

EXPLORATION OF THE VARIATION IN PRESCRIBING BEHAVIOR: A MIXED- METHODS RESEARCH

by

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(Under the Direction of Matthew Perri III)

ABSTRACT

Healthcare spending in the United States has been among the highest of all countries worldwide. One of the big elements of patient care is prescribing. Prescribing cost has been increasing in the United States for the past ten years and reached \$329 billion in 2016. Thus, it is important to understand what medications prescribers are relying on in order to potentially decrease the growth rate of prescription cost of the United States.

A sequential explanatory mixed methods study with the focus of exploring the existence of “small individual formulary” phenomenon and a retrospective cross-sectional data analysis were conducted. The mixed methods study was conducted in two phases with the first phase being secondary data analysis using 2015 Medicare prescriber utilization and payment data for Part D prescribers. Prescription medications were ranked in descending order by the number of claims associated with a specific medication. Prescribing breadth was reflected by the number of prescriptions which accounted for the top 80% of total claims. Concentration, or the frequency of prescribing of each drug, was measured by Herfindahl - Hirschman Index (HHI). The second phase of the mixed method study was 11 semi-structured interviews with active prescribers with the focus on prescribing decision making.

The retrospective cross-sectional data analysis employed the 2015 National Ambulatory Medical Care Survey (NAMCS) data. Variation in prescribing was measured using HHI and the number of unique prescriptions identified from all patient visits of each physician. The prescribing behavior was categorized as concentrated when the HHI index was greater than or equal to 1500. Logistic and Poisson regressions, weighted by survey physician weights, were conducted at the physician level to identify significant factors of variation in prescribing.

The first phase of mixed method study included a total of 651,736 prescribers, whose results, alongside the results of the second phase, suggest that prescribers rely on a limited number of guideline-recommended cheap medications in regular practice. The number of visits associated with the physician, the ability of the practice to record patients' medications and allergies, the ability of the practice to reconcile medication list were significantly associated with variation in prescribing.

INDEX WORDS: Prescribing behavior, prescribing decision making, mixed methods

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DEDICATION

I dedicate this dissertation to my dad who has always held an open mind towards what I can do as a Chinese female. To Annelie who has been so supportive and loving through all the years. To Misty who helped so much, when I felt so lost about what to do, to all my current and previous colleagues in the PHSOP program at University of Georgia who are always nice and ready to help each other. You all made this happen.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

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Statement of the problem

From patients' perspective, they expect prescribers to maximize the medical benefit and minimize the out-of-pocket cost when they are prescribed with treatment medications. But the choice of one prescription among a group of prescriptions in the same therapeutic class may encompass many facets. For example, choosing an appropriate antidiabetic agent may involve the consideration of efficacy, hypoglycemia risk, weight gain risk, other side effects, cost and so on.¹ If prescribers fully consider the preference of patients, it is their responsibility to discuss and confirm patients' treatment preference, consider all possible alternatives, identify the consequences associated with each alternative, examine the trade-offs between the alternatives and then make a final optimal treatment plan.²

When classic decision making theory is applied in the medical field, it assumes that prescription decision making happens in the way mentioned above. The process is fully rational with all the related information. However, prescriber in the real world may neither have full information to accurately diagnose patients or have all medical information about every treatment alternative. The uncertainty in each step hinders the complete use of rational decision

making. Another barrier to rational decision making is that prescribers may have to make rapid decisions because they have to see many patients within a limited time range. Previous research has shown that rapid medical decision making is aided by various kinds of heuristics, which are strategies that provide shortcuts to quick decisions. Recognition heuristics and fluency heuristics suggest that memory plays a significant role in final decision making. Drugs a physician can recall from memory and are more familiar are more likely to be prescribed.³

Previous research suggests that prescribers might only consider a limited set of prescription choices and operate within what has been termed a “small individual formulary” (SIF).⁴ The prescribing behavior tends to be highly habitual for historical preference of prescribing behavior has been demonstrated to be a highly effective predictor of future prescription choices.⁵ However, there have not been in depth studies exploring the nature and use of SIF by prescribers.

Existing prescribing decision making models

Most of the existing prescription decision models were developed from the perspective of pharmaceutical companies, attempting to understand how marketing activities and sales representative interactions influence prescription volume of the promoted drugs.⁶ Models and conceptual frameworks which are emerging in prescription decision making may not be adequate in understanding healthcare providers in today’s health care systems. A model published in 1990 by Raisch et al., was very comprehensive in incorporating the influence from administrative programs, pharmaceutical companies, colleagues, education, organization and patient characteristics as well as physicians cognitive process.⁷ The physician cognitive process was modeled as results of attitudes (beliefs about possible outcomes and evaluation of these

outcomes) and subjective norms (whether a drug should be prescribed) associated with a specific drug, which also assumes a weighted linear regression thinking process incorporating aspects of possible candidate drugs. The only model we found that dealt with the possible existence of small individual formularies considers prescription decision making to be a process from past experience and analytical thinking to a choice within a “therapy script”.⁸ While the concept of therapy script is consistent with the concept of small individual formulary in the proposed study, it did not attempt to answer the question of how therapy script form and change. It could not address the situation when a physician prescribes out of this therapy script as well.

The phenomenon of small individual formulary in prescribers

There has always been a prevalent perception that prescribers only prescribe a small number of drugs in their daily practice, especially in the population of general practitioners. It was observed that physicians in ICU normally prescribe only one favorite antibiotic for patients with pneumonia despite the existence of other possible alternative options.⁹ The World Health Organization (WHO) suggested that it is a good practice to repeatedly use a limited set of medications in order to manage a large amount of patients in a relatively short time. The concept of P-drugs (personal drugs) by WHO was the set of drugs a doctor chose and was familiar with as the major drug choices of daily practices.¹⁰

The literature suggests that some prescribers have recognized that they prescribe a limited group of drugs.¹¹⁻¹³ A more recent qualitative study also indicates that prescribers perceive themselves to only prescribe drugs they can think of immediately and take habitual prescribing behavior as granted.¹⁴ When researchers try to undercover the cognitive process of prescribing by asking a group of general practitioners speak out the thinking process while making decisions

for patients, they found out that the general practitioners attempted to consider only one possible options in 57.4% of the cases while they considered two options 25.6% of the time.¹⁵ The decision process tended to be highly habitual without gathering full information and weighing the potential options out of rationality. However, most qualitative studies on this topic were decades old and may not be representative of current physician practice patterns.

Other studies have examined the breadth of prescriber prescribing using prescription data or claims data. Joyce et al., examined the number of drugs physicians prescribe in 10 therapeutic classes within 146 different insurance plans. Prescribers were found to prescribe 3 to 4 different drugs 75% of the time in each therapeutic class, which reflects a surprisingly broad prescribing spectrum. Considering that not all prescribers prescribe all the mentioned therapeutic classes, it is not clear whether the examined prescribers operate in a limited list of prescriptions overall.¹⁶ In contrast, two other studies found a high concentration on a few favorite kinds of drugs in most prescribers treating psychotic disorders, which is in line with the belief of the existence of a small individual formulary.^{17,18} Overall, a healthcare provider's prescription writing history was found to be concentrated to a list of their favorite drugs (the small individual formulary) accompanied by a large number of rarely prescribed drugs.¹² Prescribing behavior varies substantially among prescribers. While some prescribers rely heavily on a few agents, others may prescribe a broad spectrum of familiar drugs.¹⁸ The variance can partly be explained by the fact that a single prescriber both chooses medications for new patients, and repeats the medications chosen previously by themselves or other prescribers if the patients were transitioned from other providers.¹⁹ Thus the number of drugs seen prescribed for new patients was shown to be more concentrated than the number of drugs prescribed for all patients.¹⁹ This finding is consistent

with the findings of other studies that prescriber past prescription history is the best predictor of their prescription choice for the new patients.^{5,20,21}

The appropriateness of use of small individual formulary has seldom been inspected in the literature despite that it has been recognized by the World Health Organization (WHO) as a standard of rational prescribing. Some researchers were able to relate the breadth of prescribing behavior with duration of treatment and prescription cost and found modest relevance using claims data.^{16,17} No study has scrutinized the effect of small individual formulary on other patient-level health outcomes. For example, the impact of a small individual formulary has not been evaluated for its economic impact on health outcomes (underuse, shortages, etc.).⁹

The factors contributing to the use of small individual formulary

Time Limit

Physicians are primarily the prescribers in the United States. Most health systems in the United States use one or a mixture of six payment models to pay physician. The payment models used include fee for service, capitation, bundled payments, comprehensive primary care payment, concierge care and relative value units. Fee-for service (FFS) is a payment model where services are paid for separately, which motivates physicians to provide more treatments to increase the quantity of care. In contrast with the FFS model, physicians are paid according the number of patients they see in capitation, bundled payment and comprehensive primary care payment models. These three models encourage physicians to increase the number of patients and reduce investment in individual patients. Without incentives to invest more time, physicians naturally decrease their time spent with patients using models other than value-based framework or concierge care. Concierge care, which emphasizes spending more face-to-face time with

patients, generally has been adopted by less than 5% of physicians.²² The value-based payment model is a payment model that strengthens the quality of care and the patient outcomes. With this pay structure, it's possible for a physician caring for a few patients to earn more than a physician working with very general patient cases. However, the policy of value-based drug pricing is still being developed and has not been put into use.

Physicians have been reporting the problem of lacking time to meet with patients since 1990s.²³ In the new era of healthcare, pressure on time is even more severe. Some physicians are seeing an influx of patients after the implementation of the affordable care act.²² The increased number of patients may also result from the retirement of other physicians. The current physician work force consists of 11% between 65 and 75 years old and 26% between 55 and 64.²⁴ Considering that a big proportion of physicians retire between 60 and 69, the retirement rate of active physicians in their 60s may put more pressure on the others.²⁵ Another pressure on meeting time between physicians and patients comes from the use of electronic health records system. Studies found that physicians contribute more of their working time to working on EHR system than meeting patients.^{26,27}

Overall from the physicians' perspective, it is more efficient to spend less time on decision making to increase the volume of patients and services thus increasing revenues. The Medscape compensation survey consisting of more than 19,200 physicians in more than 27 specialties shows that 59% of their respondents spend 13-24 minutes with patients while 11% spend 25 minutes or more.²² With limited meeting time between physicians and patients, time left for prescription decision making may not be sufficient. Any activity that prolongs the prescription decision making process would act as barriers to the achievement of efficiency in physicians' daily work.

Communication Cost

Communication with patients to determine their preferences for prescriptions can be challenging. A prescription choice encompasses a possibly long list of potential candidate factors including cost, insurance coverage, effectiveness, side effects, etc. The situation can be more complicated when multiple side effects exist or patients have comorbid conditions. Eliciting all aspects of essential information from physicians, helping patients understand the information and weigh each characteristic of a prescription thus would be extremely time-consuming. What makes the communication more difficult is the distrust of patients in physicians and healthcare institutions overall, unwillingness to talk about adherence and the rising rate of patient request for a specific brand name.²⁸ The trust issue is an obstacle for physicians to gather enough clinical and preference information about their patients. The resistance to discussing adherence topic makes the physician-patient relationship more vulnerable and decreases the possibility to solve the adherence problem by switching prescriptions. Physicians may feel pressured and uncomfortable with patient requests as well.²⁹ Although shared-decision making is an important topic in healthcare, it takes extra time and effort on the part of physicians. Without enough time to talk about patients' treatment goals and preferences over various outcomes of a few prescription alternatives, a well-established small individual formulary that works for most of the patients would be an effective strategy to avoid customized prescription decision making for all patients.

Learning Cost

There is always more than one prescription choice for a disease. Sometimes, there are various choices in each of the many therapeutic classes for the same disease. Physicians may not be familiar with every therapeutic class, not to say many drugs from the same therapeutic class. The reason is that a physician is unlikely to learn about the efficacy and side effect information of all the drugs for the same indication simultaneously. Physicians will learn about one drug before another. If a physician gets familiar with the medical information of a specific brand name drug and has had positive experience, they will continuously use this brand name for all the patients with the same medical situation. There is no need to learn about the competitors of this brand name drug anymore because the one in use works reasonably well for most patients. It is possible that another drug from the same therapeutic class or from another therapeutic class works better than the ones physicians currently use for some of the patients. But the ones physicians currently use still works although might come with more side effects or take more time to be effective.

Selecting prescription choices that are at the top of physicians minds is common practice. When physicians prescribe the same prescriptions from a small individual formulary over time their decision making process is more efficient and requires less cognition in drug selection since the alternatives have already been evaluated and incorporated into the small individual formulary.

Searching Cost

Physicians might be faced with more challenges when they attempt to learn about other prescriptions alternatives. As mentioned above, many of the clinical circumstances can be highly

complex. Searching for new information might be essential if the treatment options are to be customized. The barriers encountered by physicians during the information searching process may eventually contribute to the adoption of small private formulary.

Numerous possible sources of medical information have been identified that are potentially relevant to helping physicians seek information regarding prescription options. These include continuing education courses, mass media, patients, journals, textbooks, pharmaceutical representatives, colleagues, specialists, and computerized databases, etc.³⁰ However, while we see more and more research studies, physicians may feel overwhelmed by the volume of the literature. Further, getting relevant information from this literature may be difficult.^{31,32}

With the widespread use of the internet, up-to-date prescription information can easily be accessed, however, this also means physicians may have more information than is needed. It has been found that although physicians commonly attempt to use internet to for medical information seeking, there are too much information to scan and too little information specific to their questions when they search online.³³ Validating for credibility of the information remains to be another problem.³³

The various designs of insurance plans can be another factor contributing to the complexity of this issue when current physicians are faced with increasingly complicated billing systems. All the patients that one physician see in a week may belong to several insurance plans. Some of the patients might use plans that include prescription coverage while others use a different plan solely for prescriptions. All these plans have different payment policies and may cover different drugs for the same indication. That is why physicians may take extra effort to search for drug payment information if they want to consider cost for their patients. A 2004 study suggests that physicians,³⁴ perceive frustration when dealing with insurance plans and this

is a major contributor to physician burnout.³⁵ It was found out in a survey of physicians that they spent 3 hours on average interacting with health plans and the duration has been increasing over the years.³⁶

With all the barriers to new scientific information above, busy physicians may not even think of searching about new or alternative treatment options, let alone dig deep into the relevant information. When they attempt to obtain more information, they tend to search information about medical information they have had experience with than information that they have not learned about before.³⁰

Thinking Cost

From a patient's perspective, one would expect that his/her physician gather all his/her information, know all the knowledge about each possible prescriptions and integrate the collected information to arrive at a rational prescription choice. Thus information processing can be modeled as a linear multiple regression, which is rather complex because of the number of independent variables used, including patient demographics, diagnoses, disease characteristics, patients medical history, possible prescription alternatives, the characteristics of each prescription alternative, patient preference, etc.³⁷ In real life, physicians as human beings are limited by their information capacity thus inevitably use heuristic rules to make therapeutic decisions.³⁸

It is studied as the topic of heuristic decision making today. A heuristic is a simple decision strategy which uses a few pieces of relevant information to make an acceptable decision.

