Medicaid Pharmaceutical Reimbursement Analysis

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Introduction

Organization

Medicaid, a social welfare program, provides health coverage for over 80 million low-income Americans, nearly one in four people living in the United States. Title XIX of the Social Security Act authorized the establishment of the Medicaid program in 1965. Today, the Center for Medicaid and CHIP Services (CMCS) oversees all federal policies to Medicaid. All U.S. states, territories, and the District of Columbia operate a Medicaid program but do so independently of one another (U.S. Centers for Medicare & Medicaid Services, 2022). In effect, Medicaid coverage varies state-to-state and has changed over time. Similar to other federal social welfare programs, Medicaid is cited for its inefficiencies and bureaucratic challenges. The Children Health Insurance Program (CHIP) of 1997 provided health coverage to children in families with an income too high to qualify for Medicaid. And the Basic Health Program enacted by the Affordable Care Act in 2014 standardized Medicaid eligibility rules and authorized U.S. states to further expand coverage. Today, 11 U.S. states have not expanded Medicaid coverage with this authorization. Most recently, the COVID-19 pandemic impacted Medicaid pharmaceutical costs (U.S. Centers for Medicare & Medicaid Services, 2022).

Previously stable from 2015 to 2019, Medicaid net prescription drug costs increased to $72 billion in 2020. Despite increasing costs Medicaid prescription drug utilization declined. In autumn of 2022 the U.S. federal government passed the Inflation Reduction Act (IRA), including a number of prescription drug reforms to Medicaid. Starting in 2023, pharmaceutical companies will pay rebates to the U.S. federal government if drug prices rise faster than inflation. Over time, this will result in slower growth in drug prices (Cubanski, 2022). Pharmaceutical companies are expected to offset the slower price growth to increase profits, and the IRA's

inflation-related rebates are ultimately expected to increase Medicaid spending while having minimal impact on costs paid by beneficiaries (Cubanski, 2022). In effect, the U.S. federal and state governments will pay for rising costs, further adding to concerns about increasing social welfare expenditures. Medicaid-related policies are challenging, complex, and often developed in close partnership with pharmaceutical companies.

Analysis Problem

In the following analysis, our team will serve on behalf of Medicaid administrators. Reporting to a hypothetical team of federal regulators, we evaluate recent Medicaid pharmaceutical spending and flag opportunities for savings. These savings most benefit U.S. federal and state governments, not Medicaid beneficiaries. Considering the Inflation Reduction Act, pharmaceutical companies are expected to raise drug launch prices to make up for inflation-related rebates. This tactic will be less effective for drugs that have equivalent alternatives.

We will address each research question in order:

1. Which classes of drugs comprise the largest portion of Medicaid pharmaceutical costs?
2. Which individual (nonproprietary & brand name) drugs comprise the largest portion of costs?
3. What are the regional differences in prescription usage and cost? and,
4. Where are the opportunities for savings?

We hypothesize that drugs with equivalent alternatives are prime candidates for price negotiation and further regulation. As we explore this question, we consider other opportunities for savings. Our recommendations to the hypothetical team of Medicaid administrators may be

used to monitor increasing costs for existing and newly-introduced drugs in 2023, and in the long-term, inform future public policies.

Data Sources

Our first step to address Medicaid pharmaceutical spending was to review our raw data files. In order to analyze the spending budget over the last four years, we had to extract the data from 2018-2022. Our extracted data set is 8,287,474 rows and 25 columns. Each row corresponds to one prescription package type, including details about product codes, package size, prescription region and year, and reimbursement dollars. Our second data set was a collection of NDC lists. NDC code lists were provided as separate finished drug, unfinished drug, compound drug, and experimental drug files. We excluded the experimental list, as it was only for drugs and components that were not yet approved for prescription use. The finished and unfinished were compliments to each other, and the compound list was for ingredients that could be used on their own, so these were all assembled into the set. This set contained 134,170 rows and 243 columns. Many of these columns were excluded from the final set as they were beyond the scope of this analysis.

