

The role of county-level socioeconomic status on brand-name prescriptions in Medicare part D

A cross-sectional Study

Connor Volpi, MPH^{a,b}, Fadi Shehadeh, MEng^b, Eleftherios Mylonakis, MD, PhD, FIDSA^{b,*}

Abstract

The objective of this study was to examine the association between county-level socioeconomic factors and brand-name drug prescription drug patterns among medical specialties with overall high brand-name outpatient prescription use.

This cross-sectional study used data from 2 publicly available datasets. The 2015 Medicare Part D PUF data quantifies the prescription rates at the county-level and data from the US Census Bureau provides information on socioeconomic status at the county-level.

We analyzed 3,821,523 brand-name claims and 14,088,613 generic claims reported by health providers from 40 specialties as provided by the 2015 Medicare Part D dataset. Internal Medicine, Family Practice, General Practice, Cardiology, and Ophthalmology accounted for 71% of the total amount of brand-name drugs filled under Medicare Part D in 2015. As the presence of individuals with an income \geq \$100,000 increased in a given county, the likelihood of receiving a brand-name prescription claim increased.

A county-level association exists involving socioeconomic factors and outpatient brand-name drug prescription patterns. Future interventions should consider these factors in order to reduce percentage of brand-name drugs filled and decrease health care expenditures.

Abbreviations: ACS = American Community Survey, CDC = the centers for disease control and prevention, IRB = the Institutional Review Board, PUF = Medicare part D prescriber public user file, SES = socioeconomic status, U.S. = United States.

Keywords: brand-name drugs, health care spending, Medicare part D, prescriptions, socioeconomic factors

1. Introduction

United States spends more money on prescription medications than any other advanced industrialized country.^[1] A 20% increase in prescription drug spending in the U.S. occurred from 2013 to 2015,^[2] leading to an 11% increase in health care expenditures.^[3] Between 2008 to 2015, prices for popular brand-name drugs increased by 164%^[4] with escalating prices for commonly used brand-name drugs being cited as a major reason

for this upsurge.^[5] In 2015, although brand-name drugs comprised only 11% of the total prescription rate in the U.S., they accounted for 73% of prescription drug spending.^[6]

Availability of generic medicines and inclination of a health practitioner to prescribe a generic over a brand-name drug is essential in reducing prescription drug net prices.^[4] Generic drugs are produced by multiple manufacturers from a brand-name equivalent and are considerably less costly.^[7] According to the U.S. Food and Drug Administration, the same active ingredients from brand-name drugs are used to create generics.^[8] Thus, generics are considered to be clinically identical in terms of benefits and risks as its brand-name counterpart.^[8]

Despite the potential economic benefits, generic drugs remain relatively underused.^[9] The role of county-level sociodemographic factors on brand-name prescriptions over generic has rarely been studied at the quantitative level. A quantitative examination of these relationships can inform interventions aiming to increase the usage of generic over brand-name drugs. This study, therefore, aims to examine the relationship between brand-name drugs filled and sociodemographic factors among several medical specialties at the county-level.

2. Methods

The datasets for this cross-sectional study included Part D of Medicare's Provider Utilization and Payment^[10] and the American Community Survey (ACS) from the U.S. Census Bureau.^[11] This study utilized aggregate prescription data and did not require IRB approval.

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^a Brown University School of Public Health, ^b Division of Infectious Diseases, Warren Alpert Medical School of Brown University, Providence, RI.

* Correspondence: Eleftherios Mylonakis, Dean's Professor of Medical Science (Medicine, and Molecular Microbiology and Immunology), Chief, Infectious Diseases Division, Warren Alpert Medical School of Brown University, Rhode Island Hospital 593 Eddy Street, POB, 3rd Floor, Suite 328/330, Providence, RI 02903 (e-mail: emylonakis@lifespan.org).

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2.1. Percentage of brand-name claims at the county-level

The outcome variable of primary interest in this study was the percentage of brand-name claims filled per 10,000 people in a county. We used the 2015 Medicare Part D Prescriber Public User File (PUF) to determine this estimate. Medicare Part D offers outpatient prescription drug coverage to the disabled and elderly^[12] and information from 36 million Medicare beneficiaries with a part D prescription drug plan are included in the Part D PUF.^[10] We obtained data related to the total claims of brand-name drugs, including refills, from providers listed in the PUF. These data provided us information related to the percentage of brand-name drugs that have generic equivalents filled by prescribers. Claims were summarized by the provider's zip code. In order to summarize claims per county, each zip code was then matched with its county. We then summarized brand-name drug claims per county and divided by total claims in order to obtain the percentage of brand-name drugs.