³⁹ Using a small individual formulary, in this case, is an example of heuristic decision making applied in medical field.

Memory process has been postulated to be important in the recognition heuristic and the fluency heuristics. The recognition heuristic is assumed to employ simply recognition of items to make quick choices, whereas the fluency heuristic is assumed to use recognition speed to make choices. The fluency heuristics are believed to be embedded into recognition heuristics.⁴⁰ The logic of a small individual formulary is in line with recognition and recollection heuristics as only the drugs which can be remembered will be prescribed in the real world. In some extreme cases, the prescribing behavior might be explained by take-the-first heuristic, which means the decision maker may just choose the first option that they can remember. This has been seen in a study of general practitioners' antibiotic prescribing decision making where the interviewed general practitioners indicate that they would prescribe the first antibiotic they can remember.¹⁴

Based on memory of possible prescription alternatives, physicians still have to choose one if there are two or more possible solutions. Take-the-best is a one-reason decision rule, where decision making is based on a single important factor.⁴⁰ Although this heuristic rule has not been tested or applied in the field of prescription decision making, it has been proved to be an accurate predictive tool for decision making.⁴⁰

Another heuristic which might explain the behavior of being persistent of the same drugs is the number-of-alternative heuristics.³⁸ The number of options physicians can choose for the same disease might influence the way they choose, which is especially important in the time where various treatment options exist. Redelmeier & Shafir⁴¹ experimented on the one NSAIDS option/ two NSAIDS options vs. the original plan which is referred to specialist for possible surgery. The result showed that adding an option increased the likelihood to employ the original treatment plan, which is consistent with the result of another study on the effect of number of options on treatment decision.⁴² A possible explanation is that “the uncertainty in deciding

between two similar medications led some doctors to avoid this decision altogether and recommend not starting any new medication”.⁴³ The finding is also consistent with our small individual formulary theory as physicians are increasingly more prone to the original treatment option when more options emerge.

Modifiable factors influencing physicians prescribing behavior

As mentioned above, choosing prescriptions is a multidimensional and complicated process for physicians. Various clinical and non-clinical factors might play roles in any step of this process. Even studying from only physicians’ perspective, prescribing is still a complex mix of gained knowledge, skills and actual behaviors.⁴⁴

With the proliferation of pharmaceutical industry, there are more and more treatment choices by different companies for the same disease. Leading drug companies have been seen to maximize marketing efforts to promote the drug from their own companies. The promotion strategies can be divided by strategies targeting physicians and strategies targeting patients. Strategies targeting physicians include 1) gifts, including small stationaries, drugs samples, journals, invitation to dinners, free meals, etc.,^{5,45} 2) detailing by medical representatives and liaisons,⁴⁶ 3) sponsorship of conferences, medical events and continuing medical education,^{47,48} 4) using key opinion leaders such as influential clinicians and medical educators,⁴⁹ 5) advertising in medical journals,⁵⁰ and 6) funding related researches.⁵¹ The promotional strategies of pharmaceutical industry is entering a new era with the rise of health care information industry which enables pharmaceutical industry to access and monitor physicians’ information.⁵²

Another aspect of pharmaceutical marketing is to encourage patients to request for specific prescriptions from providers. Direct to consumer advertising has been influencing

patients to request for specific drugs in this manner for decades. Public health campaign is another marketing tool to encourage patients to request a specific drug from their physician. Overall, the marketing strategies aimed at patients emphasize how familiarity with a promoted product leads to patient requests.⁵³ It has been suggested that the pull strength of patients has a substantial effect on physicians' prescription choices.¹⁹

To disentangle the effect of marketing activities from physicians' prescribing behaviors, government and other healthcare agencies have been increasingly utilizing the strategy of formulary regulations to reshape physicians' prescription choices, which has been found to be effective in shifting the use of related drugs within a prescription plan.⁵⁴

In addition to the policies and marketing activities that can change physicians' behavior, patient and peer feedback on physicians also changes their prescribing patterns.⁵⁵ When physicians have direct access to their performance ratings by their colleagues and patients, they will be prone to change when their ratings get lower.⁵⁵

Overall, it is believed that physicians' prescribing behavior tends to be habitual. But marketing activities, educational activities, guidelines, reimbursement policies as well as patients' and colleagues' opinions can potentially change the prescribing patterns of physicians by either making physicians prescribe out of small individual formulary or further reshaping the small individual formulary.

References

1. Association AD. 8. Pharmacologic approaches to glycemic treatment. *Diabetes Care*. 2017;40(Supplement 1):S64-S74.
2. Gregory R, Peters E, Slovic P. Making decisions about prescription drugs: a study of doctor–patient communication. *Health, Risk & Society*. 2011;13(4):347-371.
3. Blumenthal-Barby JS, Krieger H. Cognitive biases and heuristics in medical decision making: a critical review using a systematic search strategy. *Medical decision making : an international journal of the Society for Medical Decision Making*. 2015;35(4):539-557.
4. Campo K, De Staebel O, Gijsbrechts E, van Waterschoot W. Physicians' decision process for drug prescription and the impact of pharmaceutical marketing mix instruments. *Health Mark Q*. 2005;22(4):73-107.
5. Beam AL, Kartoun U, Pai JK, et al. Predictive Modeling of Physician-Patient Dynamics That Influence Sleep Medication Prescriptions and Clinical Decision-Making. *Sci Rep-Uk*. 2017;7.
6. Murshid MA, Mohaidin Z. Models and theories of prescribing decisions: A review and suggested a new model. *Pharm Pract (Granada)*. 2017;15(2):990.
7. Raisch DW. A model of methods for influencing prescribing: Part II. A review of educational methods, theories of human inference, and delineation of the model. *DICP*. 1990;24(5):537-542.
8. Bissessur SW, Geijteman EC, Al-Dulaimy M, et al. Therapeutic reasoning: from hiatus to hypothetical model. *J Eval Clin Pract*. 2009;15(6):985-989.

9. Karir V, Kahn JM, White DB. Using Principles of Behavioral Economics to Mitigate Drug Shortages. *Am J Resp Crit Care*. 2012;185(11):1135-1137.
10. De Vries T, Henning RH, Hogerzeil HV, Fresle D, Policy M, Organization WH. Guide to good prescribing: a practical manual. 1994.
11. Berkeley JS, Richardson IM. Drug usage in general practice. An analysis of the drugs prescribed by a sample of the doctors participating in the 1969-70 North-east Scotland work-load study. *J R Coll Gen Pract*. 1973;23(128):155-161.
12. Patterson J. How many drugs do I use? *The Journal of the Royal College of General Practitioners*. 1972;22(116):191.
13. Wilson DG. Domiciliary prescribing. *J R Coll Gen Pract*. 1971;21(110):558.
14. Grant A, Sullivan F, Dowell J. An ethnographic exploration of influences on prescribing in general practice: why is there variation in prescribing practices? *Implement Sci*. 2013;8.
15. Denig P, Witteman CLM, Schouten HW. Scope and nature of prescribing decisions made by general practitioners. *Qual Saf Health Care*. 2002;11(2):137-143.
16. Joyce GF, Carrera MP, Goldman DP, Sood N. Physician Prescribing Behavior and Its Impact on Patient-Level Outcomes. *American Journal of Managed Care*. 2011;17(12):E462-E471.
17. Hodgkin D, Merrick EL, Hiatt D. The Relationship of Antidepressant Prescribing Concentration to Treatment Duration and Cost. *J Ment Health Policy*. 2012;15(1):3-11.
18. Tang Y, Chang CCH, Lave JR, Gellad WF, Huskamp HA, Donohue JM. Patient, Physician and Organizational Influences on Variation in Antipsychotic Prescribing Behavior. *J Ment Health Policy*. 2016;19(1):45-59.

19. Buusman A, Kragstrup J, Andersen M. General practitioners choose within a narrow range of drugs when initiating new treatments: a cohort study of cardiovascular drug formularies. *Eur J Clin Pharmacol.* 2005;61(9):651-656.
20. Kalkan A, Husberg M, Hallert E, et al. Physician Preferences and Variations in Prescription of Biologic Drugs for Rheumatoid Arthritis: A Register-Based Study of 4,010 Patients in Sweden. *Arthrit Care Res.* 2015;67(12):1679-1685.
21. Davies NM, Gunnell D, Thomas KH, Metcalfe C, Windmeijer F, Martin RM. Physicians' prescribing preferences were a potential instrument for patients' actual prescriptions of antidepressants. *J Clin Epidemiol.* 2013;66(12):1386-1396.
22. Grisham S. Medscape Physician Compensation Report 2017. 2017.
23. Elwyn G, Edwards A, Kinnersley P, Grol R. Shared decision making and the concept of equipoise: the competences of involving patients in healthcare choices. *Brit J Gen Pract.* 2000;50(460):892-+.
24. Colleges AoAM. The Complexities of Physician Supply and Demand: Projections from 2014 to 2025 2016.
25. Silver MP, Hamilton AD, Biswas A, Warrick NI. A systematic review of physician retirement planning. *Hum Resour Health.* 2016;14(1):67.
26. Sinsky C, Colligan L, Li L, et al. Allocation of Physician Time in Ambulatory Practice: A Time and Motion Study in 4 Specialties. *Ann Intern Med.* 2016;165(11):753-760.
27. Tai-Seale M, Olson CW, Li JN, et al. THE PRACTICE OF MEDICINE Electronic Health Record Logs Indicate That Physicians Split Time Evenly Between Seeing Patients And Desktop Medicine. *Health affairs.* 2017;36(4):655-662.

28. Bezreh T, Laws MB, Taubin T, Rifkin DE, Wilson IB. Challenges to physician-patient communication about medication use: a window into the skeptical patient's world. *Patient Prefer Adher.* 2012;6:11-18.
29. Lewis PJ, Tully MP. The discomfort caused by patient pressure on the prescribing decisions of hospital prescribers. *Research in social & administrative pharmacy : RSAP.* 2011;7(1):4-15.
30. Gruppen LD. Physician Information Seeking - Improving Relevance through Research. *B Med Libr Assoc.* 1990;78(2):165-172.
31. Smith R. What clinical information do doctors need? *Brit Med J.* 1996;313(7064):1062-1068.
32. Slawson DC, Shaughnessy AF. What clinical information do doctors need? Few doctors are expert at evaluating information. *Brit Med J.* 1997;314(7084):904-904.
33. Casebeer L, Bennett N, Kristofco R, Carillo A, Centor R. Physician internet medical information seeking and on - line continuing education use patterns. *Journal of Continuing Education in the Health Professions.* 2002;22(1):33-42.
34. Ly DP, Glied SA. The Impact of Managed Care Contracting on Physicians. *J Gen Intern Med.* 2014;29(1):237-242.
35. Dyrbye LN, Varkey P, Boone SL, Satele DV, Sloan JA, Shanafelt TD. Physician Satisfaction and Burnout at Different Career Stages. *Mayo Clinic proceedings.* 2013;88(12):1358-1367.
36. Casalino LP, Nicholson S, Gans DN, et al. What Does It Cost Physician Practices To Interact With Health Insurance Plans? *Health affairs.* 2009;28(4):W533-W543.
37. Shugan SM. The Cost of Thinking. *J Consum Res.* 1980;7(2):99-111.

38. Bornstein BH, Emler AC. Rationality in medical decision making: a review of the literature on doctors' decision-making biases. *J Eval Clin Pract.* 2001;7(2):97-107.
39. Marewski JN, Gigerenzer G. Heuristic decision making in medicine. *Dialogues Clin Neurosci.* 2012;14(1):77-89.
40. Gigerenzer G, Gaissmaier W. Heuristic decision making. *Annu Rev Psychol.* 2011;62:451-482.
41. Redelmeier DA, Shafir E. Medical Decision-Making in Situations That Offer Multiple Alternatives. *Jama-J Am Med Assoc.* 1995;273(4):302-305.
42. Schwartz JA, Chapman GB. Are more options always better? The attraction effect in physicians' decisions about medications. *Medical Decision Making.* 1999;19(3):315-323.
43. Redelmeier DA, Shafir E. Medical decision making in situations that offer multiple alternatives. *Jama.* 1995;273(4):302-305.
44. Kennedy T, Regehr G, Rosenfield J, Roberts SW, Lingard L. Exploring the gap between knowledge and behavior: a qualitative study of clinician action following an educational intervention. *Academic Medicine.* 2004;79(5):386-393.
45. Wazana A. Physicians and the pharmaceutical industry: is a gift ever just a gift? *Jama.* 2000;283(3):373-380.
46. Mizik N, Jacobson R. Are physicians "easy marks"? Quantifying the effects of detailing and sampling on new prescriptions. *Management Science.* 2004;50(12):1704-1715.
47. Moynihan R. Who pays for the pizza? Redefining the relationships between doctors and drug companies. 2: Disentanglement. *Bmj.* 2003;326(7400):1193-1196.
48. Relman AS. Separating continuing medical education from pharmaceutical marketing. *Jama.* 2001;285(15):2009-2012.

49. Moynihan R. Key opinion leaders: independent experts or drug representatives in disguise? *Bmj*. 2008;336(7658):1402-1403.
50. Lankinen KS, Levola T, Marttinen K, Puumalainen I, Helin-Salmivaara A. Industry guidelines, laws and regulations ignored: quality of drug advertising in medical journals. *Pharmacoepidemiol Drug Saf*. 2004;13(11):789-795.
51. Fickweiler F, Fickweiler W, Urbach E. Interactions between physicians and the pharmaceutical industry generally and sales representatives specifically and their association with physicians' attitudes and prescribing habits: a systematic review. *BMJ Open*. 2017;7(9):e016408.
52. Greene JA. Pharmaceutical marketing research and the prescribing physician. *Ann Intern Med*. 2007;146(10):742-748.
53. Applbaum K. Pharmaceutical marketing and the invention of the medical consumer. *PLoS medicine*. 2006;3(4):e189.
54. Happe LE, Clark D, Holliday E, Young T. A systematic literature review assessing the directional impact of managed care formulary restrictions on medication adherence, clinical outcomes, economic outcomes, and health care resource utilization. *J Manag Care Spec Pharm*. 2014;20(7):677-684.
55. Fidler H, Lockyer JM, Toews J, Violato C. Changing physicians' practices: the effect of individual feedback. *Acad Med*. 1999;74(6):702-714.

