of all medicines included in the Cost Supplement were reported in the survey and matched to claims data. An additional 44 percent were found in claims data only, meaning that they were not reported in the survey but were “discovered” in

[11] The proportion of interviews completed with beneficiaries living in facilities in 2019 was 3% (CMS 2022).

[12] The percent of interviews completed with a proxy respondent in 2019 fell between 10 percent and 11 percent, depending on the data collection round. More information is available in the MCBS 2019 Methodology Report (CMS 2021e).

[13] The MCBS asks about prescription medicines that were filled rather than taken by the beneficiary because the survey is designed to capture comprehensive health care utilization and cost information.

[14] The unconditional response rate for the 2019 MCBS Annual Cost Supplement is 30.8 percent and the conditional response rate is 73.7 percent. More information is available in the MCBS 2019 Methodology Report (CMS 2021e).

claims. This highlights the magnitude of the underreporting issue for studies that base estimates on survey reports alone. Finally, 21 percent of all medicines included in the final data were reported in the survey but could not be matched to claims. This category typically includes (1) medicines reported by beneficiaries without Part D coverage (who do not have claims data available), (2) medicines reported by beneficiaries who do have Part D coverage but paid for drugs out of pocket (e.g., because the medicines were not covered by their plans), and (3) medicines that are reported without sufficient detail to be matched to claims (e.g., if a respondent knows that a medicine is taken for a certain condition but cannot remember its name or other details).

We matched prescription medicine records from the Cost Supplement LDS file to an administrative list of opioid medicines: a subset of the September 2018 CDC Oral Morphine Milligram Equivalents file, which includes opioid analgesic medicine product names, generic names, and drug names (CDC 2018). Specifically, we matched prescription medicine records from the Cost Supplement, which include every reported prescription filled for each beneficiary, whether they were reported in the survey and/or identified in claims, and the medicine brand name and generic name, to the subset of the medicines in the CDC list with a class of “Opioid.” We executed matching in multiple steps to ensure that we categorized medicines as opioids if they contained one of 19 opioid drug names or one of 260 distinct opioid brand names from the CDC list (see examples in Appendix A). A medicine was considered an opioid if the CDC list opioid medicine’s drug name, product name, or generic name was found within either the brand or generic name of the Cost Supplement record.

After matching the prescription medicine data from the Cost Supplement with the CDC list, we appended beneficiary characteristics from the 2019 MCBS Survey File LDS (CMS 2021d)[15], which includes socio-demographics and health-related data. The analytic universe includes 7,320 MCBS beneficiaries aged 65 years and over[16] who were living in community residential settings, continuously enrolled in Medicare in 2019, and included in the Cost Supplement (CMS 2021c).[17]

[15] The unconditional response rate for the 2019 MCBS Annual Survey File is 34.5 percent. The conditional response rate is 63.3 percent. More information is available in the MCBS 2019 Methodology Report (CMS 2021e).

[16] MCBS beneficiaries under age 65, who qualify for Medicare due to certain disabling conditions, are excluded from this analysis.

[17] We used MCBS ever enrolled weights and subset the universe to represent the continuously enrolled population for select analyses. Weighted findings represent 48,615,724 community-dwelling Medicare beneficiaries aged 65 years and over (CMS, 2021e). Balanced repeated replication survey weights were used to account for the complex sample design. Respondents typically complete three interviews per year (winter, summer, and fall data collection rounds) over four years for a total of 11 interviews as long as they do not miss two consecutive interview rounds. This analysis excludes beneficiaries who were enrolled in Medicare for only a portion of the year. It includes some beneficiaries who missed one interview during the year because they were unreachable (n=1,274).

Measurement

Our predictors for this analysis include socio-demographic and health characteristics appended from the Survey File: age, gender, race/ethnicity, educational attainment, urban vs. rural status (based on Rural-Urban Commuting Area Codes[18]), household income-to-poverty ratio, neighborhood disadvantage (determined by the Area Deprivation Index[19], a national ranking of Census block groups by socioeconomic factors), dual eligibility status (for Medicare and Medicaid), self-reported health status (rated on a five-point scale from poor to excellent and dichotomized into poor or fair vs. good, very good, or excellent), number of chronic conditions (dichotomized as 0-3 vs. 4 or more conditions), experiences with chronic pain (including high-impact chronic pain which is defined by Zelaya et al., 2020 as pain limiting life or work), and number of non-opioid prescriptions filled (based on self-reported prescription fills matched to claims).[20]

Outcomes include: (1) an indicator of reporting at least one opioid prescription fill in the survey (regardless of whether that opioid was found in claims matching) and (2) an indicator of reporting zero opioid prescription fills in the survey but having at least one opioid prescription discovered during claims matching. We acknowledge that metrics on prescription fills are imperfect since they likely involve both undercounting of actual medicine use (e.g., due to recall and social desirability bias) and overcounting (for prescriptions filled but never used).