2.2. Socioeconomic and demographic variables

Socioeconomic status at the county-level was our primary exposure of interest. County data from the 2012-2016 ACS 5-year estimate dataset was used to determine socioeconomic status (SES).^[11] SES was acquired for each county from the 2012-2016 ACS 5-Year estimates and is a component of the publicly available data provided by the U.S. Census Bureau.^[11] We grouped income into specific median income ranges based upon individual zip codes and examined SES at the county-level.^[13] Research shows that a higher income is associated with better health outcomes^[13] and less overall prevalence of disease.^[14] Data from the CDC show this disparity to be greatest in households of annual income of less than \$35,000 compared to income of \$100,000 or more.^[14] Therefore, annual household income was grouped into five defined income brackets (\$34,999 or less, \$35,000–59,999, \$60,000–99,999, and \$100,000 or more) and served as our main explanatory variable of interest.

We also examined the role that other sociodemographic characteristics have on brand-name prescription patterns. The ACS was used to obtain additional sociodemographic information.^[11] The following explanatory variables were included in our analysis: a) Age, b) Gender, and c) Race. The percentage of prescriptions filled has been shown to vary according to age group.^[15] Age was grouped into three brackets (5 to 17, 18 to 64, and 65 and over) in order to examine percentage of brand-name drugs filled for several age ranges. Gender has historically been viewed as an important determinant of health behavior.^[16] Research regarding gender differences in prescription drug dispensing trends are conflicted.^[17] Moreover, little literature exists that examines the role race has on brand-name prescription patterns.^[18] In this study, self-described race was examined in three categories: White, Black, and Other. Study analysis is limited to counties in the U.S. who had available data containing information on levels of income and the percentage of brand-name drugs filled.

2.3. Analysis

Bivariate correlations and descriptive statistics were used for all study variables. Linear regression analyses examined relationships between percentage of brand-name drugs filled and county-level SES. Univariable regressions were used to determine the unadjusted relationship between SES, demographics, and

percentage of brand-name drugs. Multivariable linear regressions were completed in order to examine the relationship of the outcome and significant sociodemographic variables by the exposure. All statistical analyses were performed using Stata 14.0^[19] and accounted for complex survey design. We also conducted a hot spot analysis to obtain a visual relationship of counties and brand-name prescriptions on a national level. We first examined the relationship between the percentage of brand-name drugs filled compared to generic drugs among several medical specialties. In order to complete this analysis, a paired *t*-test was performed on medical specialties for which sufficient data was available.

3. Results

In total, we ran paired *t* test analysis for 40 unique specialties (Table 1) and analyzed 3,821,523 brand-name claims and 14,088,613 generic claims as reported by health providers from these specialties in the 2015 Medicare Part D dataset. These drugs were filled throughout the U.S. to nearly 36 million beneficiaries. The number of counties ranged from 1077 counties (Cardiology) to 2907 (Family Practice) and was dependent on whether a given county had data for that particular medical specialty.

From our paired *t* test analysis, we determined that Internal Medicine, Family Practice, General Practice, Cardiology, and Ophthalmology to be five medical specialties of high concern based upon the percentage of brand-name prescription claims. These five categories accounted for 71% of the total amount of brand-name drugs filled to Medicare Part D beneficiaries in 2015. For these five specialties, univariable linear regressions were performed to examine the relationship between our main exposure and outcome of interest at the county-level.

Internal Medicine was the specialty with the highest percentage of brand-name prescription claims. Overall, 21% of prescriptions from this specialty were brand-name. Univariable analysis for Internal Medicine determined three out of the four income brackets to show statistical significance with a prediction $P < .05$ (Table 2A). Regression revealed a 1-unit increase in percentage of individuals in a given county whom reported an income of $\geq \$100,000$ yielded a 0.13% increase in brand-name prescriptions from an internal medicine practitioner. Interestingly, two preceding income brackets yielded a significant negative value. Thus, we determined that internal medicine physicians were more likely to prescribe brand name-drugs as individuals with an income of $\geq \$100,000$ increased in a given county when compared to other income groups.

