ORIGINAL RESEARCH

An Economic Evaluation of The Budget Impact of Precision Medicine Testing for The Treatment of Psoriasis

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ABSTRACT

Background: This study was a budget impact analysis based on a budget impact model (BIM) and formularies from different commercial payer types (excluding Medicare and Medicaid). The primary objective of this study was to determine the potential cost savings utilizing precision medicine testing of biologics in patients with psoriasis. The evaluation projects the predicted cost savings of multiple formulary scenarios, simulated through the BIM.

Methods: A budget impact model was constructed to simulate the impact of Mind.Px, a transcriptomic predictive precision medicine test that can discriminate between psoriasis responders and non-responders, on psoriasis drug usage. This model simulated the impact of Mind.Px on different formularies and cost scenarios, considering the efficacy of individual biologics. All formularies used were acquired from the Policy Reporter database.

Results: Several payers representing a spectrum of covered lives populations were used to simulate the impact of Mind.Px through the budget impact model. The budget impact model returned cost savings as low as \$5,138 annually to as high as \$13,141 annually. Based on the analysis of this subset of payers, the model yielded average cost savings of \$8,492 annually as well as an average wasted spend savings of \$16,567. All savings are represented on an annual per patient basis.

Conclusions: These savings demonstrate the potential cost savings that precision medicine testing can provide to ease the economic burden on payers, clinics/hospital systems, and patients, and may fill the need for a better method to prescribe drugs for the treatment of psoriasis.

INTRODUCTION

Plaque psoriasis is a T-cell mediated, inflammatory skin disease which affects approximately 2.8% (~7.5 million people) of the United States (U.S.) population. Cutaneous lesions are often associated with marked pruritic and burning sensations. These symptoms are frequently accompanied by a significant cosmetic concern for patients, leading to a sizable impact on their overall quality of life. Furthermore. psoriasis positively is associated with the presence of cardiovascular. psychiatric, and other

medical comorbidities, and is therefore considered the second largest contributor of skin-related disabilities.¹ In fact, psoriasis has been recoanized serious as а noncommunicable disease by the World Health Organization (WHO) since 2014, with estimates that total disability-adjusted life years (DALYs) due to this auto-inflammatory condition have doubled from 0.1% in 1990 to 0.2% in 2017.¹⁻³ This effect is due in part to incorrect or delayed diagnosis, inadequate treatment, insufficient access to care, and social stigmatization.² In order to reduce the physical, psychological, and economic burden, it is imperative that physicians guickly identify a safe and effective treatment reaimen for those suffering with this chronic skin condition. In recent decades, remarkable advancements targeted biologic in immunotherapy have revolutionized the treatment of psoriasis via the development of a multitude of novel systemic agents. These therapeutic monoclonal antibodies are highly immuno-modulators which are specific proven to be exceptionally effective in the clearance of skin lesions. Due to the inhibition of unique, distinct points along the inflammatory cascade (e.g., IL-17 vs IL-23 blockade, etc), biologics are not a one-sizefits-all treatment. In other words, the agent most efficacious for one patient may differ from the option that is most suitable for someone else, supporting the need for an individualized therapeutic approach. Unfortunately, there are currently limited resources for healthcare providers to discriminate between the plethora of available systemic agents when deciding on treatment for a particular patient. Therefore, many patients try multiple medications before finding the best fit for them, leading to significant morbidity and economic burden. In fact, medication alone can cost up to \$366,645 per patient annually in order to achieve a Psoriasis Area and Severity Index Score (PASI) 100 response, or complete

clearance of skin lesions.⁴ This leads to an estimated direct cost of \$12.2 billion United States Dollars (USD; all costs are reported in USD) and estimated indirect cost of \$23 billion.^{5,6} In the U.S. alone, it is estimated that patients with psoriasis will pay a lifetime cost of \$11,498 for relief of physical and emotional symptoms, resulting in an annual national cost of an estimated \$112 billion to treat these patients.⁷ This expense is expected to increase as the prevalence of psoriasis continues to rise, highlighting the need for expedited identification of an agent with a robust and long-lasting clinical response for a given individual. Interestingly, factors such as a person's genomic profile may provide clues into their particular disease pathophysiology and, consequently, offer insight into the most effectual treatment option for them. This precision medicine testing has demonstrated clinical validity and utility across many indications and has been shown to ease the economic burden of treatment by minimizing wasted-spend and increasing netsavings.3,8,9

To date, a validated precision medicine test for predicting response to drugs for psoriasis does not exist. This study aims to simulate and predict the cost savings of congruent use of precision medicine testing for the biologic treatment of psoriasis in a world with Mind.Px. For the purposes of this work, congruent use is defined as using a biologic treatment as predicted for best response by the precision medicine test results.

Mind.Px

Mind.Px is a precision medicine test that has been developed by Mindera (San Diego, CA) that uses a proprietary minimally invasive dermal biomarker patch (DBP) to extract RNA from skin. The DBP specifically extracts mRNA from the epidermis and dermis of patients, which can then be analysed by nextgeneration sequencing (NGS). The resulting

transcriptomic data is then processed by algorithms derived using machine learning and generates a report that provides information about potential patient response to drug class to clinicians.