Process

Data Preparation

Getting ready for our analysis, we cleaned and prepared the first dataset. The primary obstacle regarded the suppresion_used field. At first glance, an entire year's entries in this column was missing. This was an important column, as suppression refers to the rows in which the data has been withheld, or suppressed, for privacy reasons. Suppressed data “protect the privacy of individual beneficiaries and other persons,” as “all direct identifiers have been removed and data that are less than eleven (11) counts are suppressed” (U.S. Centers for

Medicare & Medicaid Services, 2022). The actual data was of little use for our analysis because the data was absent - explicitly removed for privacy reasons. The null values made analysis challenging, and suppressed data extended beyond the suppresion_used field; i.e. "if one sub-group (e.g., number of prescriptions) is suppressed, then the other sub-groups are suppressed" (U.S. Centers for Medicare & Medicaid Services, 2022). Moreover, we noticed an additional supression_used field located in an unusual location in the data. The two fields: suppresion_used; and supression_used, captured similar data, and the publishers of the added an additional field instead of aggregating the results. Despite the initial confusion, we combined the columns and moved forward.

Next, we cleaned the second set of data. After researching how NDC codes are made and how they are supposed to be recorded, we created a master NDC code list. This dataset allowed us to organize all of the prescriptions by their NDC as opposed to simple descriptions and the individual names. This second data set allowed us to group the drugs by class and their generic name, as well as gain insight into individual, name brand drugs. Here, however, we encountered another problem: multiple lists of NDC codes listed their NDC codes differently. The standard NDC code format was derived from a different, variable way to write the code. Our data had both formats. After identifying which variation of the code was used, we discovered our second set accounted for all the variations. The NDC code was a field in both datasets, but formatted differently. Our first list of NDC codes simply dropped all the leading 0s and separated the code out into multiple columns. To address the discrepancy, we normalized the codes for our own purposes. After a bit of code and a crash course in CASS, we added leading 0s, combined the columns, and aggregated these codes with the second set.

With our new master set, we set about the final cleaning process. We removed any columns that had names or data only useful to those making the drugs (all with names either written in a shorthand code we are not privy to, or in something completely unpronounceable), and looked through the rows for what wouldn't be helpful. In the end, we removed 2,817,215 rows that had no current NDC match, 10,801,731 that had their data suppressed, and 772,951 rows that indicated a combination of state data: XX for the state. This left us with a final row count of 8,287,474 ready to be analyzed. With prepared data in hand, we began descriptive data analysis.

Analytical Techniques

Using JMP and Tableau, we answered our four research questions using descriptive statistics. Specifically, we analyzed the medicaid_amount_reimbursed field across different dimensions. For the first question, which asked which classes of drugs comprise the largest portion of Medicaid pharmaceutical cost, we created a bar chart on Tableau of pharm_classes by medicaid_amount_reimbursed. We did the same for individual (nonproprietary & brand name) drugs comprising the largest portion of costs by creating bar charts by medicaid_amount_reimbursed. To address differences in prescription usage and cost by state, we similarly created data visualizations in Tableau. Finally, to provide opportunities for savings for the last question, we returned to the results of questions one through three. Grouping by the pharm_classes field, and sorting by the medicaid_amount_reimbursed field, we identified the most expensive classes of drugs. We then identified the cheapest drug by unit price in each drug class. To find the unit price, we divided medicaid_amount_reimbursed by units_reimbursed.

Challenges

Performing analysis on and navigating such large quantities of data proved most challenging. Computer performance issues were a recurring obstacle. While we were able to cut down the data quite a bit in the cleaning phase, some of us borrowed computers that could handle the data, and everyone's computer, borrowed or not, would slow down, run low on ram (or run out completely). This led to long wait times and regular crashes. While this wasn't devastating - we saved often - we found that even the saving would take time. In addition, narrowing the scope of our research proved challenging.

Beyond the issue of size of the data, narrowing the scope of our research questions, how we should order them, what we wanted to answer, how we wanted to answer them presented challenges. We had some good discussions about this throughout the project and tweaked the questions as we went. In the beginning we simply wanted to answer the questions suggested in the group page: Which drugs comprise the largest portion of Medicaid pharmaceutical costs (this should involve determining classes of drugs as well as individual drugs), where are there opportunities for savings, are there some drugs that have alternative equivalents that could be used, and what are the drivers of cost? Are there regional differences? Going from there we started working with the data, and examining what the point of this project would be from a real world perspective. We decided that the main point of concern, and what the main takeaway would be, was how to reduce the cost. We refined the question and the order we were looking at them to what we have now: Which classes of drugs comprise the largest portion of Medicaid pharmaceutical costs, which individual (nonproprietary & brand name) drugs comprise the largest portion of costs, what are the regional differences in prescription usage and cost and, where are the opportunities for savings? This broke the problem down into a sequential series of

