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The geography of antidepressant, antipsychotic, and stimulant utilization in the United States ☆

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ABSTRACT

This paper analyzes local and regional geographic variability in the use of antidepressant, antipsychotic and stimulant medications in the United States. Using a data set that covers 60% of prescriptions written in the United States, we find that use of antidepressants in three digit postal codes ranged from less than 1% of residents to more than 40% residents. Stimulant and antipsychotic use exhibited similar levels of local geographic variability. A Kulldorf Spatial Scan identified clusters of elevated use of antidepressants (RR 1.46; $p<0.001$), antipsychotics (RR 1.42; $p<0.001$), and stimulants (RR 1.77; $p<0.001$). Using a multilevel model, we find that access to health care, insurance coverage and pharmaceutical marketing efforts explain much of the geographic variation in use.

1. Introduction

Mental health medications are currently among the best selling and most commonly used classes of medications in the United States. In 2010, sales of antidepressant, antipsychotic, and stimulant medications accounted for 11.4% of total U.S. spending on pharmaceuticals and grossed close to $35 billion dollars (IMS Health Incorporated, 2010). Given the dramatic increase in antidepressant, antipsychotic, and stimulant use and cost, there has been growing interest in understanding patterns of utilization. While a considerable body of literature has documented trends in use by age and other demographic characteristics, relatively little is known about local geographic variation in the use of mental health medications.

To date, the majority of studies examining the geography of antidepressant, stimulant, and antipsychotic use have produced results that are inconclusive or not generalizable due to methodological differences in population characteristics across studies. Within the literature there has also been a tendency to focus on patterns of use among children and adolescents. Adults, however, are the primary consumers of antidepressants and antipsychotics. Moreover, the vast majority of studies examine geographic variation have done so at the level of census region or state. The few local area studies that do exist have typically been restricted to local geographic variation within a limited area.

The clearest geographic pattern to emerge from existing studies is elevated use of stimulants among children and adolescents residing in the South (Olfson et al., 2002; Hoagwood et al., 2000; Cox et al., 2003). A recent study examining geographic variation in stimulant use found that children living in the South were 1.71 (99% CI; 1.28–1.87) times more likely than children living in other parts of the country to consume stimulants (Cox et al., 2003). Studies examining local level variation in the percent of children receiving at least one stimulant prescription in California and Michigan found that stimulant use varied by nine- and ten-fold, respectively (Rappley et al., 1995; Habel et al., 2005). Variation in the number of stimulant prescriptions written to children in counties in Michigan varied by close to 30-fold (Lin et al., 2005). This local variability far exceeds what has been observed between states and census regions, suggesting that further investigation into local geographic variation could be important.

Compared to stimulants, there is not a clear geographic pattern in antipsychotic use. A survey of office visits resulting in

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a prescription for an antipsychotic between 1995 and 1997 found that 35.7% (95% CI: 29.5–41.9) of such visits occurred in the South, 20.7% (95% CI: 15.5–26.0) in the Midwest and 17.8% (95% CI: 12.9–22.8) in the West. A more recent study, however, found that use was significantly lower in the South and West relative to the Northeast (Wang and Farley, 2009). Thus, studies examining large-scale geographic variability in antipsychotic use are inconclusive. To our knowledge, no study has analyzed small area geographic variation in antipsychotic use. Accordingly, the relative size of local level geographic variance versus state level variation in antipsychotic use remains unknown.

Similarly, studies of the geography of antidepressant use have not produced consistent results over time or across populations. Antidepressant prescribing rates among children and adolescents in 1997 and 2002 were consistently higher in the Northeast (Olfson et al., 2002; Vitiello et al., 2006). However, a study of antidepressant use among adults conducted in 2006, found no clear regional geographic pattern in use. Utilization varied widely, however, from 18.4% of adults in Utah to 9.1% in New York (The Express Scripts Research and New Solutions Lab, 2012). A study conducted in eleven regions in California found a ratio of high use to low use of 1.6, which led the authors to question why there was little geographic variability in medication use relative to the large variability typically observed for diagnostic and surgical procedures (Dubois et al., 2002).

Geographic variability in mental health medication utilization likely arises from a complex causal web that includes the composition of the population, underlying prevalence of mental disorders, mixed opinions about the appropriateness of treatments and their efficacy, and so forth. Thus far, the literature has primarily provided possible explanations, rather than systematic investigations of factors associated with geographic variability in the use of mental health medications. In a study that examined variability in prescribing of medications commonly used to treat five conditions, including antidepressants, Dubois et al. (2002) hypothesized that geographic variability could arise for five possible reasons: financial incentives, impact of managed care, unique characteristics of their study site, study design, or pharmaceutical marketing and education efforts. Regarding factors that could affect antipsychotic prescribing it has been suggested that geographic variation may have been due to differences in physician training backgrounds and regional and state-specific policies on antipsychotic drug use (Patel et al., 2005).