CHAPTER 2

THE POTENTIAL EXISTENCE OF “SMALL INDIVIDUAL FORMULARY” IN PRESCRIBING BEHAVIOR: A SEQUENTIAL EXPLANATORY MIXED METHODS STUDY†

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Abstract

Objective: The objective of the study was to assess the breadth and concentration of prescribing behavior, and to enhance understanding of the process of prescribing decision making in a real world context.

Method: This study employed a sequential explanatory mixed methods design in which qualitative data were collected to understand the results of quantitative analysis. A cross-sectional secondary data analysis was firstly conducted to assess the breadth and concentration of prescribing behavior using all eligible samples from 2015 Medicare prescriber utilization and payment data for Part D prescribers. Building on the quantitative results of prescribing breadth and concentration, we engaged 11 prescribers in semi-structured interviews, which provided in-depth interpretation of prescribing decision making process.

Results: The quantitative data suggest that prescribers use a limited set of medications (small individual formulary, SIF) regularly in daily practice. Approximately, 90% of a total of 651,736 prescribers used less than 49 prescriptions regularly, while 75% of prescribers used less than 25. The qualitative data further confirmed that prescribers hold an SIF for daily practice, and extend the quantitative results by indicating that prescribers establish an algorithm on the sequence of prescribing and employ formulary to narrow down the prescription choices.

Conclusions: Prescribers consider and use a limited set of prescription drugs based on their internal algorithm of prescribing behavior. Strategies could be developed to help stakeholders use this information to better understand and improve medication use.

Key Words: Physician behavior; Prescribing behavior; Medicare Part D; Healthcare utilization

Introduction

Given the high per capita spending on prescription medications in the United States, compared to other high-income countries,¹ examining prescription costs are a priority². One expressed concern is whether high medication costs in the United States are partly due to a reliance on higher cost brand name medications.³ Today's patients expect prescribers to maximize the quality of care, be available when consultation is needed, and to consider the cost of prescription medications in decision making.⁴

However, drug product selection within a therapeutic class may be complicated. For example, choosing an appropriate antidiabetic agent may involve the consideration of efficacy, hypoglycemia risk, weight gain risk, other side effects, and insurance coverage.⁵ Thus, it becomes the prescribers' responsibility to discuss and confirm patients' treatment preferences, consider all possible alternatives, identify the consequences associated with each alternative, examine the trade-offs between the alternatives, and then create an optimal treatment plan.⁶

Classic decision making theory, related to prescribing assumes the process is fully rational, is based on complete information, and considers the multivariate factors influencing prescribing.⁷ Models attempting to explain prescribing behavior rely on these assumptions.⁸ However, in practice, prescribers may not have full information when making prescribing decisions⁹⁻¹¹. Further, choice heuristics play an important role in medical decision making.^{12,13} For example, the drugs a prescriber can recall from memory, for example due to familiarity, are more likely to be prescribed when recognition and fluency heuristics are considered.¹²

Previous research suggests that prescribers might only consider a limited set of medication choices and operate within what has been termed a "small individual formulary"(SIF).^{14,15} One qualitative study indicated that prescribers generally believe they

prescribe drugs that are “top of mind” or the drugs that they think of first, and that they rely on their habits to shape prescribing behavior.¹⁶ Some studies have found that the prescribing decision process tended to be based on habits, where previous prescribing history was demonstrated to be a highly effective predictor of future prescription choices.¹⁷⁻¹⁹ In another study, researchers asked a group of general practitioners about their cognitive processes while making prescribing decisions for patients.²⁰ Their findings revealed that prescribers considered only one option in more than half (57.4%) of their prescribing decisions and considered two options 25.6% of the time.²⁰ These studies suggest that the existence of an SIF may result in more limited prescribing choices.

In addition, quantitative studies have examined the breadth of prescribing using prescription claims data. Two studies found a high “concentration” of drugs, (the frequency prescription of individual medications) to treat psychotic disorders lending support for the existence of the SIF.^{21,22} Overall, a prescriber’s prescription writing history was found to be concentrated to a list of their favorite drugs (the SIF) accompanied by a large number of rarely prescribed drugs.²³ Further, prescribing behavior can vary substantially among prescribers. While some prescribers rely heavily on a few agents, others may prescribe a broad spectrum of familiar drugs without a concentration on any particular agents.²²

To improve prescribing decision making, it is important to both scrutinize the breadth of prescribing subjectively and to comprehend how prescribers implement and interpret the prescribing behavior from their standpoint, which led the study to a mixed method research design. The purpose of this study was to (1) quantify the breadth and concentration of prescribing behavior using a large sample of prescribers, (2) confirm the quantitative results

using qualitative data, and (3) enhance understanding of how prescribing decisions have been made from the perspectives of prescribers in a real world context.

Methods

Research Design

The overarching goal of the study is to assess and understand the possible existence of SIF in prescribing decision making. We complied with pragmatism as our theoretical standpoints by combining the strength of quantitative and qualitative research to produce a mixed method study “for the purpose of breadth and depth of understanding” of the concept of SIF.²⁴ Specifically, the study used an explanatory sequential mixed-methods research design, which included an initial quantitative data analysis of Medicare Part D prescribing data to examine the existence of SIF quickly, cheaply and objectively, and a follow-up qualitative research involving semi-structured interviews with current prescribers to provide insight into the quantitative results. The quantitative and qualitative phases were connected when we decided whether to focus on the concept of SIF or ask about prescribing decision making process in general in semi-structured interviews after having the quantitative results. The purpose of the interviews was to (1) triangulate the concept of SIF from the perspective of prescribers as well as (2) get an in-depth understanding of prescribing decision making process with a focus on how to interpret SIF in the concept of SIF is applicable. Overall, it is essential to employ a mixed method approach to understand the prescribing decision making process profoundly. Figure 1 shows the diagram of the study. Our study was approved by the Institutional Review Board of University of Georgia (Appendix A).

Quantitative Phase

Data Collection

The goal of the quantitative phase is to assess the breadth and concentration of prescribing behavior in a large dataset of prescribers in order to examine the existence of the concept SIF. Medicare Provider Utilization and Payment Data: Part D Prescriber, released May 25, 2017, was obtained from www.CMS.gov and utilized as the data resource. The Part D Prescriber Public Use File is based on information from CMS's Chronic Conditions Data Warehouse, which contains Prescription Drug Event records submitted by Medicare Advantage Prescription Drug (MAPD) plans and by stand-alone Prescription Drug Plans (PDP). The dataset identifies providers by their National Provider Identifier (NPI) and includes prescriptions dispensed at their direction, by brand or generic name. For each prescriber and unique drug (brand or generic), the total number of claims, total days of supply and total drug cost were provided in the dataset. The data also included information about prescriber's specialty, address, zip code, gender, and patient's Medicare Part D coverage. Patient composition information was derived from prescription drug events file (PDEs) from CMS incurred by Medicare beneficiaries with a Part D prescription drug plan. The specialty descriptions were derived from the Medicare provider/supplier specialty code associated with the largest number of services on the NPI's Part B claims. Where a prescriber's NPI did not have associated Part B claims, the taxonomy code associated with the NPI in National Plan & Provider Enumeration System (NPES) is mapped to a Medicare specialty. A description flag was available in the data to differentiate specialties reported in Part B claims and specialties reported in NPES²⁵.

Only the top 75% of prescribers, as identified by total claim count, were included in the sample as analyzing prescribing breadth and concentration is likely not meaningful for

prescribers who generate few prescriptions. Because some of the Part D claims were filed in the name of organizations other than individual prescribers, organizations such as surgery centers, hospitals, pharmacies, facilities and suppliers are excluded from the study.

Outcome Measures

Prescribing breadth and concentration were the two outcomes of the study. Breadth was determined by taking all the drugs prescribed on an individual prescriber basis and ranking these in descending order by the number of claims associated with a specific drug. The cumulative percentage of the claims amount accounted for by all the claims was calculated. The number of drugs prescribed accounting for 80% (cumulative) of claims was defined as the number of prescriptions providers regularly use (termed “regular set”). The number of all unique ingredients for each prescriber was also calculated to compare with the number drugs in the regular set. Concentration was measured as the Herfindahl - Hirschman Index (HHI)²⁶. HHI equals the sum of squared market shares of each firm in the market. It ranges from zero to 10,000, with higher HHIs indicating greater market concentration. For each prescriber, we used the number of prescriptions written for a particular drug divided by the total number of prescriptions in the medication class to calculate market shares and then construct HHIs. A high HHI means that the individual prescriber is predominately using a few drugs, while a low HHI implies she/he prescribes across a broader spectrum of drugs. As HHI was right-skewed, we categorized HHI into 2 groups using the median HHI: high concentration and low concentration for the groups above and below the median respectively²⁷.

Exploratory Variables

Several exploratory variables were employed to understand the associations between patient composition, prescriber characteristics, and prescribing breadth and concentration.

1) Beneficiary Characteristics: This included the number of patients of each gender, race and ethnicity treated by each prescriber as well as the average age of the patients.

2) Prescriber Total Claim Amount: The total claim amount was derived from the PDE file. The total claim amount was a summation of all the medication claims from the same prescriber for new and refilled prescriptions²⁵.

3) Prescriber Specialty: There were 78 specialties reported using Medicare specialty code and 68 specialties reported using NPPES taxonomy code. We used the top 10 specialties, encompassing 70.1% of the physicians prescribing 80.12% of all claims to determine whether specialty has an influence on prescribing breadth and concentration. These specialties included: internal medicine, family practice, nurse practitioner, physician assistant, emergency medicine, psychiatry, cardiology, dentist, ophthalmology, and obstetrics/gynecology.

4) Prescriber Demographics: Prescriber demographics including gender and address were available from NPPES.

5) Rural vs Urban Status: The NPPES contains zip codes of prescribers. A crosswalk from U.S. Department of Housing and Urban Development website mapping zip codes to Federal Information Processing Standard Publication (FIPS) county codes was employed, which can be found at https://www.huduser.gov/portal/datasets/usps_crosswalk.html. The classification of rural vs urban was based on Rural-Urban Continuum Codes (RUCC) where the rural/urban status is available for each county. Prescribers whose zip codes were missing or could not be matched were identified by their address and city.

Statistical Analysis

To calculate the number of medications healthcare providers regularly prescribe, we first examined the distribution of the two outcomes (prescribing breadth and concentration) across prescribers in the study sample. For this distribution, we report the mean, standard deviation, and percentiles, and the coefficient of variation (standardized measure of dispersion of the outcome distribution), which has been used in previous research studying HHI associated with prescribing behavior related to antipsychotic medications²².

Second, we sought to identify potential factors associated with prescribing breadth and concentration. Because the number of drugs in a prescribers “regular set” is count data, a univariate Poisson regression was employed to explore the associations between prescribing breadth and concentration, and exploratory variables (gender, total claims count, beneficiary count, average age of beneficiaries, the share of patients of different demographics, rural vs. urban status and specialty) in the analytic sample. Any beneficiary count below 11 was suppressed in the PUF file thus will be excluded when exploring the characteristics of beneficiaries on outcome variables. But those were included in the analysis of prescribing breadth (number of medications used) and concentration (HHI). Univariate logistic regression was used to model the relationships between concentration (high vs. low) and total claims count, beneficiary count, average age of beneficiaries, the share of patients of different gender, race/ethnicity, rural vs. urban status and specialty in the analytic sample.

All analyses were performed using STATA statistical software (version 14.2, Stata Corporation, College Station, Texas, USA). All reported p values are two-sided with α level of 0.05 threshold for statistical significance.

Qualitative Phase

The second phase of this study was qualitative research with a thematic analysis approach building on the results of the previous phase. The qualitative phase was integrated with the quantitative results by (1) determine whether the opinions of prescribers was consistent with the quantitative findings and (2) illustrate the concept of SIF from the perspective of prescribers if applicable.

Participants

A convenience sample of healthcare professionals who were practicing and prescribing for patients was recruited through clinical faculty recommendations. The potential participants were contacted by email and phone for their intentions to participate in the qualitative research about prescribing behavior. Researchers provided the information of topic of research, procedure we use and the value of honorarium in the first contact. The potential participants who showed interest in participating were further contacted with the consent form, which details the process, risk, benefit, confidentiality, voluntariness of the research. Potential participants who agreed to participate under the conditions of the consent form were included in the study. The participants were also asked to recommend other prescribers who could be willing to participate in the study. We purposely sampled prescribers from different specialties in order to obtain results that are relevant to a broader range of settings.

Data Collection

A research assistant trained in qualitative interviewing conducted all interviews. We used semi-structured interview questions consisting of open-ended questions and flexible probes based on participant response. The questions about participants' perceptions of, and experiences with, prescribing in primary care were asked, especially on the topic of small individual formulary. A semi-structured interview guide was used to conduct the interviews. Examples of questions include: "Please share with me the process when deciding to prescribe something in your practice"; "There is a saying that prescribers may only use a few types of drugs regularly despite that a great number of different drugs exist. I would like to get your opinion about this idea". The interviewer employed a flexible, conversational approach and invited participants to reflect on emerging patterns arising from previous interviews. The private and confidential context of the interview appeared to facilitate the participants' willingness to share their perspectives in an open and candid manner. Interviews lasted from 45 minutes to an hour and were audio-recorded and transcribed verbatim. Participants received \$100 Walmart gift card to encourage participation. The study protocol was approved by the University of Georgia institutional research ethics board. All participants provided research consent. While some provided verbal consent because of inconvenience, others provided written consent form.

Data Analysis

Three researchers analyzed the data using a thematic analytic framework to identify main themes and patterns. The coding process followed the stages of thematic analysis. First, three researchers independently extracted preliminary codes from the transcripts (open coding). The researchers carefully read and reread the transcripts, and assigned text (e.g., phrases and

paragraphs) to relevant codes. Additional codes conveying new meaning were also created and existing codes were modified with new analysis. All codes were given operational definitions describing how they were to be applied during the coding process. Next, based on their prevalence and conceptual similarities, codes were then reorganized and grouped into a condensed set of themes (axial coding). Third, the themes were contextualized by identifying the most frequent topics in the transcripts. The themes and their relationships, as well as their meanings were examined. And irrelevant codes/themes were deducted to facilitate the theorizing process. As the analysis evolved, three researchers discussed the emerging themes and codes. Points of discussion were reflected upon and any discrepancies were discussed until consensus was reached.

