Scenario Analysis of Profitability through Simulation of Different Business Contract Models

by

Lauren Heintz

B.S., Electrical Engineering, Purdue University (2016)
M.S. Data Science, University of Washington (2021)

Submitted to the MIT Sloan School of Management and
Department of Electrical Engineering and Computer Science
in partial fulfillment of the requirements for the degrees of

Master of Business Administration

and

Master of Science in Electrical Engineering and Computer Science

in conjunction with the Leaders for Global Operations program

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2023

Author Lauren Heintz
MIT Sloan School of Management and
Department of Electrical Engineering and Computer Science
May 12, 2023

Certified by Y. Karen Zheng
Associate Professor, Operations Management
Thesis Supervisor

Certified by Luca Daniel
Professor of Electrical Engineering and Computer Science
Thesis Supervisor

Accepted by Maura Herson
Assistant Dean
MBA Program, MIT Sloan School of Management

Accepted by Leslie A. Kolodziejski
Professor of Electrical Engineering and Computer Science
Chair, Department Committee on Graduate Students

Scenario Analysis of Profitability through Simulation of Different Business Contract Models

by

Lauren Heintz

Submitted to the MIT Sloan School of Management and
Department of Electrical Engineering and Computer Science
on May 12, 2023, in partial fulfillment of the
requirements for the degrees of
Master of Business Administration
and
Master of Science in Electrical Engineering and Computer Science

Abstract

Many American manufacturing companies have faced supply chain distruption, and inflation on sourced goods, freight, and labor. Coupled with the growth of online retail and direct-to-consumer shipping trends, many businesses have had to rethink strategic partnerships and distribution models. These factors have incentivized the adult incontinence manufacturer "IncoMan" to seek out strategic partnerships with other businesses to reduce costs. The reimbursed healthcare market specifically has seen a decline in profitability. State-mandated reimbursement rates for products are inconsistent across the country, but have been consistently declining. Insurance agencies acting in the middle have further eroded margins. To continue to provide these necessary medical products, this incontinence manufacturer and distributor explores contract options with other business partners to leverage both companies' strengths and maximize profitability in this market. This specific application of financial modeling and scenario analysis helps quantify the risk between two different possible contract models, a distributor model and a service model. Furthermore, it takes into account the uncertainty in demand parameters via a quasi-Monte Carlo simulator. The result is a set of visualizations that can be used to analyze both models under both deterministic and stochastic scenarios. The most influential factors in profitability stem from the state-mandated reimbursement price and the insurance agency contracts. Further, customer revenue-per-order and labor cost-to-serve each customer highly impacts profitability in both models. Of the two contract models simulated, the distributor model is more risky than the service model, but the service model lacks growth potential. The simulator can be reused and customized to different ranges of data and inputs, depending on the customer engagement. Ultimately, the goal is provide business leaders with a snapshot the first-order factors in any new contract agreement.

Thesis Supervisor: Y. Karen Zheng
Title: Associate Professor, Operations Management

Thesis Supervisor: Luca Daniel
Title: Professor of Electrical Engineering and Computer Science

Acknowledgments

I would like to acknowledge those who supported me in designing my research thesis, particularly my LGO advisors Karen Zheng and Luca Daniel.

My work would not have been possible without the support of my industry supervisor J.B., partner from Private Equity Co, and the entire team at IncoMan. Their readiness to support me has made all the difference in making my work valuable and successful. Specifically, I would like to acknowledge the help of my partner G.I. for bringing me on board to an exciting project and being open to developing in new ways. Lastly, the IT and Business Intelligence teams at IncoMan were absolutely instrumental in bringing this project to life. Their tireless work has not gone unnoticed.

I would like to also thank the other associates and partners at Private Equity Co who invested in my personal growth and supported me in building foundational business and finance skills. I am also grateful for the LEAN consultants at Private Equity Co who brought my classroom education to life on the factory floors.

Finally, the biggest thanks goes to my husband, Adrian Samsel, for supporting me every late night along the way! I couldn't have done any of this without you.

THIS PAGE INTENTIONALLY LEFT BLANK

Contents

THIS PAGE INTENTIONALLY LEFT BLANK

List of Figures

List of Tables

Acronyms

COGS Cost of Goods Sold. 27, 28, 38, 39, 55, 64

D2C DiaperCo Direct-to-Consumer Incontinence Distributor. 17–19, 22, 25, 39–41, 43, 61, 63, 68, 70, 81

DME Durable Medical Equipment. 23

HCPC Health Care Product Code. 12, 20, 21, 37–39, 44, 45, 55, 71, 90

IncoMan Adult Incontinence Manufacturer in North America. 5, 17, 18, 20–23, 25, 30, 37, 39–41, 43, 61, 63, 68, 85

KDE Kernel Density Estimation. 33, 34

LGO MIT Leaders for Global Operations Program. 5

MCO Managed Care Organization. 29, 30

PDF Probability Density Function. 33

SKU Stock Keeping Unit. 20, 21

VM Variable Margin. 63, 67–70, 75

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 1

Introduction

This case study in financial simulation is based on business challenges of Adult Incontinence Manufacturer in North America (IncoMan), a manufacturer and distributor of adult incontinence products. The manufacturer IncoMan also wholly owns a subsidiary Direct-to-Consumer Incontinence Distributor (D2C DiaperCo). To understand the premise of this case, first we look at the healthcare and retail industry trends discussed in 1.2. Next, we look at the financial motivation for exploring new business models and contract models, especially for products offered to Medicaid recipients. This scenario analysis case study takes a quantitative approach to financial modeling and analysis of prospective business contracts. Furthermore, aspects of demand uncertainty are incorporated via a simulator to better incorporate uncertainty into financial forecasts and therefore recommendations.

The aim of any new proposed business model partnership is to:

1. Offer better availability and choice in adult incontinence products for Medicaid recipients

2. Offer higher quality services to Medicaid recipients

3. Lower the cost for manufacturers and distributors

IncoMan believes that by partnering with retailers whose brick-and-mortar stores are cornerstones in everyday urban and rural areas of the United States, together they can provide more accessible and trustworthy care to more Medicaid patients. The financial simulator results and scenario analysis performed on this business will determine if this can be done at a competitive margin for IncoMan.

In the United States, for-profit insurance companies play a dominant role in affecting the healthcare products and services received by patients. Historically, the healthcare providers have operated on a fee-for-service model, where they are compensated based on the number of services provided and not the overall wellness of the patients. These misaligned incentives and declining healthcare quality in the United States have been catalysts for pushes towards outcomes-based care or value-based care in America for the past decade[9]. This initiative for IncoMan could improve the quality and availability of care for low-income patients on Medicaid while maintaining a competitive price to healthcare providers. IncoMan and subsidiary D2C DiaperCo have the many accreditations needed to supply durable medical equipment to patients in the United States, as well as a longstanding reputation of outstanding care results due to a highly knowledgeable and compassionate call center. The proposed business plan has the additional benefits of potentially growing profits and market share in this industry through strategic partnerships with retailers.

1.1 Company Context

IncoMan has been an adult incontinence manufacturer for over 40 years. The adult incontinence industry consists of a portfolio of consumable absorbent hygiene products. This portfolio of products is meant to serve adults experiencing a progression of incontinence symptoms from light to severe incontinence. Key product categories ranging from light to severe needs are bladder control pads, pull-on underwear, briefs, and underpads. These product categories will be included in this study to understand the profitability factors for these products. Margins between different products can vary widely based on the amount of raw materials required. Figure 1-1 below shows examples of the categories of products produced by IncoMan.

IncoMan acquired a smaller company, known as Direct-to-Consumer Incontinence

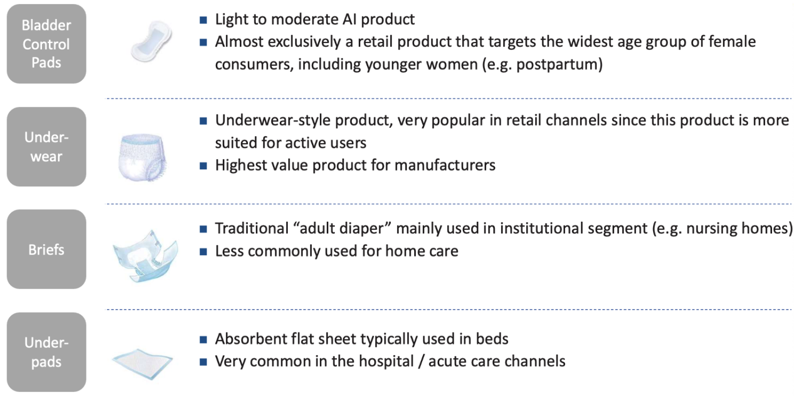

Figure 1-1: Product Category Descriptions

Distributor (D2C DiaperCo) in 2016. D2C DiaperCo has existed for over 30 years and provides direct-to-consumer home delivery services for incontinence products. They also ship additional miscellaneous convalescence items frequently used by the same customer base. D2C DiaperCo has an extremely loyal customer base due to its commitment to customer service. D2C DiaperCo has invested in a full-time call center to support customer questions and they have some of the most understanding, knowledgeable, and supportive specialists in the industry. This service gives D2C DiaperCo their edge, and it is this service that IncoMan hopes to make available to more Medicaid patients by partnering with retailers to expand their network.

1.2 Adult Incontinence Industry

The adult incontinence market in the United States has been expected to grow in the next 5 years with a compound annual growth rate of 10.2% according to a private Gerson Lehrman Group (GLG) market study [6]. Steady increased life expectancy in the U.S. until the recent pandemic of COVID-19 [1] and the baby boomer population aging contribute to the growth of the end market in the United States. Another contributor to incontinence product demand is the increase in obesity across the country [2] as well as other diseases which are highly correlative to incontinence conditions. Coupled with the desire to age at home, instead of in a long-term care facilities, post-COVID increased the demand for incontinence supplies. Online shopping has made using incontinence supplies more private and discreet than ever, removing social stigma so adults can remain active throughout later life. Furthermore, there aren't any cost-efficient or reliable substitutes at this time. Despite reusable diapers growing in popularity in the infant category, it hasn't stuck in the adult segment. The convenience of one-time use in hospital and group care settings is unbeatable, especially when these sectors are short staffed as it is.

Per interviews with tenured IncoMan employees, most typical adult incontinence customer is a post-menopausal woman in her 60s. Women represent roughly 75% of incontinence customers. A typical male customer of incontinence products is a man in his 70s who has survived prostate cancer.

1.2.1 Healthcare Trends

For state-aided health insurance, such as Medicaid, there is a complex reimbursement structure by which manufacturers can receive reimbursement for providing products to consumers. Since Medicaid is run at a state level, the reimbursement structure varies considerably by state. This makes the profit margin very geographically dependent. Each state Medicaid program publishes a state-wide reimbursement rate per Health Care Product Code (HCPC) and the rate is at the HCPC level. HCPCs are like product categories. An example of a HCPC for incontinence would be "Small Briefs" or "Large Underwear". From there, specific product SKU's are qualified under its respective HCPC. An example of a state Medicaid reimbursement rate table can be seen in Table 1.1.

Sometimes there is an intermediary organization, such as an insurance organization, operating between the state Medicaid and the manufacturer. This insurance organization will take portion of the state-published Medicaid reimbursement rate as their own revenue. This can be anywhere from 0% to 50% of the total reimbursement value taken as a fee. The remainder is then passed through to the manufacturer. This remaining amount is the revenue that the IncoMan, or any other manufacturer, has to cover their own costs and make a profit. Therefore the reimbursement rate per piece

Table 1.1: Reimbursement Rates by HCPC by State and Agency

AGENCYID	HCPCS	DESCRIPTION	REIMBURSEMENT AS A % OF MAX ACROSS STATES	COST PER PIECE (constant)
IL AGENCY 1	T4528	Large Underwear	100%	$0.XX
IL AGENCY 2	T4528	Large Underwear	65%	$0.XX
IL AGENCY 3	T4528	Large Underwear	100%	$0.XX
IL AGENCY 4	T4528	Large Underwear	100%	$0.XX
IL AGENCY 5	T4528	Large Underwear	73%	$0.XX
IL AGENCY 6	T4528	Large Underwear	100%	$0.XX
IL AGENCY 7	T4528	Large Underwear	80%	$0.XX
IL AGENCY 8	T4528	Large Underwear	73%	$0.XX
OH AGENCY 1	T4528	Large Underwear	84%	$0.XX
OH AGENCY 2	T4528	Large Underwear	84%	$0.XX
OH AGENCY 3	T4528	Large Underwear	59%	$0.XX
OH AGENCY 4	T4528	Large Underwear	84%	$0.XX

to the manufacturer can vary greatly between states and insurance organizations[1], even for the exact same SKU or Health Care Product Code. The trend over the past 20 years has been declining state Medicaid reimbursement rates, and increased fees from the insurance organizations facilitating the transactions according to an IncoMan employee.

1.2.2 Retail Trends

Meanwhile, trends in retail are gravitating towards online purchasing, recurring subscription orders, and omnichannel fulfillment options. This trend towards omnichannel fulfillment has given consumers increased flexibility on purchasing and more direct-to-consumer shipping options [19]. While it requires vendors to have better inventory management systems and better data tracking, it allows for more efficiencies in distribution. For example, products can be shipped directly to the consumer from a distribution center, shipped to the store then delivered, or shipped to the store and

[1]A sample reimbursement schedule can be found in Appendix A Table A.1

picked up by the consumer in person.

In part, the COVID-19 pandemic pushed the delivery and freight economy to its peak when brick-and-mortar stores were not an option and most customers preferred delivery. During this time, the cost of freight hit an all time high which impacted distributors, manufacturers, and retailers alike [21]. The combination of a declining work force of truck drivers and the soaring price of fuel makes cost-effective shipping more important than ever. Now, consumers have become accustomed to the convenience of direct-to-consumer shipping, while the cost of freight has not quite returned to normal levels. This is an issue still impacting retailers as well as manufacturers and distributors like IncoMan. This is a leading cause for why margins have decreased for IncoMan and D2C DiaperCo over the last 2 years (since the COVID-19 pandemic in 2020).

In addition, retail and healthcare are both slowly merging. This is seen in several recent mergers and acquisitions made in the retail and healthcare space. For example, Amazon's acquisition of primary care practice [12], CVS's merger with an insurance company [17], and Walgreens preparing to acquire a healthcare company in 2023 [16]. Consumers are turning more and more to the retail names that they trust for healthcare as well. IncoMan as a manufacturer can benefit from this partnership with retailers because retailers have larger fulfillment and distribution networks. In today's inflated freight and raw material markets post-COVID, the supply chain continues to be challenged to work together in new ways to stay healthy and profitable.

1.3 Project Motivation

The goal of this project is to evaluate new business models to increase profit margins. This new business model will revolve around a strategic partnership with a retailer, leveraging their distribution networks to deliver adult incontinence products to Medicaid customers. The retail partnership brings the added benefit of helping to increase market share through brand name recognition. Through financially modeling this future business agreement, we also model for the first time the profits and losses in the healthcare industry for IncoMan. In the past, the company has not had a way to accurately model or forecast revenues from healthcare-reimbursed products, such as Medicaid products. This is because of the complex nature of reimbursement pricing in the healthcare industry discussed in 1.2.1. IncoMan must be organized and targeted in order to expand offerings for prescriptive Durable Medical Equipment (DME) into multiple states. This research creates two models and a simulator to analyze many scenarios and outcomes in order to create better business contracts. Furthermore, the simulator captures elements of variability in demand inputs or cost parameters so that IncoMan can quantify the inherent risk and set better expectations for profitability.

1.4 Related Works

There are a few bodies of work related to the business and technical content presented in this research. The first is simluation methods and applications to financial, business, and contract negotiation applications. The second is computational implementations of random multivariate distributions.

1.4.1 Financial Simulation Applications

Crum (2019) [3] presents a method of financial statement proforma simulation in excel. However, this does not take into account dependent variables. It also does not present a comparison of potential negotiated agreements. Malaby (2021)[14] presents Monte-Carlo simulations of complex, non-trivial agreements using game theory, but does not delve in to financial forecasting. Litvak (2013)[13] presents a detailed Monte-Carlo contractual simulation for default provisions in venture capital. However, it is extremely specialized to venture capital partnership agreements and the legal variables in the contract, and it is not generalizable to other applications.

1.4.2 Random Distribution Implementations

There are various other pythonic methods to fit random distributions and sample from them for simulators. One such example is Uncertainpy, a close comparable for Chaospy [4] chosen instead for this project. Uncertainpy documentation states that it is "model independent and treats the model as a black box where the model can be left unchanged. Uncertainpy implements both quasi-Monte Carlo methods and polynomial chaos expansions using either point collocation or the pseudo-spectral method. Both of the polynomial chaos expansion methods have support for the Rosenblatt transformation to handle dependent input parameters"[23]. However, Uncertainpy is slightly more tailored towards computational neuroscience. After implementation of the simulator, there are some packages such as SALib which specialize in sensitivity analysis in Python [11]. SALib has a relevant Sobol Sensitivity Analysis capability and would be a valuable expansion opportunity in future work.

1.5 Methodology Overview

The approach to evaluating this prospective new business venture is as follows:

1. Build 2 potential financial business models for industry specific application
    - Distributor Contract Model
    - Service Provider Contract Model
2. Simulate deterministic scenarios of possible contract scenarios and outcomes
3. Fit a probabilistic distribution to unknown demand parameters
4. Simulate stochastic scenarios by sampling from random probabilistic distribution
5. Compare profitability outcomes under various scenarios

1.5.1 Product Offering

This business plan offers 10 SKUs that cover the 4 basic categories of adult incontinence products: bladder control pads, underwear, briefs, and underpads (see Figure 1-1). The 10 SKUs come from offering different sizes in the brief and underwear category. One underpad and bladder control pad is chosen to be representative of these demand groups. The other 8 SKUs are four sizes each for briefs and underwear: S, M, L, XL. Using just these ten SKUs is enough to make a representative model covering all the major categories for demand variation.

1.5.2 Contract Terms

The two models used in the simulator are models of different business contracts dictating the terms of payment between IncoMan and a prospective retail partner. The two models are the distributor contract and the service contract. Fundamentally, Adult Incontinence Manufacturer in North America (IncoMan) provides the same value in either contract. They are the manufacturer of the finished products, and provide the service of managing the patient journey from prescription to healthcare reimbursement. IncoMan has two different business units performing these roles. Later, the financial results are sometimes divided according to these business units. They are referred to either as the manufacturer margin (IncoMan margin) or service provider margin (Direct-to-Consumer Incontinence Distributor (D2C DiaperCo) margin). The retailer also acts in the same capacity in both models, providing distribution and fulfillment of the finished goods to the customer.