questions that followed a shrinking scope costs to the final, key question. We start with the overall drug class, then look at the brand of drugs. This gives us two areas of potential cost reduction, and if there is a discrepancy between the most expensive areas of treatment and the most expensive brand, it could indicate another cost saving opportunity. We then look to see if there are regional differences, both in drug class and in brand name costs. As we build the questions into each other we find cost reduction opportunities, highlight them, and can give a comprehensive suggestion and possible course of action.

Results

Drug Class Analysis

Looking at the Medicaid budget from 2018-2022, we found the top five most expensive drug classes. See Figure 1. Rising to the top, uncontested, the costliest drug class is the "Insulin Analog [EPC], Insulin [CS]" class. Insulin is primarily used to treat diabetes, and Medicaid pharmaceutical costs totaled $10.5 billion in four years. The second most expensive drug class, at $9.2 billion is the "Hepatitis B Virus Nucleoside Analog Reverse Transcriptase Inhibitor [EBC], Human Immunodeficiency Virus Nucleoside Analog Reverse Transcriptase Inhibitor [EPC]..." class. These drugs are most often prescribed to treat Hepatitis B and HIV (Medline Plus, 2022). The third most expensive class is "GLP-1 Receptor Antagonist [EPC], Glucagon-Like Peptide 1 [CS]" class, with Medicaid pharmaceutical costs of $6.6 billion. These are used to treat type 2 diabetes and obesity. (Medline Plus, 2022). The fourth most expensive drug class is the "Adrenergic beta2-Agonists [MOA], Corticosteroid Hormone Receptor Agonists [MOA]" class. This class is used to treat respiratory diseases such as bronchial asthma and chronic obstructive pulmonary disease (COPD), and totals $5.9 billion of Medicaid pharmaceutical costs (Medline Plus, 2022). The fifth most expensive drug class at $5.5 billion is

the “Insulin Analog [EPC], Insulin [Chemical/Ingredient]” class. This is primarily used to improve glycemic control in adults and children with diabetes mellitus (Medline Plus, 2022). Together these five classes totaled $37,802,469,934 of Medicaid’s total amount reimbursed $274,229,906,733. Finding some ways to reduce costs in these five classes will go a long way to reducing overall Medicaid costs. The last part of our analysis will focus on how we plan to do this.