Validity

To minimize the threats to validity in the quantitative study, we chose to use a large sample size with as few selection criteria as possible, as well as two different outcomes that complement each other. We attempted to validate the qualitative study by (1) having the quantitative results before starting the qualitative analysis in order to ensure whether SIF exists; (2) using open-ended questions and being conversational in the interviews to allow participants to talk about their opinions candidly; (3) asking participants to provide a list of medications they use regularly to triangulate the concept and the size of SIF; (4) record the whole conversation and transcribe verbatim; (5) employing three researchers to code the transcripts independently; (6) purposely sample participants from different specialties.

Results

Quantitative Results

There were 866,568 prescribers in the 2015 Medicare Provider Utilization and Payment Data: Part D Prescriber dataset. A total of 650,736 prescribers were identified as the top 75% of prescribers after excluding medical organizations. The top 75% of individual prescribers had 119 or more claims. Prescribers had a mean of 2189 total claims (SD=3862.8), generating 89,328 total days of supply (SD=153,199.2), and an average total drug cost of \$208,095 (SD=419,478.1). Prescribers treated an average of 214 beneficiaries (SD=217.4) (Table 1). As noted above, beneficiary characteristics were not available for some prescribers because of suppression.

The distributions of the number of all drugs, number of drugs in the “regular set” and HHI are shown in Figure 2 and Table 2. Overall, prescribers demonstrated the use of a “regular set” of medications in prescribing behavior. A total of 76% of prescribers used less than 50 drugs while 39% of prescribers used less than or equal to 10 drugs overall. A total of 61% of the prescribers used less than or equal to 25 different drugs overall.

Regarding the “regular set”, 90% of prescribers used less than 50 drugs while 75% of the prescribers used less than or equal to 25 different drugs. Prescribers with a larger regular set, namely those who used more than 25 drugs, had an average of 6430 total claims in 2015. This is significantly higher than the average total claim amount (813) of other prescribers with a smaller regular set ($p<0.0001$).

The drugs in prescribers’ regular set were mostly generic drugs with an average of 87.1%. Among all prescribers in the analytic sample, 39.2% regularly used only generic drugs,

while 0.4% regularly used only branded drugs. The top 50 drugs that prescribers regularly used are listed in Table 3.

All exploratory variables were found to be significantly associated with the number of top 80% claim drugs and HHI ($p < 0.0001$) in the bivariate analyses (Table 4). The pseudo R-square statistic indicated that total claim amount and specialty were the most useful in explaining the difference in providers' prescribing breadth and concentration (Table 4).

Qualitative Results

Based on the quantitative results of prescribing patterns, eleven semi-structured interviews were conducted by the author with all participants who agreed to join. Recruitment ended when saturation was achieved. The final sample consisted of 11 prescribers. The recruitment process continued from April 25, 2018 to September 24, 2018. Participant characteristics were presented in Table 5. Examples from the raw data were given to illustrate the themes more vividly Table 6.

The interviews revealed four themes related to the use of SIF in prescribing: (1) the existence of SIF is recognized but viewed as the result of involving multiple factors in prescribing decision making; (2) prescribers employ an algorithm for the sequence of medications to use for patients (3) formulary and patient affordability played a vital role in prescribing; (4) prescribers keep themselves updated with the body of literature associated with medication use

Theme 1 – SIF

Prescribers recognize themselves using limited number of medications in regular practice. The so-called SIF mainly consists of the first-line therapies for diseases. All interviewees provided a list of medications that they regularly use. The length of that list ranges from 8 to 18 in our interviewees. However, the formation and structure of that SIF could be different for different specialties.

The choice of SIF medication was first based on the common diagnosis prescribers would see in daily practice, which could be only one for some specialists or a few for general practitioners and specialists who are also responsible to manage a few diagnosis/patients' comorbidities: "A list. So it's the diabetes, hypertension and dyslipidemia. So we do metformin, sulfonylurea, and glipizide" (Participant 1, Endocrinologist).

Second, a few therapeutic classes usually exist for a specific diagnosis. Physicians show that they have their favorite 1 to 3 medications in each of the class of medications they use. The choice of what medications to include in SIF is often based on clinical evidence including the benefit, side effects profile, ease of use and the cost of medications, thus an SIF usually consists of the first-line therapies and some second-line therapies recommended by the guidelines for the specific fields.

Prescribers generally use generics as their SIF if generics are available because generics are cheap and have usually been tested in a huge amount of people for a long time for side effects. Only one nurse practitioner described their choices of medications solely based on the preferences of physicians they work with: "Well a lot of my decision making is based on the preferences of my supervising physicians. So I work with two different doctors and they have a little bit of a different idea of how they want to manage their patients pain in different

medications so I will oftentimes make my decisions based on their preferences.” (Participant 9, Nurse Practitioner).

As science develops in a field, the previous patent medications with better side effects profile could become generic. That is when a few prescribers mentioned the update of their SIF. SIF can be subject to change also through the career path of prescribers as well. When they move to a new practice, they are often faced with a new distribution of diagnosis and income level, thus need to adjust the SIF to adapt to the new patient population.

Theme 2 - Algorithm

Prescribers establish an algorithm of what factors to consider and what sequence should be medications be used to facilitate their prescribing behavior. The existence of algorithm is consistent with the existence of SIF.

The algorithm is always based on the widely acknowledged evidence in the field of the diagnosis, such as the Joint National Committee for hypertension or STAR*D trial for depression. In an established algorithm, prescribers first collect patient information to decide an initial treatment, usually first-line if newly diagnosed, then to switch or add on medications sequentially based on the algorithm until they successfully control the conditions of the patients. However, the algorithms were seen often only dictating what therapeutic classes of medications to use first but not which one to choose within a class as participants often just mention the class names when talking about algorithms: “So that's the algorithm that I usually follow but you know that doesn't really specifically say which anti-depressant to use when it comes to which SSRI or which SNRI.” (Participant 4, Psychiatrist)

However, the algorithm is not universally identical among the prescribers seeing the same diagnosis. A few participants mentioned that they observed difference in algorithms between their colleagues and themselves. The discrepancy could have come from the different weight they put on the factors including side effects, cost, compliance and efficacy or how they were trained with attendees in residency.

Theme 3 - Formulary and Affordability

Patient out-of-pocket cost appeared to be a concern for all of participating prescribers.

Prescribers consider cost to be a barrier to patient compliance, which motivates them to control the cost to the extent that patients can afford the medications in long term: “I think if I say like, oh I see you haven't taken it and they just shut down: I've been taking it. They get defensive. And I asked them like, is there any specific reason you weren't unable to? Sometimes it's, you know, they tell you, Oh I ran out of money. And so that's why. And so in those cases, then I think I want to maybe try a certain agent that's less efficacious but they can afford.” (Participant 1, Endocrinologist)

The most common way to control for cost is to go with the preferred medication on formulary when patients have a formulary. Formulary is a topic that was mentioned most often by participants. Prescribers interviewed in the study all mentioned intention to choose whatever preferred on the formulary when choosing within a therapeutic class. Often, when prescribers want to prescribe a more expensive medication after failing all the cheaper options or dose the medications higher than regular use, they will encounter formulary restrictions including prior authorization, step therapy, quantity limits, formulary tiers, where additional effort might be needed in order for patients to get the medications.

Prescribers generally would not prescribe the restricted options or deviate from regular dosage, but they are willing to make additional effort if they truly value benefits of the restricted treatment.

“I’ll refer them in that way or you know another avenue is that I would talk to their primary care doctor and say this is my recommendation if you agree you can put in the outpatient and endocrinology referral so one or the other.” (Participant 6, Hospitalist)

“I try to avoid prior authorization and I try to go at what’s in the formulary. But unless I think something’s really worth that time. Then then yes. I’ll put that time and I just want to just pick the medication because I just saw a new study that’s a great. Because in reality it’s if they can’t use the medication what’s the point of prescribing the greatest medication.” (Participant 1, Endocrinologist)

On the other hand, some of the patients are not covered or are not able to pay the out-of-pocket because of the high copayment. A few prescribers mentioned encouraging patients to use the grocery store four-dollar formulary list to get the medications patients need.

Discussion

The overarching aim of the study was to achieve an in-depth understanding of prescribing behavior with the focus on the phenomenon of SIF. Our findings suggested that prescribers use a limited set of medications (SIF) in regular practice. The content of SIF is based on the algorithm of prescribing prescribers employ and the formulary coverage of patients. The use of SIF has implications for physicians, other prescribers, medical educators and pharmaceutical marketers. Specifically, medications that are within a prescriber’s SIF will be used more often and may be difficult to displace from the minds of prescribers.

Our quantitative analysis provided a comprehensive assessment of breadth and concentration of prescribing behavior in a nationally representative sample of Medicare Part D prescribers. We also studied how prescriber characteristics and the prescribers' beneficiary (patient) characteristics were associated with prescribing patterns. Overall, we found that physicians and other prescribers tend to use a limited set of drugs in daily practice (prescribing breadth). The size of the limited set (SIF) is less than or equal to 25 medications/drugs for the majority of prescribers. The results of qualitative analysis strongly support the existence of the SIF and the size estimation of SIF by the length of the list of regular medications participants provided. Previous literature has examined the concentration of prescribing in specific diseases, using different outcome variables and different standards to define concentration, and yielded mixed results.^{21,23,28,29} For example, one study defined concentration as the percentage of claims of the drugs that were used the most in each therapeutic class and found a mean of 60% in multiple disease categories.²⁸ Another study defined concentration as the number of drugs used in each therapeutic class and found a median of greater than or equal to 3 in multiple disease categories and thus concluded that prescribing behavior is not concentrated²⁹. These disparate findings can be explained by the use of different measures of concentration. For example, a physician might use 4 drugs in the same therapeutic class but focus on only 1 of them 60% of the time.

The qualitative analysis indicates that the limited number of drugs considered in prescribing is a result of combining the common diagnosis which prescribers see with the more widely accepted, and adopted, clinical practice algorithms of the specific diagnosed disease field. Adherence to clinical algorithms may contribute to more appropriate prescribing, as evidenced based algorithm may provide for better clinical and therapeutic decisions. On the other hand,

prescribers with more patients are more likely to meet patients whose disease conditioned could not be controlled after exhausting the options in the normal prescribing algorithms. The quantitative results that prescriber specialty and total claims cost explained 35% of the variance in prescribing breadth also illustrated that busier prescribers have to use a broader range of medications to meet patient needs.

The most commonly prescribed medications in Part D, as demonstrated by Table 3, are mainly generic. The choices of SIF are predominantly generics in the qualitative results as well, which help decrease medication cost by reducing reliance on brand name medications. Meanwhile, the vital role of formulary coverage in prescribing also contributes to the narrow prescribing range and the decrease in medication cost, which meets the intention of formulary to limit prescription choices and contain medication cost.³⁰

However, the role of memory in shaping these prescribing decisions³¹, specifically recognition and fluency heuristics, are also important in forming judgements¹². Based on both recognition and fluency heuristics, the drugs a physician can recall from memory due to familiarity are more likely to be prescribed compared with drugs with which the physician is less familiar¹². A few participants described the reason why they use specific medications in SIF as “innate”, “feel comfortable with”, “familiar with”. With similar memory capacity, the prescribing patterns in specific therapeutic classes would be expected to be different for prescribers who are not the specialist in the diseases area versus those who are.

The fact that physicians operate with in their SIF, but also look outside of the SIF when necessary has implications for various stakeholders. For example, medical educators can utilize this finding to ingrain rational, non-commercialized, generic when appropriate, drug choices into physicians’ and other prescribers’ habits. For payers, who may have the goal of decreasing drug

costs, monitoring the content of SIFs through drug utilization review can identify providers who are using unexpectedly high amounts of more expensive medications. With respect to their individual SIFs, prescribers may want to consider cost-effectiveness of their most common choices. Further, when prescribing outside their SIF, prescribers may strive for more evidence-based and cost-conscious choices.

These findings also have relevance for pharmaceutical marketers in that they highlight the level of competitiveness in the market and the fact that considerable revenue can be generated if marketers can reach prescribers and increase the inclusion of their drugs in SIFs. Further, for pharmaceutical marketers, there will still be value in providing information to prescribers through marketing messages because this information will be available for consideration when prescribers look for drug choices outside their “regular set”. On the other hand, prescribers demonstrate slight differences in their algorithms for the same diagnosis, which also lend opportunities to pharmaceutical marketers to target their potential customers.

Limitations

This study has several limitations. First, Part D Prescriber PUF may not be representative of a physician’s entire practice or all of Medicare as it only includes information on beneficiaries enrolled in the Medicare Part D prescription drug program (i.e., approximately two-thirds of all Medicare beneficiaries). Second, we did not have patient level information, thus we were not able to control for potential confounders such as education, marriage and income level plus comorbidities and severity of disease which might have influenced the outcomes. Furthermore, we could not adjust for important physician level factors and organizational factors such as ownership of the facility and regional status that may shape the prescribing behavior.

For the qualitative analysis, we directly asked prescribers how they make decisions for patients. Some participants might have tended to ignore the impact of unconscious thoughts and emotions on this process while others were willing to talk about the impact of the irrational aspects. The opinions of the majority of interviewees were reported. However, the results should be interpreted with caution given the limited number of interviewed physicians.

Conclusions

Although considerable variability existed in prescribing breadth, most prescribers used a limited set of prescriptions options. The size of the limited set was closely related to the specialty and the prescription volume of the prescriber. For most, the limited set or SIF was 25 or fewer drugs. Further studies on identifying the other factors contributing to prescribing breadth and concentration as well as exploring the process of forming and changing SIF in prescribers are needed.