Figure 1-2 shows a basic illustration of the interaction between IncoMan and the retailer in the distributor model. Most importantly, IncoMan receives the revenue from the Insurance Agency in this model, and keeps any remainder that is not paid to the retailer in the distribution fee or the freight fee. They also get to keep whatever margin they make on selling the finished goods to the retailer. The distributor fee is modeled as a % of the revenue of the finished goods sold to the retailer, while the freight fee is a flat fee. The distributor contract model was defined with the IncoMan

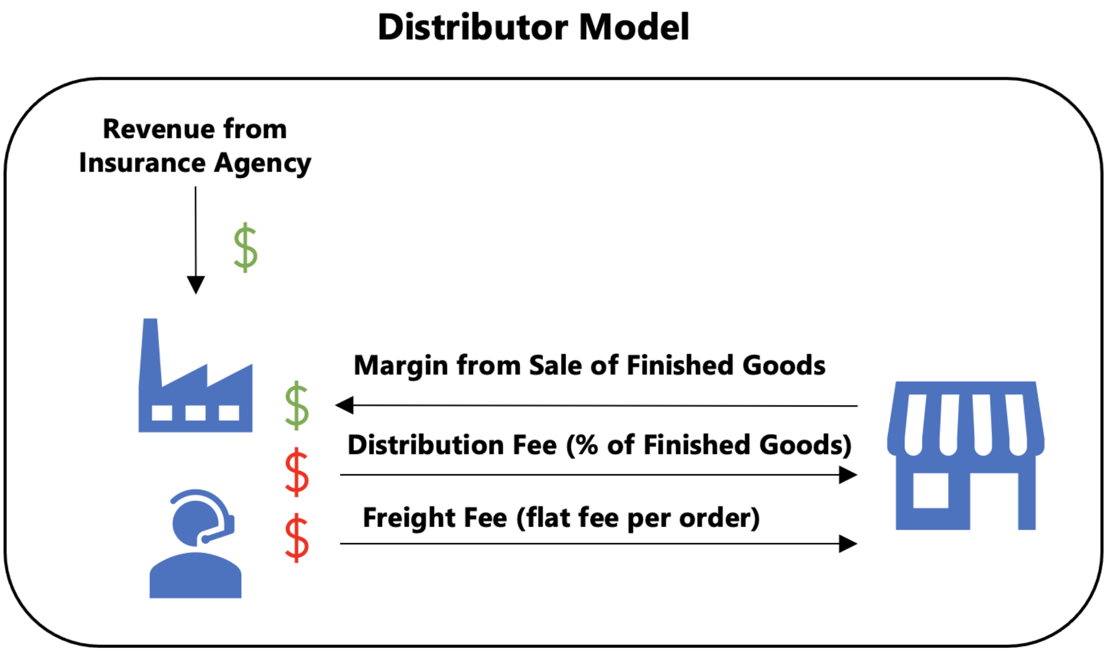

Figure 1-2: Distributor Model Illustration

team as a way to distinguish the fulfillment work needed to distribute, which scales with the number of goods. It also recognizes that distribution direct to consumer is a per order cost, and should scale with the number of orders.

Figure 1-3 illustrates the service model. The primary difference is that in the service model, the retailer receives the revenue from the Insurance Agency once it has been processed by IncoMan. The retailer keeps any remainder that is not paid to IncoMan in the form of a service fee or purchasing finished goods. The service fee, like the freight fee, is a flat fee that scales on a per-order basis. This is because the service provided by IncoMan to counsel the patient, obtain the prescription, and provide medical documentation is done for each order. Like in the distributor model, IncoMan receives some amount of margin from the purchase of finished goods, proportional to the quantity of goods purchased. Table 3.4 summarizes the differences between the two models in terms of sources or uses of money.

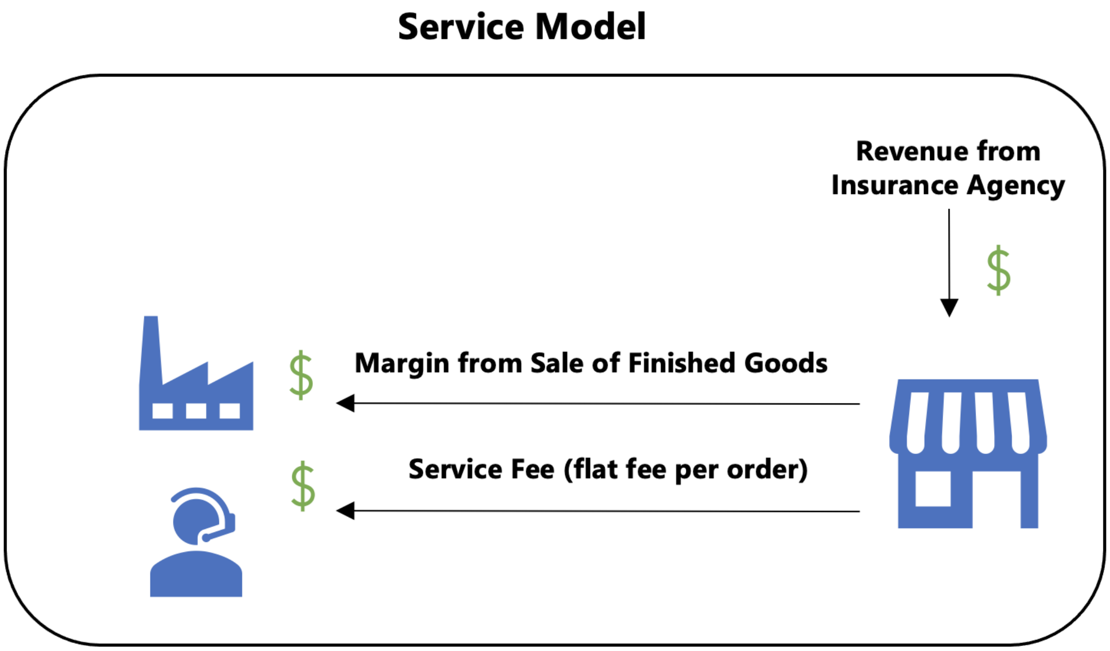

Figure 1-3: Service Model Illustration

1.5.3 Order Modeling

In both contract models, some of the revenues and costs are on a per-unit basis. For example, the revenue from the insurance agency is on a per-unit basis, the Cost of Goods Sold (COGS) and manufacturing mark-up is also on a per-unit basis. There are also costs and revenues that are on a per-order basis such as the service fee, service cost, or freight fee. This experiment required a model that ultimately mirrored the per-order economics. Without taking into account order size, frequency, and amount of effort per order, it would be incorrect to apply an average across all. Additionally, the team believed that it would be possible to change the per-order economics by increasing customer order size, or improving efficiency on the service size to process each order. For this reason, the model with built with the ability to change those parameters instead of the per-piece parameters.

These units were bridged by creating a theoretical average order, based on historical demand data. This theoretical average order consisted of all 10 SKUs, of different proportions. The proportions were determined based on 10+ years of prior sales by looking at the overall unit volume. This was also modeled separately for each state.

Figure 1-4 how units can be extracted from the theoretical order in order to apply unit costs and revenues. For example, COGS and reimbursement revenue. Then, this composite revenue per order will have order-level costs such as freight fees or service fees.

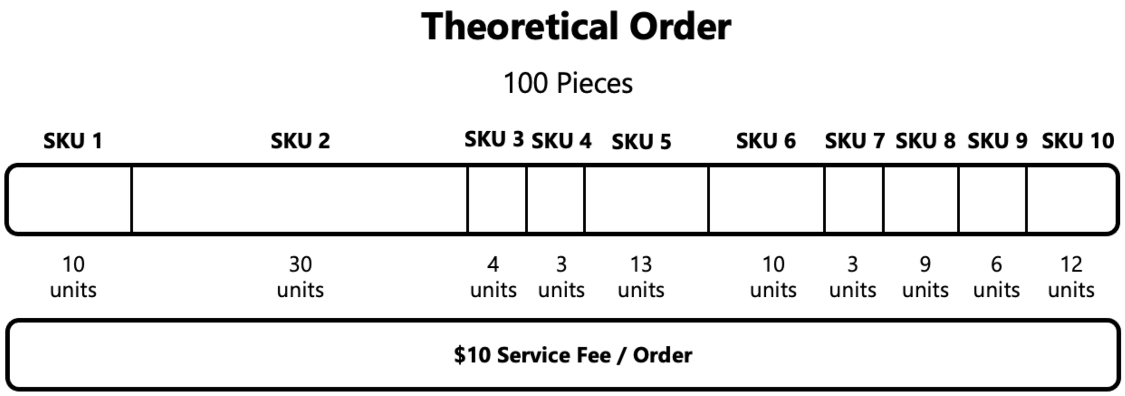

Figure 1-4: Service Model Illustration

The IncoMan team decided that past sales data was a good predictor of future sales distribution on average because Medicaid customers often have stable, recurring orders which change less than cash-pay customers. This is because they are not paying for the product themselves. They tend to find the products that work best and renew the subscription until their needs change.

Chapter 2

Background

2.1 Managed Care Organizations

Managed Care Organization (MCO)s are a crucial component of this new business plan proposal and therefore this research project. Medicaid and Medicare in the United States have grown to be so large that in order to manage the volume of patients, Managed Care Organizations are used. Each state creates its own plan of how to administer healthcare to patients, and most of them leverage Managed Care Organization's to help. A MCO is paid by the state to take a certain number of patients' lives under management for a capitated rate, which is payment on a per patient basis calculated on comprehensive risk. While the fee-for-service model was predominant in all states, where the state pays a provider a fee for services delivered to patients, most of them are moving towards capitated models under Managed Care Organization's. While the capitated model has increased budget predictability, the quality and access to care via the managed care organization model has mixed results [10]. Despite this, on average over 75% of patients in a given state are enrolled in an MCO.

One distinction to note in the MCO enrollment patterns, is that the target demographic for incontinence products, seniors and those with disabilities, are enrolled in MCO's at a lower rate than children and adults without underlying conditions. This is because the MCO's use actuarial science to calculate risk-based rates for patients on a per month basis to be enrolled in their plans. Because of this, the MCOs tend to take healthier Medicaid enrollees, and those with complex conditions tend to stay under state Medicaid. However, increasingly some Managed Care Organization's are starting to take enrollees with more complex conditions [10]. Because state Medicaid programs always have the highest reimbursement rate for adult incontinence products, it is advantageous for this business proposition that more seniors stay in the state Medicaid than being managed by MCO's (see discussion in 1.2.1).

Another note relevant to this research project is the increased involvement of large health insurance companies in the Managed Care Organization market. Since these for-profit publicly traded health insurance companies, such as UnitedHealth Group, Centene, Aetna, Molina, Anthem, make up a large percentage of Medicaid MCO enrollments (over 51%) [10], the term insurance agency will be used interchangeably for Managed Care Organization (MCO). This is simply because insurance agency is a more common term and more intuitively understood as an entity to engage with on pricing and selling healthcare products and services.

2.2 Financial Calculations

Throughout this research, financial models are created and simulated for a potential new business proposal. These are modeled as Proforma Income Statements for a particular business segment which would be a new collaborative venture for Adult Incontinence Manufacturer in North America (IncoMan). Proforma financial statements are projections of a company's future financial performance based on assumptions and estimates. Widely accepted accounting metrics and financial measures will be used in order to get down to the operating income on the Proforma Income Statement. The income statement is sometimes also referred to as a profits-and-loss (P&L) statement or earnings statement. Below are some of the measures and metric definitions [7] used in further financial calculations in both the model and simulation.

$$Gross\ Revenue = all\ sales\ generated\ in\ time\ period, \tag{2.1}$$

$$Net\ Revenue = (Gross\ Revenue) - (Allowances\ for\ bad\ debt\ and\ returns), \tag{2.2}$$

$$Cost\ Of\ Goods\ Sold = (Raw\ Material) + (Direct\ Labor) + (Freight), \tag{2.3}$$

$$Gross\ Profit = (Net\ Revenue) - (COGS), \tag{2.4}$$

$$Gross\ Margin = \frac{(Gross\ Profit)}{(Net\ Revenue)}, \tag{2.5}$$

$$Operating\ Income = (Gross\ Profit) - (Operating\ Expenses), \tag{2.6}$$

$$Variable\ Margin = \frac{(Operating\ Income)}{(Net\ Revenue)} \tag{2.7}$$

2.3 Simulation Methods

2.3.1 Monte Carlo Simulation Methods

Monte Carlo simulation is a powerful computational tool used to model complex systems and analyze their behavior over time. It has become an increasingly popular method for financial analysis and forecasting, especially in the development of proforma financial statements. Using Monte Carlo simulation techniques in financial proformas allows for a more comprehensive and accurate analysis of financial projections and the risk or uncertainty associated with those predictions. It involves running multiple simulations of a financial model, each with a set of different assumptions and variables. The results of these simulations are then aggregated to produce a range of possible outcomes and probabilities, which can help identify potential risks and opportunities.

The first step in using Monte Carlo simulation for financial proformas is to identify the variables and assumptions that will affect the financial model. Once these variables are identified, a probability distribution is assigned to each variable, indicating how likely it is to occur. Then, the Monte Carlo simulation is run with the model being executed multiple times. Each time, different values for the variables are assigned based on probability distributions. The results of each simulation are recorded and aggregated to produce a distribution of possible outcomes. From this method, summary statistics such as mean, median, min, max, standard deviation, and confidence intervals [3] can be utilized to gain a more nuanced understanding of the results for decision-makers to take into account when making a complex business decision.

2.3.2 Quasi-Random Simulation Methods

When considering random simulation methods for financial applications, it is important to use a method that generates a high-quality, random sequence of numbers that is representative of the distribution being modeled. One popular method for generating such sequences is the Sobol sequence [20], which are a class of low-discrepancy, or low variation, sequences which more closely resemble the initial distribution. Since several of the Sobol implementations have been optimized with the aim of applying them to finance [8], they are chosen here as the quasi-random method of choice for this proforma simulator.

The Sobol sequence is deterministic, which means that the same sequence can be reproduced for a given set of input parameters, providing greater consistency and reproducibility in Monte Carlo simulations. For a larger sample size it simply ad This is particularly important in financial applications, where the same simulation may need to be run multiple times with different inputs or parameters. Finally, the Sobol sequence is also efficient in high-dimensional problems, where the number of input parameters is large [8]. In these cases, the Sobol sequence can generate a larger number of independent samples with less computational effort compared to other random number generation methods, such as the Halton sequence or Faure sequence.

In conclusion, the Sobol sequence is a popular method for generating random numbers in financial applications due to its superior properties over other random number generation methods. Its low discrepancy, determinism, and efficiency in high-dimensional problems make it an ideal choice for Monte Carlo simulations in financial analysis and forecasting.

2.4 Distribution Fitting

The random variable that is simulated in this model is the demand. Demand for incontinence products (briefs, underwear, bladder control pads, and underpads) can vary state by state and month by month. There are some dependencies in this data, for example there are sizes (S, M, L, XL) for some of these products. A given patient is not likely to be a Small in one product and an X-Large in another product. Additionally, it is unlikely that all patients are the same size (Small) given a random distribution of the population. Furthermore, some product categories are complementary to others, whereas some are substitutes. For example, a bladder control pad is a light liner, and would likely not be used in conjunction with a brief which is meant for patients who need a caretaker's help to change them. An underpad that goes on top of a bed could be used at night in conjunction with any of the other products. For this reason, there are dependencies between even randomly chosen demand profiles.

2.4.1 Kernel Density Estimation

In order to take these dependencies in the demand distribution into account in the simulator, a Kernel Density Estimation (KDE) is used. Kernel Density Estimation (KDE) is a non-parametric method used to estimate the Probability Density Function (PDF) of a random variable. In the context of dependent random variables, the use of KDE functions can provide insights into the joint distribution of the variables. When dealing with dependent random variables, the joint PDF can be difficult to estimate analytically, especially if the dependence structure is complex. In such cases, KDE can be used to estimate the joint PDF numerically. This is especially valuable for multivariate polynomial expansions with dependent random variables.

2.4.2 Rosenblatt Transformation

The Rosenblatt Transformation [18], also known as the Parzen-Rosenblatt window method [15], is a method of Kernel Density Estimation (KDE). This is just one method of estimation. It can be problematic in high dimensions and computationally inefficient.

The application in this case study, detailed in Section 3.4.2, involves simulation just 10 dimensions for 10 demand variables. Therefore, it is a feasible and appropriate method for this study. It is defined as:

$$T(\xi) = F_{\zeta}^{-1}(F_{\xi}(\xi)), \tag{2.8}$$

where

$$F_{\xi}(\xi) = (F_{\xi_0}(\xi_0), F_{\xi_1|\xi_0}(\xi)..., F_{\xi_{D-1}|\xi_0,...,\xi_{D-2}}(\xi_{D-1})), \tag{2.9}$$

are conditional cumulative distribution functions [5]. The inverse distribution functions:

$$F_{\zeta}^{-1} = (F_{\xi-0}^{-1}, ..., F_{\xi_{D-1}}^{-1}), \tag{2.10}$$

are conversely created from:

$$p_{\zeta},\ where\ \zeta = (\zeta_0, ..., \zeta_{D-1})$$

are stochastically independent distributions [5].

2.4.3 ChaosPY - Fienberg and Langtangen

The implementation chosen for Kernel Density Estimation (KDE) using the Rosenblatt transformation was the python package chaospy [4]. Chaospy is described in the documentation as "a numerical toolbox for performing uncertainty quantification using polynomial chaos expansions, advanced Monte Carlo methods implemented in Python. It also includes a full suite of tools for doing low-discrepancy sampling, quadrature creation, polynomial manipulations, and a lot more."[4]. Chaospy provides a built-in way to fit chaotic multivariate polynomials to probability distribution functions. It also has several quasi-Monte Carlo simulation methods built in, including the Sobol sequence. For these reasons, this python-based implementation was chosen for the stochastic simulator in this research.

Chapter 3

Research Methodology

3.1 Architectural Overview

Figure 3-1 shows an overview of the interplay between the model, inputs, outputs, and the simulator. The details of the model and simulator configurations are detailed in the following sections within this chapter. For simplicity, they will sometimes be referred to as models DD, DS, ND, and NS as indicated by Figure 3-1.

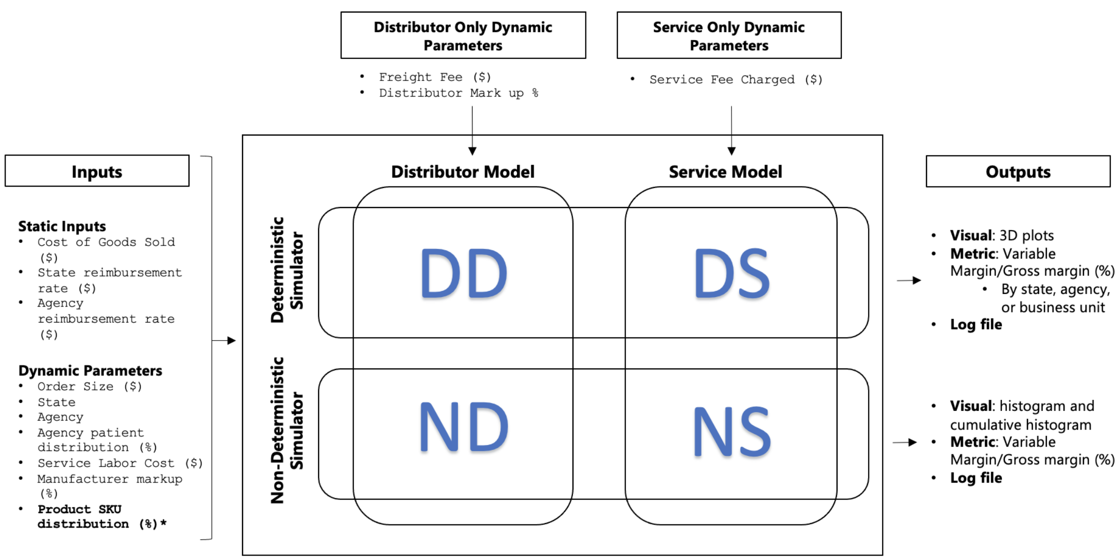

Figure 3-1: Model and Simulator Architecture

3.1.1 Model Overview

The financial model itself is broken into two sub-models, the distributor and service model. However, the primary inputs and outputs are the same to both, shown on the left hand side and right hand side of Figure 3-1. Many of the underlying assumptions and calculations are shared. These models have slightly different parameters but can be run on the same sets of data. The distributor model (mode DD and ND) runs a set of scenarios based on various ratios in the contract terms. The service model (mode DS and NS) is similar but just has one parameter. The simulator can then run deterministic (mode DD and DS) and non-deterministic (mode ND and NS) scenarios under both models. These scenarios are set by parameters in the simulator for the deterministic variables, and randomly generated by the simulator for the non-deterministic variables.