Underlying prevalence may play a key role in geographic variation. Prevalence rates of depression have been found to vary by more than three-fold across states from 4.8% in North Dakota to 15.0% in Puerto Rico (CDC, 2010). Similarly, in 2007 attention deficit hyper activity disorder (ADHD) prevalence ranged from a low of 5.6% in Nevada to a high of 15.6% in North Carolina. Thus, at the state level there is considerable variability in prevalence. However, a growing body of literature has found that there is little or no variation in the prevalence of common mental disorders once the individual characteristics of residents are controlled for Weich et al. (2005), Pickett and Pearl (2001). Thus, the extent to which geographic variation in the use of mental health medications can be explained by variation in underlying prevalence, demographics, insurance coverage, and pharmaceutical marketing remains unknown.

This study examines geographic variability in prescribing of antidepressant, antipsychotic, and stimulant medications in the United States in 2008 using Andersen's behavioral model of health care utilization (Andersen, 1995) as a framework for understanding factors associated with the use of mental health medications. Andersen's original model (Andersen, 1968) emphasized the importance of predisposing factors, enabling or impeding factors, and need as determinants of health care utilization. Consistent with Andersen's model we examine how predisposing characteristics (race and age), enabling characteristics (income, insurance status, access to care), and need (prevalence) are associated with the geography of mental health medication use. The model has been subsequently expanded to include environmental factors, characteristics of the health care delivery system, and provider characteristics (Phillips et al., 1998). Our analysis adds to existing understandings of factors associated with health care utilization by considering marketing as a possible determinant of health care utilization. The role that marketing may play in shaping conceptualizations of need, as well as treatment decisions and consequently utilization is not typically considered in the framework of health services use. By shaping patients' and physicians' knowledge about existing treatment options, as well as perceptions about the appropriateness of given treatments, marketing efforts may be an important factor in health care utilization, especially since geographic variation in clinical judgment has been associated with geographic variation in health care use in other contexts (Sirovich et al., 2008).

Our study finds that pharmaceutical marketing efforts, access to health care, and insurance coverage appear to explain much of the geographic variation in use of mental health medications. For each of the classes of mental health medications we examine, we found substantial local level geographic variability. At the level of the three-digit zip code, use of antidepressant ranged from less than 1 in 200 residents receiving a prescription for an antidepressant to more than 80 out of 200 residents. Stimulant and antipsychotic use exhibited similar levels of geographic variability. The majority of spatial variation in use of antidepressants, stimulants, and antipsychotics (psychotropic medications) occurred at the local level and yielded a consistent geographic pattern. Using a Kullordorff spatial scan, we identified regional areas of elevated risk for use of antidepressants (RR 1.46; $p<0.001$), antipsychotics (RR 1.42; $p<0.001$), and stimulants (RR 1.77; $p<0.001$). While all of these areas of elevated risk largely centered on Tennessee, they differed from each other, as well as from the geographic patterns previously reported in the literature. After identifying systematic variation in the use of mental health medications, we then utilize multilevel regression analysis to examine factors at the three-digit zip code and state level that are associated with the use of all three classes of medications. Access to health care, insurance coverage and pharmaceutical marketing efforts appear to explain much of the geographic variation in use.

2. Data

Data for this study came from IMS LifeLink® LRx Longitudinal Prescription database, which contains de-identified individual prescriptions from approximately 33,000 retail pharmacies, food stores, independent pharmacies, as well as mass retailers. The LRx database covers over 60% of all retail prescriptions in the United States. During the analysis period, a total of 236,045,684 patients were covered by the LRx database. The subset of the data we focus on covers 24,142,989 patients who received at least one prescription for an antipsychotic, stimulant,[1] or antidepressant between January 1, 2008 and December 31, 2008. During our study period 3316,043 individuals filled at least one prescription for an antipsychotic, 5000,055 for a stimulant, and 19,239,366 for an antidepressant. We included all individuals who filled a prescription in one of these classes in our analysis, regardless of age. Both the numerators and denominators in our analyses are for the entire population. This is important since the age of a profile of

[1] Stimulants included the non-stimulant ADHD medication atomoxetine.

the groups filling prescriptions in each class of medications varies considerably and we wanted to be able to draw comparisons across classes. Of prescriptions written for antidepressants, 52.3% were written by a general practitioner (defined as family medicine, general medicine, and internal medicine), 24.6% by a psychiatrist, and the remaining 23.1% written by physicians of other specialties. The primary prescribers of stimulants were psychiatrists who wrote 35.5% of prescriptions in the class, followed by pediatricians with 23.7% of scripts, and general practitioners who accounted for an additional 22.9% of stimulant prescriptions. Finally, psychiatrist were the predominant prescribers of antipsychotics writing 63.7% of prescriptions in the class.