METHODS

Model Design

This model estimates the potential budget impact of the Mind.Px precision medicine test by using a decision-tree Budget Impact Model (BIM) for patients in the treatment of moderate-to-severe psoriasis. The BIM was developed using Microsoft Excel 2016 to compare the drug costs of today's Standard of Care (SoC) vs. a future state with a new precision medicine test. The model was constructed from а U.S. healthcare commercial payer perspective (excluding Medicare and Medicaid) and the drug treatment costs are measured over a oneyear period in 2020 USD.¹¹

Model Inputs Individual Drug Performance

The model evaluated various payer formulary scenarios based on 14 available psoriasis biologics spread across three drug classes (TNFα-inhibitor, IL-17's, and IL-23's) (Table 1). Each of the 14 drugs were given an associated wholesale acquisition cost (WAC) price per dose, WAC price per loading dose week, WAC price per maintenance dose week, response rate and rate of being prescribed relative to the 14 available drugs. Food and Drug Agency (FDA) package inserts were used to determine the count of loading doses per week, maintenance doses per week, and total weeks on a loading dose which were used to determine the average loading and maintenance costs per week. Usage rates¹² represent the prescribing

patterns between the 14 drugs and were used to determine the relative weighting of each drug within a drug class based on the baseline formulary. The response rate used both two methodologies, FDA label package inserts and real-world data class averages.³⁹ The FDA label package inserts, an average was used of drug PASI 75 and Physician Global Assessment (PGA) or Investigators Global Assessment (IGA) Efficacy.

Drug Class Performance

The model creates an aggregated drug class view based on the individual drugs chosen in the formulary and weighted based on the industry usage rates for each of the 14 drugs relative to each other. Rather than account for possible drug formularv each combination, the model converted individual drugs in the baseline formulary to class averages and weighted based on usage prescribing rates. Each class has а calculated percent of patients assigned to each drug class, the average FDA label drug response rate, real-world data drug response rate, average loading dose cost, and average maintenance dose cost.

All results in this research uses the real-world data drug class average of 46.0% for TNF α , 55.9% IL-17's and 50.7% for IL-23's.³⁹ Exceptions are noted when modelling against FDA label package drug response rates.

While costs are based on WAC, the model applied a discount percent to emulate true payer costs. Tumour necrosis factor (TNF α) inhibitors were assigned a discount rate of 28%, Interleukin-17 (IL-17) inhibitors 38%, and Interleukin-23 (IL-23) inhibitors a rate of 49% respectively (Table S1).³⁹ The secondary response rate was reduced and compared to the primary response rate to account for the reduced efficacy experienced when a patient cycles from one drug in a drug class to a different drug within the same



Table 1. Characterization of Drugs of Interest [13-27]. Per Week Loading Costs – Total start-up drug costs divided by weeks in start-up. Per Week Maintenance Costs – Price per dose multiplied by average doses per week during maintenance period. Response Rate – average of drug PASI 75 and PGA or IGA Efficacy. Usage Rate – Displays the relative percent use of each drug used in this model in the treatment of mild to severe psoriasis based on the DRG [12] report. Usage Rate is an average between 2018 reported usage rates and 2028 forecast usage rates to account for future trends

Drug Class	Drug (Brand	Price Per	Per Week	Per Week	Response Rate	Usage
	Name)	Dose WAC	Loading	Maintenance Cost		Rate
			Costs			
ΤΝFα	Certolizumab	\$2,315	\$2,315	\$1,158	65.3%	1.5%
Inhibitor	Pegol (Cimzia)					
ΤΝFα	Etanercept	\$1,389	\$2,778	\$1,389	36.6%	10.0%
Inhibitor	(Enbrel)					
ΤΝFα	Etanercept-szzs	\$1,388	\$2,776	\$1,388	36.6%	
Inhibitor	(Erelzi)					
ΤΝFα	Adalimumab	\$2,745	\$5,490	\$1,372	65.3%	17.4%
Inhibitor	(Humira)					
ΤΝFα	Infliximab-dyyb	\$936	\$468	\$117	75.9%	
Inhibitor	(Inflectra)					
ΤΝFα	Infliximab	\$1,160	\$580	\$145	75.9%	2.6%
Inhibitor	(Remicade)					
ΤΝFα	Infliximab-adba	\$746	\$373	\$93	75.9%	
Inhibitor	(Renflexis)					
IL-17	Secukinumab	\$5,477	\$5,477	\$1,369	65.9%	14.6%
Inhibitor	(Cosentyx)					
IL-17	Brodalumab (Siliq)	\$1,221	\$1,221	\$611	82.0%	0.5%
Inhibitor						
IL-17	lxekizumab (Taltz)	\$5,690	\$2,845	\$1,423	85.2%	11.5%
Inhibitor						
IL-23	Tildrakizumab-	\$14,537	\$7,268	\$1,211	59.4%	2.3%
Inhibitor	asmn (Ilumya)					
IL-23	Risankizumab-	\$12,974	\$12,974	\$1,081	87.0%	7.7%
Inhibitor	rzaa (Skyrizi)					
IL-23	Ustekinumab	\$22,777	\$11,38	\$1,898	80.0%	15.1%
Inhibitor	(Stelara)					
IL-23	Guselkumab	\$11,245	\$5,623	\$1,406	78.4%	9.2%
Inhibitor	(Tremfya)					

class. As a result, a reduction was applied to the response rates and assumes a 50% drop for TNF α inhibitors, and a 75% drop for IL-17 inhibitors and IL-23 inhibitors, respectively (Table S1).³³

The reduced drug efficacy rates were applied in the model whenever a patient does not respond to a drug in a particular drug class but is forced by the confines of the formulary to be assigned a different drug within the same drug class.

