Possible Side Effects

Investigating the connection between payments from pharmaceutical companies and the prescribing habits of physicians

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Abstract

CareDash explored the relationship between pharmaceutical manufacturer payments received by physicians related to specific prescription drugs, and those physicians’ prior, contemporaneous, and subsequent prescriptions for those drugs. The study used publicly released Medicare Part D prescription data and pharmaceutical company payments reported to the Open Payments program, and focused on internal medicine, family practice, cardiology, and psychiatry practitioners, the four largest specialties in the datasets. CareDash found that physicians receiving payments on behalf of a specific drug were approximately 5 times more likely to choose that drug over other available options. We also explored these correlations for a subset of drugs classified as opioids, and found that physicians receiving payment on behalf of an opioid were approximately 14 times more likely to prescribe that opioid over alternatives.

Additionally, CareDash found that physicians receiving industry payments for specific drugs were more likely to prescribe those drugs in the following year. Physicians already prescribing drugs at higher levels were more likely to receive industry payments on behalf of those drugs in the following year. These results highlight the potential for a causal relationship between industry payments and physician prescribing practices.

1 Introduction

Prescription drug spending in the US comprised about 17-20% of all healthcare spending (1) and approximately 3.2% of total GDP in 2015 (2). Invoice spending on medicines is expected to rise from $435B in 2015 and $450B in 2016 to $580B - $610B by 2021 (3). The vast majority of this cost comes from brand-name prescription drugs. A 2016 study found that brand-name drugs account for 72% of total drug spending despite comprising just 10% of all prescriptions (4). While some of these brand-name drugs are patent-protected, many have generic alternatives within the same drug or treatment class that can drastically reduce cost when prescribed over the brand version.

Though many believe that brand-name drugs are more effective than generics, the FDA mandates that generic drugs be proven to be bioequivalent to the brand-names, as well as to have the same active ingredient, dosage strength and route of administration (5). As a result, researchers have found effectively no difference in performance between prescribing the brand-name and the more cost effective generic in the overwhelming majority of cases.

When prescribing physicians have financial relationships with pharmaceutical manufacturers, they may be more likely to prescribe specific brand-name drugs over generic alternatives. In 2010, the Affordable Care Act included a provision for a federal program called Open Payments, which required drug manufacturers to disclose financial relationships that they have with physicians (6). Starting in 2014, this information was made available to the public via the Centers for Medicare and Medicaid Services (CMS), offering transparency into these financial relationships for the first time on a national level. However, Pham-Kanter et al. (2017) found that, while 65% of patients surveyed had seen a doctor who received payments over the previous 12 months, only 5% of patients were aware of that fact (7).

Since the release of these data, the broadest research on this topic has been done by Jones & Ornstein (2016) at ProPublica, a non-profit investigative journalism organization. Their study joined 2014 Open Payments data with 2014 Medicare Part D prescription data, which contains aggregated prescription habits of physicians under the Medicare program (8). The study found physicians that accepted payments from drug companies (in general) were 2-3 times more likely to prescribe brand-name drugs at a high rate compared to those who accepted no payments. However, this analysis was limited to a correlation between payments across all drug and device manufacturers and physicians’ prescribing
habits across the broad labels of ‘brand’ and ‘generic’ drugs. Other researchers have found similar correlations between prescriptions and physician-industry relationships; Larkin et al. (2017) found doctors tended to prescribe generic drugs at a higher rate when their contact with pharmaceutical sales representatives was limited (9).

CareDash aimed to go further than previous research by investigating the relationship between payments made across all drug manufacturers and the prescribing habits of physicians who received those payments. Additionally, CareDash aimed to explore the direction of these correlations by considering situations in which physician prescriptions and industry payments were temporally distinct. Since the Open Payments program requires disclosure of the particular drug linked to each payment, we sought to analyze the correlation between payments and prescription habits at a more granular level - looking at the relationship between payments and prescriptions for specific drugs.

2 Methodology

For this analysis, CareDash combined physician prescription data from the Medicare Part D Public Use File (PUF) for the 2015 calendar year, with the Open Payments dataset for each calendar year in the 2014-2016 period.