Analytic Process

To examine underreporting of opioid prescription fills, we identified two groups of Medicare beneficiaries among those with Part D coverage: (1) those who reported at least one opioid prescription in the survey in 2019 and (2) those who did not report opioid prescriptions in the survey but had at least one claims-only opioid prescription. We ran weighted logistic models[21] predicting each of these outcomes. Next, we applied predicted probabilities from the second model to the beneficiaries without Part D, which allows us to include projected underreporting of opioids in our estimates for those without Part D. Finally, we compare our estimates against other sources.

[18] https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/

[19] https://www.neighborhoodatlas.medicine.wisc.edu/

[20] To avoid potential bias in our model-based predictions due to loss of cases with missing socio-demographic or health-related characteristics, we created additional variables as necessary to identify cases with missing data (e.g., a flag variable for cases missing race/ethnicity information).

[21] We used the SAS PROC SURVEYLOGISTIC procedure for these models to account for the complex survey design.

Results

Comparison of Socio-demographic and Health-related Characteristics between Beneficiaries with and without Part D Coverage

We provide bivariate comparisons of socio-demographic and health characteristics for beneficiaries with and without Part D coverage in Appendix B. In general, results indicate that beneficiaries with Part D coverage are more likely than those without coverage to be female, identify as Black non-Hispanic or Hispanic, have lower education and income levels, self-report being in poorer health, experience several health issues at higher rates, and report filling more non-opioid prescriptions. We account for these differences in the analyses that follow by including these characteristics in our models.

Reporting Error in Survey-Reported Opioid Prescription Fills

The weighted proportion of beneficiaries with any opioid prescription fills based on survey data alone is 22.3 percent, while the weighted proportion with combined survey/claims data is 28.0 percent (see Table 2). The difference of 5.7 percentage points between these two estimates means that roughly one in five beneficiaries who filled opioid prescriptions in 2019 did not report these opioids in the survey.

Table 2. Weighted proportions of Medicare beneficiaries aged 65 years and over with Part D coverage with any filled opioid prescriptions, 2019 Medicare Current Beneficiary Survey (MCBS)

Subgroup of interest	Weighted N	% (SE) with ≥ 1 opioid prescription: Survey reports	% (SE) with ≥ 1 opioid prescription: Survey reports + claims
Aged 65 and over with Part D	37,502,982	22.3% (0.8)	28.0% (0.9)

Multivariate Models Predicting Opioid Prescription Fills Among Beneficiaries with Part D Coverage

We ran two logistic regression models related to opioid prescription fills for beneficiaries with Part D coverage (see Table 3). The first model predicts whether a beneficiary with Part D reported at least one opioid prescription in the survey. The second model predicts whether a beneficiary reported no opioid prescriptions in the survey but had at least one opioid prescription in the matched claims data. Each model includes socio-demographic, health status, chronic condition, and chronic pain predictors.

Model 1: Survey-reported Opioid Prescription Fills Among Beneficiaries with Part D Coverage

As shown in Table 3, the likelihood of having any survey-reported opioid prescription fills tends to decrease with age, with beneficiaries in the 75-84 years and 85 years and over age groups being less likely to report opioids than younger beneficiaries. Beneficiaries who identify as Hispanic are half as likely to report any opioid prescriptions compared to White non-Hispanic beneficiaries. Females are less likely to report opioid prescription fills than males. Survey-reported opioid prescription fills are more likely among those who report “fair” or “poor” health (compared to “good,” “very good,” or “excellent” health) and those who also have more non-opioid prescription medicine fills.

Having osteoporosis or a broken hip, cancer, depression, chronic back pain, or chronic hips/knees/feet pain are also associated with increased likelihood of survey-reported opioid prescription fills. Notably, those with high-impact chronic pain are 1.8 times more likely to report filling any opioid prescriptions. Conversely, those with chronic tooth/jaw pain or heart disease are less likely to report opioid prescription fills.