Payer Drug Formulary

Of the 14 drug options, a baseline payer formulary was chosen consisting of a Tier 1 and Tier 2 (Scenario C; Figure S1). The baseline formulary was then converted to class metrics based on the industry usage patterns of each individual drug chosen. Six formulary scenarios were modelled based on different variations of the three drug classes. The baseline formula scenario C (Figure S1) was chosen as this closely emulates the average savings across all six scenarios.

Model Logic

Drug Cycling

With the model class inputs determined, the baseline scenario is fed into a one-year drug cycling model with 4 equal 13-week time periods. It is assumed all patients are continuously on a drug for the 4 cycles and non-responder patients within a cycle must complete the 13-week cycle before switching to a new drug for the next cycle (Figure 1).

Each cycle is defined as either a loading dose period or a maintenance dose period. The loading dose period includes the costs of the weeks required for the loading dose plus the maintenance weekly costs for any remaining 13-week weeks in the cvcle. The maintenance period costs include only maintenance dosing during the 13-week cycle. In the SoC base case scenario, based on the calculated class averages, 32% of patients will start Cycle 1 on a TNFa-inhibitor, and those patients will have a response rate of 46% (Table 2) with a cycle drug costs of \$15,811 (Table 2). Loading dose period costs are applied in Cycle 1 as all patients are on a new drug. Responder patients will continue the same drug class for the remainder of the model with the application of maintenance period costs. The non-responders will then be cycled to a new drug class or new drug within the same class based on both the formulary and calculated probabilities of usage (Figure 2).

A patient must cycle through all Tier 1 drugs before switching to Tier 2 drug options. Costs were represented as four 13-week cycle costs that include both drug loading periods and maintenance periods (Table 2).

Future State Cycling

The objective of this model is to show the economic impact of stratifying patients to the right drug with a high probability of response. Therefore, the drug response rates in Cycle 1 are assumed to be a baseline of 91% for the initial 13-week period as it is assumed the right patients are placed on the right drug.

For Cycle 2, it is assumed the responders will remain on the same drug class for the full year, the same methodology as SoC. Nonresponders, however, will stay on the same drug class as the Cycle 1 future state but will be prescribed a different drug.



		Respond	Stay on Current Drug Class for remaining Cycles
	Drug Class		
	Option 1	Non-Respond	Cycle to New Drug Class or New Drug within Existing Drug Class
Drug Cycle 1		Respond	Stay on Current Drug Class for remaining Cycles
(13 Weeks)	Drug Class		
	Option 2	Non-Respond	Cycle to New Drug Class or New Drug within Existing Drug Class
		Respond	Stay on Current Drug Class for remaining Cycles
	Drug Class		
	Option 3	Non-Respond	Cycle to New Drug Class or New Drug within Existing Drug Class

Figure 1. Schematic of Drug Cycling

This is because the Mind.Px precision medicine test would have guided the clinician to a specific drug class and therefore it is assumed the clinician will try another drug within the same drug class in the second cycle.

Table 2. Baseline Aggregated Characteristics of Drug Classes for Tier 1 Drug Cycling. 13-week loading costs shows weighted total costs of drug loading period plus maintenance costs for any remaining weeks up to the 13-week mark. 13-week maintenance costs shows the weighted total maintenance cost for a 13-week period. Response Rate – real world data³⁹. Secondary Response Rate – average drug class response rate when a second drug is used in the same drug class after the first drug failed.

Drug	13-	13-Week	Response	Secondary	Patient
Class	Week	Maint.	Rate ³⁹	Response	Mix
	Load	Costs		Rate	Percent
	Costs				
TNFa	\$15,81	\$12,846	46%	23%	32%
inhibitor	1				
IL-17	\$23,38	\$10,857	56%	14%	27%
inhibitor	5				
IL-23	\$27,66	\$10,431	51%	13%	42%
inhibitor	7				

With the assumption of a 91% sensitivity for the Mind.Px precision medicine test, the 91% non-response rate in Cycle 1 may be a false indication in the test and therefore the patient after a second try with the same drug class will not respond. The response rate for Cycle 2 in the future state is 0%.

For Cycle 3 and 4, assuming non-response to Cycle 1 and 2, the patient will then be switched to a new drug class with response rates equal to Tier 1 SoC baseline drug class averages. The future represents the stratification of patients to the correct biologic treatment prior to entering the model. In the future state, the distribution of patients for Cycle 1 drug classes are model inputs and sensitized for a range of results. The baseline assumes 50% of patients in the future state will use TNF α inhibitors and 25% will be placed on an IL-17 inhibitor and 25% on IL-23 inhibitor (Table S1). Drug costs for the future state are the same for SoC.