The Medicare Part D PUF contains aggregated data on physicians’ prescribing information for individual drugs and is publicly available through CMS. In particular, it contains aggregated data on prescription drug claims (both original prescriptions and refills) filed by individual physicians that were paid for by the Medicare Part D Prescription Drug Program. Records on physician prescriptions for a drug are excluded if the physician made 10 or fewer claims for that drug in the calendar year, to protect the privacy of Medicare beneficiaries. The population these prescription data are based on are Medicare Part D beneficiaries (approximately 70% of all Medicare beneficiaries, which makes up about 30 million Americans).

The Open Payments dataset details payments made to physicians by pharmaceutical and medical device manufacturers, and includes information on specific drugs linked to each payment. Pharmaceutical manufacturers are required to submit information detailing payments they make to physicians each year, which is reviewed and published by CMS annually. Physicians in the submitted data are identified by their National Provider Identifier (NPI) number, state medical license numbers, and/or other identifying information (such as names and addresses), although the first two identifiers are not included in the published data. CMS verifies that reported data are linked to valid physicians, and requires records to be corrected if they do not pass this verification step. Payments made for research contributions are excluded from the Open Payments dataset, and payments of less than $10 are not required to be reported to the program.

2.1 Defining the Scope

CareDash chose to segment the Part D data by physician specialty for this analysis, since different specialties can sometimes prescribe the same drug for different purposes, and may be considering a different set of alternative choices when choosing which drug to prescribe. A physician’s specialty, as listed in the Part D PUF, is determined by CMS using that physician’s Medicare Part B claims (10). CareDash highlighted results of the analysis from four of the largest specialties in the Part D data: family practice, internal medicine, cardiology, and psychiatry. These specialties were chosen because they have the most available data in both the Medicare Part D PUF (70% of total prescriptions) and the Open Payments data. In total, the Medicare Part D 2015 data for these four specialties contain 2,491 unique drugs, 249,451 unique physicians and 853,193,542 total prescriptions.

From the Open Payments data, CareDash only considered the first associated drug with each payment (out of five possible associated drugs). While the Open Payments program associates specific reasons, or ‘natures,’ for each payment (such as ‘food and beverage,’ ‘travel and lodging,’ ‘consulting fee,’ etc.), CareDash did not apply any additional filtering with respect to these categories. When filtered down to only payments for prescription drugs (Open Payments also includes payments for medical devices, which are not included in this analysis), the Open Payments dataset contains 25.3 million unique payments to 629,046 unique physicians over the 2014-2016 period, and the payments totaled $2.2 billion.

Due to the availability of multiple years of Open Payments data, we were also able to gain insight into how physicians’ prescribing habits are affected by payments that do not occur in the same year as prescriptions. We investigated how physicians’ prescribing habits were affected when payments occurred in the year prior to prescriptions, and how manufacturers’ payment habits were affected when prescriptions occurred in the year prior to payments.

2.2 Cleaning Drug-Level Data

The first step to joining the two datasets was to standardize and clean the drug names. Connecting the names of drugs between the two datasets required a substantial amount of manual inspection and verification of the involved data. Since all of the drug names in both datasets were user-provided, unique drug names would appear in each dataset with a number of variant for-
mats (e.g., ‘acetaminophen/codeine,’ ‘acetaminophen-codeine,’ and ‘acetaminophen with codeine’).

To accurately link physicians’ prescriptions and payments for individual drugs, CareDash reviewed drug names in the Part D data and performed a number of checks and modifications:

- Any hyphens or slashes were removed from the name.
- All drug names were lower-cased.
- Brand-name drugs with modifiers (i.e., ‘extended release’ or ‘controlled release’ modifiers) were discarded from the analysis, as it was impossible to tell whether a generic alternative for that particular variant of the drug was available when the Medicare data list a generic drug’s name with no modifiers. This filtering excluded approximately 3.5% of prescriptions from the data.
- A manual check of all drug names followed to correct any other spelling errors.

This cleaning process and the removal of drugs with modifiers (CR, XR, etc.) reduced the total number of unique drug names in the Part D data from 2,491 to 2,199, covering 249,117 physicians and 819,450,406 total prescriptions.

The same cleaning and inspection process was then conducted with the Open Payments drug names, in which drug names were modified to match the processed Part D drug names when applicable and valid. The raw Open Payments data for the years 2014-2016 contained 12,573 unique device or drug names, and this cleaning process - along with filtering out all payments for devices - reduced the total unique drug names to 1,920. Payments on behalf of medical devices (such as latex gloves, etc.) comprised the majority of records filtered out.