3.1.2 Simulator Overview

The simulator has two modes. In modes DD and DS, the simulator can manipulate the deterministic variables and the results can be explored by the user. For the purposes of visualization, two parameters can be varied at a time then explored on a 3D-axis. If more variables are desired to be changed than two at a time, then a sensitivity table can be generated and the user can manually calculate the changes.

Modes ND and NS of the simulator randomly generate possible demand distributions for each SKU based on historical demand in several states. The results can be viewed by the user in the form of a histogram of the results. This company can use this information to understand the range of results and the set of more likely results given a SKU distribution. The product SKU distribution is the only in the stochastic simulator.

3.2 New Contributions

This research project involves several new contributions to IncoMan and represents a unique application of technical concepts to a new field. As discussed in Section 1.2.1, the market for Medicaid-reimbursed adult incontinence products is complex due to the insurance company mediating between the manufacturer and the consumer of the products. The price received for a product is so highly varied, that it is risky to pick any one price assumption and extrapolate to a future year of earnings[2]. In order to account for this, the first bottoms-up model was built for this healthcare sales application. This required a revenue calculation function and a profit calculation function. These functions were used to create two novel models. Each was defined to demonstrate two different contract negotiation models. With these models, a simulator was built to simulate deterministic scenarios for analysis and a stochastic simulator to capture demand uncertainty.

3.2.1 Revenue Calculation Function

The revenue function defined in Equation 3.1 calculates the average weighted reimbursement price that the manufacturer will receive from all of the agencies in the state that they sell to.

$$\begin{aligned} &Weighted\ Revenue\ per\ Unit_H = \\ &\sum_{a}^{Agencies} (Reimbursement\ Price_a) * (Agency\ Weight_a) \\ &\forall H \in HCPC\ List \end{aligned} \tag{3.1}$$

Each insurance agency (a) has a contracted rate which they will reimburse for each unit of product in a given Health Care Product Code (HCPC). This price is weighted by the agency's proportional presence in IncoMan's customer pool. One agency could

[2]Table illustrating price variation amongst states and agencies in Appendix A Table A.1

represent 50% of the customer mix while another agency could only represent 10% of the customer mix and this must be accounted for in the weighting of this formula. In the model, the revenue calculated by Eqn 3.1 is referred to as the Gross Revenue. One additional calculation is done, the gross-to-net revenue reduction. The following are included in the gross-to-net reduction.

1. 1% Reduction for Write-Offs
2. 2% Reduction for Bad Debt

This is done based on historical financial data from IncoMan's experience in the healthcare sector for the past 25 years.

3.2.2 Profit Calculation Function

Building on the revenue function defined in Equation 3.1, the simulator also requires a profit calculation as a key metric of interest. The metric of profitability is a key driver in decision-making on terms of contract agreements going forward. Additionally, profitability is the metric of concern that must be quantified under a range of scenarios to capture uncertainty in the business plan in general. The profit equation (3.2) calculates the average weighted reimbursement price per unit and then subtracts the Cost of Goods Sold (COGS) for that Health Care Product Code (HCPC).

$$\begin{aligned} &Gross\ Profit\ per\ Unit_H \\ &= \left(\sum_{a}^{Agencies} (Reimbursement\ Price_{H,a}) * (Agency\ Weight_{H,a}) \right) - COGS_H \\ &\forall H \in HCPC\ List \end{aligned} \tag{3.2}$$

The Cost of Goods Sold $COGS_H$ for a given HCPC is pulled from historical accounting records at IncoMan, which smoothes and averages the variable costs and fixed costs per piece over a 3-month period. COGS includes raw materials, direct labor, and inbound freight. The gross profit metric then becomes the starting point for further calculations subtracting out operating costs to get down to the variable margin.

3.3 Model Definition

3.3.1 Inputs and Data Sources

The inputs can be divided in to two categories, static inputs and dynamic parameters. The static inputs do not change, and come from company datasets spanning the past 20 years of manufacturing and sales data. The static inputs, their data source, units, and collection time period details are Table 3.1. The date ranges indicated in this table are the date ranges of the subsets of data used in the results in this paper. The static input data was not necessarily the only data, however the team concluded this timeframe was the most accurate to use in future modeling.

Table 3.1: Static Input Data

Name	**Units**	**Date Range**	**Source**
Cost of Goods Sold	$/unit	Q4 2022 Forecast	IncoMan Company Database
State Reimbursement Rate	$/unit	2022 average	D2C DiaperCo Company Database
Agency Reimbursement Rate	$/unit	2022 average	D2C DiaperCo Company Database

The Cost of Goods Sold (COGS) includes raw materials, inbound freight, direct and indirect labor. The State Reimbursement Rate is the maximum rate that a given state will reimburse forHealth Care Product Code (HCPC) in that state. The Agency Reimbursement Rate is the rate a specific insurance agency actually passes through to the manufacgturer for the same HCPC.

The state parameter is one of the 50 states in the United States. For this analysis, two states of interest were chosen, OH and IL. The Order Size is defined as the average revenue generated per customer order. The Agency Patient Distribution maps each insurance agency to the percentage of the patient population that they cover. The service labor cost is the internal estimation for the direct and indirect labor required to obtain, fill, and document a prescription for an adult incontinence product. The

Table 3.2: Dynamic Parameters

Name	**Units**	**Date Range**	**Source**
State	2 letter state abbreviation	n/a	n/a
Agency	Abbreviation	2022	Company Database
Agency Patient Distribution	% of total patients in state	2022	D2C DiaperCo Company Database
Order Size	$ revenue / order	Oct 21 - Oct 22	D2C DiaperCo Company Database
Service Labor Cost	$ / order	Jan 22 - Jun 22	D2C DiaperCo Company Database
Manufacturer Mark Up	% mark up on COGS	Average across SKUs	IncoMan Company Database
Product SKU Distribution	% of all SKUs	Oct 21 - Oct 22	D2C DiaperCo Company Database

manufacturer markup is the % that the manufactured products are marked up before being sold to another supplier or customer. This is also known as the manufacturing margin. It is assumed to be a constant across all the product categories in the model. While not a constant in reality, an average estimate is used and applied across all the products to maintain confidentiality of the current pricing. Finally, the product SKU distribution is a % for all possible SKUs representing their share of the total demand in units of individual pieces.

Table 3.3: Contract Model Parameters

Contract Parameters	**Models Applicable**	**Units**
Manufacturer Markup	Distributor, Service	% mark up on COGS
Freight Fee	Distributor	$ / Order
Distributor Markup	Distributor	% mark up on COGS
Service Fee	Service	$ / Order

The inputs in 3.3 are the parameters specific to defining either the distributor model or the service model. Since this is the modeling of a new business negotiation, there is not any historical data necessarily correlating to these parameters. Instead, the user should determine what reasonable estimates or ranges are for these inputs parameters. This will be based on prior experience in the domain and evolving negotiation conversation.

3.3.2 Assumptions

- All units in the model are assumed to be on a "piece" level or a "pad" level. This would mean one brief, one underwear, one underpad, or one bladder control pad.
- All calculations are done at an order level. Orders require shipping and distribution costs associated to each specific order. There is also a service labor cost associated with each specific order. Therefore, all output metrics of variable margin are calculated at an order level.
- All customer order level calculations are done with a composite "weighted" product average. This does not require full cases or bags to compose a complete order, but instead creates an average order which contains all 10 SKUs. While this is not practical in actuality, the average is the best approximation in this case. Each piece (units) is assumed to be whole and there are no partial units.
- The order level math can be scaled to an annual value of a customer by assuming an average of 7 orders / year / customer based on historical data.
- Revenue is adjusted from gross to net using an estimation of prior years bad debt and write offs.

3.3.3 Contract Models

There are two contract models proposed. To understand why these two were initially chosen, it is important to understand that IncoMan is an incontinence manufacturer, while also being a medical service provider. The medical service is provided by the wholly owned subsidiary D2C DiaperCo. They talk to the patient on the phone and guide them through their journey of acquiring a prescription from a doctor to be reimbursed for their incontinence products by Medicaid. Then, they help the patient choose the right category and size for them. Finally, there is quite a bit of documentation and transfer of patient and product information necessary to obtain the reimbursement. These steps are done by D2C DiaperCo and then sent to the State

Medicaid or the Insurance Agency for reimbursement. IncoMan recieves reimbursement from the insurance agency, which is the top line of revenue in the income statement.

Table 3.4 shows the contract parameters listed in each contract type and indicates with colors whether that money goes to IncoMan or the retail partner.

Table 3.4: Gains and Loss Factors by Model Type

	Distributor	**Service**
Reimbursement Revenue		
Manufacturer Markup		
Freight Fee		
Distributor Markup		
Service Fee		

Colors: + $ to IncoMan +$ to retailer partner

The exact calculations of the contract implementation are calculated in a net income proforma in excel. While these exact formulas will remain confidential Table 3.4 helps indicate whether each term contributes towards a gain for IncoMan (green) or a gain for the retailer (red) and therefore an opportunity cost for IncoMan.

3.3.4 Outputs

Each model consists of two primary outputs:

1. Log File
2. 3D Visualization

The log file records all of the input conditions run in the simulator, as well as the calculated output metrics. The 3D visualization is an interactive visualization which plots all of the scenarios and outcomes so that a user can hover over the plot and see the inputs leading to this outcome. Figure 5-1 provides a sample screenshot of such a plot. A sample of a log file output can be found in Appendix B.

The output metrics plotted in the 3D visualizations and logged in the log file are:

1. Variable Margin as a % of Revenue - (Service Provider)
2. Variable Margin as a % of Revenue - (Service Provider + Manufacturer)

Where the service provider is Direct-to-Consumer Incontinence Distributor (D2C DiaperCo) and the manufacturer is Adult Incontinence Manufacturer in North America (IncoMan).

3.3.5 Methodology

The methodology for running the model follows the steps outlined in this Section 3.3 and it is summarized here in the following steps:

1. Upload all state input data to the model
2. Set all dynamic input parameters for model iteration
3. Calculate estimated revenue
4. Calculate estimated profit
5. Make additions or subtractions to gross profit based on contract parameters (distributor or service)
6. Output variable margins by business units
7. Write scenario values and outputs to log file

3.4 Simulator Definition

3.4.1 Deterministic Inputs and Data Sources

The deterministic simulator takes all of the same static and dyanmic inputs as the models do, which are defined in Tables 3.1 and 3.2. It also takes the specific contract parameters defined in Table 3.3.

First, the simulator may subset the data per dynamic criteria. Next, the axis must be specified. The deterministic simulator picks two dimensions to vary (x, y axis) and then plots the output metric in the third dimension (z). For the axis specified, the ranges must be set. All dynamic parameters must be set to either a value or a range of values. Some dynamic parameters are model specific.

Table 3.5 specifies which dynamic parameters are used to subset the data and which can be chosen as an axis. For the ones which can be an axis, the applicability to the distributor model or the service model is also indicated. All of the single variable, quantitative measures can be varied as an axis. The State and Agency is qualitative, so cannot be used as an axis. Agency Patient Distribution and Product SKU Distribution are multivariate distributions, so they cannot be shown on a single linear axis.

Table 3.5: Simulator Modes

Name	**Operation in Simulator**	**Range**	**Model Usage**
State	Subset	In list	Both
Agency	Subset	In list	Both
Agency Patient Distribution	Constant	$0 < x < 1$	Both
Product SKU Distribution	Constant	$0 < x < 1$	Both
Manufacturer Markup	Constant or Axis	$0 < x < 1$	Both
Freight Fee	Constant or axis	$0 < x$	Distributor
Distributor Markup	Constant or axis	$0 < x < 1$	Distributor
Service Fee	Constant or axis	$0 < x$	Service
Order Size	Constant or axis	$0 < x$	Both
Service Labor Cost	Constant or axis	$0 < x$	Both

Fundamentally, the deterministic simulator consists of choosing 2 axes and 2 respective ranges, and setting a constant value for the rest of the parameters. This can be done iteratively to hone in on zones of interest once more information is learned.

3.4.2 Non-Deterministic Inputs and Data Sources

The inputs to the non-deterministic simulator are the same as the dynamic parameters in the deterministic simulator (Table 3.5). The difference is that all of these parameters are set to a constant except the "Product SKU Distribution". This distribution represents the demand for different Health Care Product Code (HCPC)s as a percent of total annual demand. A sample of this input parameter can be seen in Table 3.6.

These inputs for "Product SKU Distribution" are generated by a joint probability distribution of all Health Care Product Code (HCPC)'s sampled with the Sobol

Table 3.6: Sample HCPC Demand Distribution

T4522	**T4523**	**T4524**	**T4543**	**T4525**	**T4526**	**T4527**	**T4528**	**T4535**	**T4541**
0.039	0.037	0.033	0.011	0.017	0.064	0.173	0.202	0.343	0.081

sequence discussed in Section 2.3.2. The joint probability distribution is derived using kernel density estimation, specifically the Rosenblatt transformation (see Section 2.4.2 and implemented using the Chaospy python package [4]. Consider $T(\xi)$ the distribution which is used to generate the Sobol Sequence.

$$T(\xi) = F_{\zeta}^{-1}(F_{\xi}(\xi)),$$

where $T(\xi)$ is composed of the conditional cumulative distributions $F_{\xi}(\xi)$ of each of the 10 HCPC's demand profile. This conditional distribution is represented as:

$$F_{\xi}(\xi) = (F_{\xi_{H0}}(\xi_{H0}), F_{\xi_{H1}|\xi_{H0}}(\xi)..., F_{\xi_{H9}|\xi_{H0},...,\xi_{H8}}(\xi_{H9})), \forall H_i, i \in \{0, 1, ...9\}$$

where conversely $F_{\zeta}^{-1} = (F_{\xi-0}^{-1}, ..., F_{\xi_{D-1}}^{-1})$ are stochastically independent distributions, the original historical product SKU demand. This historical demand was pulled for the most recent 5 years of demand in 11 states. The actual demand distributions are displayed in Figure 3-2.

Figure 3-2: Actual Consumer Demand for HCPCs as % of Total Units

These were transformed from their individual distribution to conditionally dependent multivariate distributions using the covariance matrix C shown in Appendix B Table B-1. This is necessary because there are dependencies in some of these HCPCs as described in Section 2.4.

The individual HCPC distributions were modeled as normal distributions and then transformed via the Rosenblatt transformation. The results of this joint conditional probability distribution can be seen in Figure 3-3. These are the distributions from which samples are generated using the Sobol sequence. Then the simulator can be set to as many iterations as desired.

Figure 3-3: Fitted Simulated Demand for HCPCs as % of Total Units

3.4.3 Assumptions

The normal probability distributions is assumed for all the HCPCs in the demand profile. When looking at Figure 3-2, some HCPC's clearly exhibit a normal distirbution more than others. While some may not look "normal", the team was consulted on the best way to represent this dispersion of HCPCs and it was agreed that in reality, the results would be more smooth than the ones depicted. Several states sampled did not contain all 10 HCPCs. This led to a few interval ranges with unnaturally high proportional demand, simply because some of the HCPCs did not exist.

Another reason that a normal distribution is more appropriate here than other instances is because there are physical limitations which dictate that the distribution not have extremely large outliers. This concept is discussed in Nassim Nicholas Taleb's book the Black Swan [22] about normal distributions. His views on normal distributions are that they are often used inappropriately in modeling real-world phenomena. He argues that many natural processes do not follow a normal distribution, and that the tails of these distributions (i.e., the rare and extreme events) are often overlooked or underestimated.

However, he acknowledges that the normal distribution can be appropriate for certain physical attributes of human beings, such as height or weight, and clothing sizes. This is because these attributes tend to follow a roughly symmetrical distribution with no extreme outliers.

It is important to be aware of the limitations of statistical models and being skeptical of any assumptions that do not align with real-world observations. However, this case of incontinence levels and sizing have more natural limits, making it reasonable to exclude potential for extreme cases.

3.4.4 Outputs

The outputs are slightly different for the deterministic simulator and the non-deterministic simulator. Both simulators output a log file. Fundamentally, the stochastic simulator output is a cumulative probability distribution, while the deterministic simulator is a discrete output calculation shown over a specified range. Therefore the stochastic simulator outputs the results in a histogram. The deterministic simulator outputs a 3D visualization of the solution space simulated.

3.4.5 Methodology

Overall, this simulator takes in data, defines random function, and uses the Sobol sequence to generate a random distribution. Once this is complete, it is the same as the deterministic case, a looped execution of the model. The steps followed were:

1. Obtain previous demand distribution data
2. Fit distribution to data
3. Generate Sobol Sequence
4. Load other input parameters and settings
5. Choose model type
6. Define axis, ranges, and number of iterations
7. Simulate
8. Generate output log file and visualations

Chapter 4

Model and Simulator Validation

4.1 Revenue Validation

Section 3.2 describes the methodology used for the revenue calculation. In order to validate the accuracy of the revenue calculation being used in the financial model, the same methodology is used on a set of historical Medicaid sales data ranging from 2018-2022. The model is applied to the historical 5 year data set generating a model revenue calculation. This is then compared to the actual revenue generated by the company in the calendar year. The topline revenue calculation is divided by the total number of units sold in the year. The validation metric:

$$(Revenue\ in\ \$)/unit\ \forall\ year,\ \forall\ HCPC \tag{4.1}$$

The validation intervals are broken up by state, by year, and by healthcare product code (HCPC). The data was collected on the monthly level, however, it was determined by talking to the team at IncoMan that the best interval to validate over would be a calendar year. This is because most customers do not order every single month. Although state Medicaid allows an order every 30 days, most customers maximize their orders for more optimal shipping. As a result the frequency is less often than every 30 days. The average number of orders per customer per year is around 7 orders.

After choosing the relevant HCPC codes for target Medicaid customers (11 HCPCs in IL and 10 HCPCs in OH), 105 sample intervals were obtained from the 5 year period and the percent error was calculated using Equation 4.2. The average HCPC Error was calculated using Equation 4.3. The average error for each year was calculated using Equation 4.4.

$$Error = \frac{(Model\ Output\ Revenue) - (Actual\ Revenue)}{Actual\ Revenue} \tag{4.2}$$

$$Average\ Yearly\ Error = \frac{\sum_{i}^{HCPCs} \frac{(Model\ Output\ Revenue_i) - (Actual\ Revenue_i)}{Actual\ Revenue_i}}{Number\ of\ Years} \tag{4.3}$$

$$Average\ HCPC\ Error = \frac{\sum_{i=2018}^{2022} \frac{(Model\ Output\ Revenue_i) - (Actual\ Revenue_i)}{Actual\ Revenue_i}}{Number\ of\ HCPCs} \tag{4.4}$$

Table 4.1: Percent Error of IL Revenue Calculation Function

HCPCS	2018	2019	2020	2021	2022	Average HCPC Error
T4522	-10.45%	-8.75%	-3.18%	-5.25%	-6.93%	-6.91%
T4523	-17.56%	-17.71%	-14.26%	-15.78%	-15.29%	-16.12%
T4524	-8.62%	-8.47%	-4.90%	-6.01%	-2.85%	-6.17%
T4525	-9.05%	-6.77%	0.51%	-3.39%	-0.61%	-3.86%
T4526	-7.53%	-6.75%	-1.42%	-2.53%	-1.51%	-3.95%
T4527	-7.96%	-7.24%	-3.50%	-4.22%	-3.90%	-5.36%
T4528	-8.07%	-7.88%	-5.38%	-5.09%	-4.67%	-6.22%
T4535	-13.96%	-15.73%	-13.08%	-13.80%	-14.04%	-14.12%
T4541	-17.99%	-15.84%	-8.20%	-10.18%	-8.05%	-12.05%
T4543	-44.97%	-46.91%	-42.03%	-41.89%	-42.85%	-43.73%
T4544	-70.93%	-52.76%	-48.77%	-44.11%	-43.01%	-51.91%
Average Yearly Error	-19.73%	-17.71%	-13.11%	-13.84%	-13.06%	

Initially, upon starting the financial modeling task, the goal set forth by the team was 80% accuracy. Another consideration on top of this was to have a more conservative model, allowing more leeway for error in an underestimation of profits than an overestimation. In order to account for this request, the direction of the magnitude of error (+/-) was retained in the reporting of error in the validation metrics in Tables 4.1, 4.2, 4.3, 4.4.