Model Output

The model quantifies the annualized prescription drug and medical cost change by showing the net cost savings created on an average per patient basis. In addition to this metric, wasted spend savings is calculated to show the savings related to drug and medical costs for non-responder patients.³⁴ Wasted spend savings is the difference in total medical and pharmacy costs spent on nonresponders currently as compared with a future state with the diagnostic; it is captured by reducing the non-responders in the future state. This metric highlights the ineffective spend dollars that were previously used on



patients who did not respond to their empirically assigned biologic.



Figure 2. Patient Flow Diagram

RESULTS

Budget Impact Analysis

The model predicts that formularies with only adalimumab as a biologic option for tier 1 treatments will have a net cost savings of \$5,607 with congruent use of the Mind.Px precision medicine test annually (Scenario A; Figure S1). It is noteworthy that as more drugs are introduced into a given formulary, an increase in cost savings can be seen. Increase in drug mix in the first tier of the sample scenarios resulted in a net cost savings range of \$5,138 - \$13,141 annually with congruent use of the Mind.Px precision medicine test (Scenarios B-F; Figure S1). The average cost savings based on Scenarios A-F resulted in \$8,492 annually (Figure S2). This analysis also predicts high annual wasted spend savings, ranging from \$14,330-\$22,909 (Figure S4).

Cumulative Drug Response

When analysing the cumulative drug response rates by cycles, it is evident that while full year response rates are nearly the same, the BIM predicts that patients who are treated initially with the correct drug (cycles 1-2, Figure 3) experience improved outcomes and treatment savings (91% for the future model versus 75.2% for SOC). Albeit small, improved outcomes and savings can even be seen between cycles 2 and 3 (Figure 3).

Sensitivity Analysis

One way sensitivity analysis of net savings by formulary scenario compared to the baseline average of \$8,492 (Scenario C) identified the tier 1 drug mix as the most influential parameter (Figure S3). Formulary scenarios with a balanced drug mix that favoured IL-23 inhibitors usually exceeded the baseline as exemplified by Scenario F with 63% IL-23 increasing the net savings by \$4,649 (Figure S3).

Additional one-way sensitivity analysis of input values compared to the baseline





average of Scenarios A-F was conducted and is presented in the tornado diagram (Figure 4).

From this analysis, compared to the average savings of \$8,492 across Scenarios A-F; (Figure S3), the next most influential uncertainty parameter affecting net savings is the drug discount from the baseline applied discount off WAC, with a 20% decrease in the discount (less of a discount) resulting in an additional net savings of \$2,085 (Figure 4). Varying the future class mix from the baseline (50% TNFi, 25% IL-17, 25% IL-23) had less of an impact on net savings, with an increase of TNFi use to 60% resulting in increased savings of \$594 above baseline average (Figure 4). This is supported in the savings in each scenario (Figure S2). the future response rate of being placed on the correct drug as predicted by Mind.Px. More cost savings are seen as the accuracy of testing is increased. For this analysis, the test accuracy is set at the reported 91%. Savings fall below baseline when the testing accuracy is set to 85% and exceeds baseline at both 95% and 100%.

Response rates based on FDA Package Inserts rather than real world data, yielded net cost savings of \$4,016 and wasted spend savings of \$6,383. The baseline scenario C response rates for FDA Package Inserts was 65% TNF α inhibitors, 66% for IL-17 inhibitor and 80% for IL-23 inhibitors compared to 46%, 56% and 51% for real world data respectively (Table S2).

Net savings are also sensitive to changes in



Figure 4. Tornado Diagram showing the most sensitive inputs of the BIM. Drug Discount one-way sensitivity varies the baseline drug discount as used against WAC pricing. Future response rate is equal to the Mind.Px test accuracy. Future Class Mix shows the mix ratio of the 3 drug classes in a future state. Drug efficacy is the reduced drug class response rate when a second drug is used in the same drug class after the first drug failed.

DISCUSSION

This analysis is the first to estimate the hypothetical economic impact of a precision medicine test for the use of prescribing a biologic treatment for psoriasis.

Savings and Wasted Spend

The annual net savings with the use of the test is substantial and predominantly formulary driven based on the structure and variability of the selected formulary averaging \$8,492 across all 6 formularies. Wasted spend however, is not directly affected by the selected formulary but rather is driven by patients being put on the correct treatment initially. Net savings and wasted spend are also somewhat influenced by the drug costs, as there is wide variability in payor WAC.

With an average wasted spend savings of \$16,567 among all 6 formularies, these predictions show strong implications of decreased wasted spend applied to any formulary, including those with a low drug mix.

Net savings were also sensitive to the future response rates. When the test accuracy is decreased, we see lower response rates and thus lower savings. This further supports the need for precision medicine testing (with high accuracy) to identify the right drug for the right patient to increase response rate and increase savings versus the "trial and error" standard of care approach. The model also showed some sensitivity to the future drug class mix. As the future drug class mix of the formularies became more varied, the model trended towards the lower end of savings. This could be due to the fact that with the use of precision medicine testing, inexpensive



biologics such as TNF α inhibitors are expected to be utilized more than they currently are without the use of precision medicine testing. Currently, IL-17 and IL-23 biologics are used more often than TNFa inhibitors due to their perceived efficacy rates. These classes of biologic are more costly and are not always an effective treatment for all patients. Sensitivity analysis of the wasted spend savings by scenario with a set baseline of \$16,567 (the average wasted spend savings of Scenarios A-F; Figure S4) yielded similar results. In addition, utilizing the higher response drug response rates listed in the FDA approvals rather than reported real world data still demonstrates significant savings.