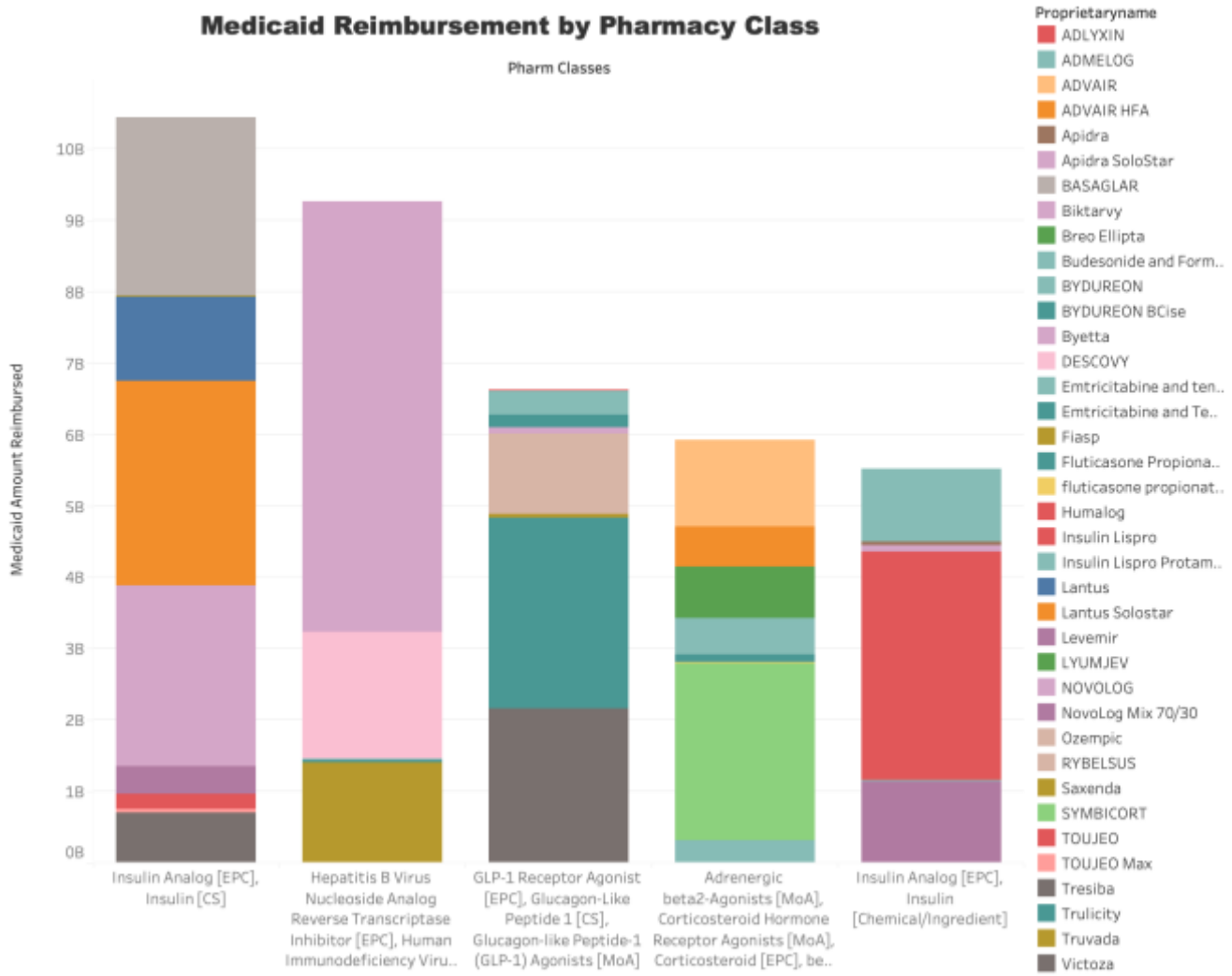

Figure 1. Medicaid Reimbursement Totals by Pharmacy Class

Individual Drug Analysis

Diving deeper into the data, we analyzed specific drug costs. We addressed both "nonproprietary" and "proprietary" drugs. Nonproprietary drugs, also known as generic drugs, are not registered with a trademark or brand name. They are simply the type of drug that proprietary drugs are classified under. Proprietary drugs are owned by pharmaceutical companies who own rights to the drugs and profit from their sales.

Nonproprietary Drugs

The most cost-intensive nonproprietary drugs are shown in Figure 2. The most expensive drug, *Adalimumab,* an immunosuppressive drug used to treat arthritis, plaque psoriasis, ankylosing spondylitis, Crohn's disease, and ulcerative colitis, totaled $11.5 billion in medicaid reimbursements (Medline Plus, 2022). The second most expensive generic drug is *bictegravir sodium, emtricitabine, and tenofovir alafenamide fumarate*, totalling $6 billion of spending. This drug compound is used to treat HIV (Medline Plus, 2022). The third most expensive nonproprietary drug, with $2.8 billion of spending, is *insulin glargine*, used to treat diabetes. The fourth most expensive generic drug, *buprenorphine hydrochloride, naloxone hydrochloride* treats opioid addiction and accounts for $3.6 billion of medicaid reimbursements (Medline Plus, 2022). The fifth most expensive generic drug, which accounts for $3.4 billion in spending, is *Glecaprevir and Pibrentasvir,* used to treat Hepatitis C (Medline Plus, 2022). Combined, these five nonproprietary drugs total $24,648,912,051 in medicaid reimbursement spending.