Table 4.2: Percent Error of OH Revenue Calculation Function

HCPCS	2018	2019	2020	2021	2022	Average HCPC Error
T4522	-8.27%	-6.73%	-7.68%	-8.66%	-7.13%	-7.70%
T4523	-17.76%	-16.90%	-11.26%	-14.55%	-25.72%	-17.24%
T4524	-14.41%	-10.85%	-12.13%	-9.95%	-8.95%	-11.26%
T4525	-12.31%	-7.11%	-5.63%	-2.32%	-2.13%	-5.90%
T4526	-9.53%	-6.88%	-0.83%	-1.50%	-0.14%	-3.77%
T4527	-10.15%	-9.72%	-4.76%	-4.88%	-4.30%	-6.76%
T4528	-6.58%	-5.67%	-4.47%	-1.59%	-1.07%	-3.88%
T4535	-16.79%	-19.01%	-16.13%	-14.22%	-9.48%	-15.13%
T4541	-19.87%	-18.19%	-13.91%	-9.43%	-5.80%	-13.44%
T4543	-7.10%	-7.36%	-16.01%	-14.28%	-31.55%	-15.26%
Average Yearly Error	-12.28%	-10.84%	-9.28%	-8.14%	-9.63%	

After the validation was complete, the results were reviewed with the team. On the whole, the revenue calculation was in line with expectations. For each year and HCPC, the average error was under 20% and all errors were in the direction of underestimation. The notable exception on HCPC consistency is HCPCs T4543 and T4544 in Illinois. These two HCPCs have higher error than what is desired (∼50%). However, it's worth noting that in the later years (2021 and 2022) the accuracy is slightly better. Ohio does not offer the HCPC T4544 but does offer T4543 and had higher accuracy (averaging ∼15% error).

4.2 Gross Profit Validation

Extending the validation done in the revenue calculation, further validation is done on the profit calculation using the metric of gross profit. Section 3.2 describes the methodology used for the revenue calculation formula. In order to validate the accuracy of the profit calculation being used in the financial model, the same methodology is used on a set of historical Medicaid sales data ranging from 2018-2022. The model is applied to the historical 5-year data set generating a model gross profit calculation. This is then compared to the actual gross profit generated by the company in that calendar year for that HCPC. The gross profit calculation is divided by the total number of units sold in that year. This makes the actual validation metric:

$$(Gross\ Profit\ in\ \$)/unit/year/HCPC \tag{4.5}$$

where $Gross\ Profit = (Revenue) - (Cost\ of\ Goods\ Sold)$.

The *Cost of Goods Sold* data is available for all HCPCs from the company's historical data set for these calculations. Again, the validation intervals are broken up by state, by year, and by healthcare product code (HCPC). Given these parameters, calculating the profit metric under 2 states within the 5 year period yielded 105 validation intervals.

Table 4.3: Percent Error of IL Gross Profit Calculation Function

HCPCS	**2018**	**2019**	**2020**	**2021**	**2022**	**Average HCPC Error**
T4522	-16.93%	-14.21%	-5.35%	-8.72%	-11.55%	-11.35%
T4523	-28.19%	-28.39%	-23.37%	-25.50%	-24.88%	-26.07%
T4524	-12.95%	-12.70%	-7.44%	-9.16%	-4.44%	-9.34%
T4525	-15.88%	-12.18%	0.98%	-6.20%	-1.16%	-6.89%
T4526	-10.97%	-9.86%	-2.12%	-3.78%	-2.28%	-5.80%
T4527	-12.16%	-11.10%	-5.48%	-6.60%	-6.13%	-8.29%
T4528	-12.56%	-12.26%	-8.51%	-8.09%	-7.45%	-9.77%
T4535	-21.94%	-24.61%	-20.57%	-21.51%	-22.34%	-22.19%
T4541	-24.25%	-22.14%	-11.43%	-13.84%	-10.49%	-16.43%
T4543	-67.94%	-70.59%	-64.39%	-63.44%	-65.03%	-66.28%
T4544	-108.28%	-82.63%	-76.97%	-69.76%	-68.10%	-81.15%
Average Yearly Error	-30.19%	-27.33%	-20.42%	-21.51%	-20.35%	

Table 4.4: Percent Error of OH Gross Profit Calculation Function

HCPCS	**2018**	**2019**	**2020**	**2021**	**2022**	**Average HCPC Error**
T4522	-12.63%	-10.34%	-11.76%	-13.27%	-10.91%	-11.78%
T4523	-26.63%	-25.48%	-17.01%	-21.93%	-38.99%	-26.01%
T4524	-22.11%	-16.80%	-18.89%	-15.71%	-14.27%	-17.56%
T4525	-21.75%	-12.56%	-10.26%	-4.52%	-4.31%	-10.68%
T4526	-14.98%	-10.97%	-1.36%	-2.45%	-0.23%	-6.00%
T4527	-15.76%	-15.25%	-7.59%	-7.93%	-7.06%	-10.72%
T4528	-11.18%	-9.77%	-7.85%	-2.88%	-1.94%	-6.73%
T4535	-26.33%	-29.72%	-25.36%	-23.25%	-16.41%	-24.21%
T4541	-34.41%	-34.67%	-25.33%	-16.90%	-9.59%	-24.18%
T4543	-9.66%	-9.90%	-23.83%	-21.39%	-50.46%	-23.05%
Average Yearly Error	-19.54%	-17.55%	-14.92%	-13.02%	-15.42%	

For the gross profit calculation validation results, these came in somewhat under expectations for the team. However, through discussions, it was revealed several possible explanations for the variation in the results and how to minimize error going forward. In Illinois, gross profit error averaged slightly over 20%, closer to 25% for each year. For each HCPC, the error actually averaged closer to 15% for HCPCs with the notable exceptions again of HCPC T4543 and HCPC T4544 being greater than 50% error. In Ohio, average errors for HCPCs and each year hover right around 20% on average. Again, all of these errors were of negative magnitude, meaning they are underestimations. This fact makes the team slightly more comfortable with the errors and the ones that are large. Two main factors could be at play causing errors in revenue and gross profit. The first is an inaccurate estimate of demand distribution across agencies, impacting primarily revenue. The second is an inaccurate estimate of Cost of Goods Sold (COGS), possibly due to abnormal raw material inflation and freight inflation occurring since 2020 due to the COVID-19 pandemic supply chain interruptions. A demonstration of the first source of error can be seen in Table 4.8. IL Agency 1 gives a much more generous reimbursement rate for HCPC than IL Agency 2. The model assumes that customers in all agencies collectively average the same ordering patterns. However, it could be the case that a customer in Agency 1 is actually twice as likely to order HCPC T4543. Customer specific ordering patterns are not included in the model, just overall demand.

For T4543 and T4544 this is especially plausible because these Health Care Product Code's are for bariatric sizes. Obese patients who require bariatric sizes often have many other comorbidities and are generally higher-cost patients to the insurance agency. Often, these high-cost patients remain on the state Medicaid plan because for-profit insurance companies are less likely to bid to have these patients in their plan. State Medicaid plans always give the maximum reimbursement rate in the state because there is no insurance agency to take a cut before passing the reimbursement through to the manufacturer. This could lead to an underestimation of the overall revenue and profit from these HCPCs if these Medicaid customers have different ordering patterns.

Errors in estimations of COGS could explain additional error in the gross profit calculation (beyond what was propagated through in the revenue calculation). A model is only as good as the data it's fed. More important than prior year errors for COGS is diligence into defining the best estimates for COGS for the fiscal year going forward. This model is meant to be used to look forward into the future at the profitability for a HCPC under a new potential business model with a strategic partner. Most importantly, the estimates for 2022 and 2023 should be tightened up to account for a conservative case for raw material pricing, local labor pricing, and the cost of freight [3].

The team understands the limitations of the revenue calculation and the profit calculation based on the validation results. While some states and HCPCs have larger error (within ~20%), they still find the results to be acceptable. This is primarily because they would like to use the model as an engine to estimate future earnings based on known engagements with insurance agencies. For example, they would engage a known number of patients in Agency 1 and Agency 2 and have clear expectations on reimbursement rates. This would minimize one of the biggest sources of error in revenue and profit.

However, in further iterations the team will intentionally exclude HCPC T4544 from the simulator and model. T4544 is removed because the revenue and profit results were both poor, and this HCPC only exists in the Illinois and not Ohio. T4543 is retained despite its poor validation scores in IL because the scores in OH are satisfactory. The IncoMan team also believes it is important to have at least one bariatric size included in the model.

4.3 Precision Validation

After having calculated the validation metrics for revenue and gross profit, a secondary validation is done on the precision of the calculation. The number of digits stored in the variable in python or excel could impact the number ultimately output by the model. For this financial application, ultimately the final answers for revenue and gross profit should be rounded to 2 places after the decimal representing 1 cent

[3] The finance team at IncoMan was consulted extensively to determine the numbers ultimately chosen for the final model. However, these numbers are subject to iteration.

or \$0.01. In this validation, several different levels of precision are tested and then rounded to 1/100th at the end and compared. The results are show in table.

Table 4.5: Precision of Stored Digits after Decimal Place

	Number of Digits Stored After Decimal Place, Rounded to 2 Digits				
	6 Digits	**5 Digits**	**4 Digits**	**3 Digits**	**2 Digits**
Sample	*\$ 0.78*	*\$ 0.78*	*\$ 0.78*	*\$ 0.78*	*\$ 0.77*
Number of Deviations	0	0	0	14	50
Number of Samples	110	110	110	110	110
Max Deviation	0	0	0	\$0.01	\$0.01
Average Margin of Error	0	0	0	0.39%	1.13%
				Average Error Rate	52.7%

The purpose was to test the precision (or perhaps false precision) of the metrics for revenue and profit. For all intents and purposes, only 2 digits after the decimal place are needed for these metrics as that represents \$0.01, or one cent. However, it could be rounded to 2 digits past the decimal from the beginning, or rounded at the end. This experiment was done with 2, 3, 4, 5, and 6 digits after the decimal stored. All values were rounded to 2 decimal places at the end and the results were compared for variation. Overall the results were not significantly different. There was no fluctuation of more than \$0.01. However, if it is desired for this \$0.01 error to be avoided then storing and computing with 4, 5, or 6 digits past the decimal place avoided any rounding error. When using 2 or 3 digits past the decimal place only avoided rounding error 52.7% of the time, however it was never more than \$0.01 different than the actual.

4.4 Software Validation

In order to validate the results of the financial model built, several intentional scenarios were run in isolation in order to ensure that the expected results were achieved. Examples of the scenarios run are in Table 4.6 which compares the expected result from manual calculation and actual result from the model.

Furthermore, successfully running the model is largely dependent on the user inputs being formatted correctly by the user. This is done in the input parameters

Table 4.6: Model Calculation Function Software Tests

	State	Agency	HCPC	Expected Outcome	Outcome
Test 1	IL	Agency 1	T4523	$0.59	$0.59
Test 2	IL	Agency 1	T4527	$0.81	$0.81
Test 3	IL	Agency 2	T4523	$0.72	$0.72
Test 4	IL	Agency 2	T4527	$0.95	$0.95
Test 5	IL	Agency 3	T4523	$0.59	$0.59
Test 6	IL	Agency 3	T4527	$0.72	$0.72
Test 7	IL	Agency 1	None	Error!	Error!
Test 8	IL	All	None	0	0
Test 9	IL	Agency 1 50%, Agency 2 50%	T4523	$0.66	$0.66
Test 10	IL	Agency 1 50%, Agency 2 50%	T4527	$0.88	$0.88
Test 11	OH	Agency 1	T4523	$0.41	$0.41
Test 12	OH	Agency 1	T4527	$0.75	$0.75
Test 13	OH	Agency 2	T4523	$0.62	$0.62
Test 14	OH	Agency 2	T4527	$0.81	$0.81
Test 15	OH	Agency 1	None	0	
Test 16	OH	$	None	0	
Test 17	OH	Agency 1 50%, Agency 2 50%	T4523	$0.58	$0.58
Test 18	OH	Agency 1 50%, Agency 2 50%	T4527	$0.69	$0.69

configuration file. In order to ensure this runs smoothly and as expected, several validations of user inputs are run in an effort to catch erroneous inputs in the code. These error-catching tests ran successfully on the code.

Table 4.7: Simulator Input Software Tests

	Input Parameter Tested	Error Tested	No. of Tests Executed	No. of Tests Passed	Pass Rate
Test 1	State	State input format is valid.	3	2	67%
Test 2	State	State data not in rebate table.	3	3	100%
Test 3	State	State data not in agency lists.	3	3	100%
Test 4	State	State data not in service cost table.	3	3	100%
Test 5	State	State data not in freight table.	3	3	100%
Test 6	Agency	Agency input format is valid.	3	3	100%
Test 7	Agency	Agency(s) is in agency lists.	3	3	100%
Test 8	Agency	Agency(s) is in rebate table.	3	3	100%
Test 9	HCPC List	HCPC list format is valid.	3	3	100%
Test 10	HCPC List	HCPC List is in rebate table.	3	3	100%
Test 11	HCPC List	HCPC List is in input COGS table.	3	3	100%
Test 12	HCPC Mix Historical	HCPC output is subset of HCPC List	3	3	100%
Test 13	HCPC Mix Historical	HCPC Mix is in rebate table.	3	3	100%
Test 14	HCPC Mix Input	HCPC input is subset of HCPC List	3	3	100%
Test 15	HCPC Mix Input	HCPC Mix input format is valid.	3	3	100%
Test 16	HCPC Mix Input	HCPC Mix is in rebate table.	3	3	100%
Test 17	Agency Mix	Agency Mix input format is valid.	3	3	100%
Test 18	Agency Mix	Agencies are in rebate table.	3	3	100%
Test 20	Service Labor	Service labor input is float.	2	2	100%
Test 21	Order Size	Order size input format is valid.	3	2	67%
Test 22	Order Size	Order size is > $0.	2	2	100%
Test 23	Distributor Model	Distributor model input format is valid.	3	2	67%
Test 24	Distributor Model	Retail mark up is $0 < x < 1$.	2	2	100%
Test 25	Distributor Model	Manufacturer mark up is $0 < x < 1$.	2	2	100%
Test 26	Distributor Model	Freight fee is > $0.	2	2	100%
Test 28	Service Model	Service fee is > $0.	2	2	100%
Test 29	Service Model	Manufacturer mark up is $0 < x < 1$.	2	2	100%

Software validation was also done on the model calculations, as well as the simulator inputs. The model calculation involved comparing expected and actual revenue outputs given different agencies to test the integrity of the revenue calculation function (see Table 4.6. The next set of validation checks on the inputs to the simulator check that the formats and value of the parameters specified in the simulator are correct. Examples include ensuring that the uploaded data sets match the geographic state requested. The only one which did not pass had to do with checking valid strings. Additional exceptions were added to the code to catch these string checks.

Table 4.8: Reimbursement Rates by HCPC by State and Agency

AGENCYID	**HCPCS**	**DESCRIPTION**	**REIMBURSEMENT AS A % OF MAX ACROSS STATES**	**COST PER PIECE (constant)**
IL AGENCY 1	T4528	Large Underwear	100%	$0.XX
IL AGENCY 2	T4528	Large Underwear	65%	$0.XX
IL AGENCY 3	T4528	Large Underwear	100%	$0.XX
IL AGENCY 4	T4528	Large Underwear	100%	$0.XX
IL AGENCY 5	T4528	Large Underwear	73%	$0.XX
IL AGENCY 6	T4528	Large Underwear	100%	$0.XX
IL AGENCY 7	T4528	Large Underwear	80%	$0.XX
IL AGENCY 8	T4528	Large Underwear	73%	$0.XX
OH AGENCY 1	T4528	Large Underwear	84%	$0.XX
OH AGENCY 2	T4528	Large Underwear	84%	$0.XX
OH AGENCY 3	T4528	Large Underwear	59%	$0.XX
OH AGENCY 4	T4528	Large Underwear	84%	$0.XX

Chapter 5

Model and Simulator Results and Analysis

The following section shows the results generated from the models and simulator, and a brief description of the data and axis. Discussion on the results follows in Chapter 6.

5.1 Deterministic Simulator

5.1.1 Distributor Model Results

There are two major categories of visuals from the deterministic simulator. The first set displays variable margin outcomes by business unit and the second displays variable margin outcomes by insurance agency plan.

The two business units displayed are Direct-to-Consumer Incontinence Distributor (D2C DiaperCo), which represents the service provider margin, and Adult Incontinence Manufacturer in North America (IncoMan), which represents the service provider margin plus the manufacturing margin, since IncoMan is the manufacturer which wholly owns the subsidiary and service provider Direct-to-Consumer Incontinence Distributor. Figures 5-1, 5-2, 5-3 show 3 different variations of possible variable margin outcomes based on possible distributor contract terms and other cost factors.

The axis varied are distributor markup %, freight fee, service cost, and order size.