Moreover, univariable regressions involving the Internal Medicine specialty revealed significant differences in outpatient prescription patterns based upon age and race. At the county-level, those aged 65 and over were found to be less likely to have brand-name drug prescriptions filled compared to generics ($R^2 = 0.008$). A 1-unit increase in percentage of individuals aged ≥ 65 in a given county yielded a 0.08% decrease in brand-name prescription claims from an internal medicine specialist.

Analysis involving race determined individuals of a race 'Other' than 'White' or 'Black' to have a significant positive coefficient ($R^2 = 0.008$). A 1-unit increase in percentage of individuals in a given county of a race of 'Other' yielded a 0.04% increase in brand-name prescriptions from an internal medicine practitioner. We then conducted a multivariable analysis (Table 2B) for three high-interest variables from our univariate analysis. At the county-level, 2% of the variance in brand-name

Table 1
Paired *t* test of brand-name and generic drug claims from medical specialties, mean (Ratio; SD).

Specialty	Brand Claims	Generic Claims	<i>t</i> value	<i>P</i> value
Optometry	45,530 (53%; 45,594)	38,945 (47%; 35,131)	3.09	.0032
Ophthalmology	157,632 (54%; 217,443)	135,469 (46%; 174,763)	2.89	.0056
Pulmonary Disease	92,808 (49%; 100,274)	95,439 (51%; 123,927)	-0.44	.6600
Pharmacist	2,977 (40%; 10,726)	4,406 (60%; 19,211)	-1.10	.2782
Intensivists	7,245 (47%; 9,101)	8,187 (53%; 13,258)	-1.12	.2683
Endocrinology	116,096 (48%; 141,951)	124,886 (52%; 157,114)	-1.96	.0553
General Practice	106,485 (19%; 252,850)	449,931 (81%; 1,177,945)	-2.70	<.001
Registered Nurse	1,161 (19%; 2,390)	4,930 (81%; 9,2650)	-3.81	<.001
Podiatry	6,592 (14%; 10,924)	39,540 (86%; 66,289)	-4.35	<.001
Thoracic Surgery	567 (19%; 1,652)	2,370 (81%; 5,095)	-4.48	<.001
Preventive Medicine	1,412 (22%; 2,241)	5,053 (78%; 7,584)	-4.55	<.001
Plastic Surgery	68 (16%; 107)	352 (84%; 491)	-4.55	<.001
Infectious Disease	23,617 (40%; 35,344)	35,716 (60%; 52,869)	-4.71	<.001
Neuropsychiatry	1,677 (15%; 2,598)	9,678 (85%; 14,511)	-4.74	<.001
Palliative Care	1,438 (21%; 2,122)	5,444 (79%; 7,441)	-4.88	<.001
Colorectal Surgery	1,111 (27%; 1,393)	3,015 (73%; 3,777)	-5.29	<.001
Vascular Surgery	707 (12%; 1,127)	5,151 (88%; 7,866)	-5.86	<.001
Allergy/Immunology	15,588 (38%; 18,310)	25,611 (62%; 26,698)	-5.98	<.001
Anesthesiology	10,276 (14%; 13,886)	65,804 (86%; 92,217)	-5.18	<.001
Nephrology	47,730 (25%; 81,451)	143,275 (75%; 208,290)	-5.46	<.001
Cardiac Surgery	877 (17%; 1,219)	4,214 (83%; 5,287)	-5.54	<.001
Dermatology	14,074 (14%; 19,248)	83,907 (86%; 109,257)	-5.63	<.001
Gastroenterology	40,285 (30%; 55,458)	92,319 (70%; 120,487)	-5.75	<.001
Hematology	9,179 (22%; 16,281)	33,399 (78%; 55,007)	-6.01	<.001
Internal Medicine	1,408,719 (21%; 1,917,686)	5,449,084 (79%; 6,862,665)	-6.13	<.001
Cardiology	92,442 (22%; 175,998)	337,451 (78%; 579,398)	-6.18	<.001
Psychiatry	34,407 (13%; 67,685)	229,775 (87%; 446,164)	-6.18	<.001
Otolaryngology	10,249 (15%; 13,090)	60,059 (85%; 70,936)	-6.23	<.001
Pediatric Medicine	8,301 (22%; 9,573)	29,951 (78%; 34,767)	-6.24	<.001
Geriatric Medicine	44,603 (21%; 50,822)	164,271 (79%; 184,768)	-6.36	<.001
Urology	21,784 (21%; 27,681)	83,587 (79%; 97,886)	-6.40	<.001
Physical Medicine	12,204 (15%; 14,822)	71,769 (85%; 86,317)	-6.40	<.001
Emergency Medicine	33,510 (17%; 41,667)	164,038 (83%; 192,657)	-6.40	<.001
Hematology/Oncology	15,272 (21%; 19,607)	56,179 (79%; 64,595)	-6.55	<.001
Orthopedic Surgery	9,106 (10%; 11,083)	86,731 (90%; 96,650)	-6.56	<.001
Pain Management	8,111 (13%; 11,758)	52,301 (87%; 79,269)	-6.61	<.001
Obstetrics/Gynecology	23,313 (32%; 29,388)	49,783 (68%; 57,595)	-6.70	<.001
Rheumatology	28,292 (22%; 34,482)	102,843 (78%; 110,498)	-6.92	<.001
General Surgery	11,259 (18%; 12,901)	50,248 (82%; 53,927)	-6.94	<.001
Family Practice	1,319,404 (19%; 13,888,384)	5,540,935 (81%; 5,662,061)	-7.31	<.001
Neurology	34,567 (19%; 54,678)	147,497 (81%; 208,133)	-7.59	<.001