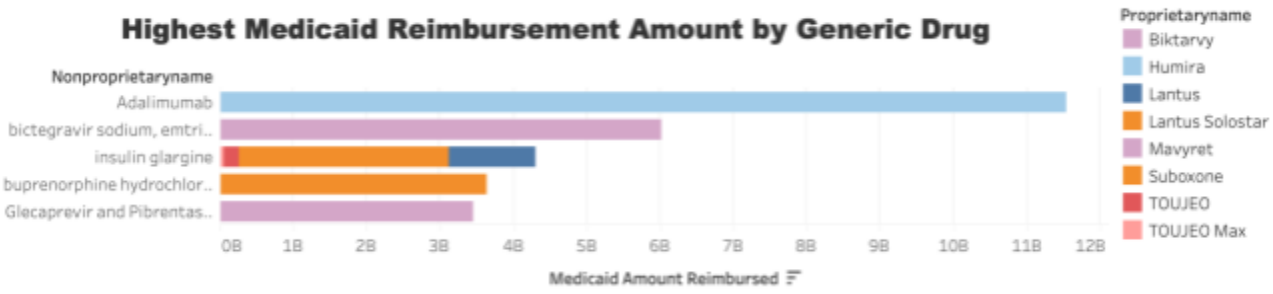

Figure 2. Medicaid Reimbursement Total by Individual Drug

Proprietary Drugs

Next we address the most expensive proprietary, or "brand name" drugs. See Figure 3. The most government spending was on *Humira*, a type of *Adalimumab* drug at $11,536,480,247. *Biktarvy*, a type of *bictegravir sodium, emtricitabine, and tenofovir alafenamide fumarate* drug accounts for the second most spending totalling $6,027,058,506. Third was *Suboxone*, a type of *buprenorphine hydrochloride, naloxone hydrochloride* drug, accounting for $3,629,957,697 in reimbursements. $3,455,415,601 of medicaid pharmaceutical spending was spent on *Mavyret*, a type of *Glecaprevir and Pibrentasvir* drug at $3,455,415,601. And finally, the fifth most expensive brand name drug was *Genvoya*, a type of *elvitegravir, cobicistat, emtricitabine, and tenofovir alafenamide* drug used to treat HIV/AIDS. This drug accounts for $3,240,794,443 of spending (Medline Plus, 2022).

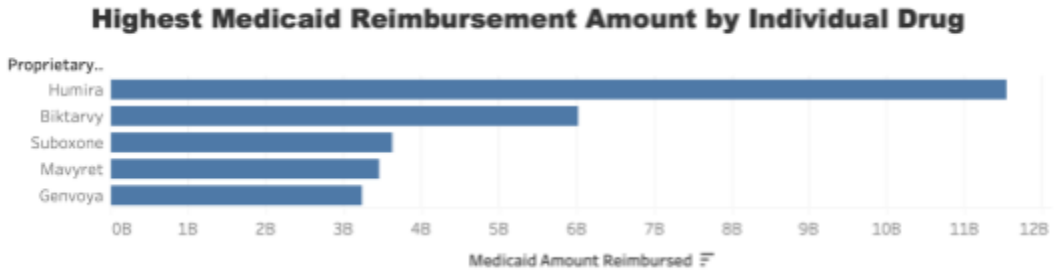

Figure 3. Medicaid Reimbursement Total by Proprietary Name

Regional Analysis

We also investigated if there was a regional component to prescription usage and costs. Figure 4 depicts Medicaid reimbursement amounts by state and population. Prescriptions by state are most significant in California and New York, where the population is also the highest. Though it is no surprise the number of prescriptions are higher in densely populated areas, there are some states that have rather expensive budgets considering they are lower on the population spectrum. For example, we can see in figure 4 that Michigan and Wisconsin are two states that

have larger circles showing they have spent more on Medicaid Reimbursements than states with similar population sizes. This could be due to a number of reasons that could possibly be looked further into such as environmental factors, demographics, or average income.