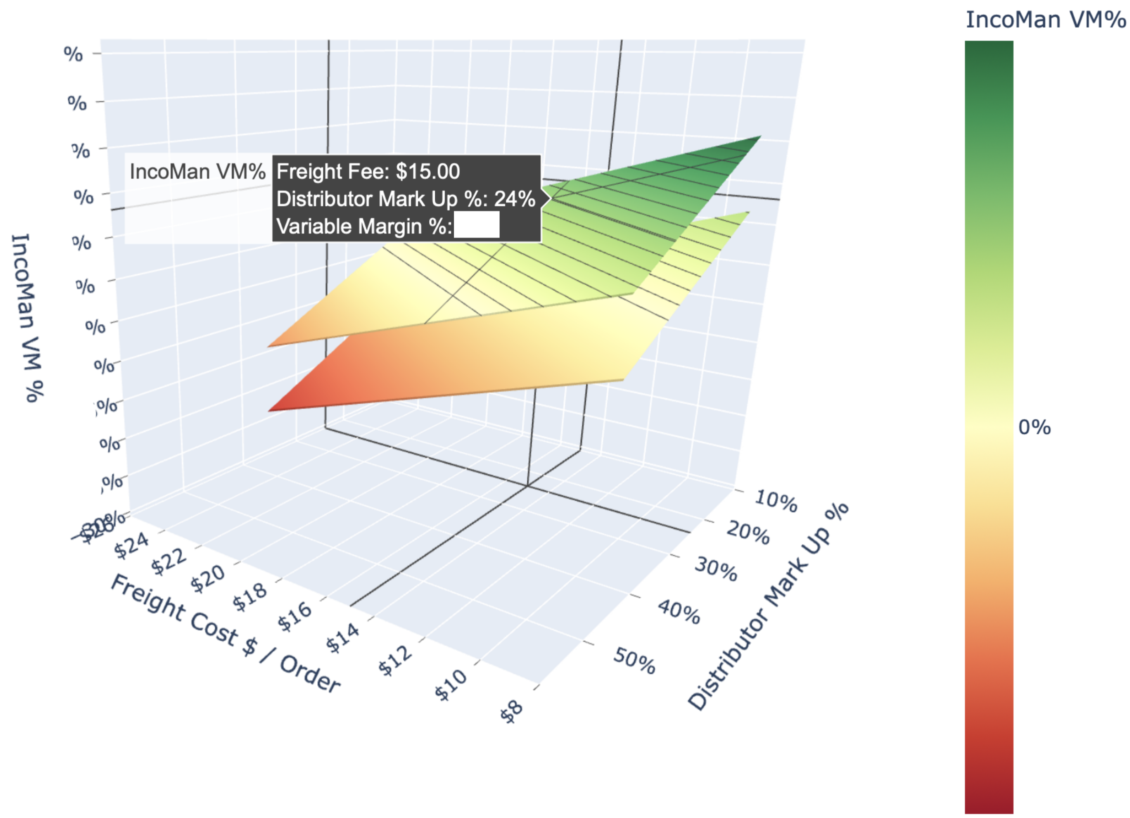

Figure 5-1: OH Distributor Contract Variable Margin Outcomes Under Deterministic Contract Terms varying Freight Fee and Distributor Markup

The second visualization shows variable margin outcomes based on the insurance agency plan. The same data is plotted on Figures 5-4, 5-5, and 5-6. Figure 5-4 hovers on Agency 1 data plane, Figure 5-5 hovers on Agency 2 data plane, and Figure 5-6 hovers on the combined agency plan based on the proportional mix of the insurance plans in OH.

5.1.2 Distributor Model Analysis

Overall, the deterministic simulator results are useful for evaluating the outcomes of potential contract terms. However, it's most useful when a few data points are already known about the conditions of the contract. The deterministic simulator results are simply a snapshot in time, calibrated to specified input parameters to show a range of

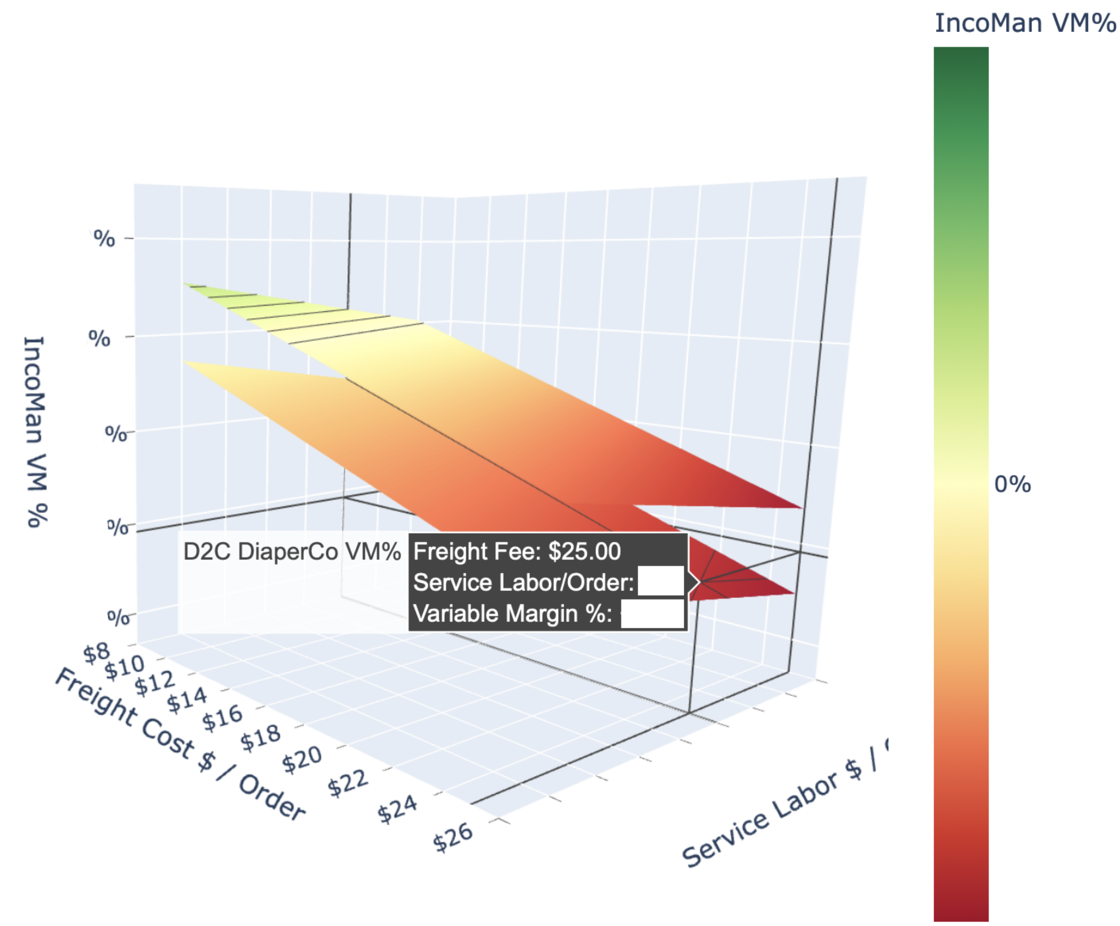

Figure 5-2: OH Distributor Contract Variable Margin Outcomes Under Deterministic Contract Terms varying Freight Fee and Service Cost

options. The more information known ahead of time, the better the ranges can be chosen in the outputs to study the subsection of trade-offs with the most interest.

Figures 5-1, 5-2, 5-3 all have 2 planes representing Variable Margin (VM). These two planes represent the 'business units' within IncoMan. In all cases, the top plane is the IncoMan cumulative variable margin for the whole business, which includes the manufacturer's margin on the products. This is assumed at a constant for all product types throughout the experiments and all runs of the simulator. The bottom plane always represents just D2C DiaperCo, the subsidiary of IncoMan. The 3D visuals include hovering, magnification, and rotation of the plot.

The four different axes used are Freight Cost $/ Order, Distributor Markup %, Service Labor $/ Order, and Order Size ($). The freight cost represents the contracted

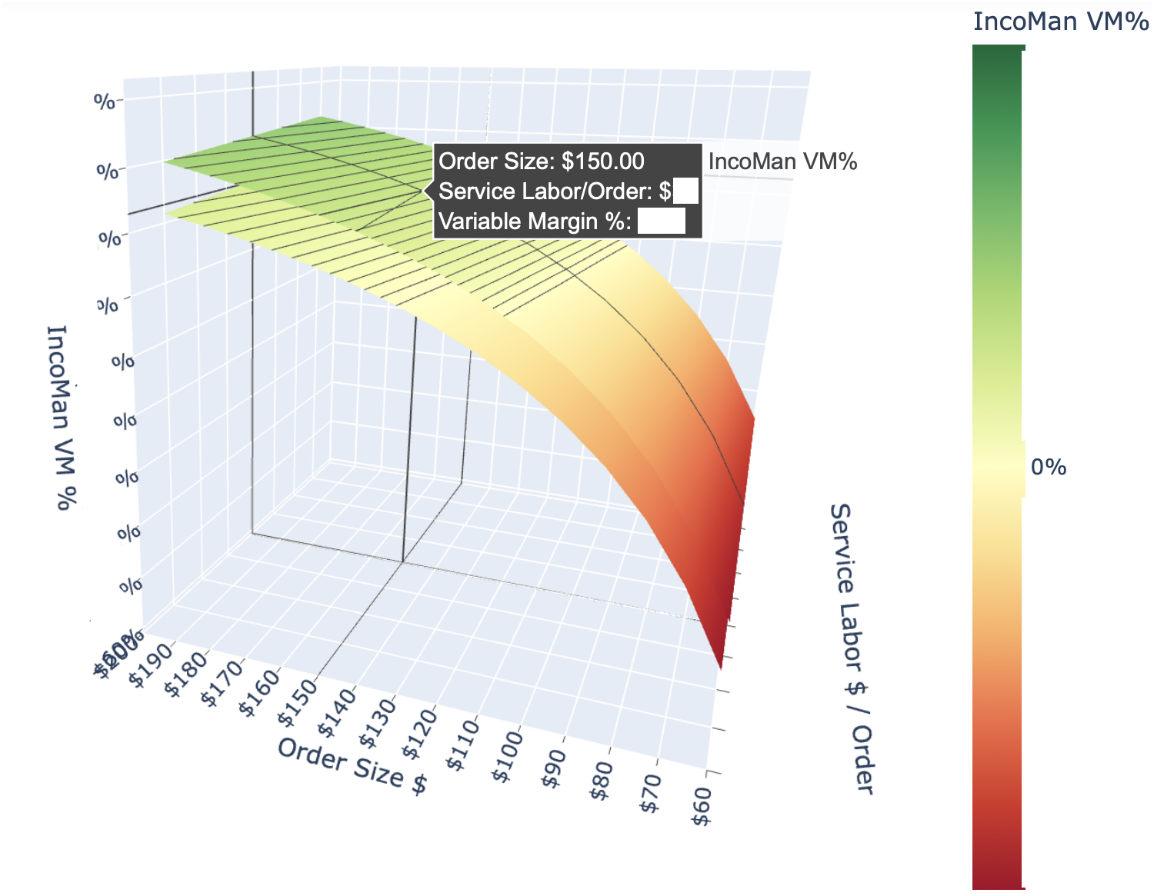

Figure 5-3: OH Distributor Contract Variable Margin Outcomes Under Deterministic Contract Terms varying Order Size and Service Cost

payment that would be made to the retailer to cover the cost of freight. The distributor markup would be the value that the retailer would charge back to the manufacturer for the effort of distributing the product, marked up as a % of COGS. The service labor is the internal cost of the labor associated with managing the patient needs, prescription, and properly documenting the paperwork in order to receive reimbursement from the state Medicaid or insurance agency. Order size is the revenue per order of an average customer in a given state.

Most of the relationships are linear and intuitive. Higher internal service labor costs lowers variable margin for IncoMan, a higher freight fee paid to the retailer or higher distributor markup paid the retailer lower variable margin as well. Although all these levers are obvious, there would need to be an agreement with the retailer as well on what is an acceptable margin. Therefore, it's helpful to have a range of

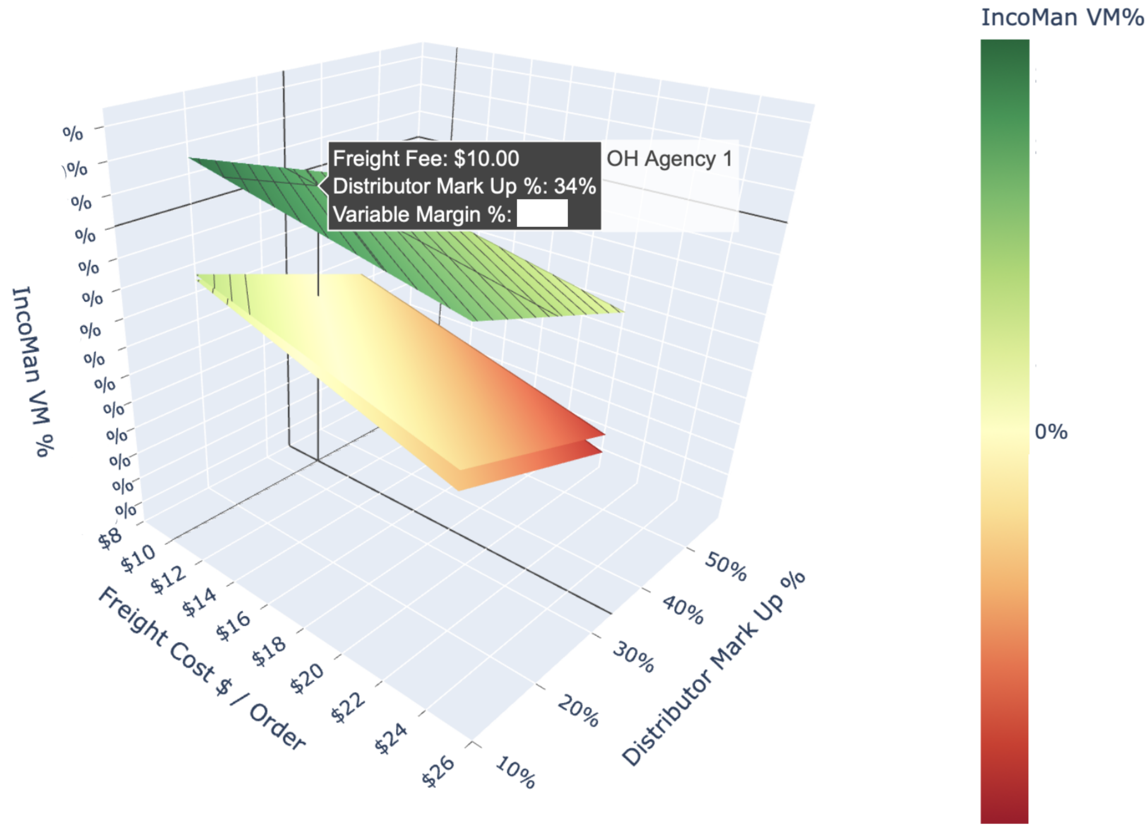

Figure 5-4: OH Comparison of Agency Plans - Variable Margin Outcomes Under Deterministic Terms varying Freight Fee and Distributor Markup

scenarios to discuss.

One relationship which is less obvious at first is the one between Order Size and variable margin. This one is powerful, because inherently in a business involving Direct-to-Consumer shipping, the economics at an order level matter since you must ship each order to a different customer's home. This is why the freight fee would need to be directly negotiated on an order level. All of the paperwork regarding the patient, prescription, and state legal/medical needs are also done at an order level. With this in mind, maximizing the order size is the most important lever to pull to improve the financial outcomes. The relationship is not linear, because much of the service labor and freight cost stays the same. While order size is clearly an important factor, it's important to note that it cannot be prescribed or set directly. This objective order size would be a target revenue per order for each customer, yet it cannot be strictly enforced. Therefore there is some risk in assuming a specific order size, and it's related

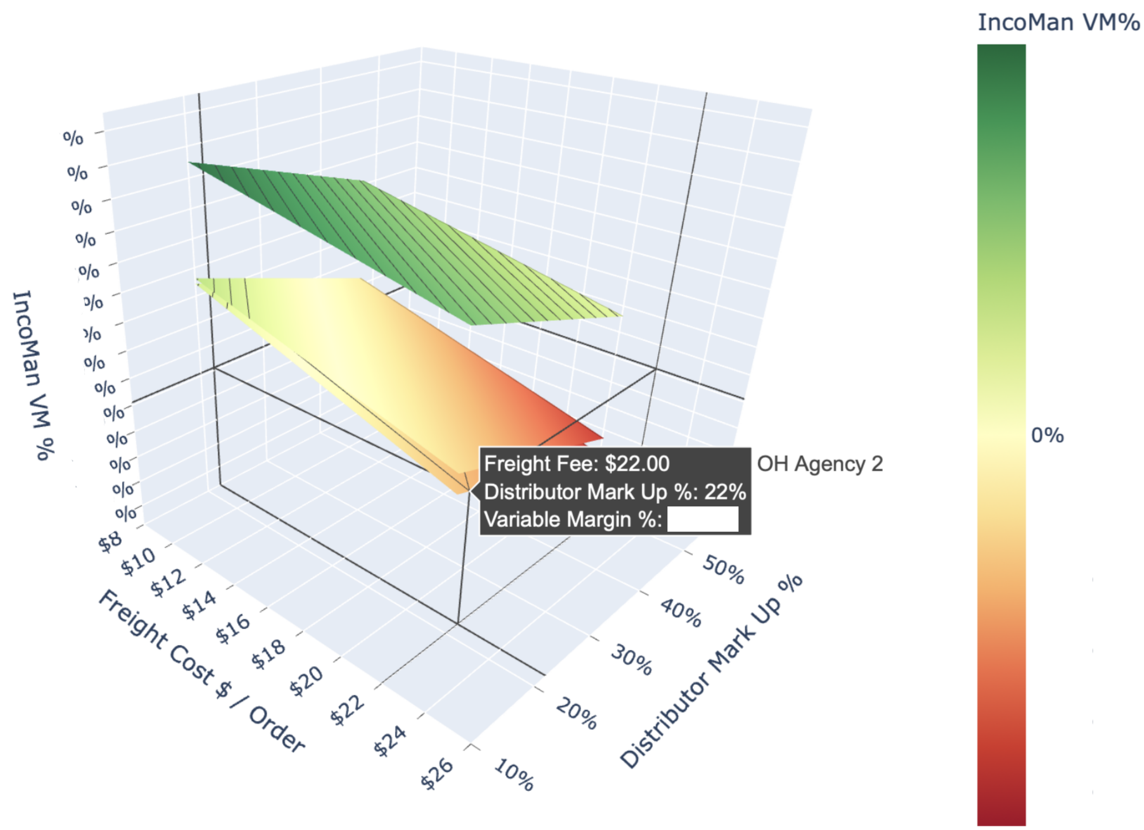

Figure 5-5: OH Comparison of Agency Plans - Variable Margin Outcomes Under Deterministic Terms varying Freight Fee and Distributor Markup

to a spectrum of outcomes.

Another important finding that can be visualized in the deterministic simulator is the impact that different Insurance Agency Plans have on financial outcomes. Figures 5-4, 5-5, and 5-6 all show the same data, however, the hover tool labels the Insurance Agency plans respectively. These variable margin outcomes for IncoMan can vary drastically from plan to plan. This shows how important the mix of Insurance Agency plans is to the overall profitability metric. The simulator allows IncoMan to understand the extent to which they would need to adjust their customer base in order to achieve specific profitability outcomes. Using this knowledge, they can pursue insurance agencies with better rates and understand what proportion of customers is influential in affecting profitability.