prescription claims among internal medicine practitioners was associated with an income of $\geq \$100,000$, an age of ≥ 65 , and a race of 'Other' ($P_{\text{model}} < 0.001$, $R^2 = 0.02$).

Family Practice analysis found 19% of filled drugs in this specialty to be brand-name. Results were similar to our findings for Internal Medicine (Table 3A) and again provided statistical significance with a prediction $P < .05$ and explained up to 3% of the variance. As shown in our analysis for Internal Medicine, other significant income brackets were found to have a negative coefficient except for the bracket of \$100,000 or more ($R^2 = 0.003$). We determined that a 1-unit increase in percentage of individuals in a given county whom reported an income of $\geq \$100,000$ yielded a 0.07% increase in family practice filled brand-name prescription claims.

Differences were again present in prescription patterns involving race and gender. However, the only variables to provide significance were the variables: age 65 and over ($R^2 = 0.002$) and a race of 'Other' ($R^2 = 0.008$). For those aged ≥ 65 , a

1-unit increase in percentage of individuals in this age group yielded a 0.03% decrease in amount of brand-name prescription claims from a family practice practitioner. Whereas, a 1-unit increase in percentage of individuals with a race of 'Other' yielded a 0.04% increase in amount of brand-name prescription claims from a family practice practitioner. A multivariable regression (Table 3B) demonstrated that 1% of the variance in brand-name prescription claims among family practice practitioners can be associated with an income of $\geq \$100,000$, an age of ≥ 65 , and a race of 'Other' ($P_{\text{model}} < .001$, $R^2 = 0.01$).

Next, we examined the relationship between SES and demographics and outcome among general practice practitioners (Table 4A). Among the overall prescriptions filled in this specialty, 19% were found to be brand-name. However, the only significant income bracket to yield a positive coefficient was \$100,000 or more ($R^2 = 0.008$). The income bracket \$34,999 or less ($R^2 = 0.007$) had a significant negative coefficient value. The only other variable determined to be significant by univariable

Table 2**Regression model(s) – Medical Specialty: Internal Medicine.**

	Coeff	P value	SE	t statistic	R²	
<i>A. Association of brand claims with SES and demographics (Univariable)</i>						
SES:						
\$34,999 or less	−0.15	<.001	0.03	−4.94	0.01	
\$35,000–59,999	−0.20	.001	0.06	−3.39	0.0052	
\$60,000–99,999	0.01	.838	0.50	0.20	<0.001	
\$100,000 or more	0.13	<.001	0.03	4.55	0.009	
Age:						
5–17	0.09	.006	0.03	2.74	0.003	
18–64	0.04	.088	0.02	1.71	0.001	
65 and over	−0.08	<.001	0.02	−4.27	0.008	
Gender:						
Male	0.07	.087	0.04	1.71	0.001	
Race:						
White	−0.01	.074	0.01	−1.79	0.001	
Black	<0.001	.918	0.01	−0.10	<0.001	
Other	0.04	<.001	0.01	4.03	0.008	<i>P value (model)</i>
<i>B. Association of brand claims with selected SES and demographics (Multivariable)</i>						
SES:						
\$100,000 or more	0.11	<.001	0.03	3.60	0.02	<.001
Age:						
65 and over	−0.05	.015	0.02	−2.45		
Race:						
Other	0.03	.003	0.03	3.02		

Coeff=coefficient, SE=standard error.

analysis was a race of ‘Other’ ($R^2=0.003$). A multivariable analysis was run with key variables (Table 4B). At the county-level, only 1% of the variance in brand-name prescription claims among general practice practitioners was associated with an income of $\geq \$100,000$ and a race of ‘Other’ ($P_{\text{model}} < .001$, $R^2 = 0.01$).