2.3 Determining Groups of Drugs

Exploring whether a physician receiving payment for a specific drug may be connected to that physician’s prescribing behavior for that drug over other available options required a framework for determining what the other available options were for each drug. In other words, CareDash needed to formulate a method of determining which groups of drugs were reasonable alternatives to one another.

To determine these ‘drug groups,’ CareDash used the information given in the Part D data that specified the name of the generic option associated with each drug listed in the dataset. Note that, in cases in which the generic drug was prescribed, the prescribed drug’s name equaled the generic drug’s name after preliminary data inspection and processing. For example, if the generic drug’s name was ‘acetaminophen,’ and the prescribed drug’s name was ‘acetaminophen,’ we would mark that record as a prescription of a generic drug. However, if the generic drug’s name was ‘acetaminophen’ and the prescribed drug’s name was ‘Tylenol,’ we would mark that record as a prescription for a brand-name drug. The drug group in this example would be [‘Tylenol,’ ‘acetaminophen’].

Note that, because different specialties might have different uses for a drug, we assumed that drug groups should be determined within a specialty.

For example, consider a cardiologist who has prescribed the brand-name drug ‘Oxycontin’ (the associated generic drug is ‘oxycodone’). To determine which other drugs should be in this drug group with ‘Oxycontin,’ we filtered our prescription data to to only include cardiologists who have prescribed a drug in which the associated generic drug is ‘oxycodone.’ When we apply this filtering, we see that cardiologists have prescribed three drugs in which the associated generic drug is ‘oxycodone’: ‘Roxicodone,’ ‘Oxycontin,’ and ‘oxycodone.’ In this case, the drug group would be [‘Oxycontin,’ ‘Roxicodone,’ ‘oxycodone’].

Once these drug groups were determined from the Part D data, CareDash filtered out all drug groups that only contained a single drug, as physicians prescribing from these ‘groups’ would not be making any choices between drugs that a payment could potentially bias.

After this process, the data contained 469 drug groups for the family practice specialty, 468 drug groups for the internal medicine specialty, 212 drug groups for the cardiology specialty, and 159 drug groups for the psychiatry specialty. 1,418 drugs were able to be placed into one of these groups, covering 247,235 unique physicians and 712,355,284 total prescriptions.

2.4 Connecting Prescriptions to Payments

To link physicians across the two datasets, CareDash matched data using the first and last name, city, and state of each physician. If more than one physician matched between the two datasets using these fields, data on all ambiguous physicians were discarded from the analysis. After joining the two datasets, between 17,917 to 21,466 unique physician-drug relationships were associated with industry payments (depending on the year of payment data being considered).

In addition to the above identifying information provided by both Part D and Open Payments, both of these datasets include their own unique identifier for physicians. While Part D includes NPI numbers, Open Payments includes internal, randomly generated IDs as required by the law that established the program. Because these datasets do not use a common identifier, CareDash decided to match physicians using name and address.
2.5 Evaluating Physician Prescription Behavior

To determine how physicians’ prescription behavior varied within groups of drugs, CareDash calculated a ‘prescribing-rate’ for physician-drug relationships, which was the number of claims a physician made for each drug in the group as a fraction of the number of claims the physician made across all drugs in the group. To maintain the quality of results, physicians were required to have at least 100 claims across a group of drugs for their data within that drug group to be considered.

In cases in which a physician was not recorded as prescribing a drug despite having prescribed at least one other drug from a group, they were still given a prescribing-rate of zero for that drug. Including prescribing-rates for the drugs physicians did not prescribe from a group is equivalent to assuming that every choice a physician made to prescribe one drug from a group was an active choice to not prescribe every other drug from that group.

For example, consider a physician who was associated with a drug group consisting of Drug A, Drug B, and Drug C. The physician was recorded as having prescribed Drug A and Drug C in the Part D data, and since we assumed that they were also able to prescribe Drug B by association but simply chose to not do so, we gave them a prescribing-rate of zero for Drug B. The physician was not associated with Drug B in the raw data, but our analysis creates an association between the two.