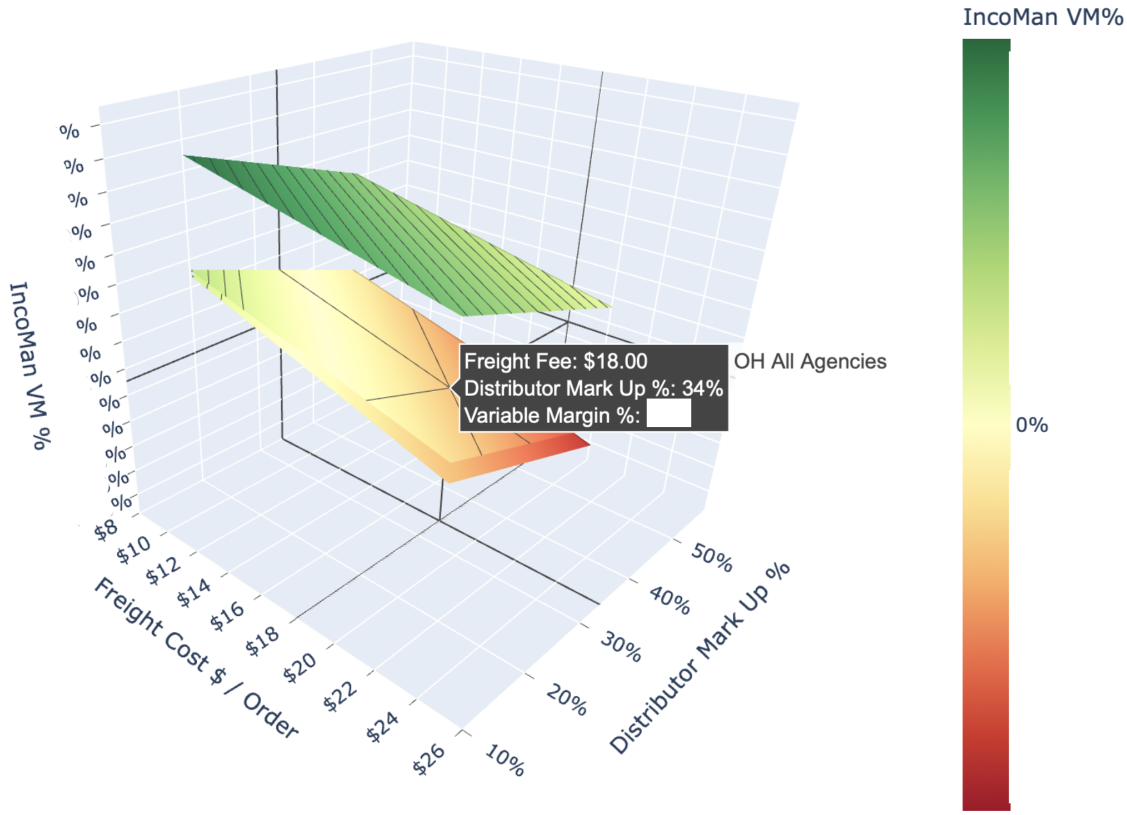

Figure 5-6: OH Comparison of Agency Plans - Variable Margin Outcomes Under Deterministic Terms varying Freight Fee and Distributor Markup

5.1.3 Service Model Results

Similar to the distributor model contract results, there are two categories of views output from the deterministic simulator. The first set (the majority) displays variable margin outcomes by business unit and the second displays variable margin outcomes by insurance agency plan.

Figures 5-7, 5-8, 5-9 show 3 different variations of possible variable margin outcomes based on possible service contract terms and other cost factors. The axis varied are service fee (the fee to the retailer), service cost (internal labor cost), and order size.

The second visualization shows variable margin outcomes based on the insurance agency plan. There are two planes in Figure 5-10 which represent 2 different Agency Plans. The service provider + manufacturer VM is on the Z-axis.

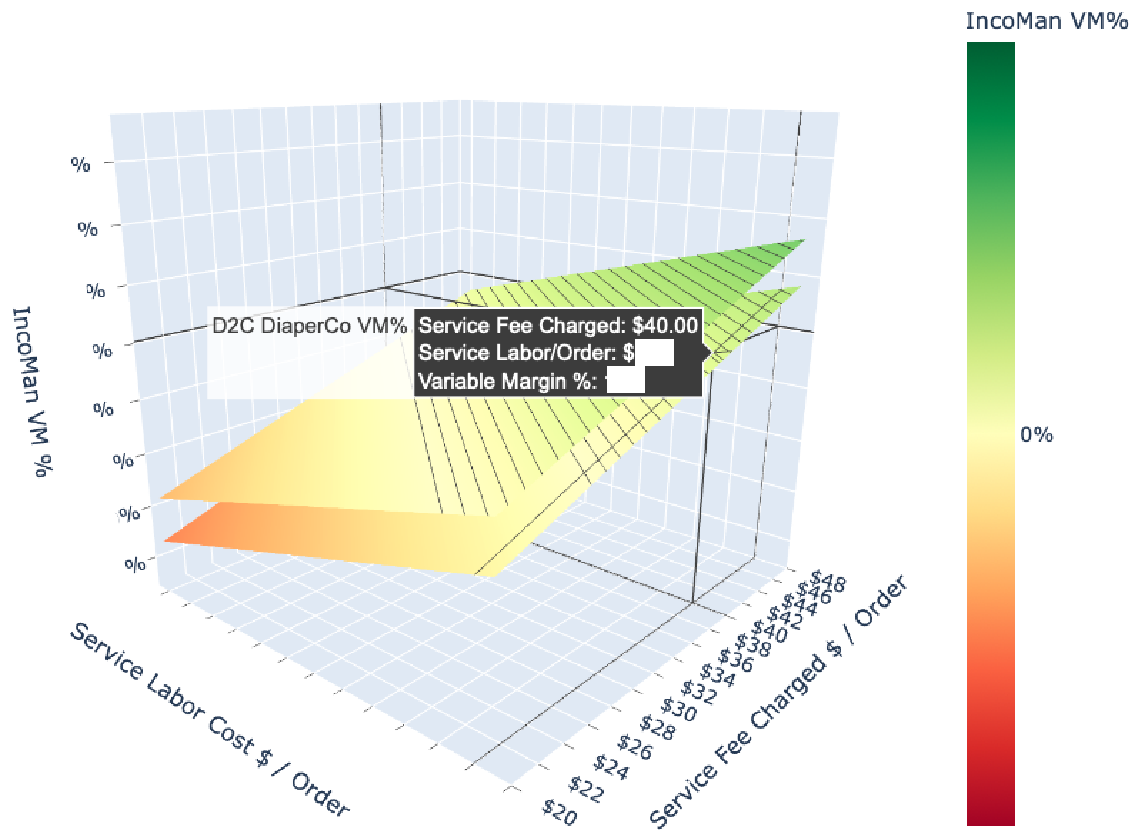

Figure 5-7: OH Service Contract Variable Margin Outcomes Under Deterministic Terms varying Service Cost and Service Fee

5.1.4 Service Model Analysis

Similar to the distributor model results, Figures 5-7, 5-8, 5-9 all have 2 planes correlating to Variable Margin. These two planes represent the 'business units' within IncoMan.

The three different axes used are Service Fee Charged $/ Order, Service Labor $/ Order, and Order Size ($). Like before, Order Size is defined as revenue per customer order. Service Labor $/ Order is the internal cost of the labor associated with managing the patient needs and insurance agency documentation. The Service Fee Charged $/ Order is the amount that the service provider (IncoMan and D2C DiaperCo) would charge to the retailer in order to cover the cost of prescribing the patient order and obtaining the reimbursement from the state Medicaid or Insurance Agency. It is important to note that while IncoMan may have estimates, it is difficult to

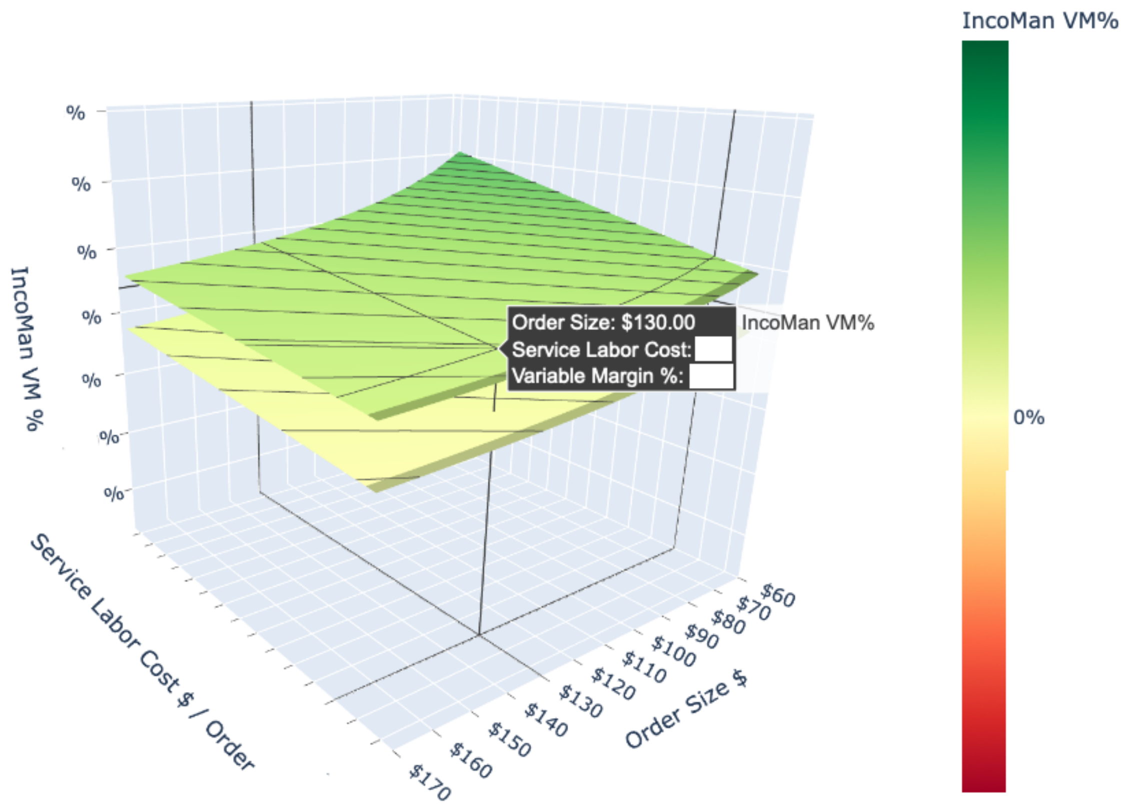

Figure 5-8: OH Service Contract Variable Margin Outcomes Under Deterministic Terms varying Service Cost and Order Size

predict exactly the cost of servicing an order, especially when it passes between several different job functions. For this reason, it is useful to have the axis of comparison of the Service Labor Cost vs. Service Fee Charged (Figure 5-7). The relationship between Order Size and the Variable Margin is actually inversely related in the service model. While in the distributor model, Variable Margin increases, in the service model VM decreases. This is because if service fee and cost is fixed, IncoMan earns profit from the medical service provided per revenue dollar from product sales. The order size does impact the retailer's margin, due to the cost of distribution and freight mentioned before. In Figures 5-8 and 5-9 there is a nonlinear relationship with variable margin when order size changes, and it is a less useful metric because changing the order size can't be used to increase overall profit margin in the service model. In Figures 5-8 and 5-9 both Service Labor Cost and the Service Fee Charged have a linear relationship with Variable Margin. A dollar difference in this category directly

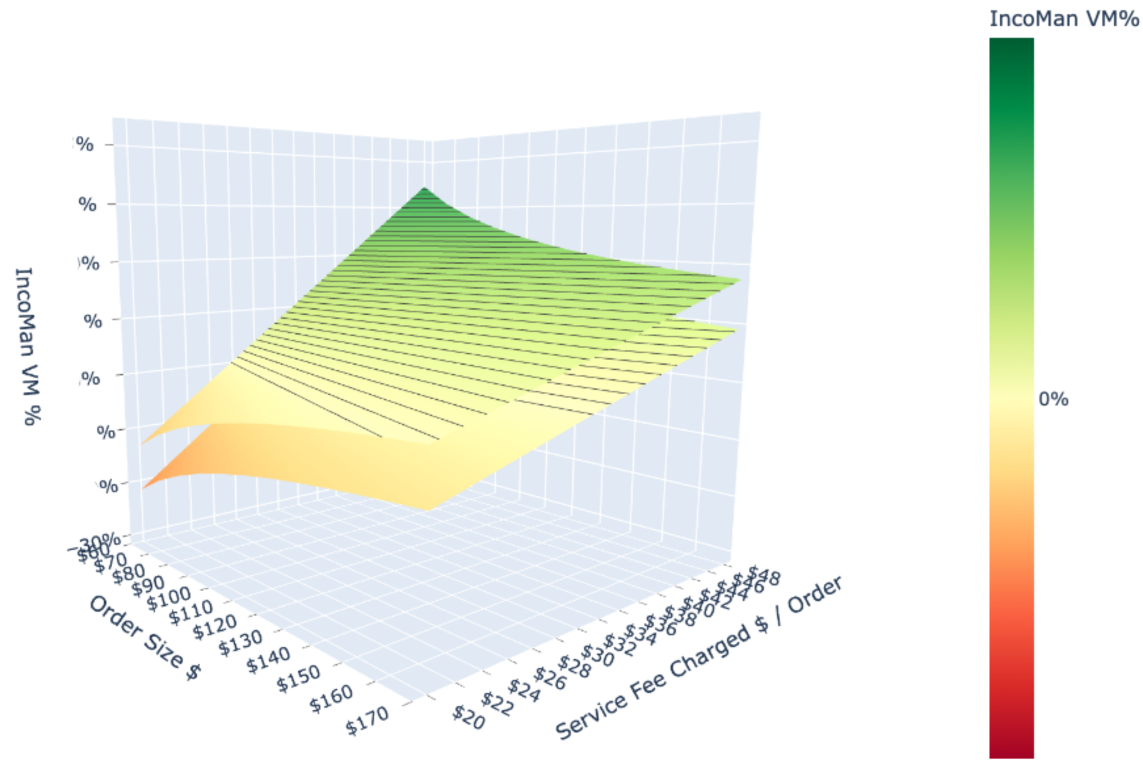

Figure 5-9: OH Service Contract Variable Margin Outcomes Under Deterministic Terms varying Service Fees and Order Size

relates to a dollar of earned profit.

Under the service contract model, comparing the different Insurance Agency plans as in Figure 5-10 shows minimal difference. The slight difference in variable margin between the two plans only applies to the IncoMan VM, not the D2C DiaperCo variable margin. The D2C DiaperCo variable margin is not shown because it is identical for all plans. The small difference comes from the fact that plans reimburse different rates for the same product, and this affects the total revenue per customer per order. Since the service fee is a flat fee, this results in a different nominal percentage change for variable margin.

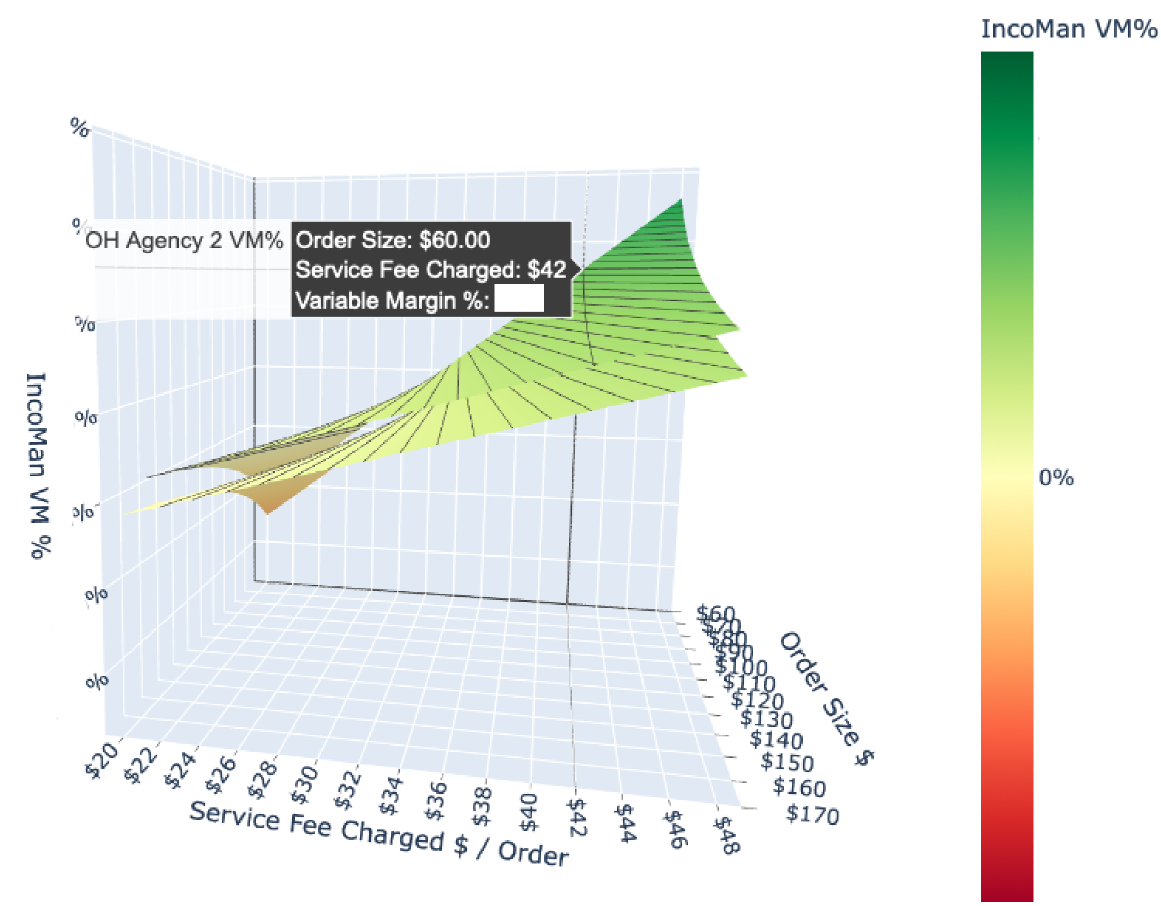

Figure 5-10: OH Comparison of Agency Plans - Service Contract Variable Margin Outcomes Under Deterministic Terms varying Service Fees and Order Size

5.2 Stochastic Simulator

The stochastic simulator simulates many demand scenarios where the demand for each HCPC is a random distribution using the Sobol sequence as discussed in Section 2.3.

5.2.1 Distributor Model Results

The following figures are generated for the stochastic distributor model for the states of OH and IL, each run on 1000 scenarios. Figure 5-11 shows a distribution of the simulator results in histogram where the X-axis is the variable margin outcome for the scenario and the y-axis is the number of scenarios falling into this category. Figure 5-12 shows the same data from the same simulator run, however the y-axis represents the cumulative number of scenarios falling at or below the corresponding value on the x-axis. Figure 5-13 and Figure 5-14 show the same data but for runs on the state of Ohio instead of Illinois.