Each prescription in the LRx database contains a unique patient identification number, prescriber identification number, the date the prescription was dispensed, and the medication dispensed. We obtained the three-digit zip-code where the prescription was written by linking the de-identified prescriber identification number to the American Medical Association Physician Master File. While we would ideally have the three-digit zip code of the patient's residence, this is not possible with the data available. However, patients typically do not live far from a physician. In a study of 23 states with low physician to population ratios, even in the most remote counties with populations less than 2500, the mean distance to a physician was 5 miles (Rosenthal et al., 2005). Given that the mean area of a three-digit zip code was 3392.6 square miles and less than 5% of three-digit zip codes were less than 55.1 square miles, our use of the three-digit zip code in which the physician practiced is likely an adequate proxy for three-digit zip code of residence. This would not be true if people purposely selected distant physicians, but this seems unlikely. Using the three-digit zip code of the physician, we calculated the rate of stimulant, antipsychotic, and antidepressant use using population data from ESRI's Community Sourcebook as our denominator. IMS data is geographically representative. IMS patient count rates at the state level correlate with U.S. Census data at 0.99 ($p<0.001$). While IMS data is geographically representative and is representative by sex, age, and insurance coverage, there are small variations in coverage rates across three-digit zip codes. Using coverage rates obtained from IMS health we adjusted the population denominator to take into account variance in overall coverage.

3. Analysis

We first examine local level geographic variability in the use of antidepressants, stimulants, and antipsychotics by mapping utilizations rates by three-digit zip code and examining the descriptive statistics for each class using box plots. While the definition of what is "local" is certainly debatable we use it to describe analyses that use three-digit zip codes as the unit of analysis. The second goal of our analysis was to determine whether it was possible to identify clusters of stimulant, antipsychotic, and antidepressant use. To do so, we employed a Kulldorff spatial scan (Kulldorff and Nagarwalla, 1995) using an elliptical window with a medium penalty for non-compactness with SaTScan software (Kulldorff & Information Management Services, 2009). The Kulldorff scan is ideal because it adjusts for heterogeneity in the distribution of the underlying population. Further, it does not rely on pre-defined administrative boundaries, thereby circumventing the modifiable areal until problem, which results from the artificial imposition of geographic boundaries onto a continuous surface.

The scan works by constructing a series of cells based on a population radius, denoted as ξ. The radius varies continuously from 0 up to a predetermined percent of the population (R). If ξ is less than the radius, R, then the nearest-neighboring cells are absorbed into the zone. The population radius for our analyses was 25% of the population. Using a large radius helps reduce statistical and geographical uncertainty in cluster detection (Silverman, 1978). We obtained similar results using radii ranging from 10% to 50% of the population. Kulldorff and Nagarwalla's method identifies regions in which the number of users relative to the underlying population is most likely consistent with significant excess or low risk. A test statistic, which maximizes the likelihood ratio over many candidate clusters can then be expressed by:

$$LLR = Oln\left(\frac{O}{E}\right) + Oln\left(\frac{a-O}{n-E}\right)$$

where, LLR is the logarithm of the likelihood ratio, O is the observed number of users, E is the expected number of users, and n is the total number of users in the United States. The likelihood ratio assumes that the observed number of users follows a Poisson distribution. Using Monte Carlo randomizations, the likelihood ratio is then compared to the simulations to assess statistical significance. The area with the highest likelihood ratio is the primary cluster. This method obviates the problem of repeated tests, which has long been problematic for cluster detection methods (Mazumdar et al., 2010). We used SatScan to detect clusters of excess use for all three classes of medications.

After identifying a systematic geographic pattern to stimulant, antidepressant, and antipsychotic use, we wanted to see how much of the variance in use occurred at the state level versus the level of the three-digit zip code. To do this, we used a multilevel model to calculate the Intraclass Correlation Coefficient, which is:

$$\hat{\rho} = \frac{\hat{\tau}_{00}}{\hat{\tau}_{00} + \sigma^2}$$

where $\hat{\tau}_{00}$ is the variance at the state level and σ^2 is the variance among three-digit zip codes.