2.6 Comparing Prescribing Behavior Across Physicians

Since this analysis required a measure of how a physician’s prescribing behavior for a group of drugs compared to other physicians’ prescribing behavior for that group of drugs within that physician’s specialty, CareDash evaluated the z-score of a physician’s prescribing-rate. While the z-score is most descriptive of symmetric distributions and the vast majority of prescribing-rate distributions were asymmetric, the limited capacity in which the z-score was used retained its validity as a measure of how far an individual physician’s prescribing behavior for a given drug deviated from the mean behavior for that drug across his or her specialty.

Since the z-score is an inherently statistical quantity (meaning that this process implicitly required a statistical idea of what is ‘normal’ prescribing behavior within a specialty for each drug), this step also involved drugs that had been prescribed by fewer than 10 physicians within a specialty not being considered for that specialty.

Following the filtering of data according to our thresholds for the number of claims across each group of drugs per physician and for the number of prescribers for a given drug, the number of physicians and prescriptions that made it into the final analysis were:

- 139,596 unique physicians
- 410,063,931 total prescriptions

2.7 Physician Payments and Prescription Behavior

Having computed the z-scores of how atypical a physician’s prescribing behavior for each drug was compared to other physicians in his or her specialty, CareDash was then able to compare these quantities with the payments physicians received from companies on behalf of some of those drugs.

To view the results of this comparison within the context of those achieved by ProPublica, CareDash chose to consider physicians as having received payment if at least one payment was made to them within the calendar year. Additionally, a physician would be labelled as a ‘high-prescriber’ of a drug if his or her prescribing-rate for that drug was greater than one standard deviation above the average prescribing-rate for that drug within his or her specialty (i.e., they had a z-score greater than 1 for that drug).

These discretized variables were then aggregated into four values:

(a) The number of physicians who had received a payment on behalf of a drug, and were high-prescribers of that drug

(b) The number of physicians who had received a payment on behalf of a drug, and were not high-prescribers of that drug

(c) The number of physicians who had not received a payment on behalf of a drug, and were high-prescribers of that drug

(d) The number of physicians who had not received a payment on behalf of a drug, and were not high-prescribers of that drug

For a physician-drug pair to be considered in this analysis, it is required to be able to be placed in any of the four above categories. Since a drug needs to have a payment made on its behalf to be considered for categories (a) and (b), CareDash excluded generic drugs from all of the categories for not meeting this requirement. Through our analysis of the Open Payments dataset, we determined that physicians do not receive payments on behalf of generic drugs within our analyzed dataset.
data. Since these generic drugs could never be considered for categories (a) and (b), including generic drugs would have over-filled categories (c) and (d).

Table 1 provides summarized information for the number of records per specialty that remained after data processing was concluded, and which were then distributed across these categorical bins as indicated in Table 2.

These quantities were then used to calculate relative risk, or risk ratios, to evaluate how much more likely physicians were to be considered high-prescribers if they had received an industry payment over physicians who had not received payments. The 95% confidence intervals for these values were also computed and reported in Table 3.

For example, consider Synthroid, a drug used to treat hypothyroidism. The above discretized variables for this drug are as follows: (a) 1,017; (b) 2,490; (c) 10,630; (d) 86,292. These variables can be interpreted as: 96,922 physicians did not receive payment; 10,630 of these physicians were high-prescribers. 3,507 physicians did receive payment; 1,017 of these were high-prescribers. This means that 1,017/3,507 (29%) of physicians who receive payments were high-prescribers, while only 10,630/96,922 (11%) of physicians who didn’t receive payments were high-prescribers. Therefore, physicians who received payments for Synthroid were 2.6x more likely to be high-prescribers of the drug, which can be represented as a risk ratio of 2.6.

### Table 1 Medicare Part D PUF 2015 Record Counts By Specialty After Data Processing

<table>
<thead>
<tr>
<th>Specialty</th>
<th>Physicians</th>
<th>Physician-Drug Pairs</th>
<th>Physician-Drug Pairs w/ Payments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>139,596</td>
<td>4,784,335</td>
<td>20,750</td>
</tr>
<tr>
<td>Internal Med</td>
<td>54,697</td>
<td>2,213,326</td>
<td>8,616</td>
</tr>
<tr>
<td>Family Prct</td>
<td>58,774</td>
<td>2,104,154</td>
<td>7,354</td>
</tr>
<tr>
<td>Cardiology</td>
<td>15,235</td>
<td>291,725</td>
<td>332</td>
</tr>
<tr>
<td>Psychiatry</td>
<td>10,890</td>
<td>175,130</td>
<td>4,448</td>
</tr>
</tbody>
</table>