In Cardiology, 22% of the drugs filled were brand-name and all income levels showed statistical significance with a prediction $P < .05$, explaining up to 8% of the variance (Table 5A). A 1-unit increase in percentage of individuals in a given county whom reported an income of $\geq \$100,000$ yielded a 0.41% increase in brand-name prescriptions from a cardiologist. Additionally,

Table 3**Regression model(s) – Medical Specialty: Family Practice.**

	Coeff	P value	SE	t statistic	R²	
<i>A. Association of brand claims with SES and demographics (Univariable)</i>						
SES:						
\$34,999 or less	−0.07	.003	0.02	−2.96	0.003	
\$35,000–59,999	−0.05	.271	0.04	−1.10	<0.001	
\$60,000–99,999	−0.04	.233	0.04	−1.19	<0.001	
\$100,000 or more	0.07	.003	0.02	2.96	0.003	
Age:						
5–17	0.01	.632	0.02	0.48	<0.001	
18–64	0.03	.089	0.02	1.70	0.001	
65 and over	−0.03	.017	0.01	−2.40	0.002	
Gender:						
Male	0.04	.155	0.03	1.42	<0.001	
Race:						
White	−0.01	.154	0.01	−1.42	0.007	
Black	−0.01	.426	0.01	−0.80	<0.001	
Other	0.04	<.001	0.01	4.89	0.008	
<i>B. Association of brand claims with selected SES and demographics (Multivariable)</i>						
SES:						
\$100,000 or more	0.06	.012	0.02	2.52	0.01	<i>P value (model) = <.001</i>
Age:						
65 and over	−0.01	.567	0.01	−0.57		
Race:						
Other	0.03	<.001	0.03	4.42		

Coeff=coefficient, SE=standard error.

Table 4
Regression model(s) – Medical Specialty: General Practice.

	Coeff	P value	SE	t statistic	R²	
<i>A. Association of brand claims with SES and demographics (Univariable)</i>						
SES:						
\$34,999 or less	−0.25	.002	0.79	−3.11	0.007	
\$35,000–59,999	−0.24	.149	0.17	−1.44	<0.001	
\$60,000–99,999	0.41	.765	0.14	0.30	<0.001	
\$100,000 or more	0.25	.001	0.78	3.18	0.008	
Age:						
5–17	0.01	.893	0.09	0.13	<0.001	
18–64	0.07	.267	0.64	1.11	<0.001	
65 and over	−0.08	.120	0.05	−1.56	0.002	
Gender:						
Male	−0.12	.260	0.11	−1.13	0.001	
Race:						
White	−0.01	.355	0.01	−0.93	<0.001	
Black	<0.001	.978	0.02	−0.03	<0.001	
Other	0.05	.039	0.03	2.07	0.03	
<i>B. Association of brand claims with selected SES and demographics (Multivariable)</i>						
SES:					0.01	<i>p</i> value (model) = 0.011
\$100,000 or more	0.24	.002	0.08	3.08		
Race:						
Other	0.04	.058	0.03	1.90		

Coeff = coefficient, *SE* = standard error.

outpatient prescription patterns were seen to differ based upon other demographics. An increase in 1-unit in percentage of individuals aged 18 to 64 in a given county yielded a 0.24% increase in brand-name prescription claims from a cardiologist. Univariable analysis involving race determined ‘White’ to have a negative coefficient ($R^2=0.01$) while ‘Black’ ($R^2= <0.001$) and ‘Other’ ($R^2=0.03$) were shown to have a positive coefficient. A county-level multivariable regression (Table 5B) determined 12%

of the variance in brand-name prescription claims among cardiologists was associated with an income of $\geq \$100,000$, an age of 18 to 64, and a race of ‘Other’ ($P_{\text{model}} < .001$, $R^2=0.12$).