The second goal of the multilevel analysis was to examine whether any area level covariates were associated with the geographic patterns we identified. To do this, we used a multilevel model where the dependent variable was the rate of use in the three digit zip code and covariates were measured at the three-digit zip code when possible and at the state level if data were not available for three-digit zip codes. All analyses were run in HLM 6. A multilevel model was necessary for our analysis since three-digit zip codes are nested in states.

Based on prior research that has found differences in use of mental health medications by race, age, and income level (CDC, 2010; Olfson et al., 2002; Zito et al., 2007), we included the percent of the population that was African American, Hispanic, Asian, or of another racial background, percent of residents over 18 years of age, as well as the median household income of the three-digit zip code in our analysis since these individual level characteristics likely aggregate to influence rates of use. In addition, we included the population density since urban–rural differences in use have consistently been identified (Wang and Farley, 2009; Zuvekas et al., 2006). All of these covariates were calculated using data from the 2008 ESRI Community Sourcebook. Finally, to identify whether access to health care was associated with patterns of use, we included the number of physicians per 10,000 residents. We choose to use the total density of physicians, rather than one particular type of physician specialty (e.g., psychiatrist), since there is not a consistently dominant prescribing specialty for all of the medications of interest. In addition, physician density and the density of psychiatrists highly correlated (0.80, $p<0.01$). Data on physician density was obtained from the AMA Directory of Physicians in the United States.

We were further interested in the role that pharmaceutical marketing, insurance coverage, and underlying prevalence would have on rates of psychotropic utilization. Unfortunately, these variables were only available at the state level. We obtain state level pharmaceutical marketing expenditure data from the Dollars for Docs Database (ProPublica, 2011). In an effort to increase transparency, several pharmaceutical companies have begun to disclose payments made to physicians for meals, consulting, speaking fees, travel, and gifts. The 2009 fiscal year was the first time that companies began disclosing payments. During the 2009 fiscal year, five companies (Cephalon, Eli Lilly, GlaxoSmithKline, Merck and Pfizer) reported payments to physicians. GlaxoSmithKline only reported payments made in the second through fourth quarters and Merck and Pfizer only reported for the third and fourth quarters. Companies do not provide information on the specific drug or class for which payments were made so marketing expenditures are the expenditures for all drugs. While we would have liked to measure payments prior to or at least concurrent with our study period, it is not possible given the date range of our data and the timing of disclosures. We conducted two robustness checks to see whether it was reasonable to assume that the distribution of payments over time were relatively constant. First, we compared the distribution of payments during the 2009 fiscal year to the 2010 fiscal year. The correlation of the payment distribution was 0.99 ($p < 0.001$) across the 2 years. This suggests that there is minimal geographic variation in payments over time, which increased our confidence in using payment data from October 2008 to September 2009. In addition, we have data on antipsychotic prescribing that extends through 2010. Using this data we reran our analysis with payment data measured prior to the prescribing dates and obtained almost identical regression results, which further assuaged our concerns about the time period of the marketing expenditure data. To further examine whether the importance of marketing efforts varied depending on the density of physicians in a three digit zip code, we included a cross-level interaction of marketing dollars and physician density. At the state level, we also obtained insurance coverage from the Census. State-based ADHD prevalence among 4–17 year olds in 2007 (CDC, 2010a) and the age standardized percent of adults meeting the criteria for any form of depression in 2008 (CDC, 2010b) were obtained from the Centers for Disease Control and Prevention. The age groups for both of these variables were defined by the CDC. We do not know of any other data source for state-level ADHD or depression prevalence. In order to increase the interpretability of the model results, all covariates were grand mean centered.

4. Results

Stimulant, antidepressant, and antipsychotic use had a clear regional pattern but also displayed considerable local area variation. Fig. 1 maps utilization rates at the three-digit zip code using Jenks breaks. For all three classes of medications, use was lowest in the western part of the country. Stimulant use, in particular, had very little penetration in the west. In addition to lower use of all three medications in the west, there was substantial local geographic variability.