### Table 2 Counts of Categories Used to Calculate Risk Ratios

<table>
<thead>
<tr>
<th>Category</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>3,676</td>
<td>3,789</td>
<td>3,398</td>
</tr>
<tr>
<td>(b)</td>
<td>23,799</td>
<td>26,106</td>
<td>20,850</td>
</tr>
<tr>
<td>(c)</td>
<td>83,651</td>
<td>83,538</td>
<td>83,929</td>
</tr>
<tr>
<td>(d)</td>
<td>3,196,544</td>
<td>3,194,237</td>
<td>3,199,493</td>
</tr>
</tbody>
</table>

(a): The number of physicians who had received a payment on behalf of a drug, and were high-prescribers of that drug  
(b): The number of physicians who had received a payment on behalf of a drug, and were not high-prescribers of that drug  
(c): The number of physicians who had not received a payment on behalf of a drug, and were high-prescribers of that drug  
(d): The number of physicians who had not received a payment on behalf of a drug, and were not high-prescribers of that drug

### 2.8 Opioid Sub-Analysis

CareDash also investigated the relationship between payments and prescriptions for the class of drugs that the CMS designates as opioids (11).

The specific drugs considered in this analysis as part of the opioid drug class are listed in the Appendix Table A4.

### 2.9 Sensitivity Analysis

The methodology followed by CareDash included two free parameters that were arbitrarily chosen during the process:

- A physician must have at least 100 prescriptions of a particular drug group to be included in the analysis.
- A drug must be prescribed by at least 10 physicians to be included in the analysis.

To verify that the choice of value for each of these parameters did not affect the results of the analysis, CareDash performed sensitivity analysis on the choice of value for these parameters. CareDash computed results considering every possible combination of group-claim cutoff up to 500 claims (in 50-claim increments) and physician-count cutoff up to 100 (in 10-physician increments), and found that the choice of value for these parameters did not significantly affect the result of the analysis.
3 Results

CareDash found that physicians receiving payments on behalf of specific drugs were 4.97 times more likely to prescribe those drugs at high levels than physicians in their specialty who did not receive payments for those drugs. When the industry payments were known to occur in the year preceding the prescriptions (i.e., subsequent, rather than contemporaneous, prescriptions), the risk ratio was 5.25. When the prescriptions were known to occur in the year preceding the industry payments (i.e., subsequent, rather than contemporaneous, payments), the risk ratio was 5.48.

These results along with the 95% confidence interval for each risk ratio are reproduced in Table 3. The 95% confidence intervals indicate that the relationship between payments by industry and prescribing drugs by physicians was statistically significant. Due to the overlapping confidence intervals, CareDash was not able to establish a statistically significant difference in results between payments occurring before and after prescriptions.

Note that the overall result includes physician-drug relationships for smaller physician specialties outside the four explicitly included in the analysis: ‘general practice,’ ‘emergency medicine,’ ‘neurology,’ and ‘gastroenterology.’ These four specialties did not have sufficient data associated with them to produce specialty-specific results, but their data was included in computing the general trend across all specialties.

Across physician specialties, a consistent trend that emerges across years of payment data is with family practitioners exhibiting almost twice the risk ratio of cardiologists, the largest and smallest risk ratios in the results respectively.

In addition to calculating risk ratios for all drugs, CareDash also looked at risk ratios for opioids by filtering the results to that specific category of drugs. Within the opioid drug class, it was found that physicians receiving payment on behalf of an opioid were 14.5 times more likely to choose that drug over its alternatives in the same year. For prescriptions occurring the year after payments, we found physicians were 14.1 times more likely to choose that drug significantly more often and when the prescriptions occurred the year before payments, the risk ratio was 13.4.

4 Discussion

In performing this analysis, CareDash aimed to identify whether payments from industry to physicians for specific drugs were associated with those physicians’ tendency to choose those drugs over their alternative options, and to shed some light on the potential for a causal link between the two events. We found a significant relationship between physicians’ prescribing habits and industry payments made to those physicians on behalf of the specific drugs they prescribe. The risk ratios reported in this study should be interpreted to mean that, for example, physicians receiving payments on behalf of specific drugs in 2015 were 4.97 times more likely to prescribe those drugs at high levels than the physicians who did not receive payments on behalf of those specific drugs.