Tables

Table 2.1: Descriptive Statistics of The Sample

Variables	All sample (N=650,734)	
	Non missing N	Mean(SD)/Percent
Prescriber Characteristics		
Female	650,734	40.31%
Rural	650,734	0.74%
Specialty	650,734	
<i>Internal Medicine</i>	100,110	15.38%
<i>Family Practice</i>	94,250	14.48%
<i>Nurse Practitioner</i>	81,210	12.48%
<i>Physician Assistant</i>	51,614	7.93%
<i>Emergency Medicine</i>	29,130	4.48%
<i>Psychiatry</i>	21,241	3.26%
<i>Cardiology</i>	19,459	2.99%
<i>Dentist</i>	17,841	2.74%
<i>Ophthalmology</i>	16,679	2.56%
<i>Obstetrics/Gynecology</i>	14,933	2.29%
Total Claims Count	650,734	2188.9(3862.8)
Prescribers' Beneficiary Characteristics		
Beneficiary Count	648,224	214.1(217.4)
Percentage of Female	613,598	59.9%(11.9%)
Percentage of Caucasian	435,451	73.2%(21.2%)
Percentage of African American	238,968	18.1%(22.8%)
Percentage of Hispanic	229,564	15.7%(23.6%)
Average Age	648,224	69.2(6.2)

Table 2.2: Distribution of number of top 80% claims, number of all drugs and HHI

Variables	Top 80% claim drugs	All drugs	HHI
Mean (SD)	18.10(19.44)	37.12(48.19)	605.71(711.25)
5th percentile	2	2	120.79
25th percentile	4	6	179.21
Median	10	16	353.71
75th percentile	25	48	735.12
95th percentile	61	144	1994.40
Range	1-134	1-559	7.83-10000
Coefficient of variation	1.07	1.30	1.17

Table 2.3: Top 50 Drugs Prescribers Regularly use

Medication Name	Frequency	Percent of Physicians Using
LISINOPRIL	259,318	0.397888102
AMLODIPINE BESYLATE	247,384	0.379577007
ATORVASTATIN CALCIUM	244,608	0.375317613
OMEPRazole	233,153	0.357741478
HYDROCODONE- ACETAMINOPHEN	228,557	0.350689543
GABAPENTIN	221,907	0.340486025
LEVOTHYROXINE SODIUM	219,936	0.337461794
FUROSEMIDE	215,781	0.331086514
SIMVASTATIN	211,994	0.325275879
METFORMIN HCL	198,323	0.304299594
METOPROLOL TARTRATE	197,437	0.302940148
HYDROCHLOROTHIAZIDE	186,756	0.28655161
LOSARTAN POTASSIUM	185,319	0.284346729
METOPROLOL SUCCINATE	171,783	0.263577584
TRAMADOL HCL	160,744	0.246639744
PREDNISONE	152,813	0.234470706
PANTOPRAZOLE SODIUM	146,580	0.224907018
CLOPIDOGREL	144,939	0.222389127
FLUTICASONE PROPIONATE	143,084	0.219542882
CARVEDILOL	140,437	0.215481422
SERTRALINE HCL	140,023	0.214846195
ATENOLOL	138,028	0.21178514
PRAVASTATIN SODIUM	136,922	0.210088134
WARFARIN SODIUM	134,788	0.206813802
POTASSIUM CHLORIDE	133,293	0.204519928
ALPRAZOLAM	126,010	0.193345158
TRAZODONE HCL	125,894	0.193167172
TAMSULOSIN HCL	123,837	0.190010986
PROAIR HFA	123,807	0.189964955
CITALOPRAM HBR	118,961	0.182529429
LORAZEPAM	113,088	0.173518112
AZITHROMYCIN	108,962	0.167187327
OXYCODONE-ACETAMINOPHEN	105,074	0.161221722
ZOLPIDEM TARTRATE	101,775	0.156159856
ALLOPURINOL	101,367	0.155533836
CLONAZEPAM	98,696	0.151435551
MELOXICAM	96,734	0.148425129
CRESTOR	95,182	0.146043797

MONTELUKAST SODIUM	92,475	0.141890275
DULOXETINE HCL	89,046	0.136628942
LISINOPRIL-		
HYDROCHLOROTHIAZIDE	88,660	0.136036677
CIPROFLOXACIN HCL	88,657	0.136032074
ALENDRONATE SODIUM	88,269	0.135436741
ESCITALOPRAM OXALATE	87,422	0.134137135
RANITIDINE HCL	83,154	0.127588471
FLUOXETINE HCL	79,711	0.122305658
DONEPEZIL HCL	74,982	0.115049652
LOSARTAN-		
HYDROCHLOROTHIAZIDE	65,324	0.100230768
ADVAIR DISKUS	65,302	0.100197012

Table 2.4: Influence of the Exploratory Variables on Number of Top 80% Claim Drugs and HHI

Variables	Number of Top 80% Claim drug		Concentrated vs. not	
	Coefficient	Pseudo R2	Odds Ratio	Pseudo R2
Prescriber Characteristics				
Female	-0.074*	0.0011	1.365*	0.0041
Rural	0.511*	0.0023	0.759*	0.0016
Specialty	*	0.2543	*	0.2043
<i>Internal Medicine</i>				
<i>Family Practice</i>	0.157		0.611	
<i>Nurse Practitioner</i>	-0.625		3.437	
<i>Physician Assistant</i>	-0.821		4.654	
<i>Emergency Medicine</i>	-1.525		26.545	
<i>Psychiatry</i>	-0.628		5.556	
<i>Cardiology</i>	-0.452		5.610	
<i>Dentist</i>	-2.327		8327.676	
<i>Ophthalmology</i>	-1.396		3114.3.5	
<i>Obstetrics/Gynecology</i>	-1.633		112.447	
Total Claims Count	0.00003*	0.1364	0.9989*	0.1522
Prescribers' Beneficiary Characteristics				
Beneficiary Count	0.0002*	0.0353	0.9905*	0.0369
Percentage of Female	0.002*	0.0006	0.7980*	0.0271
Percentage of Caucasian	0.005*	0.0122	0.8293*	0.0337
Percentage of African American	-0.0006*	0.0002	1.0109*	0.0000
Percentage of Hispanic	0.003*	0.0049	0.9210*	0.0020
Average of Benes age	0.031*	0.0263	0.9333*	0.0279

*(p<0.0001)

Table 2.5: Qualitative Sample

Sample Characteristics (n=11)	
Method	1 in-person interview and 10 telephone interviews
Gender	7 females and 5 males
Specialization	8 specialists and 3 general practitioners
Experience	2 subjects were prescribing less than or equal to 5 years, 7 subjects were active between 6 to 15 years, 2 subjects have been working for more than 15 years.
Involvement in research	6 subjects were also researchers in academic institutions

Table 2.6: Themes and examples

SIF	Diagnosis	I'm a general psychiatrist so I'm mostly treating neural disorders like major depression and bipolar disorder, anxiety disorders such as generalized anxiety, panic disorder, PTSD, a little bit of schizophrenia in my practice and a good bit of ADHD (Participant 4, Psychiatrist)
		So I would say like based on the class of medications, for heart failure for example, it would be metoprolol or carvedilol, lisinopril or Losartan, aspirin, usually atorvastatin sometimes simvastatin. For diabetes so oftentimes it's metformin, and insulin such as Lantus or NovoLog. Occasionally sulfonylureas. For pulmonary, I would say a lot of Symbicort, a lot of Spiriva, a lot of nebulizer treatments albuterol. I think those are the big ones that pop into my mind in really chronic medical (Participant 6, Hospitalist)
	Favorite Drug in a Class	For example what we called ACE inhibitors and if we have an ACE inhibitors, you have probably ten, fifteen, twenty kinds of ACE inhibitors, but we tend to use one two or three the most frequently because partly we feel comfortable using them because of using them so often (Participant 10, Geriatriist).
		You know SSRIs, I might lean towards Sertraline, Escitalopram and Citalopram, Fluoxetine, probably those four (Participant 5, Psychiatrist).
	Choice of SIF	obviously at the core of it is you want to make sure that whatever you prescribe your patient is data driven that has a mortality benefit or some shown benefit to your patient or is being used to make them feel better (Participant 6, Hospitalist) .
		You know I choose typically from among 3 or 4 you know the guidelines recommending you know an ACE inhibitor or an ARB or hydrochlorothiazide or chlorthalidone as initial drug. And if I don't have to (It right there for a comparison) I might be more likely to choose calcium channel blockers (one of those two initial drugs). Again I think based on guidelines and my reading of the evidence (Participant 8, Family Physician)

		So that these then have, they've been around longer so there is more data. Some of them actually have... Clinical indications for a lot of the disorders but then they're generally very inexpensive, well tolerated, shown to be effective for much larger samples of people (Participant 3, Psychiatrist)
	SIF change	You know in training we didn't really useful sulfonylurea because those patients had good insurance and you know they didn't have to worry about cost as much like those co-pays. But here use more just because of the cost. I didn't use to use pre-mixed insulins and when I was in training again, most patients can afford the newer insulins and probably had the resources to do those multiple shots. But now I do because again it's cheaper and it's twice a day versus four injections (Participant 1, Endocrinologist).
		so although there are dozens of medications that are available for HIV. Many of them are from kind of early days of HIV epidemic in the early ninety's late ninety's and early two thousand. And they had significantly more side effects and toxicities for the patients (Participant 2, Infectious Disease)
Algorithm	Algorithm Establishment	So I thought patient last week who had hypertension and we had to add a second drug to his blood pressure regimen. And so the current JNC. So usually so it depends on what I'm treating. Is it something like hypertension where there are very well written guidelines. I tend to try to as much as possible follow those guidelines (Participant 2, Infectious Disease).
		When you're in pulmonary with asthma and COPD, there's an algorithm, the gold guidelines (Participant 11, Nurse Practitioner).
		I've actually kind of developed over time like algorithm for myself like if the patient comes in my office because of how often I prescribe these drugs I've come up with an algorithm for myself (Participant 3, Psychiatrist).
	Difference in Algorithm	I think most of us typically go like Metformin and some may use a DPP4 before they go on to sulfonylurea as I think. But I go. But again I think the same thought process goes through all of us (Participant 1, Endocrinologist).

		So I think those of us who were trained here are more similar to each other in terms of our our practices, because we're trained at the same place and so much of what you do I think it's based on how you were trained (Participant 11, Pediatric Endocrinologist).
Formulary	Cost as a concern	Yeah but you know I'm also feeling that physicians should always consider costs just as (stewards) of healthcare resources. I mean if a ten dollar drug works as well as hundred dollar drug. We should prescribe the ten dollars drug. You know I think it's just foolish to push for the waste of money on things that aren't any better (Participant 8, Family Physician).
		It's more that you have to discuss costs with them and most of the time they can't afford it. Even though I have probably like the middle class on average patients. I mean I think a lot of people have that you know people have other things that they gotta pay and so I do find it very common and patient so even if they, even with a co-pay card (Participant 3, Psychiatrist).
		And yet those people unfortunately in that role, those people can't afford 50, \$60 a month to pay for an inhaler. So they choose of course to smoke their cigarettes over their inhaler cuz there are limited finances. So that was a big issue in that role that I had there. On prescribing, it would be very frustrating (Participant 7, Nurse Practitioner).
	Preferred medications on formulary	I didn't prescribe it up until I knew that it was covered which was about a month ago so I've started prescribing Biktarvy as well (Participant 2, Infectious Disease).
		Yeah but it with tends to me more insurance dependant. Like you know there's all these new long acting insulin like basaglar was not out when I was in training. We really just had. At that time we just had like Lantus and levemir. But you know I don't choose to prescribe basaglar or any other long acting insulins like over each other. It tends to be dependent on which of those is on the formulary for the insurance because there's typically only going to be one that's going to be on their formulary (Participant 11, Pediatric Endocrinologist).
	Formulary	Taken one that wasn't very good in the class then go to Latuda, they can't afford it and it depends on what the insurance company says you know. If they reject it because they have to

	Restrictions	try something else first, well then we go with something else first then the insurance usually has a list things it will cover. If a patient has tried you know, almost everything already, and then can't afford it (Participant 3, Psychiatrist).
		Yeah, so as the patient tells us it's not approved, then our nurses will contact the pharmacy to get whatever forms need to be filled out or whatever. And then we will document what they've tried, why we're recommending this over whatever their insurance company is saying we should prescribe first. And then we provide clinical documentation, and then submit that back. And sometimes you have some companies have a website where you have to go on and plug in the information, sometimes they just have to fax it back. It just kind of depends on each prior authorization in terms of the plan and stuff (Participant 7, Nurse Practitioner).
	Grocery store formulary	So the reason I like to use four dollar medication is mainly for my patients' cost. I think that if they can't afford the medication and they're definitely not going to take them. And so I think taking away as many barriers as possible, such as you know sometimes doing the 90-day refill so that I protect my patients don't have to arrange for the monthly trips to the pharmacy, finding cheaper medications. These can all help improve adherence (Participant 2, Infectious Disease).
		And then I think I'm going to be inclined to prescribe them the cheapest possible medication. Work with their pharmacies drug plan or their insurance plan, whatever is the cheapest. There are medications on the Wal-Mart three dollar plan which means three dollars for one month's supply or ten dollars for three months supply. And those end up costing the patients a lot less. And so they can afford to get them and so we will try those (Participant 10, Geriatrist).