The box plots in Fig. 2 show the extent of local level geographic variability in the use of mental health medications. At the level of

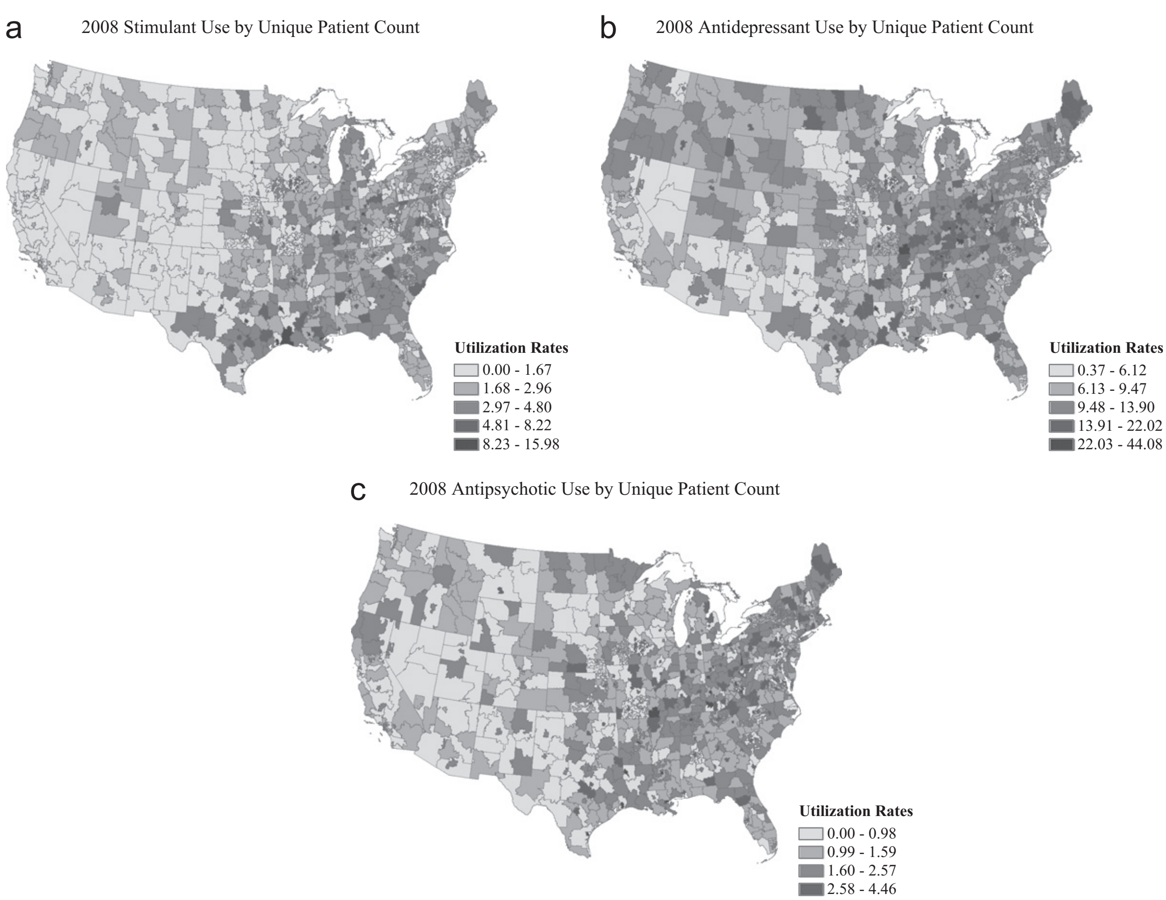

Fig. 1. (a) Map of stimulant use in 2008 by three-digit zip code. (b) Map of antidepressant use in 2008 by three-digit zip code. (c) Map of antidepressant use in 2008 by three-digit zip code. *Source:* Authors calculations from IMS LifeLink® Information Assets-LRx Longitudinal Prescription Database, 2008, IMS Health Incorporated. All Rights Reserved.

the three-digit zip code, the mean percent of the population filling at least one prescription for a stimulant was 2.6(SD 1.9). Use in zip codes in the 75th percentile was 2.4 times greater than use in zip codes in the bottom 25th percentile. There were numerous extreme observations with a maximum utilization rate of 16% in Cape Cod, Massachusetts. On average, 10.4% of residents in three-digit zip codes filled a prescription for an antidepressant in 2008. There was less variability across zip codes in use of antidepressants. Use in the top 25% was 1.8 times greater than utilization in the bottom 25th percent of zip codes. Antidepressant use was highest in Alexandria, Virginia where two out of five residents received an antidepressant. The mean use of antipsychotics was 0.8 (SD 0.6). The interquartile range was 0.4 to 1, a two and a half fold difference. Gainsville, Florida had the highest utilization rate at 4.6% of residents.