This relationship could suggest that the industry payments influence the prescribing decisions made by physicians among various brand-name drugs, whether that is through informational campaigns or through direct relationship-building efforts on the part of the drug manufacturers. At the same time, it could also suggest that physicians who choose a particular drug significantly more often than others in their specialty are more likely to be sought out by pharmaceutical manufacturers to act as promotional speakers and to attend conferences (which are recorded as payments in the Open Payments database).

It is also important to note that these explanations are not mutually exclusive. Previous work by ProPublica involved overlapping time-frames for both payments and prescriptions (similar to our analysis using 2015 payment data with 2015 prescription data), preventing any conclusions being made towards the direction of the correlation. However, CareDash was able to make use of the additional years of Open Payments data available at the time of writing to expand our understanding of that direction.

By comparing prescribing behavior in the context of both preceding and subsequent payments (i.e., comparing 2014 payments to 2015 prescriptions, and 2016 payments to 2015 prescriptions), CareDash was able to determine that relationships exist in both directions between industry payments and physician prescriptions. Our results suggest that a physician is approximately as likely to be a high-prescriber of a drug and go on to receive industry payments on behalf of it, as they would be to receive industry payments on behalf of a drug and go on to become a high-prescriber of it. However, more data are needed to speak definitively on the relative strength of these two scenarios.

CareDash was not able to, and did not attempt to, establish a causal link between industry payments and physician prescriptions. However, statistically significant directional correlations were successfully established, which indicate the potential for causal relationships in both directions.

4.1 Limitations

In the process of linking physicians across the prescription and payment data, CareDash matched physician records using the first and last name, city, and state of each physician. If more than one physician matched
between the two datasets using these fields, data on all ambiguous physicians were discarded from the analysis. While the rigor of this method - combined with manual inspection of the physician record matches it produced - gave CareDash confidence in how the disparate datasets were connected, it is still possible that physicians that had received industry payment were not successfully linked to those payment records.

The method by which CareDash determined which drugs were considered ‘alternatives’ to one another operated on the assumption that physicians were deciding between multiple drugs that shared the same generic equivalent when choosing which drug to prescribe. While this may form a part of the prescribing decision process, a larger decision that is also made by prescribers is between different classes of drugs to treat a given situation. CareDash was unable to explore the relationship between industry payments and prescribers’ decision-making between different drug classes, but future work may be able to explore that area more thoroughly.

Multiple stages of the data-cleaning process could have allowed discrepancies to enter the analysis, despite care being taken to avoid that possibility. During cleaning of the drug names, drugs may have had their names incorrectly modified in a way that compromised a record’s integrity.

CareDash was also limited by the data available to the analysis. Our process assumed that all relevant payments were recorded by Open Payments. However, there are a variety of situations in which physicians could have received unrecorded payments. CareDash could not control for payments absent from Open Payments. Since the analysis was done without adjusting for any potential confounders, the risk ratios are crude and might be inflated. Future analyses may be able to identify confounders and estimate adjusted risk ratios.

Another important factor to consider was the timeframe of available data. The earliest full calendar year of publicly available Open Payments data was 2014, meaning physicians that were identified to have received payment subsequent to their prescriptions may have also received payment prior to those prescriptions. CareDash could not control for those occurrences.

Finally, all raw drug names (for both brand-name and generic drugs) in the Medicare Part D data were obtained by CMS through linking the National Drug Codes of drugs involved in prescription events, with a commercially available drug information database (10). Due to inconsistencies in the National Drug Code data, it was possible that drugs with modifiers were reported in the Medicare Part D PUF without those modifiers, allowing them to erroneously escape filtering during the drug name cleaning process. CareDash was not able to control for the possibility of incomplete reporting.

5 Conclusion

CareDash explored the relationship between pharmaceutical industry payments received by physicians related to specific prescription drugs, and those physicians’ prior, contemporaneous, and subsequent prescriptions for those drugs. The analysis found that physicians receiving at least one industry payment on behalf of a specific drug were 5 times more likely than their peers to choose that drug over other available options. Additionally, CareDash found that this correlation existed in approximately equal strength in both directions between industry payments and physician prescriptions.