Figures

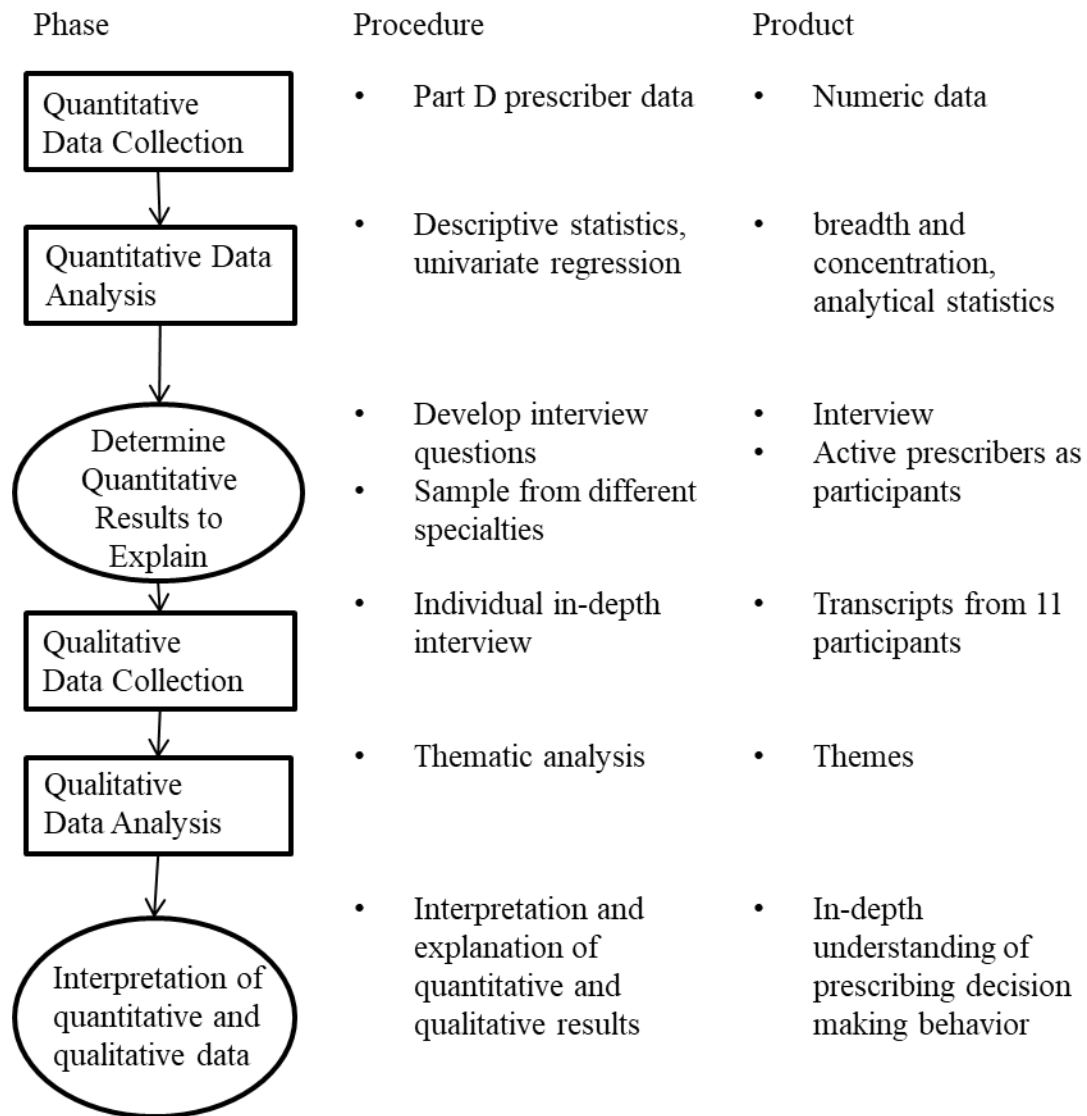


Figure 2.1 Diagram of the mixed-method study

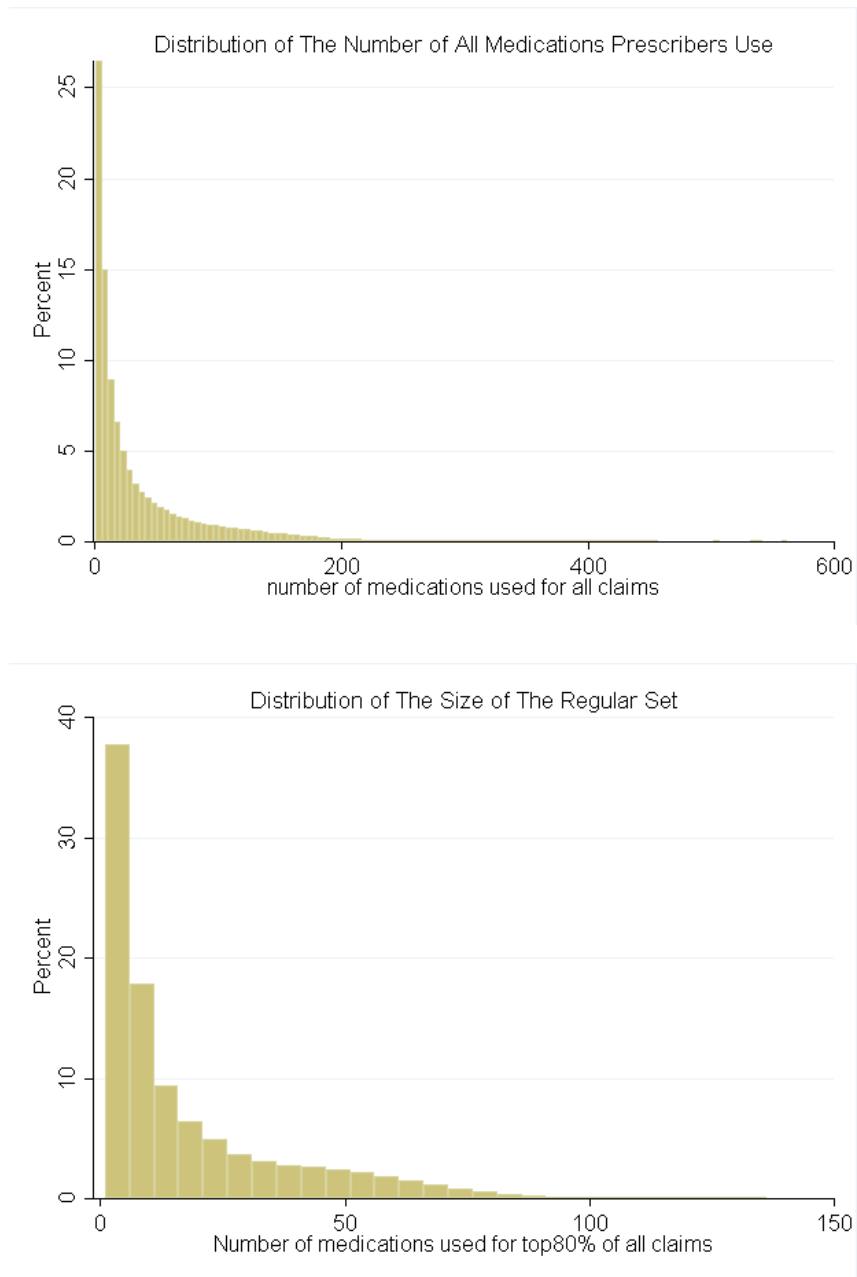


Figure 2.2 Distribution of number of all medications, top 80% drugs

References

1. Sarnak DO, Squires D, Kuzmak G, Bishop S. Paying for Prescription Drugs Around the World: Why Is the US an Outlier? *Issue brief (Commonwealth Fund)*. 2017;2017:1-14.
2. Kesselheim AS, Avorn J, Sarpatwari A. The High Cost of Prescription Drugs in the United States Origins and Prospects for Reform. *Jama-J Am Med Assoc*. 2016;316(8):858-871.
3. Kesselheim AS, Avorn J, Sarpatwari A. The high cost of prescription drugs in the United States: origins and prospects for reform. *Jama*. 2016;316(8):858-871.
4. Dormohammadi T, Asghari F, Rashidian A. What Do Patients Expect from Their Physicians? *Iran J Public Health*. 2010;39(1):70-77.
5. Association AD. 8. Pharmacologic approaches to glycemic treatment. *Diabetes Care*. 2017;40(Supplement 1):S64-S74.
6. Gregory R, Peters E, Slovic P. Making decisions about prescription drugs: a study of doctor–patient communication. *Health, Risk & Society*. 2011;13(4):347-371.
7. Doyle J. Rational decision making. *MIT encyclopedia of the cognitive sciences*. 1999:701-703.
8. Murshid MA, Mohaidin Z. Models and theories of prescribing decisions: A review and suggested a new model. *Pharm Pract (Granada)*. 2017;15(2):990.
9. Elwyn G, Edwards A, Kinnersley P, Grol R. Shared decision making and the concept of equipoise: the competences of involving patients in healthcare choices. *Brit J Gen Pract*. 2000;50(460):892-+.

10. Shrank WH, Asch SM, Joseph GJ, et al. Physicians' perceived knowledge of and responsibility for managing patients' out-of-pocket costs for prescription drugs. *Ann Pharmacother*. 2006;40(9):1534-1540.
11. Shrank WH, Joseph GJ, Choudhry NK, et al. Physicians' perceptions of relevant prescription drug costs: do costs to the individual patient or to the population matter most? *Am J Manag Care*. 2006;12(9):545-551.
12. Blumenthal-Barby JS, Krieger H. Cognitive biases and heuristics in medical decision making: a critical review using a systematic search strategy. *Med Decis Making*. 2015;35(4):539-557.
13. Marewski JN, Gigerenzer G. Heuristic decision making in medicine. *Dialogues Clin Neurosci*. 2012;14(1):77-89.
14. Campo K, De Staebel O, Gijsbrechts E, van Waterschoot W. Physicians' decision process for drug prescription and the impact of pharmaceutical marketing mix instruments. *Health Mark Q*. 2005;22(4):73-107.
15. Bissessur SW, Geijteman EC, Al-Dulaimy M, et al. Therapeutic reasoning: from hiatus to hypothetical model. *J Eval Clin Pract*. 2009;15(6):985-989.
16. Grant A, Sullivan F, Dowell J. An ethnographic exploration of influences on prescribing in general practice: why is there variation in prescribing practices? *Implement Sci*. 2013;8.
17. Beam AL, Kartoun U, Pai JK, et al. Predictive Modeling of Physician-Patient Dynamics That Influence Sleep Medication Prescriptions and Clinical Decision-Making. *Sci Rep-Uk*. 2017;7.

18. Kalkan A, Husberg M, Hallert E, et al. Physician Preferences and Variations in Prescription of Biologic Drugs for Rheumatoid Arthritis: A Register-Based Study of 4,010 Patients in Sweden. *Arthrit Care Res.* 2015;67(12):1679-1685.
19. Davies NM, Gunnell D, Thomas KH, Metcalfe C, Windmeijer F, Martin RM. Physicians' prescribing preferences were a potential instrument for patients' actual prescriptions of antidepressants. *J Clin Epidemiol.* 2013;66(12):1386-1396.
20. Denig P, Witteman CLM, Schouten HW. Scope and nature of prescribing decisions made by general practitioners. *Qual Saf Health Care.* 2002;11(2):137-143.
21. Hodgkin D, Merrick EL, Hiatt D. The Relationship of Antidepressant Prescribing Concentration to Treatment Duration and Cost. *J Ment Health Policy.* 2012;15(1):3-11.
22. Tang Y, Chang CCH, Lave JR, Gellad WF, Huskamp HA, Donohue JM. Patient, Physician and Organizational Influences on Variation in Antipsychotic Prescribing Behavior. *J Ment Health Policy.* 2016;19(1):45-59.
23. Patterson J. How many drugs do I use? *The Journal of the Royal College of General Practitioners.* 1972;22(116):191.
24. Medicare Cf, Services M. Medicare fee-for service provider utilization & payment data part D prescriber public use file: a methodological overview. 2016.
25. Rhoades SA. The herfindahl-hirschman index. *Fed Res Bull.* 1993;79:188.
26. Tang Y, Chang CC, Lave JR, Gellad WF, Huskamp HA, Donohue JM. Patient, Physician and Organizational Influences on Variation in Antipsychotic Prescribing Behavior. *J Ment Health Policy Econ.* 2016;19(1):45-59.
27. Frank RG, Zeckhauser RJ. Custom-made versus ready-to-wear treatments: Behavioral propensities in physicians' choices. *Journal of health economics.* 2007;26(6):1101-1127.

28. Joyce GF, Carrera MP, Goldman DP, Sood N. Physician prescribing behavior and its impact on patient-level outcomes. *Am J Manag Care*. 2011;17(12):e462-471.
29. Schwikert SR, Curran T. Familiarity and recollection in heuristic decision making. *J Exp Psychol Gen*. 2014;143(6):2341-2365.

CHAPTER 3

PATIENT, PHYSICIAN AND ORGANIZATIONAL INFLUENCES IN VARIATION OF
PHYSICIAN PRESCRIBING BEHAVIOR†

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Abstract

Purpose: We examined the association between patient composition, physician and organization characteristics with physicians' variation in prescribing behavior.

Methods: A retrospective secondary analysis was executed using the 2015 National Ambulatory Medical Care Survey (NAMCS) data. Variation in prescribing was measured using Herfindahl-Hirschman Index (HHI) and the number of unique prescriptions identified from all patient visits of each physician. Physicians' prescribing was categorized as concentrated when the HHI index was greater than or equal to 1500. Logistic and Poisson regressions, weighted by survey physician weights, were conducted at the physician level to identify significant factors of variation in prescribing. The significance level was set at alpha 0.10.

Results: Of 1,410 physicians identified in the 2015 NAMCS data set, 1,280 with prescription records available were included in the analysis. The weighted average HHI of for these physicians was 1254.8. The weighted average number of medications was 47. The number of visits associated with the physician, the ability of the practice to record patients' medications and allergies, the ability of the practice to reconcile medication list were significantly associated with variation in prescribing. The number of diagnoses encountered was significant in explaining more concentrated prescribing.

Conclusions: Physicians' variation in prescribing behavior was shown to have been influenced by the organizational ability to record and reconcile medication lists as well as patient caseload, indicating potential to reshape physician prescribing pattern with organizational level policies.

Introduction

A prescription choice may encompass a possibly long list of relevant factors including cost, insurance coverage, effectiveness, or side effects. The decision can be more complicated when patients have comorbid conditions. When patients' opinions are considered, the physician is also responsible for helping patients understand and weigh each characteristic of a prescription. From a physicians' perspective, prescribing is a complex mix of knowledge, skills and experience.¹

The phenomenon of a "small individual formulary" (SIF) has been recognized for many years, but there has been only limited research into this phenomenon.²⁻⁴ Recent research has demonstrated that prescribers tend to rely on a few drugs in their daily practice both qualitatively^{5,6} and quantitatively.^{7,8} From the perspective of payers, the idea of a SIF might be beneficial if the content of the SIF consists primarily of generics, rather than high cost, name brand prescriptions.⁹ However, cost is just one dimension to consider in the prescribing process. To balance all aspects of drug selection, prescribers must consider costs, therapeutic benefit, risk and patient adherence.¹⁰ Prescribing behavior should be individualized according to patient needs.¹¹ Previous researchers were able to relate the breadth of prescribing behavior with duration of treatment and prescription cost and found modest relevance using claims data^{7,12}.

Researchers have found that while some physicians rely heavily on a few agents, others may prescribe a broad spectrum of drugs.⁸ The variance in prescribing behavior may partly be explained by the fact that the claims associated with a single physician is a mixture of drugs initiated by other physicians, repeat prescriptions, and new drugs chosen by the physician himself. Therefore, the number of drugs seen prescribed for new patients may be smaller than the number of drugs prescribed for all patients.¹³ It has been shown that gender of the prescriber

and percentage of severely ill patients was associated with the number of different drugs used in antipsychotic agents.⁸ Further, the antipsychotic prescribing behavior study also showed that prescribing variation might be shaped by the characteristics of the affiliated organization.⁸ But overall, scant research has examined factors related to the variation of physicians in prescribing.