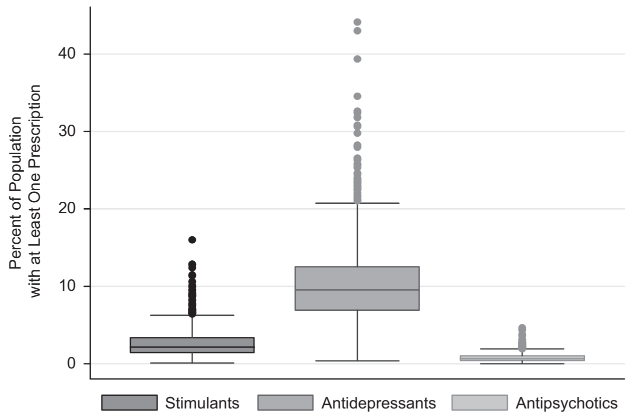

Fig. 2. Box plot showing the mean and interquartile range of the percent of persons in a three-digit zip code who filled at least one prescription for a stimulant, antidepressant, and antipsychotic. *Source:* Authors calculations from IMS LifeLink® Information Assets-LRx Longitudinal Prescription Database, 2008, IMS Health Incorporated. All Rights Reserved.

Local geographic variability in utilization presented in Fig. 1, particularly in the eastern part of the country, belies very clear geographic clusters in use. Using the Kuldorff spatial scan, which does not rely on pre-defined administrative boundaries, significant clusters were identified for all three classes of medications. These clusters are mapped in Fig. 3. Consistent with prior research, a cluster of elevated risk was identified in the south. Residents living within this region were 77% more likely than people residing outside the cluster to be using stimulants (RR 1.77; $p<0.001$). The antidepressant cluster was geographically similar to the stimulant cluster, though the antidepressant cluster did not penetrate into Texas. The relative risk within the antidepressant cluster was 1.46 ($p<0.001$). The cluster of