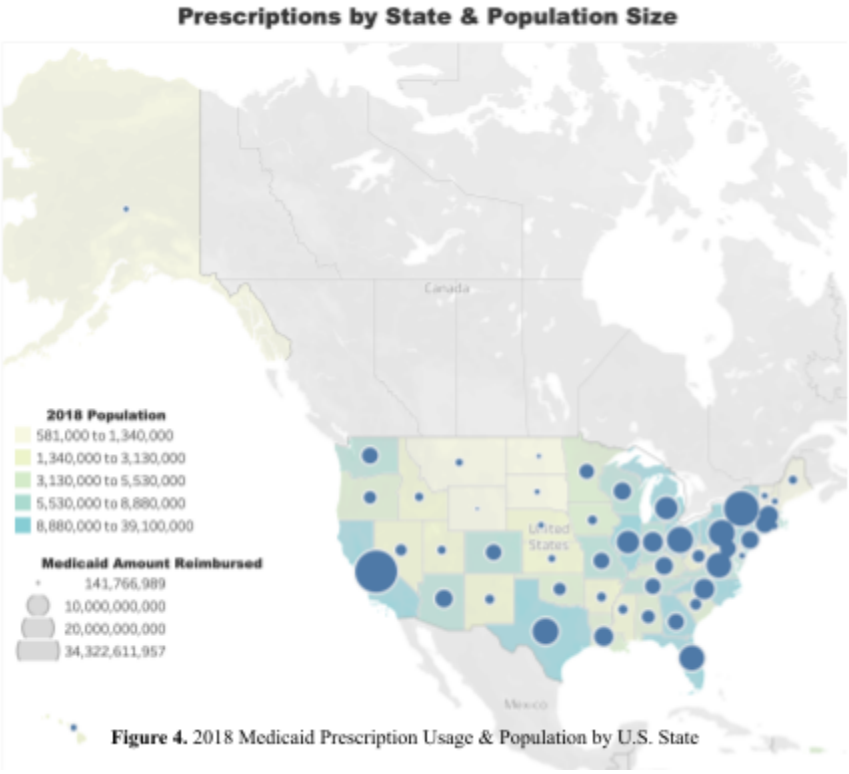

Figure 4. 2018 Medicaid Prescription Usage & Population by U.S. State

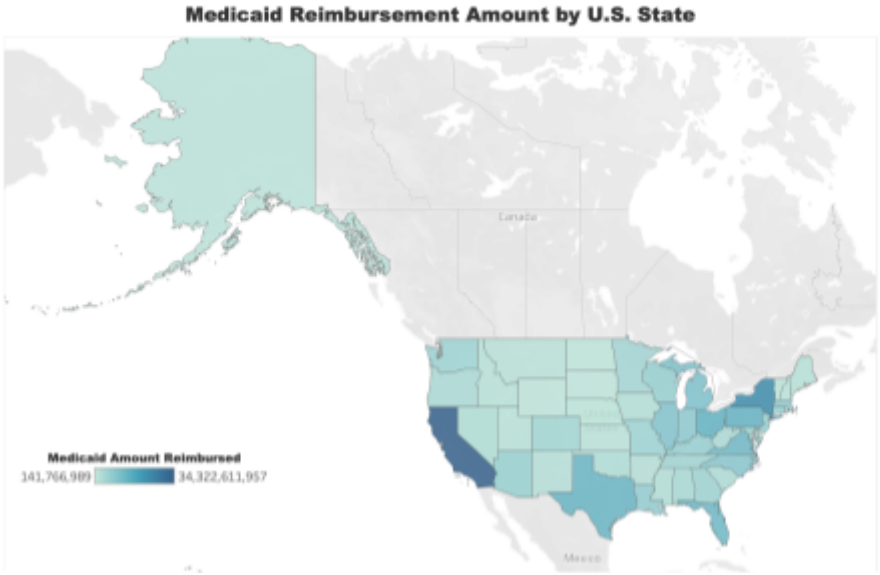

Figure 5. Medicaid Reimbursement Amount Total by U.S. State

Opportunities for Savings

Having worked through the first three questions, we return to our final question: "Where are there opportunities for savings?" After preliminary analysis, we determined the best way to find opportunities for savings would be to find alternatively cheaper drugs in the five most expensive drug classes we found in the *Drug Class Analysis* section (Figure 1). We did this by dividing the *Medicaid Amount Reimbursed* by *Units Reimbursed* to get a price per unit. Figures 6 through 10 present the results.