In the present study, we examined an array of patient, physician, organizational factors and their association with variation of prescribing for all prescriptions in a nationally representative sample of ambulatory patient visits in an attempt to identify factors that may have played a role in prescribing variation.

Methods

Data Source

The 2015 National Ambulatory Medical Care Survey (NAMCS) is a nationally representative sample of physician office visits. It utilizes a multi-stage probability sampling strategy to collect data. In the first stage of sampling, 112 primary geographic sampling units (PSU) were selected. For the second stage, a probability sample of practicing physicians from the master files maintained by the American Medical Association and the American Osteopathic Association were chosen from PSUs. In the last stage, office visits of chosen physicians were randomly sampled over a predefined week. Data were obtained on patient characteristics such as age and ethnicity, and visit characteristics such as patient's reason for visit and physician's diagnosis. In addition, data about the physician and his or her practice characteristics are collected as part of a survey induction interview. Each patient visit was given a patient weight and each physician was given a physician weight to create the nationally representative results on both the patient and physicians levels.¹⁴

Inclusion Criteria

All patient visits that involved prescriptions were included in the analysis.

Outcome Variables

Two assessments of prescribing variation were used due to a lack of consensus regarding how prescribing variation should be measured.^{8,15} First, prescribing variation was measured as the number of unique prescriptions (by different ingredients) ever prescribed through the year 2015. A higher number of different prescription medications prescribed by a physician indicates greater variation in prescribing by the physician.

Second, prescribing variation was also measured as HHI, which incorporates the number of different prescriptions used and gives more weights to drugs that are prescribed more often. HHI equals the sum of squared market shares of each firm in the market. It ranges from zero to 10,000, with higher HHIs indicating greater variation. In the current context of individual physician prescribing behavior, we listed all the brand name and generic drug each physician used in 2015 identified by different National Center for Health Statistics (NCHS) classification codes. NCHS coded the drugs. NCHS-based coding reflected exactly what was written on the Patient Record form, which identifies brand name drugs with the same ingredient as different drugs. We then summed up the patient visit weight associated with each drug and each physician as the weighted number of prescriptions for the drug. We also calculated the total patient visit weight for all the drugs as weighted total number of prescriptions of the physician. The ratio of weighted number of prescriptions written for a particular drug divided by the weighted total number of prescriptions was used to compute market shares and then construct HHIs. A high

HHI means that the individual prescriber is using a few drugs predominately, while a low HHI implies she/he prescribes in a greater variation. As HHI was right-skewed, we categorized HHI into 2 groups by 1500: high concentration and low concentration for the groups above and below the 1500 respectively.¹⁶

The two outcome measures of variation in prescribing capture two different aspects of prescribing habits for each physician. When used together, we can explore how prescribing variations are influenced by patient, physician and organization characteristics.

Predictor Variables

Patient measures included age, gender, race (white, black, other), ethnicity (Hispanic, non-Hispanic), patient source of payment (private, Medicare, Medicaid, self, other), tobacco use, obesity and total number of chronic conditions. NAMCS imputed values for race and ethnicity were used when data were missing. Physician measures included provider specialty type (general and family practice, dermatology, internal medicine, urology, pediatrics, psychiatry, general surgery, neurology, obstetrics and gynecology, ophthalmology, orthopedic surgery, otolaryngology, cardiovascular diseases, others), type of doctor (M.D.-Doctor of Medicine, D.O. - Doctor of Osteopathy), practice ownership (full owner, part owner, employee, contractor), whether patient medication lists were routinely checked and number of visits included in the sample. The number of different diagnoses encountered and HHI of the diagnosis were included in the physician measure to adjust for the range of diagnoses made by physicians.

Diagnosis was identified by unique ICD-9 codes recorded for each patient visit. HHI of diagnosis was calculated the same way as HHI of prescriptions. Practice measures included ownership of the practice (physician or physician group, medical/academic health center or

hospital, insurance company/health plan/HMO/others), region (Northeast, Midwest, South, and West), practice location (metropolitan status or nonmetropolitan status, as defined by the US Office of Management and Budget), whether the practice records patient's medications and allergies (yes/no), whether the practice reconciles lists of patients' medications to identify the most accurate list (yes/no) and whether the practice provides patients with opportunities to view online/download/transmit information from their medical record (yes/no).

Statistical Analysis

The unit of analysis in this study was the physician rather than individual patient visit. The outcome variables are measured at the physician (i.e., macro) level and some of explanatory variables are measured at the patient (i.e., micro) level. Classic approaches to address measurement at different levels include aggregating the patient level data to physician level or disaggregating the physician level data to the patient level to perform the analyses.¹⁷ However, the aggregation approach is recommended as it yields more accurate regression estimators.¹⁷ We employed Hoffman's aggregation approach instead of disaggregation because physician weights cannot be incorporated into analysis using disaggregation¹⁷. Weighted average of patient characteristics were calculated for each physician based on patient visit weights.

Poisson regression was used to examine the associations between the number of unique prescription drugs and the predictor variables. Logistic regression was used to examine the associations between HHI (high versus low variation) and the predictor variables. The regression models were weighted by the physician weights provided in the NAMCS data.

Initially, all independent variables were singularly entered into univariate models. Those with a statistically significant relationship with the outcome variables, at the 10% level, were

entered into a multivariable regression model. Backward elimination was executed in the multivariate model until all included variables had p values less than 0.10. In order to find how much variation in prescribing could be explained by our final model, an R square statistic was needed. A pseudo R square can be produced in logistic regression and Poisson regression. However, pseudo R square is computed using log likelihoods, and log likelihoods assume that cases are all independent of each other. The clustering in NAMCS data indicated that patient visits are not independent, so pseudo R² is not considered appropriate. Weighted least square (WLS) regression was then executed on two outcome variables using the final multivariate model to explore the efficiency of the model. We conducted all analyses using Stata 14 (StataCorp, College Station, Texas) applying survey weights to account for NAMCS' complex sampling design and obtain population estimates.

Results

Based on an unweighted total of 27,877 patient visits with medication prescribing records, 1,280 physicians were identified, excluding 130 physicians without any prescribing records during the sampling period. The included sample was representative of 381,629,479 patient ambulatory visits nationally with 314,084 physicians nationally. Of the included physicians, 94.7% had M.D. degrees, and 47.1% were primary care doctors, 27.7% of which owned their own practice. The majority of physicians belonged to physician owned practices (73.4%), and practiced in metropolitan areas (94.0%). While the reporting rate of the ability to reconcile patients' medication lists (82.5%) and recording patients' medications/allergies (85.2%) were high, only 54.1% of physicians reported that their patients had the ability to view/download/transmit their own medical records (Table 1).

On average, a physician saw 59.3% female, 80.2% Caucasian and 11.8% African American, 13.1% Hispanic, 31.9% obese, 12.5% with history of tobacco use, 55.1% with private insurance, 25.9% Medicare and 14.8% Medicaid patients (Table 1). Further, physicians had 50.7 visits recorded during their sample week with 26 different diagnoses by median. The average HHI of diagnosis was 1111.9.

The included physicians had an average HHI of prescribing of 942.7 with range from 76.1 to 10,000. They also used 44 drugs during their sample week on average (SD=40.3) which came from an average of 30.7 therapeutic classes. The included physicians had a weighted HHI median of 540.34, which indicates that the distribution of HHI was right skewed.

Predictors of variation in prescribing

The results of the initial weighted univariate regression with HHI as the outcome were shown in Table 2. The results indicated that physicians who were specialists, saw fewer diagnoses and patients, used fewer therapeutic classes and had more concentrated diagnosis were more likely to prescribe in a concentrated manner. As for organization features, physicians in Northeast medical organization, in MSA area, that did not have the ability to record patient's medications and allergies, that could not reconcile lists of patients' medications and that could not provide patients with opportunities to view online/download/transmit information from their medical record were more likely to prescribe in a concentrated manner.

The physicians who see more self-paid patients, who see younger patients, more Hispanic patients, more self-paid/Medicaid reimbursed patients, more patients with no tobacco use history, more patients with few comorbidities would be more likely to be concentrated in prescribing. The Poisson regression results were generally consistent with the logistic regression results.

However, the metropolitan status of the practice and the patient factors became significant in the Poisson regression (Table 2).

The multivariate model for concentrated vs. diversified prescribing after backward elimination is shown in Table 3. In the parsimonious model, physician specialty, number of different diagnosis physicians encountered (odds ratio [OR] 0.869; $p < 0.001$), number of sampled visits (OR 0.999; $p = 0.072$), whether organizations were able to record patient's medications and allergies (OR 0.215; $p = 0.029$) and whether organizations were able to reconcile lists of patients' medications (OR 5.286; $p = 0.004$) were significant in explaining the possibility of physicians prescribing in concentrated manner. The WLS model using the same independent variables had R square of 0.4230.

Results from the Poisson regression model are presented in Table 4. Physician specialty, number of sampled visits (HHI of diagnosis, average number of chronic conditions of patients, whether organizations were able to record patient's medications and allergies, whether organizations were able to reconcile lists of patients' medications were the final predictors remained in the model. However, the coefficient of HHI of diagnosis was small. The WLS model using the same independent variables had R square of 0.5708.

Discussion

Our analysis provides a comprehensive assessment of possible factors contributing to the variation in physician prescribing. We attempted to explain the number of medications typically prescribed (a specific prescribing behavior) as a whole, rather than examining a specific disease. The sampled physicians used on average 43 unique prescriptions during the sample week. But the mode of number of unique medications prescribed was 6 representing 3.49% of the

physicians. A total of 22.5% physicians prescribed less than or equal to 10 different drugs, while 31.1% physicians prescribed 10 to 20 different drugs. Thus, an HHI of 942.7 must be interpreted carefully. It can mean a physician uses 10.6 drugs fairly consistently, or, on the other end of prescribing possibilities, that the physician uses 1 drug 29.1% of the time and use other 43 drugs each for 1.65% of the time; and many other permutations of utilization. But all the permutations suggest that physicians in our sample tend to use 10 or fewer medications more than the others in prescribing practice.

However, overall, it is shown that physicians' prescriptions were concentrated on less than or equal to 11 types of medications. The findings suggest that physicians might consider a limited set of drug choices regularly in their daily practice and operate within this "small individual formulary" (SIF). The existence of SIF (under 20 for more than 53.6% of the physicians) indicates that it may be exceptionally difficult for pharmaceutical companies to get into physicians' SIF or to get physicians to prescribe medications not in their SIF. The level of competitiveness in the pharmaceutical market signals the importance of further educating physicians with credible information sources in order to generate more sales of effective medications.

On the other hand, despite the existence of SIF in many physicians, there are still physicians who tend to use a wide palette of drugs, which make good potential customers for pharmaceutical products that need broad initial trials. The finding that 77.5% of physicians use more than 10 drugs indicates that physicians use other drugs beyond their SIF. One reason for this might be that they see patients with uncommon diagnoses or the drugs in their current SIF fail to work, requiring alternative drugs. The hypothesis of uncommon diagnosis or severe health condition leading to prescribing outside one's SIF could be supported by the fact that the number

of visits associated with the physician or the number of unique diagnosis encountered had a high R square in explaining variation in prescribing, which was consistent with the previous literature.^{7,8}

When we regressed the number of different drugs on the number of different therapeutic classes physicians use (identified by level 3 Multum classification of therapeutic classes), we found that physicians' overall number of unique prescriptions was 1.58 (SE=0.018) times of their number of unique therapeutic classes, indicating physicians use only 1 or 2 drugs in the therapeutic classes they choose. So, within a therapeutic class the SIF is quite small. This leads to the possibility that when physicians need another choice within a therapeutic class, they may switch to another therapeutic class instead of switching to a different drug in the same therapeutic class. Combining this interesting finding with the possible existence of the SIF, suggests that physicians have favorite drugs in therapeutic classes they use more often. These favorite drugs, in a given class, may be the generic drugs that are usually covered by insurance. Based on these results, for any patient, the starting point in prescribing would be their physicians' favorite drug with a potential switch to a drug in another therapeutic class if the previous one does not achieve expected effectiveness.

For diseases such as hypertension, it is highly possible that physicians are following national guidelines to decide the sequence of therapeutic classes that they try. However, for diseases such as bipolar disorder where no up-to-date guideline exist, physicians might behave more various in choosing the sequence of medications that they would try on patients. The sequence of the medications physicians use also points out the importance for pharmaceutical companies to notify physicians on time when their products switch to a preferred formulary

status in the insurance plan. Physicians can change their prescribing practice according to the new coverage information, which also enables patients to get their medications on time.

The decreased concentration with medication reconciliation was also consistent with previous literature.¹⁸ Medication reconciliation is the process of maintaining the records of all medications that the patient has or is currently taking, and the process of determining the exact amounts and combinations of medications being taken at the time of each patient visit.¹⁹ By enabling providers to know what medications have been prescribed before, medication reconciliation might help physicians to avoid prescribing the drugs that their patients have tried but were not satisfied with. On the other hand, the result that recording patients' medications and allergies is associated with increased concentration might be because the recording process added to physicians' workload. The increasing time spent on electronic health records has been shown to pressure physicians to shorten their time to meet with patients.²⁰ The inadequacy of time with patients and the pressure might have influenced physicians to make repetitive prescription choices.

Limitations

Our study has a few limitations. First, the exact sample size without survey weight was small. NAMCS emphasizes that only variables with relative standard error < 30% are considered reliable.²¹ Thus many of the independent variables in the final model were not reliable. However, the ever-changing method of recording medication and diagnosis as well as emerging questions that did not exist in the previous data made it difficult to pool NAMCS data across years. Second, although a considerable number of possible contributors to prescribing variation were identified, we may not have all variables needed in explaining the outcomes.

Third, NAMCS recorded at most 5 diagnoses in each patient visit. We found patient visits without the diagnosis of diabetes but with antidiabetic agents. The number of diagnosis encountered then could have been underestimated.

Conclusions

In conclusion, variation of prescribing in a nationally representative sample differed substantially across physicians. Physicians' variation in prescribing behavior was associated with the organizational ability to record and reconcile medication lists as well as patient caseload. With policy change on the organizational level, the healthcare entities may be able to reshape the prescribing variation of its affiliated physicians.