Model 2: Survey Underreporting of Opioid Prescription Fills Among Beneficiaries with Part D

In Model 2 (also shown in Table 3), the outcome of interest is whether a respondent reported no opioid prescription fills in the survey but had at least one opioid prescription fill in claims data. This outcome is somewhat rare, observed for approximately 6 percent of beneficiaries with Part D (weighted N = 2,125,134). Characteristics associated with an increased likelihood of survey underreporting include having heart disease and reporting many non-opioid prescription medicines. Females have a lower likelihood of underreporting compared to males.

Table 3. Odds Ratios (OR) indicating the propensity of Medicare beneficiaries aged 65 years and over with Part D coverage 1) to report any opioid prescriptions and 2) to report no opioid prescriptions in the survey but have opioid prescriptions identified in Part D claims matching, 2019 Medicare Current Beneficiary Survey (MCBS)

Characteristics of beneficiaries with Part D coverage	Model 1: Opioid prescriptions reported in survey		Model 2: Opioid prescriptions not reported in survey but found in claims	
	OR	95% CI	OR	95% CI
Age (ref: 65-74 years)				
75-84 years	0.74**	(0.63, 0.88)	-	-
85+ years	0.65***	(0.53, 0.79)	-	-
Female	0.79+	(0.66, 0.95)	0.63*	(0.45, 0.89)
Race/ethnicity (ref: White non-Hispanic)				
Hispanic	0.48**	(0.33, 0.7)	-	-
Poor health status	1.39*	(1.11, 1.73)	-	-
Osteoporosis/broken hip	1.35*	(1.1, 1.65)	-	-
Depression	1.25+	(1.02, 1.53)	-	-
Heart disease	0.85+	(0.74, 0.99)	1.52*	(1.15, 2.00)
Cancer	1.28*	(1.06, 1.54)	-	-
High-impact chronic pain	1.78*	(1.25, 2.53)	-	-
Back pain	1.57*	(1.15, 2.13)	-	-
Hips/knees/feet pain	1.41+	(1.06, 1.87)	-	-
Tooth/jaw pain	0.45*	(0.25, 0.8)	-	-
>=9 non-opioid prescription medicines	3.17***	(2.59, 3.88)	3.04***	(2.14, 4.33)

NOTE: Variables that were initially included in the models but were not significant are not displayed. These include identifying as Black non-Hispanic or other race/ethnicity, educational attainment, rural/urban status, dual eligibility for Medicare and Medicaid, living at or below poverty, neighborhood disadvantage, pulmonary disease, mental conditions other than depression, Alzheimer's disease, high cholesterol, diabetes, dementia, hypertension, Parkinson's disease, stroke, and pain in other sites (headache/migraine/facial and abdominal/pelvic/genital).
NOTE: + $p < 0.05$, * $p < 0.01$, ** $p < 0.001$, *** $p < 0.0001$.
NOTE: - indicates that the characteristic does not significantly predict the odds of the outcome.

Predicting Opioid Underreporting among Beneficiaries without Part D

Finally, we use predicted probabilities from Model 2 to estimate underreporting of opioid prescription fills among beneficiaries without Part D based on the underreporting evident for those with Part D. Our goal is to assess the likelihood that individuals without Part D who did not report filling opioid prescriptions in the survey may have actually filled opioid prescriptions based on our model results and beneficiary characteristics. We use coefficients from the model to score each beneficiary without Part D coverage who did not report an opioid in the survey based on their characteristics. The resulting scores of likelihood of underreporting of opioid prescription fills were all low probabilities, which was expected because failing to report at least one opioid was a rare outcome in Model 2. To account for this, we summed up these fractional probability scores to generate predictions. In essence, this approach allowed us to scale the potential underreporting up to a larger group (e.g., if ten beneficiaries without Part D each had a predicted 10 percent chance of underreporting opioid prescription fills, this was tallied up as a prediction that one of the ten likely underreported). Using these predictions, we generated updated estimates of opioid prescription fills for the subsets of the Medicare population without Part D coverage and more broadly (Table 4).

Table 4. Weighted proportions of Medicare beneficiaries aged 65 years and over who filled opioid prescriptions by Part D coverage status, including modeled projections for those without Part D coverage, 2019 Medicare Current Beneficiary Survey (MCBS)

Beneficiary subpopulation	Weighted N	% (SE) Survey reports	% (SE) Survey reports + claims + projections for no Part D
Part D	37,502,982	22.3% (0.8)	28.0% (0.9)
No Part D	11,112,742	18.3% (1.2)	22.9%† (1.1)
All beneficiaries	48,615,724	21.4% (0.7)	26.9%† (0.7)

† Indicates estimates that include predicted probabilities based on Model 2 results.