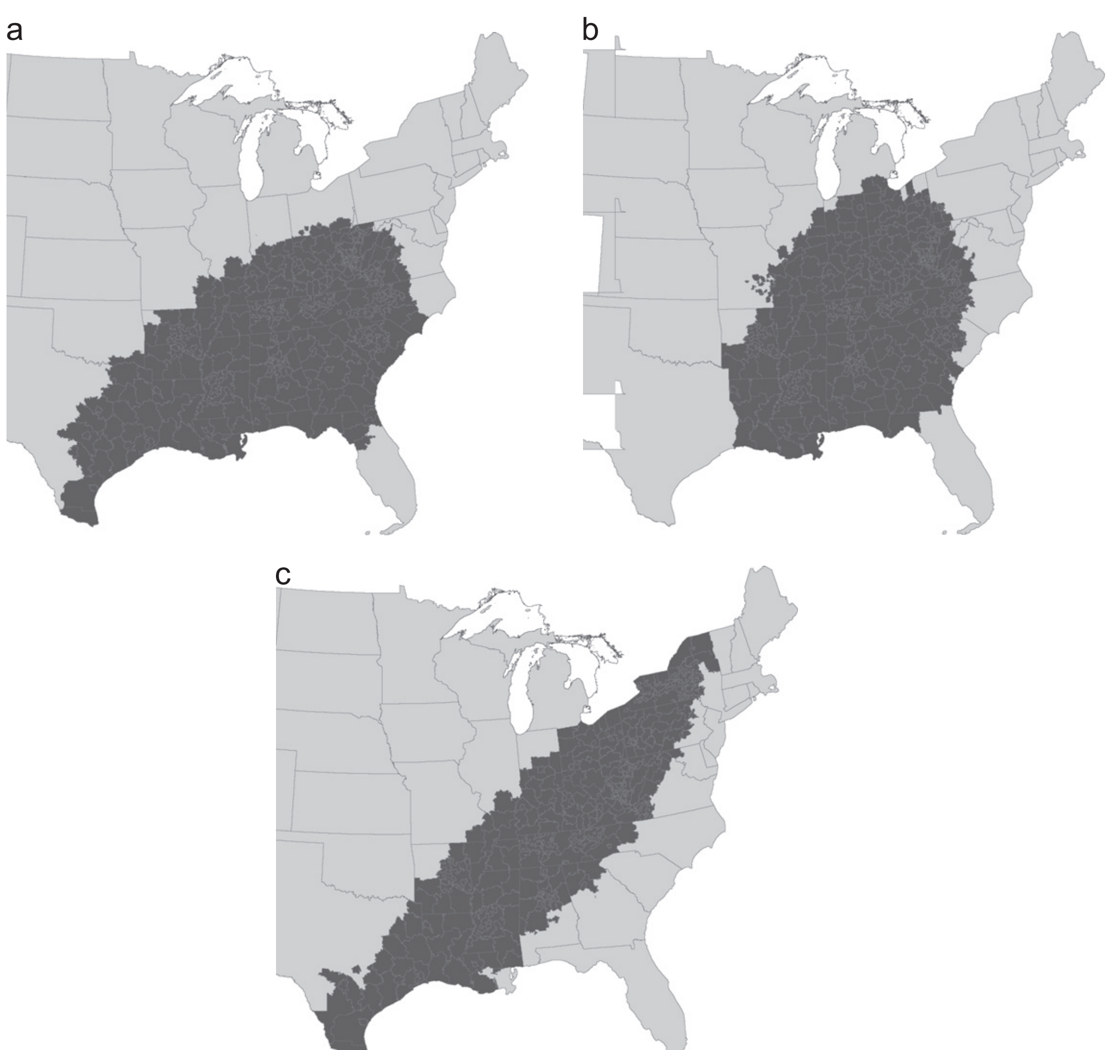

Fig. 3. (a) Stimulant use cluster. Relative risk in the cluster was 1.77 ($p<0.001$). (b) Antidepressant use cluster. Relative risk in the cluster was 1.46 ($p<0.001$). (c) Antipsychotic use cluster. Relative risk in the cluster was 1.42 ($p<0.001$). *Source:* Authors calculations from IMS LifeLink® Information Assets-LRx Longitudinal Prescription Database, 2008, IMS Health Incorporated. All Rights Reserved.

antipsychotic use differed substantially from the antidepressant and stimulant use cluster, largely covering Appalachia and continuing south (RR 1.42; $p<0.001$).

After identifying both geographic variation regionally and at a smaller geographic scale, we wanted to quantify how much variation occurred at each level and then see what variables were correlated with the spatial patterns we observed. For stimulants, the intraclass correlation coefficient (ICC) for stimulants was 0.18. Thus, 18% of the variance is attributable to between state differences and the remaining 82% of the variance occurs at the zip code level. Similarly, the ICC for antidepressants and antipsychotics were 0.12 and 0.23, respectively. Accordingly, the vast majority of spatial variation occurred between three-digit zip codes, rather than between states.

Turning to the multilevel models presented in Table 1, which included both zip code level and state covariates, the covariates in each set of models explained a considerable amount of geographic variation in the utilization of stimulants, antidepressants, and antipsychotics presented in Fig. 1. For all three classes of medications local access to health care, measured as the number of physicians of any specialty per 10,000 has the strongest association with use. Relative to areas in the bottom quartile of physician density, areas in the top quartile had predicted use rate that were 80% higher for stimulants, 56% higher for antidepressants, and 73% higher for antipsychotics, after controlling for all other covariates in the model. At the three-digit zip code level, characteristics of the population also had significant associations with rates of use, though these patterns were not consistent across classes of medications. Utilization rates of antidepressants and stimulants tended to be higher in areas that were predominantly white. There was no significant association between racial composition and rates of antipsychotic use. Antipsychotics were also the only class that had a significant association between utilization rates and per capital income, as well as population density. Antipsychotic use was more common in rural areas and locals with lower average per capita incomes. Collectively, the Level 1 covariates explained 54%, 59.2%, and 68% of the within state variance in stimulant, antidepressant, and antipsychotic use, respectively.

At the state level, there was a positive and significant association between pharmaceutical marketing expenditures and rates of utilization for all three classes of mental health medications. Predicted rates of use in states in the top quartile of marketing expenditures were 11% higher for stimulants, 13% higher for antidepressants, and 10% higher for antipsychotics relative to areas in the bottom quartile of marketing expenditures after controlling for all other covariates in the model. Our study demonstrates that marketing efforts have a substantial impact on utilization rates. Moreover, we found that the association between utilization rates and marketing efforts varied depending on the density of physicians in the area.

Surprisingly, prevalence rates were not associated with rates of antidepressant use. However, there was a positive and statistically significant association between rates of stimulant use at the three-digit zip code and ADHD prevalence at the state level.

5. Conclusion

This is the first study to examine local and regional level geographic variation in the utilization of stimulant, antidepressant, and antipsychotic medications in the United States. Clusters of elevated use that centered on Tennessee and crossed numerous state boundaries were identified for all three classes of medications. People residing within these clusters were 77% more likely to fill a prescription for a stimulant, 46% more likely to fill an antidepressant prescription, and 42% more likely to receive an antipsychotic prescription than residents outside of the cluster. Local level geographic variation, however, was far greater than regional variation. For all three classes of medications, the interquartile range of use by three-digit postal code varied by close to two fold.