Clinical Impact

Dermatologists are aware of the high annual costs of drugs to psoriasis patients and payers.^{35,36} Studies have shown the increased costs of switching, which may occur within the first 3-6 months of a new drug due to primary failure.³⁶ These initial 3-6 months overlap with the more expensive loading dose period of most drugs. The clinician value derived from the test may potentially reduce unnecessary switches in the first 3-6 months due to primary failure and prevent multiple loading doses of different drugs in a relatively short time period.

The Mind.Px precision medicine test may also reduce the risk of anti-drug antibodies against the failed drugs. Once the immune system 'sees' a drug and then it is stopped, anti-drug antibodies are often produced against these drugs. If for some reason the patient is prescribed these biologics again in the future, these anti-drug antibodies may make the drug even less effective.

Patients have high hopes for rapid skin clearance, so with every failed drug, there is

less confidence and hope in the science of medicine and in the dermatologist.³⁷ Adherence may be negatively impacted with each new drug that has to be prescribed. The Mind.Px precision medicine test could improve clinical practice in these important ways as well as reducing costs to the medical system.

Payer Impact

The value to a payer of a diagnostic tool to determine a priori patient response to a drug is ultimately dependent on several factors. Immediate and future drug spend savings are variable and may be significant based on the difference in post-rebate price the payer ultimately pays for the original drug and the drug being switched to. Using a precision medicine test to determine a priori response forces a shift in drug utilization that deviates from formulary tiering, which does not take patient response into account, creating to negotiate better leverage rebates depending on the change in use as some increase would be expected for some mechanisms of action (MOAs) and attributable to the lowest cost drug. In order to proactively negotiate for the best price per drug class, each payer can model the effects of using the precision medicine test on their respective share of each drug/class and consider their Pharmacy Benefit Manager's (PBM's) ability to adjust the formulary accordingly. However, PBM-rebate administration is a significant source of revenue, which could be impacted by use of a precision medicine testing strategy that decreases use of certain classes of drugs if countermeasures in the form of other economic incentives are not put in place for the PBM.

Limitations

This study did not consider indirect patient



costs or the cost of the Mind.Px precision medicine test, thus net savings could not be concluded. Because there are no currently published data with the use of Mind.Px in clinical practice, no direct health outcomes or benefits cost could be determined. Additionally, the current model does not contemplate any potential differential response between those patients who have prior biologic exposure and those that are biologic naïve. These limitations should be considered for future analyses of the Mind.Px precision medicine test and its overall pharmacoeconomic impacts.

CONCLUSION

The clinical utility of precision medicine testing has previously been demonstrated in other indications as an effective means to lower the economic burden of high-cost drugs and improve overall health outcomes of patients. This study applied similar principles for biologic psoriasis treatment and found that the utilization of precision medicine testing resulted in significant drug cost and wasted spending savings, a financial benefit which will impact payers, clinicians, and patients in substantial ways. Because clinicians currently do not have a means to evaluate а patient's genomic/transcriptomic profile for а biomarker response prior to prescribing a biologic for psoriasis treatment, the clinician must use a trial-and-error approach. This often leads to patients being initiated on nonoptimal treatment and requiring trials with multiple medications, resulting in an overall higher treatment cost. The findings from this study show that in a hypothetical world with a precision medicine test as described, payers will save on the cost of biologic psoriasis treatment by using such testing to ensure that the most effective biologic is utilized first.

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References:

- Mehrmal S, Uppal P, Nedley N, Giesey RL, Delost GR. The global, regional, and national burden of psoriasis in 195 countries and territories, 1990 to 2017: A systematic analysis from the Global Burden of Disease Study 2017. J Am Acad Dermatol. 2021;84(1):46-52.
- Michalek IM, Loring B, John SM. A systematic review of worldwide epidemiology of psoriasis. J Eur Acad Dermatol Venereol. 2017;31(2):205-212. doi:10.1111/jdv.13854
- Brezinski EA, Dhillon JS, Armstrong AW. Economic Burden of Psoriasis in the United States: A Systematic Review. JAMA Dermatol. 2015;151(6):651-658. doi:10.1001/jamadermatol.2014.3593
- Wu JJ, Feldman S, Rastogi S. Comparison of the Cost-Effectiveness of Biologic Drugs Used for Moderate-to-Severe Psoriasis Treatment in the United States. Journal of Dermatological Treatment. 2018.
- Liu J, Thatiparthi A, Martin A, Egeberg A, Wu JJ, Prevalence of Psoriasis Among Adults in the U.S. 2009-2010 and 2013-2014 National Health and Nutrition Examination Surveys. *Journal of the American Academy of Dermatology* (2020), doi: https://doi.org/10.1016/j.jaad.2020.10.035.