"Insulin Analog [EPC], Insulin [CS]"			
Name	Medicaid Amount Reimbursed	Units Reimbursed	Unit Price
Basaglar	$ 5,002,072,078.00	238495119	$ 20.97
Lantus	$ 2,360,585,425.00	89034422	$ 26.51
Lantus Solostar	$ 5,721,290,317.00	212709407	$ 26.90
Fiasp	$ 46,124,418.00	1607389	$ 28.70
Novolog	$ 5,077,834,052.00	165070881	$ 30.76
Novolog Mix 70/30	$ 765,005,148.00	23376932	$ 32.72
Tresiba	$ 1,401,813,348.00	30987348	$ 45.24
TOUJEO	$ 411,735,905.00	5241498	$ 78.55
TOUJEO MAX	$ 124,891,306.00	1534929	$ 81.37

Figure 6. Insulin Analog Cost-Saving Alternatives (class 1)

"Hepatitis B Virus Nucleoside…"			
Name	Medicaid Amount Reimbursed	Units Reimbursed	Unit Price
Emtricitabine and tenofivir disoproxil fumarate	$ 140,294,650.00	9000551	$ 15.59
Truvada	$ 2,812,194,376.00	52083869	$ 53.99
DESCOVY	$ 3,581,588,644.00	62667355	$ 57.15
Biktarvy	$ 12,058,718,237.00	114913257	$ 104.94

Figure 7. Hepatitis B Treatment Cost-Saving Alternatives

"GLP-1 Receptor Antagonist [EPC], Glucagon-Like Peptide 1 [CS]"			
Name	Medicaid Amount Reimbursed	Units Reimbursed	Unit Price
RYBELSUS	$ 178,709,771.00	6693526	$ 26.70
Saxenda	$ 113,706,755.00	1434184	$ 79.28
Victoza	$ 4,311,962,387.00	42841425	$ 100.65
ADLYXIN	$ 5,450,952.00	51032	$ 106.81
BYDUREON	$ 700,811,599.00	4136456	$ 169.42
BYDUREON Bcise	$ 373,214,973.00	1813893	$ 205.75
Ozempic	$ 2,077,192,870.00	5629782	$ 368.97
Trulicity	$ 5,349,905,160.00	13832994	$ 386.75
Byetta	$ 163,276,236.00	413303	$ 395.05
WEGOVY	$ 17,792,488.00	34930	$ 509.38

Figure 8. GLP Cost-Saving Alternatives

"Adrenergic beta2-Agonists [MOA], Corticosteroid Hormone Receptor Agonists [MOA]"			
Name	Medicaid Amount Reimbursed	Units Reimbursed	Unit Price
Wixela Inhub	$ 632,659,588.00	189904219	$ 3.33
Fluticasone Propionate and Salmeterol	$ 736,382,304.00	148866882	$ 4.95
Breo Ellipta	$ 1,460,049,230.00	260444257	$ 5.61
ADVAIR	$ 2,425,433,998.00	391669692	$ 6.19
Budesonide and Formoterol Fumarate Dihydrate	$ 993,468,553.00	39945705	$ 24.87
SYMBICORT	$ 4,954,230,627.00	155009377	$ 31.96
ADVAIR HFA	$ 1,132,175,819.00	34344162	$ 32.97

Figure 9. MOA Cost-Saving Alternatives

"Insulin Analog [EPC], Insulin [Chemical/Ingredient]"			
Name	Medicaid Amount Reimbursed	Units Reimbursed	Unit Price
Insulin Lispro	$ 602,166,353.00	40393813	$ 14.91
Insulin Lispro Protamine and Insulin Lispro Injectible Suspension	$ 23,124,395.00	1411539	$ 16.38
ADMELOG	$ 2,037,631,167.00	117253490	$ 17.38
Apidra	$ 104,704,925.00	3905800	$ 26.81
Levemir	$ 2,310,147,614.00	80374206	$ 28.74
Humalog	$ 5,858,318,223.00	200787540	$ 29.18
LYUMJEV	$ 2,575,899.00	84188	$ 30.60
Apidra SoloStar	$ 203,432,581.00	5956641	$ 34.15

Figure 10. Insulin Analog Cost-Saving Alternatives (class 2)