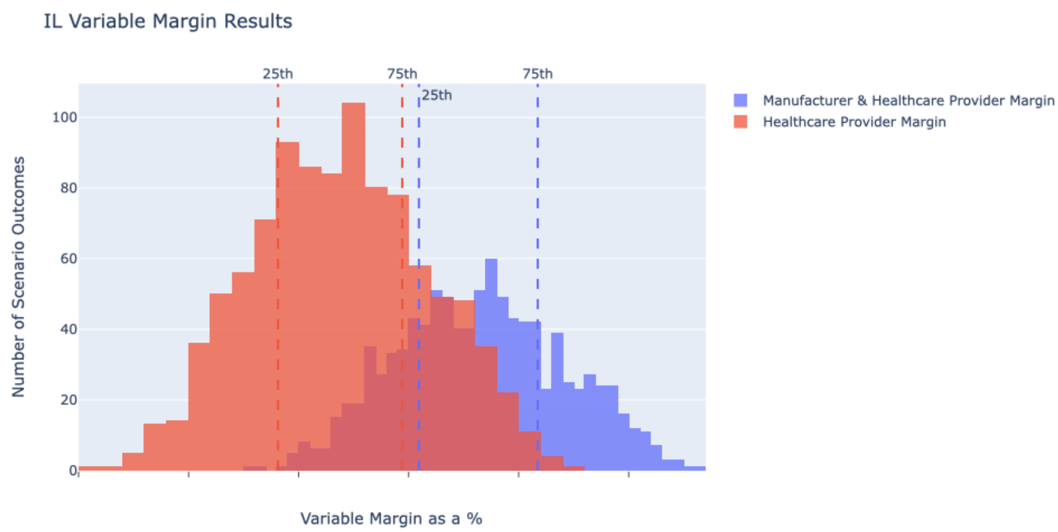

Figure 5-11: IL Distributor Model Possible Variable Margin Outcomes Under Stochastic Demand Profiles

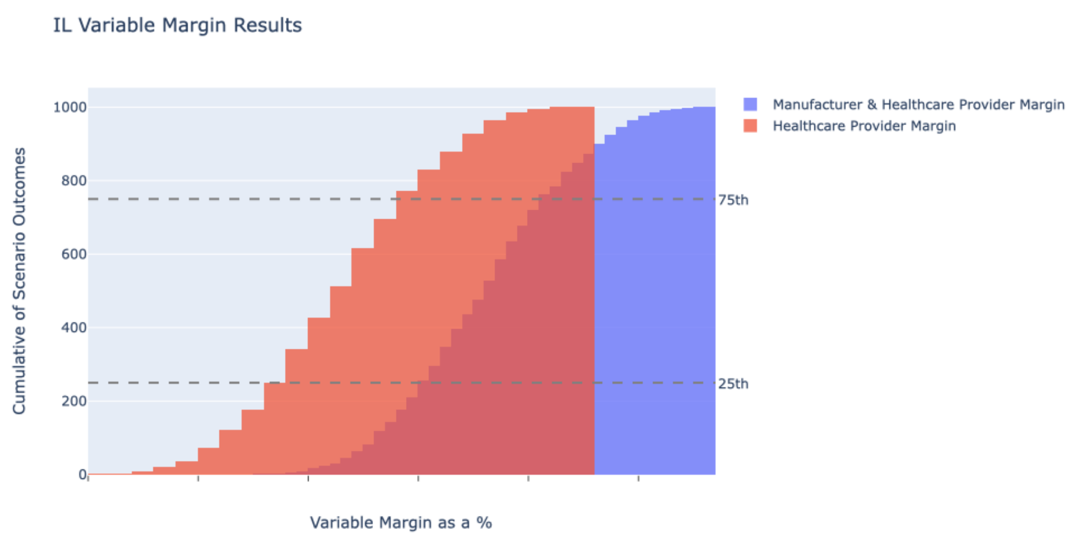

Figure 5-12: IL Distributor Model Cumulative Variable Margin Outcomes Under Stochastic Demand Profiles

Tables 5.1 and 5.2 show sample logs for IL and OH that are created for every

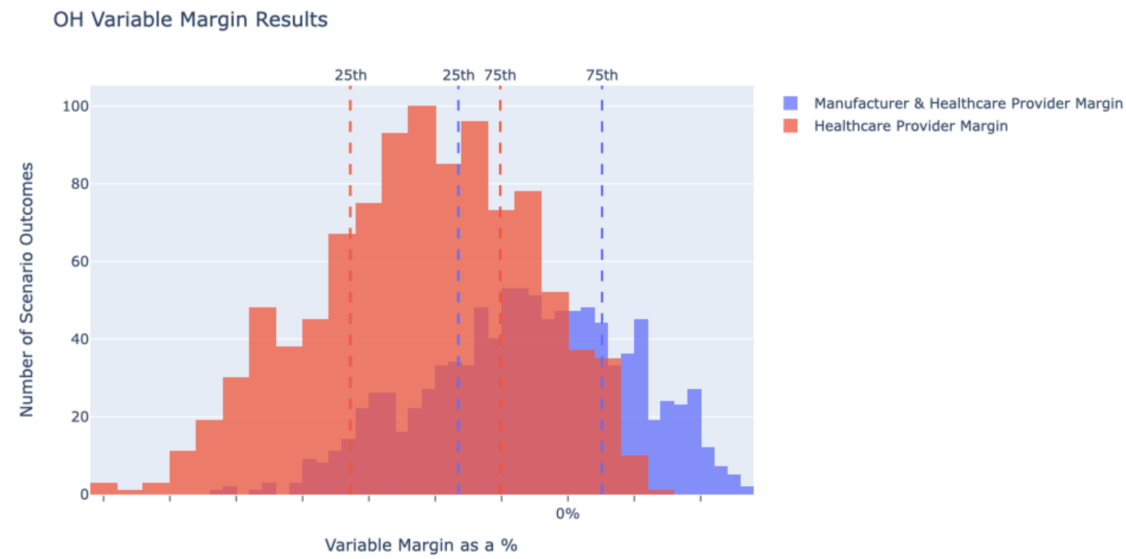

Figure 5-13: OH Distributor Model Possible Variable Margin Outcomes Under Stochastic Demand Profiles

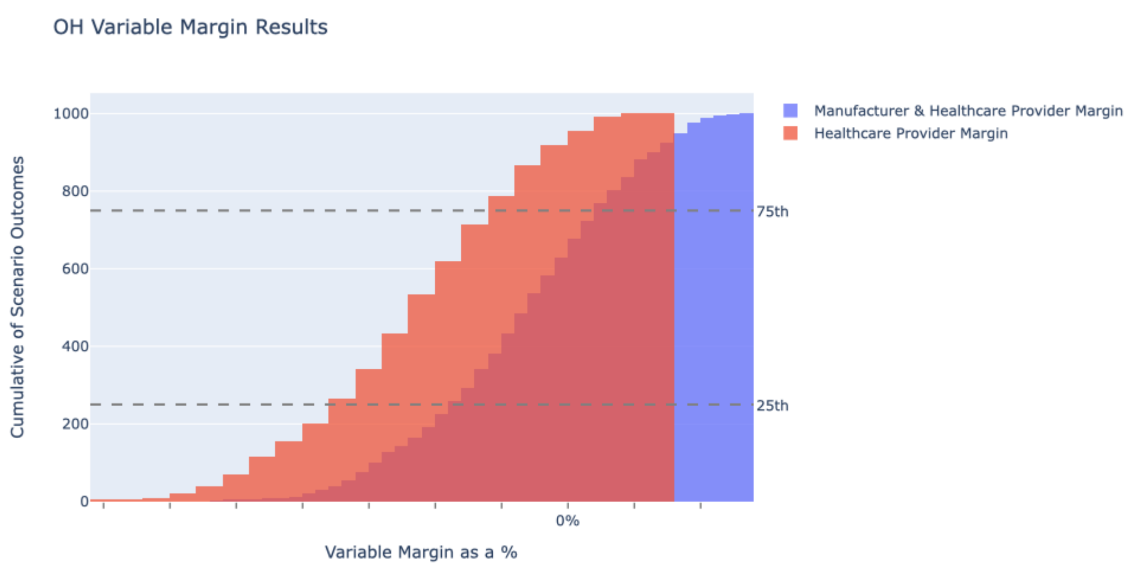

Figure 5-14: OH Distributor Model Cumulative Variable Margin Outcomes Under Stochastic Demand Profiles

parameter scenario run under the simulation. Appendix B, Figures B.1, B.2, and B.3 show a detailed sample log file of input parameters and outcomes generated from each simulator run for one state (Ohio in this example).

Table 5.1: Sample Output Log from Stochastic Distributor Model for IL

	T4522	T4523	T4524	T4543	T4525	T4526	T4527	T4528	T4535	T4541	State	Agencys	Model Type	Manufacturer Markup	Distributor Markup	Freight Fee	Order Size	Service Cost	ManuProv VM	Prov VM
0	0.045	0.032	0.016	0.013	0.008	0.211	0.157	0.075	0.326	0.118	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	0.175	0.3	16	134.291339	23.0312358	0.29832465	0.23696944
1	0.043	0.029	0.021	0.006	0.004	0.084	0.112	0.034	0.411	0.257	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	0.175	0.3	16	134.291339	23.0312358	0.2488122	0.18674053
2	0.180	0.056	0.012	0.002	0.088	0.124	0.088	0.024	0.028	0.398	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	0.175	0.3	16	134.291339	23.0312358	0.23114254	0.16170454
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
997	0.038	0.020	0.014	0.015	0.007	0.074	0.126	0.115	0.341	0.251	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	0.175	0.3	16	134.291339	23.0312358	0.28749899	0.22701284
998	0.003	0.039	0.033	0.006	0.023	0.047	0.140	0.061	0.363	0.285	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	0.175	0.3	16	134.291339	23.0312358	0.26015524	0.19808539
999	0.053	0.018	0.017	0.007	0.029	0.070	0.208	0.077	0.177	0.344	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	0.175	0.3	16	134.291339	23.0312358	0.28728087	0.22556909

Table 5.2: Sample Output Log from Stochastic Distributor Model for OH

	T4522	T4523	T4524	T4543	T4525	T4526	T4527	T4528	T4535	T4541	State	Agencys	Model Type	Manufacturer Markup	Distributor Markup	Freight Fee	Order Size	Service Cost	ManuProv VM	Prov VM
0	0.039	0.037	0.033	0.011	0.017	0.064	0.173	0.202	0.343	0.081	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%	$ 16.00	$ 115.23	$ 32.67	5.49%	-1.88%
1	0.194	0.042	0.031	0.008	0.059	0.149	0.089	0.023	0.160	0.246	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%	$ 16.00	$ 115.23	$ 32.67	-6.40%	-14.81%
2	0.083	0.026	0.022	0.008	0.039	0.238	0.291	0.188	0.005	0.099	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%	$ 16.00	$ 115.23	$ 32.67	8.84%	1.22%
3	0.092	0.064	0.040	0.009	0.048	0.067	0.146	0.128	0.131	0.276	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%	$ 16.00	$ 115.23	$ 32.67	-2.72%	-10.88%
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
997	0.083	0.046	0.012	0.010	0.047	0.132	0.128	0.088	0.147	0.308	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%	$ 16.00	$ 115.23	$ 32.67	-5.21%	-13.36%
998	0.123	0.077	0.046	0.007	0.068	0.012	0.122	0.077	0.220	0.246	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%	$ 16.00	$ 115.23	$ 32.67	-6.12%	-14.50%
999	0.059	0.009	0.007	0.005	0.011	0.196	0.154	0.156	0.328	0.075	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%	$ 16.00	$ 115.23	$ 32.67	3.93%	-3.45%

5.2.2 Distributor Model Analysis

The stochastic simulator is used to characterize the non-deterministic portions of a potential profits and loss statement. In this analysis, the Sobol Sequence is used to characterize the demand profile for different products. This variation in product demand leads to large variations in revenue earned, in turn leading to different financial outcomes. All scenarios are run over 1000 iterations of simulated demand distribution.

Figure 5-11 demonstrates the wide standard deviation of variable margin outcomes. As observed from the histogram of possible outcomes, there is a wide range which points to the inherent high risk of this contract. This does not even account for different deterministic contract parameters. For Illinois, the deterministic parameters of order size, freight fee, retailer markup, and service cost per order are fixed throughout the simulation. The range of outcomes is purely from fluctuation in demand. Figure 5-12 shows the same set of outcomes cumulatively. This visual highlights that the difference between the 25th percentile total variable margin (manufacturer + provider) and the 75th percentile margin is around 6% which is still a fairly wide range.

Figures 5-13 and 5-14 show the same results described above, but with data from

Ohio. The deterministic parameters are again fixed, but calibrated differently for Ohio. The service cost is different between the states because each state Medicaid can have different documentation and processing requirements, requiring a different level of effort to fulfill the prescription. The stochastic demand parameters are sampled from the Sobol sequence. The Ohio distribution represents a similar shape with a wide standard deviation, however the mean VM is 30% lower in Ohio than it was in Illinois. This is a demonstration of just how impactful the choice of state is to financial outcomes. The state ultimately determines the top line revenue, and the requirements from the state Medicaid or the insurance agency in that state affect the underlying Service Labor Cost per order.

5.2.3 Service Model Results

Figures 5-15, 5-16, 5-17, and 5-18 are generated for the stochastic service model for the states of OH and IL, each run on 1000 scenarios.

Figure 5-15: IL Service Model Possible Variable Margin Outcomes Under Stochastic Demand Profiles

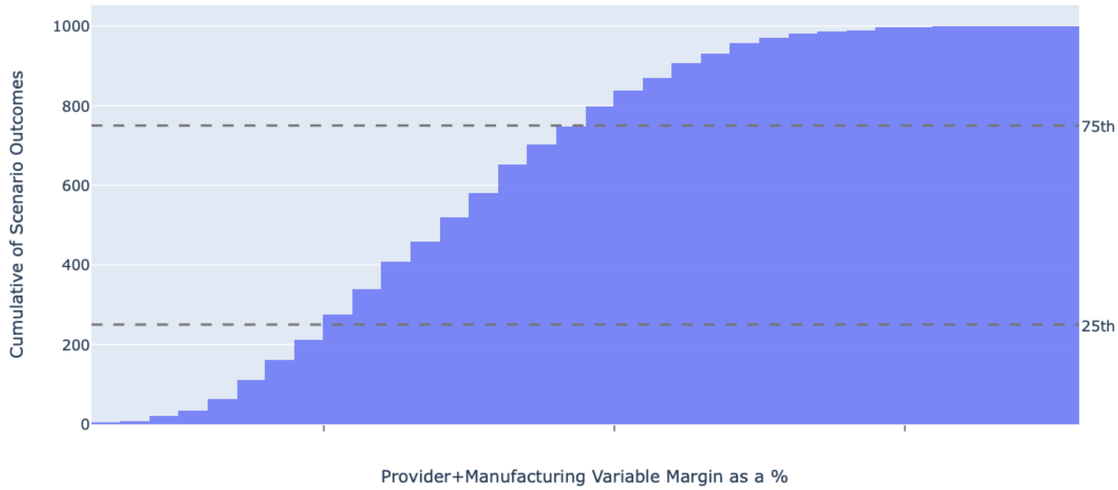

Figure 5-16: IL Service Model Cumulative Variable Margin Outcomes Under Stochastic Demand Profiles

Figure 5-17: OH Service Model Possible Variable Margin Outcomes Under Stochastic Demand Profiles

5.2.4 Service Model Analysis

Figures 5-15 and 5-16 show the results for the service model in Illinois, while Figures 5-17 and 5-18 show the results for the service model in Ohio. For the service model, since the Service Labor Cost ($) and Service Fee Charged are constants in the simulation, the variable margin for the service provider is a constant. This is displayed by a vertical line in Figures 5-15 and 5-17. The IncoMan Variable Margin, defined

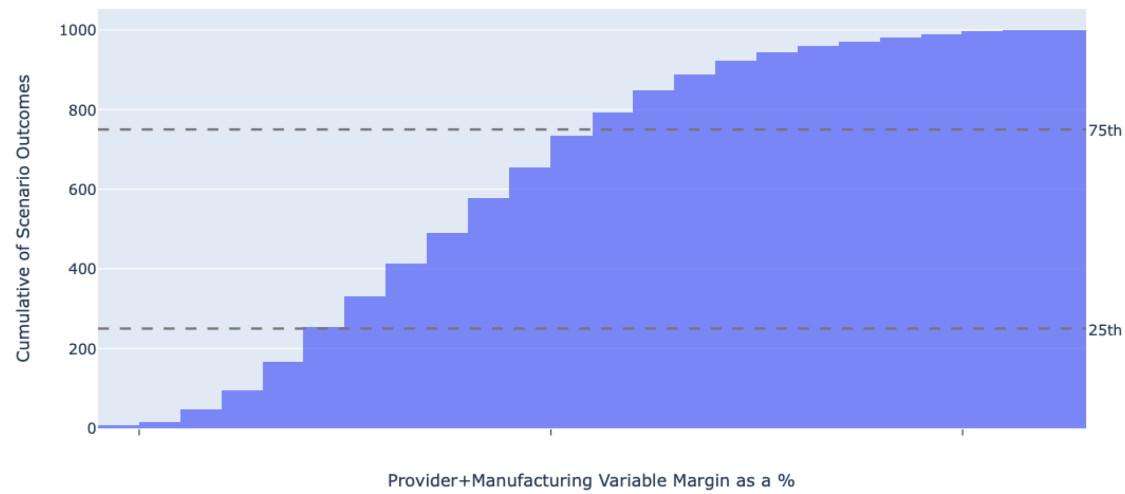

Figure 5-18: OH Service Model Cumulative Variable Margin Outcomes Under Stochastic Demand Profiles

as the manufacturer plus service provider margin, is however subject to fluctuation from demand. This is simply because some products in the demand assortment have lower margins and others have higher margins. A variable assortment will be supplied to the retailer. In addition, the customer will be serviced through the call center and guided through the diagnosis and prescription process in return for a service fee. The service model exhibits a much tighter standard deviation than the distributor model. The difference in the service model between the 25th percentile total variable margin (manufacturer + provider) and the 75th percentile margin is around 1.5%, significantly lower than the 6% range on the distributor model. There are smaller tails on both sides, and output is far more predictable. However, it is worth noting that this small range of profitability outcomes (roughly 1-2%) are highly dependent on choosing a profitable service fee and choosing a predictable service cost. The service model analysis does not quantify risks in inaccurate service cost and service fee scenarios, however that topic is covered in Limitations 6.2 and Future Works 6.3.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 6

Discussion of Results and Limitations

6.1 Comparing of Distributor and Service Models

These two models fundamentally carry different risks and rewards based on their assumptions. The distributor model overall has a higher risk but higher potential reward. The outcome is highly dependent on the realized demand profiles on consumers in various states. It is also highly dependent on the size of each order (revenue per order). In the distributor model, by increasing the order size (revenue per order) can significantly increase profit margins for IncoMan. Finally, the distributor model could have distinctly different profitability ranges based on the state and the agencies engaged, which can be seen from the agency comparisons.

In contrast, the service model is instead reliant on internal labor cost, processing efficiency, and agency requirements across the states. This will likely be more stable as time goes on; however, the stochastic variation from this is not accounted for in this model (see Section 6.2.1). The variation in demand and shipping distance is less of a factor for IncoMan in this model. While there is less variation in the results, it is also a more conservative strategy and likely to have a lower margin overall than the distributor model. The service model on the other hand is highly dependent on the assumption of internal service cost to serve the customer. This cost could also be sensitive to the state or the agency based on their documentation requirements. Along with an accurate assumption of costs comes the necessity for an appropriate service fee determined. An inappropriate gap between these two parameters would not create an economically viable return. It's important to understand internally all the costs which need to be covered by the service fee.

The major benefit to both of these models is that IncoMan is partnering with a major retailer for the D2C shipping and fulfillment of the products. Retailers would have more scale and better coverage than existing InocMan distribution networks. A large retailer is likely to have cheaper negotiated shipping rates and more efficient fulfillment operations than IncoMan. This efficiency helps both IncoMan and the retailer to retain more margin in both scenarios by working together from manufacturing, to service, to fulfillment.

6.2 Limitations

6.2.1 Data Limitations

As with most quantitative exercises, the results are only as good as the data input into the system. That is true for all modes of the model and simulator.

One noteworthy data limitation is the data on some of the product SKUs, specifically the XL bariatric sizes. These are a small percent of the overall demand profile (less than 1%) so they were excluded from the model and the simulator. The validation data was not a reliable predictor for revenue or profit and was excluded. However, it would be good to obtain additional data in order to include this SKU in future iterations.

Another data limitation is the service labor cost. While the company did have estimates for several years of service labor, due to some recent changes in their accounting methods, four years prior to 2022 were not accurate estimates of the actual cost to the business. Therefore, at this time there were only 6 months of service labor data available for 18 states. This is not much data, yet is a crucial parameter. Since some of the processes recently moved over to new IT systems, this is a risky estimate to carry over and should be considered carefully.

6.2.2 Model Limitations

The analysis in this report is limited to two models, distributor and service model. In the future the model could be expanded to adjust for additional contract types or contract parameters. The model currently only looks at gross margin and variable margin. In order to get to a lower level such as EBITDA margin, more information about fixed costs would be required. The model does not calculate the respective margins of the retailer/business partner, however it could be modified to do so.