- Evans C. Managed Care Aspects of Psoriasis and Psoriatic Arthritis. *American Journal of Managed Care*. 2016. 22:S238-S243
- Pilon D, Teeple A, Zhdanava M, et al. The economic burden of psoriasis with high comorbidity among privately insured patients in the United States. J Med Econ. 2019;22(2):196-203. doi:10.1080/13696998.2018.1557201
- 8. Arthur M. Institute for health metrics and evaluation. *Nursing Standard*. 2014.
- Verbelen M, Weale ME, Lewis CM. Costeffectiveness of pharmacogenetic-guided treatment: are we there yet?. *Pharmacogenomics* J. 2017;17(5):395-402. doi:10.1038/tpj.2017.21
- Faruque F, Noh H, Hussain A, Neuberger E, Onukwugha E. Economic Value of Pharmacogenetic Testing for Cancer Drugs with Clinically Relevant Drug-Gene Associations: A Systematic Literature Review. J Manag Care Spec Pharm. 2019;25(2):260-271. doi:10.18553/jmcp.2019.25.2.260
- U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: Medical Care in U.S. City Average [CPIMEDSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIMEDSL, December 30, 2020.
- Decision Resource Group (DRG), Market Forecast Dashboard Psoriasis 2018 – 2028. April 2020.
- 13. Cimzia [package insert]. Smyrna, GA: UCB, Inc; 2016.
- Ucb-usa.com. https://www.ucbusa.com/Responsibility/Affordability/Cimzia-Pricing-Info. Published 2021. Accessed September 1, 2020.
- 15. Enbrel [package insert]. Thousand Oaks, CA: Immunex Corporation; 2012.
- Enbrel.com. https://www.enbrel.com/support/financial-support. Published 2020. Accessed September 1, 2020.
- 17. Erelzi [package insert]. Princeton, NJ: Sandoz Inc.; 2016.
- 18. https://www.goodrx.com/. Published 2020. Accessed September 1, 2020.
- 19. Humira [package insert]. North Chicago, IL: AbbVie Inc.; 2018.
- 20. https://www.goodrx.com/. Published 2020. Accessed September 9, 2020.
- 21. Inflectra [package insert]. Lake Forest, IL: Hospira; 2016.
- 22. Remicade [package insert]. Horsham, PA: Janssen Biotech Inc.; 2013.
- 23. Renflexis [package insert]. Kenilworth, NJ: Merch Sharp & Dohme Corp.; 2017.

- 24. Cosentyx [package insert]. East Hanover, NJ: Novartis Pharmaceuticals Corp.; 2016.
- 25. Siliq [package insert]. Bridgewater, NJ: Valeant Pharmaceuticals North America LLC; 2017.
- 26. Taltz [package insert]. Indianapolis, IN: Eli Lilly and Company; 2017.
- Lillypricinginfo.com. https://www.lillypricinginfo.com/taltz. Published 2020. Accessed September 1, 2020.
- 28. Ilumya [package insert]. Whitehouse Station, NJ: Merck & Co., Inc.; 2018.
- Ilumya Prices, Coupons & Patient Assistance Programs - Drugs.com. Drugs.com. https://www.drugs.com/price-guide/ilumya. Published 2020. Accessed September 1, 2020.
- Skyrizi [package insert]. North Chicago, IL: AbbVie Inc.; 2019.
- 31. Stelara [package insert]. Horsham, PA: Janssen Biotech, Inc.; 2016.
- 32. Tremfya [package insert]. Horsham, PA: Horsham, PA; 2017.
- 33. Menter A, Strober B, Personal Communication, October 16, 2020.
- 34. Chaihorsky L, Fried M, Long B, Mamuszka H, Harrington T, Lukazewski A, Modeling the impact and value of a Precision Medicine approach from a payer perspective: an economic evaluation of stratifying rheumatoid arthritis patients for response to anti-TNF inhibitors prior to treatment. JMCP. 2021
- 35. Wu JJ, Pelletier C, Ung B, Tian M, Khilfeh I, Curtis JR. Real-world switch patterns and healthcare costs in biologic-naive psoriasis patients initiating apremilast or biologics. J Comp Eff Res. 2020;9(11):767-779. doi:10.2217/cer-2020-0045
- No DJ, Inkeles MS, Amin M, Wu JJ. Drug survival of biologic treatments in psoriasis: a systematic review. *J DermatologTreat*. 2018;29(5):460-466. doi:10.1080/09546634.2017.1398393
- Wu JJ, Armstrong AW, Gordon KB, Menter MA. Practical Strategies for Optimizing Management of Psoriasis. Semin Cutan Med Surg. 2018;37(2S):S52-S55. doi:10.12788/j.sder.2018.012
- Menter A, Gottlieb A, Feldman SR, et al. Guidelines of care for the management of psoriasis and psoriatic arthritis: Section 1. Overview of psoriasis and guidelines of care for the treatment of psoriasis with biologics. J Am Acad Dermatol. 2008;58(5):826- 850. doi: 10.1016/j.jaad.2008.02.039
- Enos, C. W., O'Connell, K. A., Harrison, R. W., McLean, R. R., Dube, B., & Van Voorhees, A. S. (2021). Psoriasis severity, comorbidities and treatment response differ among geographic



regions in the united states. *JID Innovations*, 100025. https://doi.org/10.1016/j.xjidi.2021.100025

Supplemental Tables and Figures

 Table S1.
 Baseline input variables

Drug Cost Discounts	
TNFa inhibitor	28%
IL-17 inhibitor	39%
IL-23 inhibitor	49%
Reduced Efficacy	
TNFa inhibitor	50%
IL-17 inhibitor	25%
IL-23 inhibitor	25%
Mind.Px Test Accuracy	91%
Future Drug Class Mix	
TNFa inhibitor	50%
IL-17 inhibitor	25%
IL-23 inhibitor	25%



Table S2. Baseline Aggregated Characteristics of Drug Classes for Tier 1 Drug Cycling. 13-week loading costs shows total costs of drug loading period plus maintenance costs for any remaining weeks up to the 13-week mark. 13-week maintenance costs shows the total maintenance cost for a 13-week period. Response Rate – average of drug PASI 75 and PGA or IGA Efficacy. Secondary Response Rate – average drug class response rate when a second drug is used in the same drug class after the first drug failed.