Comparison to External Benchmarks

To evaluate how MCBS estimates of opioid use based on prescription fill data compare with other studies, we identified opioid use estimates in the literature with similar populations (i.e., ages 65 and over) based on both survey and administrative data. We limited our comparisons to sources with complex survey designs such as the MCBS, including the length of reference periods and unit of reporting.

Our primary interest is to compare the blended survey and claims data from the MCBS to external benchmarks that use other methodologies. Table 5 compares the weighted MCBS estimate against two benchmark estimates from a similar time frame. We find that our overall estimate of any opioid prescription fills for beneficiaries ages 65 and over (26.9 percent) is higher than both external benchmark values. The 2015-2016 Medical Expenditure Survey (MEPS), which has a substantially different methodology from the MCBS with one respondent providing data per household and no claims matching (Bernard, Machlin, Fang, and Cohen 2019), yielded an estimate of 19.3 percent. The 2018 IQVIA™ TPT® generated an estimate of 25 percent based on administrative data from pharmacies.

Table 5. Comparison of benchmarks of opioid use among Medicare beneficiaries or similar populations, 2015-2018

Year	Population	Data Source	Methodology	% Opioid Prescription	Citation
2019	Beneficiaries ages 65+ with complete cost and use data*	MCBS: Survey reports and claims data	Opioids were identified within all enumerated medicines in survey data and matched claims, with predictive modeling for individuals without Part D coverage	26.9%	N/A: Present study
2015-2016	Adults ages 65+*	MEPS: Survey reports	Opioid prescription data from enumerated medicines (survey-reported with additional data from pharmacies, when respondents provide consent)	19.3%	Moriya & Miller (2018)
2018	Adults ages 65+*	IQVIA™ TPT®: Administrative data	Opioid prescription data from retail pharmacies	25%	CDC (2019b)

NOTE: * indicates the study was limited to adults living in community settings and excludes those living in long-term care settings.

Discussion

Prescription opioid misuse is a significant public health crisis at the forefront of recent policy, prevention, and intervention efforts, with a primary focus on younger populations (Dowell et al. 2016; 115th Congress 2021). Opioid misuse among the elderly is frequently regarded as uncommon, unintended, or even misdiagnosed as conditions like dementia (Carter et al. 2019; Dean 2017), but misuse of painkillers is the most common type of prescription misuse among older populations. The Medicare population faces unique and complex challenges, which may put beneficiaries at higher risk for opioid misuse as it becomes difficult to maintain a comfortable quality of life (Dean 2017). As such, accurate measurement of opioid use among older adults is critical to addressing the potential for misuse.

This study contributes to public health knowledge in multiple ways. First, our findings suggest that estimates of opioid use among adults ages 65 and over (excluding those in long-term care settings) may undercount opioid usage for a variety of reasons. For example, we suspect that the 2015-2016 MEPS estimate of 19.3 percent is lower than the 2019 MCBS estimate of 26.5 percent primarily because (1) MEPS does not include claims matching (Bernard et al. 2019), (2) it uses a substantially different methodology from the MCBS with one respondent providing data per household, which could lead to underreporting if the respondent is unaware of any medicines prescribed to household members, and (3) it has longer reference periods than the MCBS (interviewing five times total across two years rather than three times per year for four years). In addition, the 2018 IQVIA™ TPT® estimate of 25 percent could be slightly lower than the MCBS estimate because TPT covers 92 percent of outpatient prescriptions using retail pharmacy data and does not include medicines from sources such as the VHA and mail order pharmacies (CDC 2019b), which the MCBS covers.

Second, this study fills a knowledge gap by including beneficiaries without Part D coverage in estimates and attempts to quantify opioid underreporting among this subgroup. Relying on prescription claims data alone overlooks potential opioid use among those without Part D. Our results suggest that self-reports of opioid prescription fills may suffer from substantial underreporting. Among beneficiaries aged 65 and over covered by Part D, 22.3 percent reported at least one opioid medicine prescription fill in 2019 and an additional 5.7 percent (or roughly one in five of the combined 28 percent) had opioids "discovered" during claims matching after failing to report them in the survey. Among those without Part D coverage, 18.3 percent reported at least one opioid prescription fill in the survey, and we project that an additional 4.6 percent likely had at least one opioid prescription fill but failed to report it in the survey. Importantly, some limitations remain since several sources of error may be mitigated rather than completely eliminated, and the MCBS methodology focuses on prescriptions filled for beneficiaries, regardless of medication adherence. In addition, this approach likely does not include any medicines prescribed to other individuals being taken by beneficiaries. Still, we believe that our approach offers higher accuracy than estimates based on combined survey reports and claims data without predictive modeling for beneficiaries without Part D coverage.