<table>
<thead>
<tr>
<th>Specialty</th>
<th>2014 RR</th>
<th>2014 95% CI</th>
<th>2015 RR</th>
<th>2015 95% CI</th>
<th>2016 RR</th>
<th>2016 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>5.25</td>
<td>5.09 – 5.40</td>
<td>4.97</td>
<td>4.83 – 5.12</td>
<td>5.48</td>
<td>5.31 – 5.66</td>
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<tr>
<td>Internal Medicine</td>
<td>4.70</td>
<td>4.44 – 4.98</td>
<td>4.27</td>
<td>4.03 – 4.51</td>
<td>4.93</td>
<td>4.66 – 5.22</td>
</tr>
<tr>
<td>Family Practice</td>
<td>5.95</td>
<td>5.59 – 6.33</td>
<td>5.57</td>
<td>5.23 – 5.93</td>
<td>6.99</td>
<td>6.61 – 7.40</td>
</tr>
<tr>
<td>Cardiology</td>
<td>3.28</td>
<td>2.43 – 4.42</td>
<td>2.80</td>
<td>1.54 – 5.10</td>
<td>3.35</td>
<td>1.75 – 6.40</td>
</tr>
</tbody>
</table>

RR+ and RR− represent the upper and lower bounds of the 95% confidence interval for each result, respectively.
Appendix

A Reproducing ProPublica’s Findings

In a precursor to CareDash’s analysis, ProPublica used Open Payments data for the 2014 calendar year and 2014 Medicare Part D prescription data (obtained through a Freedom of Information Act request), to explore the relationship between physicians receiving industry payments, and their prescribing habits relating to the fraction of their prescription claims made for brand-name drugs. CareDash was able to reproduce their result using the Open Payments 2015 year of data and the 2015 Medicare Part D PUF, and found that physicians receiving industry payments for brand-name drugs were 2-3 times more likely, in general, to prescribe brand-name drugs significantly more than other physicians in their specialty.

Mirroring the methodology of Jones & Ornstein (2016), CareDash considered a physician to have received industry payments if they received at least one payment from pharmaceutical or medical device companies in 2015. CareDash also limited the analysis to physicians having at least 1,000 prescription claims in the 2015 year of Medicare Part D data.

Table A1 shows the number of doctors in each specialty having at least 1,000 claims, and the subset of those physicians who received at least one payment. Despite the two studies using different years of data, the fraction of physicians receiving industry payments were similar across both analyses.

To determine the rate at which physicians prescribed brand-name drugs, CareDash (and ProPublica) calculated the fraction of each physician’s claims that went to brand-name drugs. A main difference between the analyses of ProPublica and CareDash was how these claim counts were calculated. From their data-request, ProPublica received aggregated annual counts of ‘generic,’ ‘brand-name,’ and ‘other’ prescription counts for each physician. In contrast, CareDash did not receive categorical counts, and instead used the 2015 year of the Medicare Part D Public Use File to determine claim counts for each physician. After performing the data-cleaning outlined in §2.2, CareDash determined which records in the data indicated prescriptions for generic versus brand-name drugs by identifying cases where the name of the prescribed drug matched the name of the associated generic drug. All records where the prescribed drug did not match the associated generic drug were considered prescriptions for brand-name drugs. CareDash did not define any category of ‘other’ prescriptions. A comparison of the brand-name prescribing-rates found by CareDash and ProPublica by physician specialty is reproduced in Table A2.

To determine if physicians who received industry payments had different brand-name prescribing-rates to physicians who did not receive industry payments, CareDash (and ProPublica) compared the brand-name prescribing-rates of physicians to their peers within their specialty, in order to account for variances in the mean brand-name prescribing-rate across different specialties.

Physicians with brand-name prescribing-rates that were at least one standard deviation or more above the mean for their specialty were labelled ‘high brand-name prescribers.’ CareDash (and ProPublica) calculated risk ratios to compare the likelihood of being a high brand-name prescriber for physicians who received industry money and those who did not.

CareDash and ProPublica found that physicians who received payments were, on average, two times more likely to be high brand-name prescribers than physicians who did not receive payments. Table A3 presents a comparison of the results of both CareDash’s and ProPublica’s studies by specialty, with each result’s 95% confidence interval.