Tables

Table 3.1: Participant Characteristics

Characteristics	Weighted Physicians (N=314084)	Percent/ Weighted Mean
Physician		
Specialty		
General and family practice	58850	18.74%
Dermatology	31279	9.96%
Internal medicine	30993	9.87%
Urology	6737	2.14%
Pediatrics	28578	9.10%
Psychiatry	16859	5.37%
General surgery	14559	4.64%
Neurology	8282	2.64%
Obstetrics and gynecology	7784	2.48%
Ophthalmology	22819	7.27%
Orthopedic surgery	6911	2.20%
Otolaryngology	12618	4.02%
Cardiovascular diseases	6578	2.09%
Others	61237	19.50%
Specialty type		

Primary	147883	47.08%
Surgical	60963	19.41%
Medical	105238	33.51%
type of doctor		
MD	297570	94.74%
DO	16513	5.26%
ownership		
Full owner	118324	37.67%
Part owner	72553	23.10%
Employee	112536	35.83%
Contractor	9942	3.17%
Unknown	729	0.23%
whether routinely check patient medication lists		
No	46460	14.79%
Yes	141300	44.99%
Unknown	126324	40.22%
Number of diagnosis		29.07
HHI of diagnosis		1111.97
Number of therapeutic classes		30.7
Number of visits		50.7
Organization		

Practice ownership		
Physician or physician group	230760	73.47%
Medical/academic health center or hospital	34256	10.91%
Insurance company/health plan/HMO/others	33012	10.51%
Unknown	16056	5.11%
Region		
Northeast	63612	20.25%
Midwest	65316	20.80%
South	102020	32.48%
West	83135	26.47%
Metropolitan status		
MSA	295157	93.97%
Non-MSA	18926	6.03%
Record patient's medications and allergies		
Yes	267656	85.22%
No	45485	14.48%
Unknown	943	0.30%
Reconcile lists of patients' medications		
Yes	259174	82.52%
No	52307	16.65%
Unknown	2603	0.83%
Provide patients with opportunities to view		

online/download/transmit information from their medical record		
Yes	169858	54.08%
No	135761	43.22%
Unknown	8464	2.69%
Patient Composition		
Age		48.44
Gender		
Female		59.25%
Male		
Race		
White		80.30%
Black		11.81%
Other		
Ethnicity		
Hispanic		13.07%
Non-Hispanic		
Obesity		
Yes		31.86%
No		
Patient source of payment		

Private		55.13%
Medicare		25.85%
Medicaid		14.82%
Self		7.41%
Other		
Tobacco use		
Used		12.53%
Never		
Total number of chronic conditions		1.4671

Table 3.2: Weighted Univariate Regression with HHI

Variable	Odds ratio of being concentrated	P value	Coefficient of Poisson regression	P value
Physician				
Specialty		<0.001		<0.001
General and family practice				
Dermatology	2.684		-0.252	
Internal medicine	1.046		0.105	
Urology	2.064		-0.131	
Pediatrics	3.886		-0.933	
Psychiatry	5.145		-0.950	
General surgery	3.487		-0.487	
Neurology	1.381		-0.215	
Obstetrics and gynecology	3.745		-0.668	
Ophthalmology	3.373		-0.436	
Orthopedic surgery	2.200		-0.343	
Otolaryngology	2.446		-0.272	
Cardiovascular diseases	0.765		0.097	
Others	1.945		-0.126	
type of doctor		0.215		0.913
MD				

DO	0.549		-0.016	
ownership		0.661		0.041
Full owner				
Part owner	1.076		0.12571	
Employee	0.774		0.298	
Contractor	1.277		-0.047	
whether routinely check patient medication lists		0.260		0.996
No				
Yes	0.690		-0.001	
Number of diagnosis	0.862	<0.001	0.025	<0.001
HHI of diagnosis	1.001	<0.001	-0.001	<0.001
Number of visits	0.935	<0.001	0.014	<0.001
Organization		0.974		0.733
Practice ownership				
Physician or physician group				
Medical/academic health center or hospital	0.917		0.102	
Insurance company/health plan/HMO/others	1.015		-0.002	

Region		0.002		0.002
Northeast				
Midwest	0.358		0.442	
South	0.661		0.148	
West	0.354		0.371	
Metropolitan status		0.014		0.427
MSA				
Non-MSA	0.317		0.126	
Record patient's medications and allergies		0.021		<0.001
Yes				
No	1.945		-0.610	
Reconcile lists of patients' medications		0.001		<0.001
Yes				
No	2.449		-0.696	
Provide patients with opportunities to view online/download/transmit information from their medical record		0.049		<0.001
Yes				

No	1.597		-0.482	
Patient(weighted mean or weighted mean proportion)				
Age	0.998	0.725	0.018	<0.001
Gender				
Female	0.680	0.582	-0.265	0.121
Male				
Race				
White	1.141	0.823	0.278	0.149
Black	0.685	0.591	0.076	0.726
Other				
Ethnicity				
Hispanic	1.800	0.377	-0.892	<0.001
Non-Hispanic				
Obesity				
Yes	0.795	0.811	0.754	<0.001
No				
Patient source of payment				
Private	0.740	0.488	0.291	0.030
Medicare	0.692	0.547	0.980	<0.0001

Medicaid	0.814	0.768	-0.477	0.004
Self	3.148	0.048	-0.858	0.006
Other				
Tobacco use				
Used before	0.577	0.700	0.379	0.160
Never				
Total number of chronic conditions	0.774	0.135	0.294	<0.001

Table 3.3: Multivariate Logistic Model

	Coefficient	Standard Error	P value	t
Specialty				
General and family practice				
Internal medicine	0.959	0.570	0.943	-0.07
Pediatrics	0.456	0.232	0.124	-1.54
General surgery	1.453	0.787	0.491	0.69
Obstetrics and gynecology	0.623	0.288	0.307	-1.02
Orthopedic surgery	5.700	2.833	<0.001	3.5
Cardiovascular diseases	0.540	0.470	0.479	-0.71
Dermatology	0.927	0.486	0.885	-0.14
Urology	1.344	0.594	0.504	0.67
Psychiatry	0.271	0.150	0.019	-2.35
Neurology	0.232	0.154	0.028	-2.2
Ophthalmology	3.782	1.986	0.011	2.53
Otolaryngology	4.082	2.185	0.009	2.63
Other specialties	0.478	0.270	0.192	-1.31
diagnosis	0.869	0.020	<0.001	-6.12
visit	0.999	<0.001	0.072	1.8
Record patient's medications and allergies				
No	0.215	0.151	0.029	-2.19

Yes				
Reconcile lists of patients' medications				
No	5.286	3.026	0.004	2.91
Yes				

Table 3.4: Poisson Regression Model

	Coefficient	Standard Error	P value	t
Specialty				
General and family practice				
Internal medicine	-0.099	0.089	0.266	-1.11
Pediatrics	-0.327	0.096	0.001	-3.41
General surgery	-0.015	0.121	0.901	-0.12
Obstetrics and gynecology	-0.132	0.134	0.324	-0.99
Orthopedic surgery	-0.153	0.100	0.127	-1.53
Cardiovascular diseases	-0.149	0.126	0.236	-1.19
Dermatology	-0.054	0.106	0.608	-0.51
Urology	0.034	0.121	0.776	0.28
Psychiatry	-0.337	0.106	0.002	-3.17
Neurology	0.019	0.118	0.869	0.16
Ophthalmology	-0.258	0.117	0.028	-2.2
Otolaryngology	-0.095	0.107	0.374	-0.89
Other specialties	-0.085	0.098	0.384	-0.87
HHI of diagnosis	0.001	0.001	0.001	-7.02
visit	0.009	0.001	<0.001	11.8
Record patient's medications and allergies				
No	0.453	0.179	0.010	-2..53

Yes				
Reconcile lists of patients' medications				
No	-0.441	0.163	0.007	-2.71
Yes				
Total number of chronic conditions	0.147	0.033	0.000	4.44

References

1. Kennedy, T., et al., *Exploring the gap between knowledge and behavior: a qualitative study of clinician action following an educational intervention*. Academic Medicine, 2004. **79**(5): p. 386-393.
2. Berkeley, J.S. and I.M. Richardson, *Drug usage in general practice. An analysis of the drugs prescribed by a sample of the doctors participating in the 1969-70 North-east Scotland work-load study*. J R Coll Gen Pract, 1973. **23**(128): p. 155-61.
3. Patterson, J., *How many drugs do I use?* The Journal of the Royal College of General Practitioners, 1972. **22**(116): p. 191.
4. Wilson, D.G., *Domiciliary prescribing*. J R Coll Gen Pract, 1971. **21**(110): p. 558.
5. Bissessur, S.W., et al., *Therapeutic reasoning: from hiatus to hypothetical model*. J Eval Clin Pract, 2009. **15**(6): p. 985-9.
6. Grant, A., F. Sullivan, and J. Dowell, *An ethnographic exploration of influences on prescribing in general practice: why is there variation in prescribing practices?* Implementation Science, 2013. **8**.
7. Hodgkin, D., E.L. Merrick, and D. Hiatt, *The Relationship of Antidepressant Prescribing Concentration to Treatment Duration and Cost*. Journal of Mental Health Policy and Economics, 2012. **15**(1): p. 3-11.
8. Tang, Y., et al., *Patient, Physician and Organizational Influences on Variation in Antipsychotic Prescribing Behavior*. Journal of Mental Health Policy and Economics, 2016. **19**(1): p. 45-59.
9. Sarnak, D.O., et al., *Paying for Prescription Drugs Around the World: Why Is the US an Outlier?* Issue brief (Commonwealth Fund), 2017. **2017**: p. 1-14.

10. De Vries, T., et al., *Guide to good prescribing: a practical manual*. 1994.
11. Rissmann, R., et al., *Concept-based learning of personalized prescribing*. Br J Clin Pharmacol, 2012. **74**(4): p. 589-96.
12. Joyce, G.F., et al., *Physician prescribing behavior and its impact on patient-level outcomes*. Am J Manag Care, 2011. **17**(12): p. e462-71.
13. Buusman, A., J. Kragstrup, and M. Andersen, *General practitioners choose within a narrow range of drugs when initiating new treatments: a cohort study of cardiovascular drug formularies*. European Journal of Clinical Pharmacology, 2005. **61**(9): p. 651-656.
14. Statistics, N.C.f.H., *National Ambulatory Medical Care Survey*. 2015: centers for disease control and prevention.
15. Frank, R.G. and R.J. Zeckhauser, *Custom-made versus ready-to-wear treatments: Behavioral propensities in physicians' choices*. Journal of health economics, 2007. **26**(6): p. 1101-1127.
16. Calkins, S., *The new merger guidelines and the Herfindahl-Hirschman Index*. Cal. L. Rev., 1983. **71**: p. 402.
17. Hofmann, D.A., *Issues in multilevel research: Theory development, measurement, and analysis*. Handbook of research methods in industrial and organizational psychology, 2002: p. 247-274.
18. Monte, A.A., et al., *Accuracy of Electronic Medical Record Medication Reconciliation in Emergency Department Patients*. J Emerg Med, 2015. **49**(1): p. 78-84.
19. Barnsteiner, J.H., *Medication Reconciliation*, in *Patient Safety and Quality: An Evidence-Based Handbook for Nurses*, R.G. Hughes, Editor. 2008: Rockville (MD).

20. Sinsky, C., et al., *Allocation of Physician Time in Ambulatory Practice: A Time and Motion Study in 4 Specialties*. Ann Intern Med, 2016. **165**(11): p. 753-760.
21. *Reliability of Estimates*. Available from:
https://www.cdc.gov/nchs/ahcd/ahcd_estimation_reliability.htm.

CHAPTER 5

CONCLUSIONS

This mixed-method research aims to get an in-depth understanding of healthcare provider prescribing decision making behavior with a focus on the construct of “small individual formulary” (SIF) in prescriber daily practice. The high cost of prescriptions in the United States highlight the necessity to examine the nature of prescribing behavior. Findings of this study suggests that 75% of the prescribers used less than or equal to 25 different drugs regularly, indicating the existence of SIF phenomenon. The qualitative research results further validated the use of SIF as a general practice in prescribers.

However, the formation of SIF has been shown to be dependent on an established individual algorithm of prescribing. The algorithms of prescribers were found to be generally evidence-based, which is shown by the fact that algorithms are usually based on the guidelines or the big clinical trials of the field. On the other hand, prescribers highly rely on the formulary coverage and patient affordability to dictate what to prescribe for the fact that access has to be promised in order for patients to get treated.

The analysis focusing on potential factors associated with prescribing variation suggests that instead of individual prescriber characteristics, the ability of the practice to record patients’ medications and allergies and the ability of the practice to reconcile medication list play a more vital role in how various healthcare providers prescribe.

The purpose of this research is to help various stakeholders in adjusting their prescription policy. Medical educators can employ these findings to entrench healthy prescribing habits in medical students. Payers can use the findings to monitor associated prescribers' behavior to avoid unnecessary use of expensive brand name medications. Prescribers can reconsider their most familiar treatment choices and the rules to use when prescribing outside their SIF. Pharmaceutical marketers might be able to see the potential of revenue increase if their products get included in SIFs and the value in having their product information always available to prescribers through marketing messages.

This mixed-method research has significant implications in new research directions as well. More in-depth research is needed to examine the cause and outcomes of the nuances in prescribing habits in healthcare providers who are treating the same diseases. For example, prescribers demonstrate differences in the sequence of what to use as second and third line medications for the same disease. Prescribers were seen to be different from each other on the number of medications to try within the same therapeutic class as well. The results of these research questions would further benefit the stakeholders in regulating prescribing practice.

APPENDIX A
INSTITUTIONAL REVIEW BOARD LETTER



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Office of Research
Institutional Review Board

EXEMPT DETERMINATION

April 17, 2018

Dear [Matthew Perri](#):

On 4/17/2018, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title of Study:	Physicians choose within a narrow range of drugs when initiating new treatments: a qualitative study.
Investigator:	Matthew Perri
Student Co-Investigator:	Yu Wang
IRB ID:	STUDY00005875
Funding:	None
Grant ID:	None
Review Category:	Exempt 2

The IRB approved the protocol from 4/17/2018 to 4/16/2023.

Please close this study when it is complete.

In conducting this study, you are required to follow the requirements listed in the Investigator Manual (HRP-103).

Sincerely,

Brooke M. Harwell
University of Georgia
Institutional Review Board