6.3 Future Work

6.3.1 Data Augmentation

Several steps could be taken to augment the analysis. Primary improvement comes from improving data fidelity. Particularly when looking at cost parameters such as raw materials, freight, and direct labor costs, it is important to have accurate measures in place as these directly affect the profitability measures. Continuing to accurately capture these costs and project them in the future is crucial.

Another area in which the data could be sliced at a more granular level is the labor cost to service an order. This is currently done at a state level, however, it may be meaningful to evaluate if there are differences in time to service different insurance agencies within the same state. The integrity of this data would need to be validated as well, with D2C DiaperCo employees, who indicate some agencies require more work than others. So this would be valuable to break down in further detail in the model.

The data could also be expanded in the future by adding more insurance agencies and more product varieties. This would require getting reimbursement pricing and cost of goods sold for any additional items to be added to the model. This could be extended to products outside of the incontinence category as well.

6.3.2 Expanding Analysis Toolbox

Because this was a preliminary business proposal for a new venture, the analysis level was appropriate with the data available. Once the retail partner has been more thoroughly engaged and can provide more data points to better refine the parameters of the contract, more analysis can be done. For example, doing more aggregate analysis of several states combined into one financial outcome would be important once the project moves forward. Comparing and contrasting states and their plans would be a useful visualization to include as well as the combined income statement including all states. One might also wish to compare insurance agency plans across many states at a time instead of just one state in the future. Without engaging the retail partner in conversation on the detailed strategy, this cannot be done at this time but is recommended going forward.

Furthermore, the analysis could be expanded to include estimations of the retailer's gross margins and possibly variable margins to better conclude what would be a reasonable proposal from each side. Again, once engaging in deeper conversation with the retail partner, this exercise has more value as the inputs are no longer a guess. More realistic ranges can be set for future analysis.

6.3.3 Expanding Simulation Parameters

In future iterations, it would be valuable to expand the stochastic simulator for the service model. Currently, the stochastic simulated variables only cover demand. The service labor cost is variable and fluctuates from month to month and state to state. This would greatly impact the profitability of the service model. For that reason, including more random variation in the service labor cost would improve the robustness of the service model results.

6.3.4 User Experience

Finally, to improve the usefulness of this work, it could be built into a graphical user interface. This way, adaptations could be made in real-time by non-programmers.

Currently, the analysis is executed in Jupyter notebook, and it requires knowledge of Python. If a larger team wishes to use this in the future, having a more developed user interface would be helpful. Whether it is for this particular engagement or a different one, specifying realistic ranges of interest in real-time is necessary in order to inform business decisions.

THIS PAGE INTENTIONALLY LEFT BLANK

Chapter 7

Conclusion

Overall, the process of modeling the financial reimbursement structure with the team was one of the most valuable parts of this research. Regardless of the exact model outcomes, the knowledge of how to financially model the healthcare market will be used in future proformas by the business. The deterministic simulator results show the range of possible contract agreements for both the distributor and service contracts. Even from a preliminary look at these models with comparable parameters, it is clear that Illinois is a much more profitable state than Ohio, simply from the reimbursement rates in the state. The distributor contract is a more aggressive contract to make, with higher upsides and higher downsides. The service model has a tighter range of results. While the results look more consistent for the service contract, it hinges crucially on the retailer agreeing on a profitable service fee to cover the internal costs. If this internal cost is incorrectly estimated, Adult Incontinence Manufacturer in North America will need another way to recoup this cost.

In the end, the incontinence manufacturer IncoMan is not alone in its challenges. Other manufacturers and distributors face similar challenges of shrinking margins, inflation, supply chain issues that have eroded profitability in some markets. The approach of financial modelling and simulation is one that could be taken up more widely to help make data-driven decisions. In this case, the model created was specific to a healthcare product in the Medicaid market in America. However, the use of quantitative tools like python and historical data could be employed in many other domains to do more detailed financial modeling of complex markets. Adding in the stochastic simulator provides a way to start to quantify the uncertainties in the forecast and bound them. This gives a voice to the "known unknowns" that many other retailers and distributors face concerning consumer demand cycles. However, even with all the historical data in the world, it is impossible to accurately predict the future. It is even more difficult to predict future earnings in a business agreement that does not yet exist. IncoMan's approach to addressing uncertainty was to generate many scenarios, and provide meaningful visualizations that domain experts understand. The primary goal was to bring awareness to the range of possible outcomes. The secondary goal was empowering the executive team with the information to propose better contract agreements with future business partners. Both of these goals were achieved, and could be replicated using the same methods in other industry applications.

Appendix A

Tables

Table A.1: Sample Reimbursement Schedule by HCPC Code

Insurance Agency	HCPCS	Description	Reimbursement as a % of Max	State Medicaid Reimbursement	Insurance Agency Fee	Manufacturer Reimbursement
IL AGENCY 1	T4528	Large Underwear	100%	$1.00	$0.00	$1.00
IL AGENCY 2	T4528	Large Underwear	65%	$1.00	$0.35	$0.65
IL AGENCY 3	T4528	Large Underwear	100%	$1.00	$0.00	$1.00
IL AGENCY 4	T4528	Large Underwear	100%	$1.00	$0.00	$1.00
IL AGENCY 5	T4528	Large Underwear	73%	$1.00	$0.27	$0.73
IL AGENCY 6	T4528	Large Underwear	100%	$1.00	$0.00	$1.00
IL AGENCY 7	T4528	Large Underwear	80%	$1.00	$0.20	$0.80
IL AGENCY 8	T4528	Large Underwear	73%	$1.00	$0.27	$0.73
OH AGENCY 1	T4528	Large Underwear	84%	$0.84	$0.13	$0.71
OH AGENCY 2	T4528	Large Underwear	84%	$0.84	$0.13	$0.71
OH AGENCY 3	T4528	Large Underwear	59%	$0.84	$0.34	$0.50
OH AGENCY 4	T4528	Large Underwear	84%	$0.84	$0.13	$0.71

Appendix B

Simulator Details

$$C_{10} = \begin{bmatrix} 0.004322 & 0.000352 & 0.000169 & 0.000776 & -0.000443 & -0.001655 & -0.001765 & -0.001457 & 0.000186 & -0.000082 \\ 0.000352 & 0.000345 & 0.000028 & 0.000127 & 0.000104 & 0.000237 & 0.000237 & -0.000554 & -0.000695 & -0.000029 \\ 0.000169 & 0.000028 & 0.000167 & 0.000055 & -0.000225 & -0.000285 & -0.000312 & 0.000297 & 0.000184 & 0.000006 \\ 0.000776 & 0.000127 & 0.000055 & 0.000621 & -0.000182 & -0.000466 & -0.000504 & -0.001408 & 0.001208 & -0.000020 \\ -0.000443 & 0.000104 & -0.000225 & -0.000182 & 0.003874 & 0.001841 & 0.001320 & -0.002094 & -0.003868 & -0.000055 \\ -0.001655 & 0.000237 & -0.000285 & -0.000466 & 0.001841 & 0.007897 & 0.004859 & -0.004003 & -0.007804 & -0.000090 \\ -0.001765 & 0.000237 & -0.000312 & -0.000504 & 0.001320 & 0.004859 & 0.008242 & -0.003200 & -0.008193 & -0.000076 \\ -0.001457 & -0.000554 & 0.000297 & -0.001408 & -0.002094 & -0.004003 & -0.003200 & 0.015227 & -0.002877 & -0.000067 \\ 0.000186 & -0.000695 & 0.000184 & 0.001208 & -0.003868 & -0.007804 & -0.008193 & -0.002877 & 0.021660 & 0.000352 \\ -0.000082 & -0.000029 & 0.000006 & -0.000020 & -0.000055 & -0.000090 & -0.000076 & -0.000067 & 0.000352 & 0.000038 \end{bmatrix}$$

Figure B-1: Covariance Matrix for all HCPC Demand Data

Table B.1: OH Stochastic Simulator Log Pt. 1

	T4522	**T4523**	**T4524**	**T4543**	**T4525**	**T4526**	**T4527**	**T4528**	**T4535**	**T4541**
0	0.039	0.037	0.033	0.011	0.017	0.064	0.173	0.202	0.343	0.081
1	0.194	0.042	0.031	0.008	0.059	0.149	0.089	0.023	0.160	0.246
2	0.083	0.026	0.022	0.008	0.039	0.238	0.291	0.188	0.005	0.099
...	...	...	...	...	...	...	...	...	...	...
998	0.123	0.077	0.046	0.007	0.068	0.012	0.122	0.077	0.220	0.246
999	0.059	0.009	0.007	0.005	0.011	0.196	0.154	0.156	0.328	0.075

Some results have been redacted and set to 0.00 to maintain confidentiality.

Table B.2: OH Stochastic Simulator Log Pt. 2

	State	Agencys	Model Type	Manufact-urer Markup	Distributor Markup
0	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%
1	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%
2	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%
...	...	...	...	...	...
998	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%
999	OH	['OHAETNA', 0.5, 'OHCARE', 0.5]	distributor	17.5%	30.0%

Table B.3: OH Stochastic Simulator Log Pt. 3

	Freight Fee	Order Size	Service Cost	ManuProv VM	Prov VM
0	$ 16.00	$ 115.23	$ 0.00	0.00%	0.00%
1	$ 16.00	$ 115.23	$ 0.00	0.00%	0.00%
2	$ 16.00	$ 115.23	$ 0.00	0.00%	0.00%
...	...	...	...	...	...
998	$ 16.00	$ 115.23	$ 0.00	0.00%	0.00%
999	$ 16.00	$ 115.23	$ 0.00	0.00%	-0.00%

Table B.4: IL Stochastic Simulator Log Pt. 1

	T4522	T4523	T4524	T4543	T4525	T4526	T4527	T4528	T4535	T4541
0	0.045	0.032	0.016	0.013	0.008	0.211	0.157	0.075	0.326	0.118
1	0.043	0.029	0.021	0.006	0.004	0.084	0.112	0.034	0.411	0.257
2	0.180	0.056	0.012	0.002	0.088	0.124	0.088	0.024	0.028	0.398
...	**...**	**...**	**...**	**...**	**...**	**...**	**...**	**...**	**...**	**...**
997	0.038	0.020	0.014	0.015	0.007	0.074	0.126	0.115	0.341	0.251
998	0.003	0.039	0.033	0.006	0.023	0.047	0.140	0.061	0.363	0.285
999	0.053	0.018	0.017	0.007	0.029	0.070	0.208	0.077	0.177	0.344

Table B.5: IL Stochastic Simulator Log Pt. 2

	State	Agencys	Model Type	Manufacturer Markup	Distributor Markup
0	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	17.5%	30.0%
1	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	17.5%	30.0%
2	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	17.5%	30.0%
...	...	...	...	...	...
997	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	17.5%	30.0%
998	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	17.5%	30.0%
999	IL	['ILAETNA', 0.019, 'ILBCBS', 0.051, 'ILBCBS2', 0.021, 'ILHUMANA', 0.011, 'ILILLINCAR', 0.044, 'ILMED', 0.591, 'ILMERIDIAN', 0.148, 'ILMERIDYOU', 0.01, 'ILMOLINA', 0.081, 'ILYOUTHCAR', 0.024]	distributor	17.5%	30.0%

Table B.6: IL Stochastic Simulator Log Pt. 3

	Freight Fee	Order Size	Service Cost	ManuProv VM	Prov VM
0	\$ 16.00	\$ 134.29	\$ 0.00	0.00%	0.00%
1	\$ 16.00	\$ 134.29	\$ 0.00	0.00%	0.00%
2	\$ 16.00	\$ 134.29	\$ 0.00	0.00%	0.00%
...	\$ 16.00	\$ 134.29	\$ 0.00	0.00%	0.00%
997	\$ 16.00	\$ 134.29	\$ 0.00	0.00%	0.00%
998	\$ 16.00	\$ 134.29	\$ 0.00	0.00%	0.00%
999	\$ 16.00	\$ 134.29	\$ 0.00	0.00%	0.00%

THIS PAGE INTENTIONALLY LEFT BLANK

Bibliography

[1] Elizabeth Arias and Farida B Ahmad. "Provisional Life Expectancy Estimates for 202". en. In: (Aug. 2022). URL: https://www.cdc.gov/nchs/data/vsrr/vsrr023.pdf.

[2] Gail Christopher et al. "The State of Obesity: Better Policies for a Healthier America 2022". en. In: *Trust for America's Health* (Sept. 2022).

[3] Michael Crum and Charles Rayhorn. "Using Monte Carlo Simulation for Pro Forma Financial Statements". en. In: *Journal of Accounting and Finance* 19.5 (Sept. 2019). ISSN: 2158-3625, 2158-3625. DOI: 10.33423/jaf.v19i5.2248. URL: https://articlegateway.com/index.php/JAF/article/view/2248 (visited on 02/20/2023).

[4] Jonathan Feinberg. *jonathf/chaospy*. original-date: 2014-08-11T17:54:25Z. Feb. 2023. URL: https://github.com/jonathf/chaospy (visited on 02/24/2023).

[5] Jonathan Feinberg, Vinzenz Gregor Eck, and Hans Petter Langtangen. "Multivariate Polynomial Chaos Expansions with Dependent Variables". en. In: *SIAM Journal on Scientific Computing* 40.1 (Jan. 2018), A199–A223. ISSN: 1064-8275, 1095-7197. DOI: 10.1137/15M1020447. URL: https://epubs.siam.org/doi/10.1137/15M1020447 (visited on 02/04/2023).

[6] *GLG Market Research*. 2019. URL: https://glginsights.com/insights/tags/market-research/ (visited on 04/09/2023).

[7] Michelle Hanlon, Robert Magee, and Glenn Pfeiffer. *Financial Accounting, 7e*. Seventh Edition. Cambridge Business Publications, Jan. 2023. ISBN: 978-1-61853-431-6.

[8] Shin Harase. "Comparison of Sobol' sequences in financial applications". In: *Monte Carlo Methods and Applications* 25.1 (Mar. 2019). arXiv:1809.03122 [cs, math, stat], pp. 61–74. ISSN: 0929-9629, 1569-3961. DOI: 10.1515/mcma-2019-2029. URL: http://arxiv.org/abs/1809.03122 (visited on 02/20/2023).

[9] Change Healthcare. *Value-Based Care in America: State-by-State*. en. Apr. 2019. URL: https://www.pcpcc.org/resource/value-based-care-america-state-state (visited on 02/01/2023).

[10] Elizabeth Hinton, Lina Stolyar Published: Feb 23, and 2022. *10 Things to Know About Medicaid Managed Care*. en-US. Feb. 2022. URL: https://www.kff.org/medicaid/issue-brief/10-things-to-know-about-medicaid-managed-care/ (visited on 02/14/2023).

[11] Takuya Iwanaga, Will Usher, and Jon Herman. *Toward SALib 2.0: Advancing the accessibility and interpretability of global sensitivity analyses*. Issue: 1 Pages: 1–15 Publication Title: Socio-Environmental Systems Modelling Volume: 4 original-date: 2013-05-30T13:38:10Z. May 2022. DOI: 10.18174/sesmo.18155. URL: https://github.com/SALib/SALib (visited on 02/24/2023).

[12] Heather Landi. *One Medical Bought Out by Amazon in $3.9B all-cash deal | Fierce Healthcare*. July 2022. URL: https://www.fiercehealthcare.com/health-tech/amazon-shells-out-39b-primary-care-startup-one-medical (visited on 02/04/2023).

[13] Kate Litvak. "Monte Carlo Simulation of Contractual Provisions: An Application to Default Provisions in Venture Capital Limited Partnership Agreements". en. In: *Cornell Law Review* 98.6 (2013), p. 1495. ISSN: 0010-8847. URL: https://scholarship.law.cornell.edu/clr/vol98/iss6/5 (visited on 02/24/2023).

[14] Elijah Alden Malaby and John Licato. "Exploring Monte Carlo Negotiation Search with Nontrivial Agreements". In: *The International FLAIRS Conference Proceedings* 34.1 (Apr. 2021). ISSN: 2334-0762. DOI: 10.32473/flairs.v34i1.128504. URL: https://journals.flvc.org/FLAIRS/article/view/128504 (visited on 02/24/2023).

[15] Emanuel Parzen. "On Estimation of a Probability Density Function and Mode". en. In: *The Annals of Mathematical Statistics* 33.3 (Sept. 1962), pp. 1065–1076. ISSN: 0003-4851. DOI: 10.1214/aoms/1177704472. URL: http://projecteuclid.org/euclid.aoms/1177704472 (visited on 02/24/2023).

[16] Walgreens Media Relations. *Walgreens Boots Alliance Accelerates Full Acquisition of CareCentrix*. en. Oct. 2022. URL: https://news.walgreens.com/press-center/walgreens-boots-alliance-accelerates-full-acquisition-carecentrix.htm (visited on 02/04/2023).

[17] Eli Richman. *CVS closes $69B acquisition of Aetna in a 'transformative moment' for the industry*. en. Section: Fierce Healthcare Homepage, Health Tech, Hospitals, Practices, Finance, Regulatory. Nov. 2018. URL: https://www.fiercehealthcare.com/payer/cvs-closes-69-billion-acquisition-aetna (visited on 02/04/2023).

[18] M. Rosenblatt. "A CENTRAL LIMIT THEOREM AND A STRONG MIXING CONDITION". en. In: *Proceedings of the National Academy of Sciences* 42.1 (Jan. 1956), pp. 43–47. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.42.1.43. URL: https://pnas.org/doi/full/10.1073/pnas.42.1.43 (visited on 02/24/2023).

[19] Satta Sarmah Hightower. *What Is the Future of Omnichannel Retail? | Salsify*. Feb. 2021. URL: https://www.salsify.com/blog/what-is-future-of-omnichannel-retail?hs_amp=true&utm_term=&utm_campaign=Dynamic+Search+Ads+-+NA&utm_source=adwords&utm_medium=ppc&hsa_acc=3845902118&hsa_cam=11827556306&hsa_grp=141301972929&hsa_ad=

608846596552&hsa_src=g&hsa_tgt=dsa-1499812326424&hsa_kw=&hsa_mt=&hsa_net=adwords&hsa_ver=3&gclid=Cj0KCQiAofieBhDXARIsAHTTldpU7QjiHvOP-mGubbL5ummj8iNCATYFMxinSJqRv_8SvK7dBNrhbuIaAt78EALw_wcB (visited on 02/04/2023).

[20] I.M Sobol'. "On the distribution of points in a cube and the approximate evaluation of integrals". en. In: *USSR Computational Mathematics and Mathematical Physics* 7.4 (Jan. 1967), pp. 86–112. ISSN: 00415553. DOI: 10.1016/0041-5553(67)90144-9. URL: https://linkinghub.elsevier.com/retrieve/pii/0041555367901449 (visited on 02/20/2023).

[21] Holly Stanley. *Shipping trends 2023: Key trends for retailers to watch this year*. en. Nov. 2022. URL: https://www.shopify.com/enterprise/freight-container-shipping-trends (visited on 02/04/2023).

[22] Nassim Nicholas Taleb. *The Black Swan : the impact of the highly improbable*. Random House Trade Paperbacks, 2010. ISBN: 978-0-8129-7381-5.

[23] Simen Tennøe. *A python toolbox for uncertainty quantification and sensitivity analysis tailored towards computational neuroscience.* original-date: 2015-04-23T16:17:46Z. Jan. 2023. URL: https://github.com/simetenn/uncertainpy (visited on 02/24/2023).