B Acknowledgements

We would like to thank Dr. Aaron S. Kesselheim, associate professor of medicine at Harvard Medical School, for his review of the methodology and results of this study.

References

Centers for Medicare & Medicaid Services, 2017. "National Health Expenditures 2016 Highlights"
Blue Cross Blue Shield. May 3, 2017. "Rising costs for patented drugs drive growth of pharmaceutical spending in the U.S."
Patient Protection & Affordable Care Act, 42 USC 18001 § 6002.
### Table A1  Percentage of Physicians Receiving Payments, by Specialty

<table>
<thead>
<tr>
<th>Specialty</th>
<th>CD(^a) &gt;1,000 claims</th>
<th>PP(^b) w/ payments</th>
<th>CD w/ payment</th>
<th>PP w/ payment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family Medicine</td>
<td>61,021</td>
<td>43,094</td>
<td>46,753</td>
<td>70.6%</td>
</tr>
<tr>
<td>Internal Medicine</td>
<td>54,519</td>
<td>38,532</td>
<td>36,329</td>
<td>70.7%</td>
</tr>
<tr>
<td>Cardiovascular Disease</td>
<td>14,619</td>
<td>13,171</td>
<td>12,308</td>
<td>90.1%</td>
</tr>
<tr>
<td>Psychiatry</td>
<td>10,557</td>
<td>8,650</td>
<td>8,650</td>
<td>81.9%</td>
</tr>
<tr>
<td>Ophthalmology</td>
<td>8,436</td>
<td>7,137</td>
<td>7,117</td>
<td>84.6%</td>
</tr>
</tbody>
</table>

\(^a\)CareDash \(^b\)ProPublica

### Table A2  Brand-name Drug Prescribing-Rates, by Specialty

<table>
<thead>
<tr>
<th>Specialty</th>
<th>CD(^a) Mean Prescribing-Rate</th>
<th>PP(^b) Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family Medicine</td>
<td>0.11</td>
<td>0.046</td>
</tr>
<tr>
<td>Internal Medicine</td>
<td>0.13</td>
<td>0.074</td>
</tr>
<tr>
<td>Cardiovascular Disease</td>
<td>0.16</td>
<td>0.058</td>
</tr>
<tr>
<td>Psychiatry</td>
<td>0.074</td>
<td>0.049</td>
</tr>
<tr>
<td>Ophthalmology</td>
<td>0.34</td>
<td>0.17</td>
</tr>
</tbody>
</table>

\(^a\)CareDash \(^b\)ProPublica

### Table A3  Risk Ratios for Brand-name vs. Generic Drug Prescribing, by Specialty

<table>
<thead>
<tr>
<th>Specialty</th>
<th>CareDash</th>
<th>ProPublica</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR^-</td>
<td>RR</td>
<td>RR+</td>
</tr>
<tr>
<td>RR^-</td>
<td>RR</td>
<td>RR+</td>
</tr>
</tbody>
</table>

### Table A4  Drugs Classified as Opioids

<table>
<thead>
<tr>
<th>Hydrocodone Acetaminophen</th>
<th>Tramadol</th>
<th>Norco</th>
<th>Vicodin</th>
<th>Lortab</th>
<th>Xodol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oxycodeone Acetaminophen</td>
<td>Oxycodeone</td>
<td>Conzip</td>
<td>Endocet</td>
<td>Percocet</td>
<td>Primlev</td>
</tr>
<tr>
<td>Tramadol Acetaminophen</td>
<td>Oxycontin</td>
<td>Roxicodone</td>
<td>Fentanyl</td>
<td>Duragesic</td>
<td>Subsys</td>
</tr>
<tr>
<td>Acetaminophen Codeine</td>
<td>Tylenol Codeine</td>
<td>Methadone</td>
<td>Dolophine</td>
<td>Diskets</td>
<td>Kadian</td>
</tr>
<tr>
<td>Morphine Sulphate</td>
<td>Avinza</td>
<td>Hydromorphone</td>
<td>Dilaudid</td>
<td>Exalgo</td>
<td>Ultracet</td>
</tr>
<tr>
<td>Meperidine</td>
<td>MS Contin</td>
<td>Methadose</td>
<td>Roxicet</td>
<td>Ultram</td>
<td>Demerol</td>
</tr>
</tbody>
</table>