In Ophthalmology, univariable regression determined 3 out of the 4 income brackets to be statistically significant with a prediction $P < .05$ (Table 6A) and explained up to 2% of the variance. Out of the medical specialties examined, Ophthalmology was unique in that brand-name drugs accounted for more

Table 5
Regression model(s) – Medical Specialty: Cardiology.

	Coeff	P value	SE	t statistic	R²	
<i>A. Association of brand claims with SES and demographics (Univariable)</i>						
SES:						
\$34,999 or less	−0.48	<.001	0.05	−9.18	0.07	
\$35,000–59,999	−0.88	<.001	0.10	−9.00	0.07	
\$60,000–99,999	−0.33	<.001	0.09	−3.52	0.01	
\$100,000 or more	0.41	<.001	0.04	9.88	0.08	
Age:						
5–17	−0.16	.003	0.05	−2.94	0.008	
18–64	0.24	<.001	0.04	6.86	0.04	
65 and over	−0.12	<.001	0.03	−3.93	0.01	
Gender:						
Male	0.11	.0015	0.09	1.27	0.002	
Race:						
White	−0.03	<.001	0.01	−3.80	0.01	
Black	0.01	<.001	0.01	0.81	<0.001	
Other	0.10	<.001	0.02	5.85	0.03	
<i>B. Association of brand claims with selected SES and demographics (Multivariable)</i>						
SES:					0.12	<i>P</i> value (model) = <.001
\$100,000 or more	0.34	<.001	0.04	8.01		
Age:						
18–64	0.16	<.001	0.03	4.49		
Race:						
Other	0.07	<.001	0.02	4.35		

Coeff = coefficient, *SE* = standard error.

Table 6
Regression model(s) – Medical Specialty: Ophthalmology.

	Coeff	P value	SE	t statistic	R ²
<i>A. Association of brand claims with SES and demographics (Univariable)</i>					
SES:					
\$34,999 or less	−0.69	<.001	0.15	−4.57	0.02
\$35,000–59,999	−0.61	.023	0.27	−2.28	0.005
\$60,000–99,999	0.17	.508	0.25	0.66	<0.001
\$100,000 or more	0.48	<.001	0.10	4.21	0.02
Age:					
5 to 17	−0.11	.445	0.14	−0.76	<0.001
18–64	0.15	.116	0.09	1.57	0.002
65 and over	−0.07	.408	0.08	−0.83	<0.001
Gender:					
Male	0.36	.114	0.23	1.58	0.002
Race:					
White	−0.02	.376	0.02	−0.89	<0.001
Black	<0.001	.807	0.02	−0.24	<0.001
Other	0.09	.031	0.01	2.16	0.03
<i>B. Association of brand claims with selected SES and demographics (Multivariable)</i>					
SES:					0.02
\$100,000 or more	0.45	<.001	0.12	3.92	<i>p</i> value (model) = <0.001
Race:					
Other	0.07	.128	0.05	1.53	

Coeff=coefficient, SE=standard error.

than half of the prescription drugs filled. Analysis determined a similar trend as to what was noted in our previous regressions from the other medical specialties examined. At the county-level, we determined that a 1-unit increase in percentage of people with an income of \$100,000 or more yielded a 0.48% increase in brand-name prescriptions from an ophthalmologist. A county-level multivariable analysis (Table 6B) determined 2% of the variance in brand-name prescription claims among ophthalmologists to be associated with an income of \geq \$100,000 and a race of ‘Other’ ($P_{\text{model}} < .001$, $R^2 = 0.02$).

Findings from the hot spot analysis offered a visual as to what counties in the U.S. had high amounts of brand-name drugs filled (Fig. 1). We determined a highly significant cluster of counties with high brand-name prescription rates throughout the U.S. From a national perspective, we see that the Midwest, Southwest, and regions of the Mid-Atlantic/Northeast to have a large number of counties with high brand-name drugs filled clustered together. Moreover, we found a cluster of counties with low brand-name prescription rates spread throughout the U.S. that were highly significant.

4. Discussion

The Medicare Part D program spent over \$397 billion on prescription drugs between 2012 and 2015^[20] and projections predict expenditures to increase by 77% over the next decade.^[21] As medication use continues to rise,^[22] preferential increase in usage of generic medications is required in order to achieve a reduction in pharmaceutical health care expenditure.^[5] Further, utilization of generics can help patients improve their medication adherence by reducing the price barrier to access^[23] and greater adherence leads to additional cost-benefits with reduced hospitalization rates.^[24] Research has shown that certain demographics can influence generic drug prescription^[25] but this research has largely been qualitative and the role of county-level socioeconomic status (SES) on the percentage of brand-name drugs filled has rarely been studied.