In addition to offering potential improvements to the methodologies used to estimate opioid use, this study offers insights into various socio-demographic and health conditions associated with increased risk of potential opioid misuse among beneficiaries, including being under 75 years of age, male, White non-Hispanic, filling many other non-opioid prescription medicines, being in poor health, and having certain health conditions (e.g., chronic pain, depression, osteoporosis or a broken hip).This background regarding subgroup differences is essential to tailoring public health guidelines, awareness campaigns, prevention efforts, and treatment programs to the sub-populations that need them most. Future analyses might extend this work by exploring whether this methodology can be applied to answer research questions about the quantities of opioids obtained by beneficiaries and their frequency of use.

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Appendix A

Opioid drug names and brand names, condensed from the 2018 CDC Oral Morphine Milligram Equivalents file list and used for matching against the MCBS 2019 Cost Supplement file

Drug name	Example brand names
Buprenorphine	Buprenorphine Hydrochloride Suboxone Belbuca
Butorphanol	Butorphanol Tartrate Stadol NS
Codeine	Acetaminophen-Codeine Phosphate Empracet Febridyne
Dihydrocodeine	Panlor SS Acetaminophen-Caffeine-Dihydrocodeine Synalgos-DC
Fentanyl	Fentanyl Transdermal System Duragesic Abstral
Hydrocodone	Hydrocodone Bitartrate-Acetaminophen Norco Vicodin
Hydromorphone	Hydromorphone HCL Dilaudid Exalgo
Levomethadyl	Orlaam
Levorphanol	Levorphanol Tartrate Levo-Dromoran
Meperidine	Meperidine HCL Meperitab Demerol Hydrochloride
Methadone	Methadone HCL Methadose Dolophine HCL
Morphine	Morphine Sulfate Kadian MS Contin

Drug name	Example brand names
Opium	Belladonna/Opium B & O Supprettes 16a
Oxycodone	Oxycodone HCL – Acetaminophen Oxycontin Endocet
Oxymorphone	Opana ER Oxymorphone HCL Numorphan HCL
Pentazocine	Pentazocine HCL – Naloxone HCL Talwin NX Talacen
Propoxyphene	Acetaminophen-Propoxyphene Napsylate Propoxacet-N Darvocet-N 100
Tapentadol	Nucynta
Tramadol	Tramadol HCL Ultram Ultracet

Appendix B

Bivariate differences in socio-demographic and health-related characteristics between Medicare beneficiaries with and without Part D coverage, 2019 Medicare Current Beneficiary Survey (MCBS)

Characteristic	Part D Coverage	No Part D Coverage
75-84 years of age	40.3%+	37.0%
Female	57.9%***	45.3%
Black non-Hispanic	9.1%***	5.4%
Hispanic	11.8%***	4.8%
Less than high school degree	19.1%***	9.0%
Lives at or below poverty	43.1%***	24.9%
Lives in urban area	77.8%***	72.3%
Lives in disadvantaged neighborhood	17.6%***	13.3%
Dual eligibility	17.7%***	0.3%
Poor health status	17.2%**	13.5%
Four or more chronic conditions	40.6%**	35.5%
Osteoporosis/broken hip	24.5%***	16.7%
Hypertension	67.6%+	54.3%
Diabetes	33.7%+	30.4%
High cholesterol	69.2%*	65.7%
Depression	21.5%+	18.6%
Mental condition other than depression	22.7%+	20.1%
Alzheimer's disease	3.1%+	2.1%
Hips/knees/feet pain	44.1%*	38.0%
>=9 non-opioid prescription medicines	54.0%***	34.9%

NOTE: Characteristics that were not significantly different between beneficiaries with and without Part D coverage are excluded from this table. These include: heart disease, cancer, stroke, Parkinson's disease, pulmonary disease, dementia other than Alzheimer's, high-impact chronic pain, and chronic pain categorized as back, hands/arms/shoulders, headaches/migraines/facial, tooth/jaw, and abdominal/pelvic/genital.
NOTE: + $p < 0.05$, * $p < 0.01$, ** $p < 0.001$, *** $p < 0.0001$.