We recommend the Medicaid administrators institute policies that encourage practitioners of Medicaid beneficiaries to prescribe the lowest drugs in each class, by unit price. This method would increase cost-savings. For example, within the *Insulin Analog [EPC], Insulin [CS]* class, *Basaglar* is the most cost-affordable drug *a*t $20.97 per unit. Medicaid would spend less in reimbursements if beneficiaries selected *Basaglar* in place of the more expensive alternatives. Among the *Hepatitis B Virus Nucleoside Analog Reverse Transcriptase Inhibitor [EBC], Human Immunodeficiency Virus Nucleoside Analog Reverse Transcriptase Inhibitor [EPC]... class, Emtricitabine and tenofovir disoproxil fumarate* should be prioritized at $15.59 per unit. Within the *GLP-1 Receptor Antagonist [EPC], Glucagon-Like Peptide 1 [CS]* class, *RYBELSUS* at $26.70 per unit, is preferred. For *Adrenergic beta2-Agonists [MOA], Corticosteroid Hormone Receptor Agonists [MOA]* drugs, prescriptions for *Wixela Inhub* at $3.33 per unit would lead to

cost-savings. Last, among the *Insulin Analog [EPC], Insulin [Chemical/Ingredient]* class, *Insulin Lispro* is the most cost-affordable at $14.91 per unit. We estimate had Medicaid beneficiaries switched to these five alternative drugs, Medicaid reimbursements would have decreased by up to $43,615,199,509.08.

Discussion

Implications of Results

Resulting from our analysis of Medicaid spending from 2018-2022, we see notable opportunities for savings in regards to the varying cost of prescriptions available. By choosing the alternatively cheaper drug in the five most expensive drug classes, we were able to save over $43 billion across five years. There are 70,479 classes listed in this dataset. If this approach was applied to all other drug classes, U.S. federal and state governments could institute more savings. However, this approach requires the administrative tools to regulate and promote certain drugs over others. Moreover, administrators must consider the quality of the alternatively cheaper drug, as drugs are products manufactured by pharmaceutical companies.

We analyzed alternative drug efficacy by looking at the second most expensive drug class, *Hepatitis B Virus Nucleoside Analog Reverse Transcriptase Inhibitor*, which has 4 different brands: *Emtricitabine and tenofovir disoproxil fumarate*, *Truvada*, *DESCOVY*, and *Biktarvy*. The least expensive option would be *Emtricitabine and tenofovir disoproxil fumarate* at $15.59 per unit also known as the generic form of the medication. We consider the development process of nonproprietary drugs: i.e. “When a drug company makes a new medicine, it is controlled under a patent. It has an approved, or generic name, as well as its own brand name, chosen by the company…Once the patent runs out, other drug companies can make the drug at a lower cost. These are called ‘generic’ drugs” (HIVPA, 2022). In effect, *Emtricitabine and*

tenofovir disoproxil fumarate, the generic version of *Truvada,* is just as effective as its more expensive counterpart. HIV patients saw similar results when switching to the generic version (HIVPA, 2022). The same is true for every generic brand of prescription medicine. The FDA writes, " A generic medicine is required to be the same as a brand-name medicine in dosage, safety, effectiveness, strength, stability, and quality, as well as in the way it is taken" (FDA, 2022). With this information, we can conclude that switching to the cheaper alternative drug will not cause harm to the individual affected. Medicaid spending will decrease, andU.S. governments can use our savings towards medical research to effectively lower cases of HIV, asthma, obesity, and other deadly diseases across the country.

Conclusion

At the onset of the project, our team was confident we would be able to find answers to our Medicaid questions in the data collected by medicaid.gov. We were anxious to apply our newly acquired data analytics skills to a real world problem of helping people afford critical pharmaceuticals. After our first iteration it became apparent we had some issues to navigate. In order to find the drug classes we needed to combine the Medicaid dataset with an NDC (national drug code) directory dataset. On top of that, the datasets were much larger than anything we had dealt with before. Fortunately, our team was able to overcome these issues and gain informed insight into the questions we were asking. While the data analytics used were all descriptive, and not predictive or prescriptive, they still provided the information we needed to make better business decisions. Once we were able to build our result tables and visualizations, we knew we would be able to answer all of our questions, and make recommendations. We were a bit surprised by our findings, namely Medicaid reimbursement amounts by drug class. We did not expect such a few classes to account for so much of the spending. Much progress can be made in

pharmaceutical cost savings by addressing only a few drug classes, which suggest enormous potential savings of approximately $46.3 billion over 5 years.

Medicaid pharmaceutical spending will remain relevant throughout the next decades, as social welfare spending is frequently debated at the highest levels of government. The consequences of COVID-19, and the resulting passage of The Inflation Reduction Act renewed interest in spending. We hope this analysis serves Medicaid administrators in reducing government spending while also providing the pharmaceuticals required by 80 million low-income Americans.

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