The combination of data from the Medicare Part D Public Use File and the U.S. Census Bureau allowed the opportunity to further identify if a relationship exists involving the prescription of brand-name drugs and county-level SES. Study findings provided insight as to what income brackets at the county-level have greater likelihood of higher brand-name prescription rates. Our main finding revealed an increased likelihood of brand-name drug prescriptions as the percentage of individuals with an income of \$100,000 or more increased in a given county.

Part D plans are delivered primarily in 2 distinct forms, fee-for-service or Medicare Advantage with 61% of Part D beneficiaries enrolled in fee-for-service plans.^[26] Medicare Advantage is associated with lower out-of-pocket costs of managed care compared to fee-for-service^[27] and is popular among lower income groups.^[28] Medicare Advantage beneficiaries are usually concentrated among a subset of medical providers in inner-city or rural communities.^[29] This is relevant to our hot-spot analysis finding as we determined many rural areas and counties surrounding major cities to have a large cluster of counties with a high rate of brand-name drugs. Moreover, Medicare Advantage beneficiaries may elect to enroll for a low-income subsidy which restricts them from utilizing certain medications^[29] and some plans prevent beneficiaries from receiving brand-name drug prescriptions.^[30] Individuals of higher income are less likely to qualify for subsidies associated with restrictions on brand-name drug prescriptions.^[31] As a result, the structure of these plans might incentivize some patients to request generic drugs.

There are limitations to our study. The availability of data prevented us from fully examining the effects of residual confounding. Although we controlled for three variables in our final model analysis, the possibility of other confounders that contribute to a higher likelihood of brand-name drugs exists. An estimated 50% of individuals enrolled in Medicare Part D also have supplemental or private insurance for medication coverage, therefore, overall claims may differ from those found in Medicare Part D.^[32] Additionally, we were unable to omit brand-name