Drug Class	13-Week	13-Week	Response	Secondary	Patient Mix
	Loading	Maintenance	Rate	Response	Percent
	Costs	Costs		Rate	
TNFα inhibitor	\$15,811	\$12,846	65%	33%	32%
IL-17 inhibitor	\$23,385	\$10,857	66%	16%	27%
IL-23 inhibitor	\$27,667	\$10,431	80%	20%	42%

Scer	nario A	Sce	enario B	Sce	nario C		
Tier 1	Tier 2	Tier 1	Tier 2	Tier 1	Tier 2		
Humira	Cosentyx	Humira	Taltz	Humira	Siliq		
	Stelara	Cosentyx	Stelara	Cosentyx	Tremfya		
	Skyrizi		Skyrizi	Stelara	Cimzia		
	Taltz		Siliq	Skyrizi	Ilumya		
	Ilumya		Ilumya				
	Cimzia						
Net Savings	\$5,607	Net Savings	\$5,138	Net Savings	\$8,492		
Tier 1 Humira 100	0% of TNFα	Tier 1 Humira 1	00% of TNFα	Tier 1 Humira 100	Tier 1 Humira 100% of TNFα		
Tier 1 Drug Class	es: 100%, 0%, 0%	Tier 1 Cosentyx	100% of IL-17	Tier 1 Cosentyx 1	Tier 1 Cosentyx 100% of IL-17		
		Tier 1 Drug Clas	Tier 1 Drug Classes: 54%, 46%, 0%		Tier 1 Stelara 71% & Skyrizi 29% of IL		
		ner i brug ela.		Tier 1 Drug Class	es: 32%, 27%, 42%		
Scer	nario D	Sco	enario E	Tier 1 Drug Class	es: 32%, 27%, 42% nario F		
Scer Tier 1	nario D Tier 2	Sco Tier 1	enario E Tier 2	Tier 1 Drug Class Scen Tier 1	es: 32%, 27%, 42% nario F Tier 2		
Scer Tier 1 Humira	nario D Tier 2 Taltz	Sco Tier 1 Humira	enario E Tier 2 Taltz	Tier 1 Drug Class Scer Tier 1 Humira	es: 32%, 27%, 42% nario F Tier 2 Cosentyx		
Scer Tier 1 Humira Cosentyx	nario D Tier 2 Taltz Ilumya	Sco Tier 1 Humira Cosentyx	enario E Tier 2 Taltz Ilumya	Tier 1 Drug Class Scer Tier 1 Humira Stelara	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz		
Scer Tier 1 Humira Cosentyx Stelara	nario D Tier 2 Taltz Ilumya Siliq	Sco Tier 1 Humira Cosentyx Stelara	enario E Tier 2 Taltz Ilumya Siliq	Tier 1 Drug Class Scer Tier 1 Humira Stelara Skyrizi	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz Ilumya		
Scer Tier 1 Humira Cosentyx Stelara Skyrizi	nario D Tier 2 Taltz Ilumya Siliq Cimzia	Sco Tier 1 Humira Cosentyx Stelara	enario E Tier 2 Taltz Ilumya Siliq Tremfya	Tier 1 Drug Class Scer Tier 1 Humira Stelara Skyrizi Tremfya	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz Ilumya Siliq		
Scer Tier 1 Humira Cosentyx Stelara Skyrizi Tremfya	nario D Tier 2 Taltz Ilumya Siliq Cimzia	Sco Tier 1 Humira Cosentyx Stelara	enario E Tier 2 Taltz Ilumya Siliq Tremfya Cimzia	Tier 1 Drug Class Scer Tier 1 Humira Stelara Skyrizi Tremfya Cimzia	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz Ilumya Siliq		
Scer Tier 1 Humira Cosentyx Stelara Skyrizi Tremfya Net Savings	nario D Tier 2 Taltz Ilumya Siliq Cimzia \$9,546	Sce Tier 1 Humira Cosentyx Stelara Net Savings	enario E Tier 2 Taltz Ilumya Siliq Tremfya Cimzia \$8,492	Tier 1 Drug Class Scer Tier 1 Humira Stelara Skyrizi Tremfya Cimzia Net Savings	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz Ilumya Siliq \$13,141		
Scer Tier 1 Humira Cosentyx Stelara Skyrizi Tremfya Net Savings Tier 1 Humira 100	Tier 2 Taltz Ilumya Siliq Cimzia \$9,546	Sco Tier 1 Humira Cosentyx Stelara Net Savings Tier 1 Humira 10	enario E Tier 2 Taltz Ilumya Siliq Tremfya Cimzia \$8,492	Tier 1 Drug Class Scer Tier 1 Humira Stelara Skyrizi Tremfya Cimzia Net Savings Tier 1 Drug Class	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz Ilumya Siliq \$13,141 es: 37%, 0%, 63%		
Scer Tier 1 Humira Cosentyx Stelara Skyrizi Tremfya Net Savings Tier 1 Humira 100 Tier 1 Cosentyx 1	Tier 2 Taltz Ilumya Siliq Cimzia \$9,546 % of TNF` 00% of IL-17	Sco Tier 1 Humira Cosentyx Stelara Net Savings Tier 1 Humira 1 Tier 1 Cosentyx	Enario E Tier 2 Taltz Ilumya Siliq Tremfya Cimzia \$8,492 00% of TNFα 100% of IL-17	Tier 1 Drug Class Scer Tier 1 Humira Stelara Skyrizi Tremfya Cimzia Net Savings Tier 1 Drug Class	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz Ilumya Siliq \$13,141 es: 37%, 0%, 63%		
Scer Tier 1 Humira Cosentyx Stelara Skyrizi Tremfya <u>Net Savings</u> Tier 1 Humira 100 Tier 1 Cosentyx 1 Tier 1 Drug Classe	Tier 2 Taltz Ilumya Siliq Cimzia \$9,546 0% of TNF` 00% of IL-17 es: 27%, 23%, 50%	Sco Tier 1 Humira Cosentyx Stelara Net Savings Tier 1 Humira 1 Tier 1 Cosentyx Tier 1 Stelara 10	Enario E Tier 2 Taltz Ilumya Siliq Tremfya Cimzia \$8,492 00% of TNFα 100% of IL-17 00% of IL-23	Tier 1 Drug Class Scer Tier 1 Humira Stelara Skyrizi Tremfya Cimzia Net Savings Tier 1 Drug Class	es: 32%, 27%, 42% nario F Tier 2 Cosentyx Taltz Ilumya Siliq \$13,141 es: 37%, 0%, 63%		