Geographic patterns in the use were only correlated with underlying prevalence for one of the classes of medications we examine. However, utilization of stimulants, antidepressants, and antipsychotics showed a consistent and positive association with local access to health care and pharmaceutical marketing efforts. Further, the effect of marketing efforts varied with the density of physicians in the area. Two factors could possibly account for the association. The simplest explanation is that pharmaceutical companies do not evenly spread spending across physicians in a state, so in areas where there is a higher physician density pharmaceutical companies are more likely to direct marketing dollars per doctor to that area. Alternatively, spillovers in pharmaceutical marketing expenditures could also create the observed association, if physicians who are targeted by pharmaceutical companies also interact more often with other physicians in areas that have a greater physician density. If the conversation

Table 1
Factors associated with the rate of stimulant, antidepressant, and antipsychotic use at the three-digit zip code. *Source:* Authors calculations from IMS LifeLink® Information Assets-LRx Longitudinal Prescription Database, 2008, IMS Health Incorporated. All Rights Reserved.

	Stimulants		Antidepressants		Antipsychotics	
	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
Intercept	2.66	< 0.001	10.6	< 0.001	1.73	< 0.001
Three-digit zip code						
Physicians/10,000	0.07	< 0.001	0.21	< 0.001	0.04	< 0.001
Population density	0.01	0.62	−0.01	0.52	−0.01	< 0.001
% African American	−0.003	0.64	−0.07	< 0.001	0.001	0.94
% Asian	−0.03	< 0.001	−0.14	< 0.001	−0.003	0.28
% Hispanic	−0.02	0.09	−0.08	0.001	−0.001	0.99
% Other	−0.02	0.40	−0.02	0.63	−0.02	0.10
% White (Reference)	–	–	–	–	–	–
Per capital income	0.16	0.19	−0.43	0.09	−0.24	< 0.001
% Over 18	−0.07	< 0.001	−0.06	0.19	0.004	0.63
State level						
Marketing expenditures	0.02	0.04	0.08	< 0.001	0.01	< 0.001
Prevalence	0.14	0.01	−0.25	0.19	–	–
% Insured	−0.07	0.01	−0.14	0.001	0.01	0.46
Cross level						
Marketing × Physician density	0.001	< 0.001	0.003	< 0.001	0.001	0.001

turns towards prescribing behavior, marketing efforts aimed at one physician could spillover and have a greater impact on prescribing behavior in the area. Likely, both of these factors are operating at the same time, though further research will be required to distinguish between them.

Our study has several limitations. First, we do not have individual level data on the complete population, which necessitated conducting our analyses with aggregated individual characteristics. Ideally we would be able to control for the characteristics of individuals in our analysis. Second, our analysis relied on the three-digit zip code in which the physician practiced, rather than the practice location of the physician. In addition, three-digit zip codes are often larger than counties which have been used as another unit of analysis in other studies of local variation in mental health medication use. However, datasets at the county level have typically been limited to a single drug in a single state. Finally, data on marketing was only available at the state level and did not perfectly correspond to the study period.

One persistently puzzling question in medical geography is why states in the South, particularly in the "stroke belt," have poorer health outcomes. Since it was first identified over 50 years ago, the eleven state region in the southeastern United States known as the "stroke belt" has also been found to have higher rates of lung cancer, sepsis, diabetes, and most recently, cognitive decline. While the geographic clusters identified in our analysis do not perfectly match the contours of the stroke belt, the overlap suggests that future research examining possible connections and causal links between the geography of health outcomes generally and the geography of mental health treatment could prove insightful. This is particularly true given the lack of or weak association between prevalence and treatment of depression and ADHD we find in our study. While a host of factors ranging from socioeconomic status to more proximate causes likely underlie these common geographic patterns, our work suggests that access to clinical care and pharmaceutical marketing may also be critical factors. While Andersen's behavioral model of access to care and subsequent extensions has recognized the importance of predisposing characteristics, need, access to care, the nature of the delivery system, and characteristics of the provider in explaining health care use, until recently less attention has been given to how local contextual factors may influence clinical judgment and thereby geographic treatment patterns (Sirovich et al., 2008). Our work found that marketing expenditures were associated with the geographic patterns of psychotropic utilizations. Future research should examine whether marketing efforts may be another key factor for understanding the common geographic patterns in health disparities, medication use, and health care utilization.

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