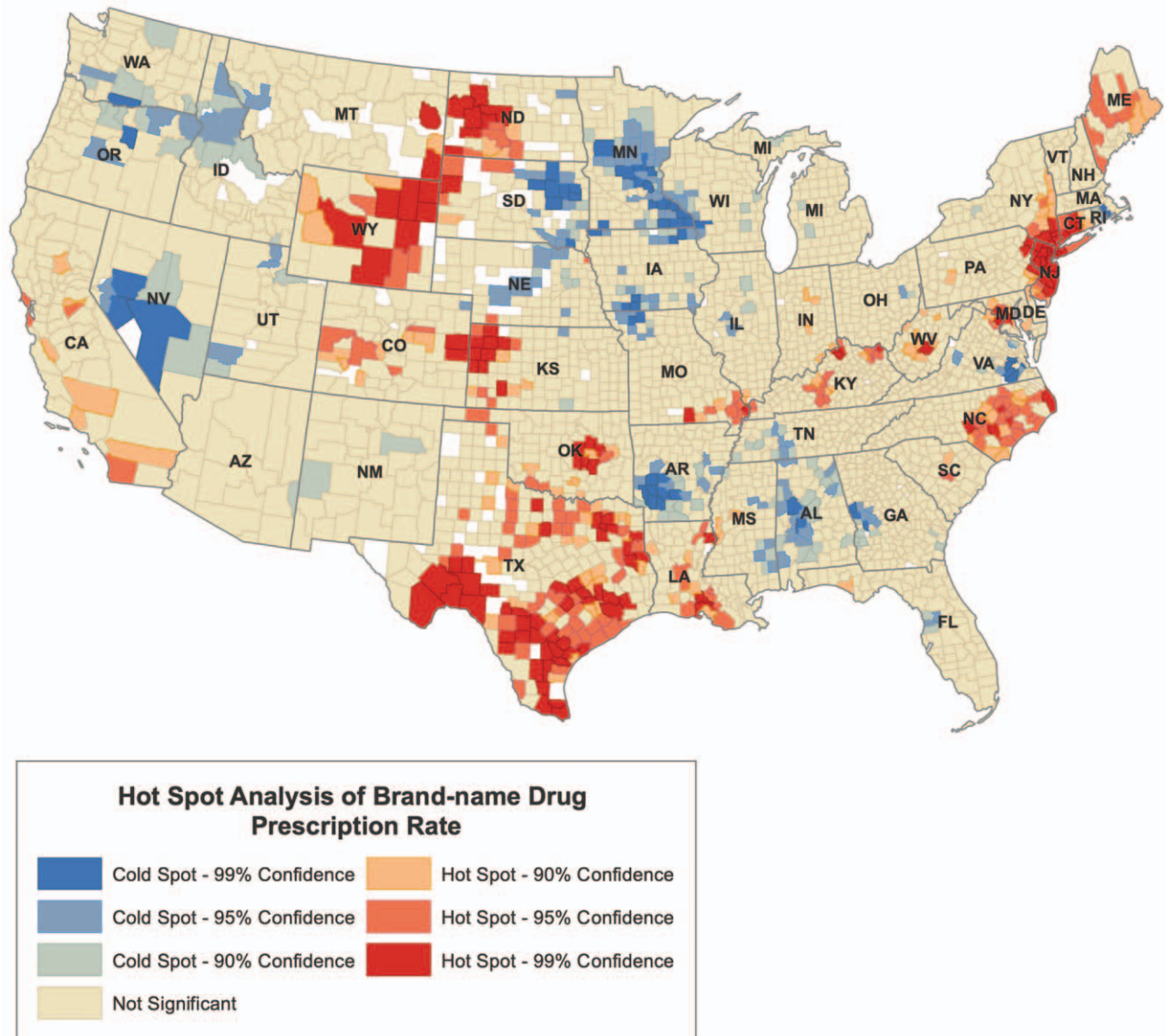


Figure 1. Hot spot analysis of brand-name drug prescription rate.

drugs for which no approved generic version exists. Nevertheless, previous work suggests that therapeutic substitution, or the practice of promoting the prescription of in-class generic drugs, could generate substantial savings for when no approved version exists for a brand-name drug.^[33]

Data were collected at the county-level since data from individual cases were not available for analysis. Moreover, the data used for analysis are limited to 2015 for the Medicare data and 2012 to 2016 for the sociodemographic data and has the potential to not accurately represent the U.S. population. However, the ACS is representative of the general population and the beneficiaries of Medicare Part D are an especially significantly population to consider as they consist of nearly two-thirds of those who receive Medicare and comprise 10% to 15% of the total US population.^[34] Furthermore, analysis into Medicare spending revealed that the substitution of 62 generic medications to a brand-name alternative using Part D beneficiaries could result in a savings of \$3.4 billion.^[35]

Finally, this study is retrospective and cross-sectional and thus subject to the limitations inherent in the study design. We are unable to account for regional variation due to drug shortages or to establish a causal relationship between socioeconomic status and brand-name drug prescription rates. Additionally, we did not have access to patient-level data and were unable to determine additional clinician rationale, including negotiated plans with pharmaceutical manufacturers, visits from pharmaceutical sale representatives, or patient-level factors. Despite these limitations, this was one of the first known studies to determine a quantitative county-level association between patient income and outpatient brand-name drug prescription patterns.

5. Conclusion

We found SES and demographics to influence brand-name drug prescription in a wide range of medical specialties. At the county-level, this effect was most closely associated with an increase in

the percent of individuals with an income of \geq \$100,000. We determined that an increase of individuals in this income group is more likely to result in higher brand-name prescription claims in a given county. Additional research is needed in order to evaluate causality. However, the consideration of SES and demographics, particularly patient income at the county-level, may be a key component in achieving a reduction in brand-name drug prescriptions. This is particularly true for counties that have a large proportion of high-income households. Interventions that aim to reduce the percentage of brand-name prescriptions can benefit from our study findings. Such interventions may wish to initially focus on counties with a large proportion of high-income households to best mitigate brand-name drug prescription rates. The implementation and delivery of successful interventions that apply our county-level findings have the capability to decrease patient costs and reduce health care expenditures significantly at the national level.

Author contributions

Conceptualization: Connor Volpi, Fadi Shehadeh, Eleftherios Mylonakis.

Data curation: Connor Volpi, Fadi Shehadeh.

Formal analysis: Connor Volpi, Fadi Shehadeh.

Investigation: Connor Volpi.

Visualization: Fadi Shehadeh.

Writing – original draft: Connor Volpi.

Writing – review & editing: Connor Volpi, Fadi Shehadeh, Eleftherios Mylonakis.

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