Figure S1. Sample Payer Formularies at 91% accuracy. The following parameters were used; Future State Class Mix: TNFα inhibitor 50%, IL-17 inhibitor 25%, IL-23 inhibitor 25%; Discount Rate: TNFα inhibitor: 28%, IL-17 inhibitor: 39%, IL-23 inhibitor: 49%; Reduced Drug Class Efficacy: TNFα inhibitor: 50%, IL-17 inhibitor: 25%, IL-23 inhibitor: 25%. Drug Class mix percentages TNFα/IL-17/IL-23.



\$5,607 \$5,270 \$5,945	\$4,565 \$5,712	\$8,492 \$7,919 \$9,066	\$9,546 \$8,973 \$10,120	\$ 8,492 \$7,359 \$9,626	\$13,141 \$12,770 \$13,513
\$14,000	\$14,000	\$14,000	\$14,000	\$14,000	\$14,000
\$12,000	\$12,000	\$12,000	\$12,000	\$12,000	\$12,000
\$10,000	\$10,000	\$10,000	\$10,000	\$10,000	\$10,000
\$8,000	\$8,000	\$8,000	\$8,000	\$8,000	\$8,000
\$6,000	\$6,000	\$6,000	\$6,000	\$6,000	\$6,000
\$4,000	\$4,000	\$4,000	\$4,000	\$4,000	\$4,000
	\$5,607 \$5,270 \$5,945 \$14,000 \$10,000 \$8,000 \$6,000 \$4,000	\$5,607 \$5,138 \$5,270 \$4,565 \$5,945 \$5,712 \$14,000 \$14,000 \$12,000 \$12,000 \$10,000 \$10,000 \$6,000 \$6,000 \$4,000 \$4,000	\$5,607 \$5,138 \$8,492 \$5,270 \$4,565 \$7,919 \$5,945 \$5,712 \$9,066 \$14,000 \$14,000 \$12,000 \$14,000 \$12,000 \$12,000 \$12,000 \$10,000 \$10,000 \$10,000 \$10,000 \$10,000 \$6,000 \$6,000 \$6,000 \$6,000 \$4,000 \$4,000 \$4,000 \$4,000	\$5,607 \$5,138 \$8,492 \$9,546 \$5,270 \$4,565 \$7,919 \$8,973 \$5,945 \$5,712 \$9,066 \$10,120 \$14,000 \$14,000 \$12,000 \$14,000 \$14,000 \$10,000 \$12,000 \$12,000 \$10,000 \$10,000 \$10,000 \$10,000 \$10,000 \$10,000 \$10,000 \$4,000 \$4,000 \$4,000 \$4,000 \$4,000	\$5,607 \$5,138 \$8,492 \$9,546 \$8,492 \$5,270 \$4,565 \$7,919 \$8,973 \$7,359 \$5,945 \$5,712 \$9,066 \$10,120 \$14,000 \$14,000 \$14,000 \$12,000 \$12,000 \$14,000 \$12,000 \$10,000 \$12,000 \$10,000





Figure S3. One-way Sensitivity Analysis of Scenarios A-F cost savings



Figure S4. One-way Sensitivity Analysis of Scenarios A-F wasted-spend savings